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Analysing Motion Characteristics and Metabolic Power in Elite Male Handball Players

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Abstract

This study analysed physiological demands of male handball players based on position data from 77 professional handball matches from the German Handball Bundesliga. Distance covered by wings, backcourts, and pivots in different velocity zones and metabolic power were investigated. Results showed that total distance covered varied with playing position with wings covering 3568 ± 1459 m in 42 ± 17 min, backs covering 2462 ± 1145 m in 29 ± 14 min, and pivots covering 2445 ± 1052 m in 30 ± 13 min per game. Wings covered more distance using greater running velocities than backs and pivots, while backs covered the largest distance per minute playing time. Distance covered and equivalent distance showed moderate to large interaction effects between wings and backs ($p < .01$, ES = 0.73) and between wings and pivots ($p < .01$, ES = 0.86). The results underline the need for an individualized management of training loads and the potential of using information about locomotion accelerations and decelerations to obtain more precise descriptions of physiological demands underlying handball game performance at the highest level of competition. Future studies should investigate the influence of physical performance on smaller match sequences, like ball possession phases.

Keywords: position data; performance analysis; big data, LPS, player load

Introduction

In complex team sports like handball, analysis of player load during competition is a challenging task. However, correctly assessing load and physiological requirements underlying successful game performance is critical for efficient training regimes to optimize performance and prevent injuries (Akenhead & Nassis, 2016; Bourdon et al., 2017; Miguel et al., 2021). Game performance in handball is characterized by repeated sprints, cutting movements, jumps, tackles, and throws (Karcher & Buchheit, 2014). Therefore, multidirectional movement behaviour has to be included when analysing player load. Recent approaches, like the metabolic power concept, use instantaneous velocities and accelerations from position data to model player load (di Prampero & Osgnach, 2018), which promises a more precise analysis of player load in team sports. In contrast to other team sports, like football (Rein & Memmert, 2016), less research on time-motion data has been done in handball using large samples of high-quality position data. The present study therefore investigates player load in high-performance team handball using position data from the German Men's Handball Bundesliga and compares different player load modelling approaches to provide important information for practitioners.

Related Work

Recent work analysed player load during official team handball matches with similar methodologies. Cardinale et al. (2017) analysed position data from 384 players during the Handball World Cup 2015 (n = 88). Time on court and total distance covered as well as distance covered in six velocity zones for each field position (left wing, left back, centre back, pivot, right back, and right wing) was reported. Büchel et al. (2019) analysed 176 players during 16 league games of German Bundesliga season 2015/16. Time on court and distance covered, as well as distances covered in five velocity zones were investigated. Comparisons across positions (backcourts vs wings vs pivots), half (fist vs second), playing time (low vs high) revealed a slight decrease of average speed and time spent running in the second vs. first half. Wings covered greater distance (4057 m) than backs (2882 m) and pivots (2702 m). Velocity profiles were associated with playing duration where shorter playing duration groups spent more time in high velocity zones and vice versa, implying more intense game performance with less time on court (Büchel et al., 2019). However, due to the relatively small sample size, results might have been biased towards the performing home team. The data exhibited relatively large coefficients of variation (5.1% for distances and 3.1% for speed; Jakobsmeyer, Rasmus et al., 2013) which may be problematic especially at high running velocities (Scott et al., 2016). González-Haro et al. (2020) analysed position data from 19 players during one game of the Spanish 2nd Division (4th league). Several load measures, including distance covered in five velocity zones, maximum velocities and number of accelerations and decelerations were analysed. The results showed equal distances per minute for low to moderate intensity running and low to moderate acceleration variables when normalized by time on court. Wings covered larger distances per minute in high intensity running than pivots, backs, centre backs, and defence specialists. Wings also performed greater maximum accelerations compared to pivots and backs and more high accelerations (> 3m · s-2) per minute. Although the sample size was rather small and therefore might have been influenced by match tactics (e.g., a 5:1 defensive system; González-Haro et al., 2020). Manchado et al. analyzed 40 players during the European Champions League Final Four games (2020) as well as 414 players in 65 matches during the EURO 2020 (2021). They analysed time on court and distances covered in six velocity zones for each position left wing, left back, centre back, right back, right back, line player (pivot) and compared players during offense and defence. However, the high competition density during tournaments may pose difficulties when generalizing results to less dense competition, like league play (Manchado et al., 2021).

All studies measured distance covered in different intensity zones (standing – sprinting) differentiated by playing positions. Similar outcomes were found between wing players and all other positions. Wing players cover statistically significantly greater distances in general as well as at higher speeds (Büchel et al., 2019; Cardinale et al., 2017; González-Haro et al., 2020; Manchado et al., 2020, 2021). In contrast, centre backs and pivots perform more shots, goals and tackles (Cardinale et al., 2017). Overall, most distances were covered at low intensities either walking or jogging. Despite those similarities in respect to playing position, absolute magnitudes differed between the studies (Manchado et al., 2021). Manchado et al. (2021; EURO 2020) reported 15% less time on pitch and 22% less distance covered than Manchado et al. (2020; Champions League Final Four) and even 28% less time on pitch and 19% less distance covered than Cardinale et al. (2017; World Cup 2015). These differences may be in parts due to differences in the used tracking technologies (Gómez-Carmona et al., 2020) as well as competition mode. During a tournament with high match frequency, more substitutions might take place (Manchado et al., 2021). Also, individual and team tactics have to be taken into account, when comparing small samples, like González-Haro et al. (2020; 1

game) or Manchado et al. (2020; 4 games). Therefore, generalization of findings to league matches may be limited. Accordingly, more studies investigating league matches with appropriate sample sizes are necessary to characterize player load during this major part of the season.

One problem pertaining to previous studies stems from the use different cut-off values with respect to running velocities (5 zones; Büchel et al., 2019 vs. 6 zones; Manchado et al., 2021) makes comparisons problematic (Bradley & Ade, 2018). Even though there is a large variety of different speed zones to choose from (see Miguel et al., 2021 for a comprehensive review), it is questionable if any 'one size fits all' model can capture the complex relationship between individual physical capacity and game demands. Distance covered at certain intensities further gives relatively little insight into player load during handball because of player's frequent accelerations and decelerations made which are not captured. Energy demands may be up to 12 times greater during maximum accelerations compared to constant sprint running (di Prampero et al., 2005). Similar, change of direction movements pose high demands on the lower extremities (Dos'Santos et al., 2018) which are not captured using velocity zones. Thus, using instantaneous velocity and acceleration seems more appropriate to assess physiological load during game play (Polglaze & Hoppe, 2019).

One possible approach is the concept of metabolic power (MP). MP is defined as the energy expenditure per unit of time necessary to move at a certain speed, and is calculated as the product of energy cost of transport, per unit body mass and distance (J · kg-1 · m-1) and velocity (m · s-1) (di Prampero & Osgnach, 2018). In football, the MP approach has been used to monitor player load during training (Guerrero-Calderón et al., 2021; Manzi et al., 2014) and competition (Malone et al., 2017; Nobari et al., 2021; Reche-Soto et al., 2019). The measure was first introduced by di Prampero et al. (2005), who used the biomechanical equivalence of accelerated (or decelerated) running on flat terrain and constant running uphill (or downhill) to estimate the energy requirement for a specific displacement. Since then it has been widely discussed for its validity (Polglaze & Hoppe, 2019) and used in several studies to characterize player load (Miguel et al., 2021). Although generally seen as an improvement in player load characterization, previous results have to be considered carefully. The original model was cautioned by the authors because its' formulation might overestimate player load as every locomotion is assumed to be performed running (di Prampero & Osgnach, 2018). However, typically a fair amount of locomotion is actually done walking, which is more energy efficient at constant, low velocities. The authors updated the model accordingly which led to a 13.7% lower energy cost estimate (di Prampero & Osgnach, 2018). Accordingly, the updated and combined concept of MP provides a more realistic estimate of player load during game play.

Conceptually, the assessment of MP faces another problem, as the model frequently involves usage of high-degree polynomials (4th or 5th) to fit the data. This is the case for both the original model (di Prampero et al., 2005) and the updated model (di Prampero & Osgnach, 2018). To address this problem, Minetti and Pavei (2018) proposed a new model for running, which uses an exponential and a linear term to give stable and valid results for large range of accelerations. Unfortunately, di Prampero et al. (di Prampero & Osgnach, 2018) did not implement Minetti and Pavei (2018)'s new function, nor did Minetti and Parvei (Minetti & Pavei, 2018) model data for walking. However, as the model itself is modular, the updated models can be merged. In summary, using a MP approach to assess physiological load in handball game performance appears warranted. To circumvent some of the problems of the earlier formulation of the MP approach the new model should be used.

The aim of this study is to characterize player load in elite team handball players. We report different player load models using a large sample (N = 77 games). Large data samples are crucial for match analysis to get accurate insights that are representative for the level and mode of competition (Lepschy et al., 2020). We compare previous approaches using distance covered in different velocities to the novel approach of MP to get further insights into total and individual player load. Loads are then compared across different playing positions. We analyse the predictive power of running performance for the match result. We expect to confirm general findings of the related work regarding distances covered by different player roles but will expand them in multiple ways:

First, we will set an accurate benchmark for player load in elite handball league matches. Second, we make detailed description of various load measures to be able to compare player load within handball as well as different team sports. Third, we investigate the predictive power of running performance for game success, as it has been discussed controversially (Klemp et al., 2021; Lepschy et al., 2020). Finally, since the game of wings is characterized by more high intensity accelerations (González-Haro et al., 2020), we expect that total distance underestimates wing players demands compared to equivalent distance from the MP model.

Methods

Subjects

Data from 290 male field players of 18 teams during 77 games of the 2019/20 German Men's Handball Bundesliga (HBL) were analysed. In total of 1102 observations were analysed. Anthropometric data is presented in Table 1. Data was collected by SportsRadar (St. Gallen, Switzerland) and made available through the HBL. For position-specific differences, the participants were split according to their playing role (wings, backcourts, pivots). The institutional review board approved all procedures, in the spirit of the Helsinki Declaration.

Table 1: Anthropometric data of the players as mean ± standard deviation.

Position	n	Height	Body Mass	BMI	Age
Wings	80	184.8 ± 4.7	83.9 ± 5.2	24.6 ± 1.3	28.0 ± 4.5
Backs	158	194.1 ± 6.2	96.9 ± 8.5	25.7 ± 1.5	28.3 ± 4.9
Pivots	52	196.4 ± 4.3	108.1 ± 8.0	28.0 ± 2.0	29.6 ± 4.0
Total	290	191.9 ± 7.1	95.3 ± 11.1	25.8 ± 1.9	28.5 ± 4.6

Instruments

Position data was collected using the LPS KINEXON ONE (KINEXON GmbH, Munich, Germany) system at 20 Hz. Accuracy of the system is estimated to lie around 0.1 m (see Blauberger et al., 2021; Fleureau et al., 2020; Hoppe et al., 2018 for detailed description and validity). Sensors were worn by the players between their shoulders. The system was installed and calibrated by the manufacturer for all matches. Data recording interrupted by a trained operator when the game clock was inactive during game stoppages (e.g., fouls).

Data Processing

The raw position data was smoothed using a Butterworth low pass filter (4th degree, cut-off 1 Hz) following Linke et al. (2020). Velocity and acceleration for every frame were calculated via central difference method. For every player, time on court was determined as the time his sensor was tracked by the LPS, as each sensor was only tracked while on the pitch and when game clock was running. Percentages of time spent and total distance covered in different velocity zones were calculated. The zones were (1) standing (< 1 m·s-1); (2) walking

(1 – 2 m·s-1); (3) jogging (2 – 4 m·s-1); running (4 – 5.5 m·s-1); high-intensity running (5.5 – 7 m·s-1); sprinting (> 7 m·s-1) following Manchado et al. (2020, 2021).

MP variables were calculated following di Prampero & Osgnach (2018) using the modified formula from Minetti & Pavei (2018). Dependent variables calculated were: (1) Metabolic work (total and per minute); (2) Equivalent distance (total and per minute), (3) Equivalent distance index; (4) Time spent running; (5) Energy spent running; (6) Time over 10 W; (7) Time over 20 W. Absolute equivalent distance and distance covered on a team level and match outcome as the score line was calculated for every match.

Statistical Analysis

All analyses were done using Python 3.8 (Python Software Foundation, Wilmington, Delaware, US) using pingouin v0.5.0 (Vallat, 2018) for statistical analyses. Visual inspection of histograms and QQ-plots were used to test normal distribution of the data. As the data was not normally distributed, Welch ANOVA with Games-Howell adjusted post-hoc test was performed to analyse differences between the roles for every dependent variable. For MP, differences between distance and equivalent distance was analysed using a 2 (distance vs. equivalent distance) by 3 (wings vs. backs vs. pivots) mixed-effects ANOVA. In case of statistically significant effects post-hoc tests were performed using a Bonferroni adjustment. To analyse the relationship between physical performance and match outcome, a linear regression between distance covered and score line, and between equivalent distance and score line was conducted. Cohen's d was calculated to estimate the effect size and interpreted as < 0.5 = small effect, 0.5 – 0.8 = moderate effect, > 0.8 = large effect. Statistical significance was set at $\alpha = 0.05$.

Results

Descriptive results for each dependent variable by player role are presented in Tab. 2. Fig. 1 presents the influence of player role on total player load. The graph shows absolute distances covered separated by velocity zones and player roles. On average, wings cover the largest distances in all velocity zones. While all player roles cover the largest distances in the low intensity zones, only wings cover a substantial amount of distance in high intensity running and sprinting. Fig. 2 shows the intensity distribution of running as time spent in velocity zones normalized by total playing time. When controlled for playing time, backs cover longer distances walking and jogging. However, wings also cover higher distances per minute running, high intensity running, and sprinting. The mixed-effects ANOVA for distance and equivalent distance revealed statistically significant group ($F(2, 262) = 16.77$; $p < .01$), distance ($F(1, 262) = 932.55$; $p < .01$), and interaction ($F(2, 29.82)$; $p < .01$) effects. Post-hoc analysis showed a significant group effect between wings vs. backs ($t(689) = 14.04$; $p < .01$; $d = 0.92$), wings vs. pivots ($t(737) = 12.99$; $p < .01$; $d = .92$), but no group effect between backs vs. pivots ($t(689) = 0.60$; $p = 1$). Repeated measure effects between distance and equivalent distance were significant for wings ($t(410) = 29.30$; $p < .01$; $d = 0.32$), backs ($t(902) = 39.13$; $p < .01$; $d = 0.25$), and pivots ($t(350) = 22.83$; $p < .01$; $d = 0.23$). Interaction effect for groups and (equivalent) distance were significant for wings vs. backs ($t(582) = 10.67$; $p < .01$; $d = 0.73$), wings vs. pivots ($t(682) = 12.28$; $p < .01$; $d = 0.86$), and backs vs. pivots ($t(710) = 3.70$; $p < .01$; $d = 0.22$), meaning that differences between distance and equivalent distance were greater for wings than for backs and pivots by moderate to large effect sizes.

The linear models for both distance ($r = .03$; $p = .67$) and equivalent distance ($r = .05$; $p = .50$) did not indicate an association with the score line.

Table 2: Descriptive results for every dependent variable as mean ± standard difference.

	Unit	Wings	Backs	Pivots
n		411	903	351
Time				
On court	min	41.90 ± 17.31 ^{BP}	28.67 ± 13.75 ^{W}	30.39 ± 13.36 ^{W}
Standing	%	0.55 ± 0.05 ^{BP}	0.47 ± 0.08 ^{WP}	0.53 ± 0.05 ^{WB}
Walking	%	0.25 ± 0.04 ^{BP}	0.30 ± 0.05 ^{WP}	0.27 ± 0.04 ^{WB}
Jogging	%	0.10 ± 0.02 ^{BP}	0.16 ± 0.03 ^{WP}	0.13 ± 0.02 ^{WB}
Running	%	0.06 ± 0.01 ^{BP}	0.05 ± 0.01 ^{W}	0.05 ± 0.01 ^{W}
HI Running	%	0.03 ± 0.01 ^{BP}	0.01 ± 0.01 ^{WP}	0.01 ± 0.01 ^{WB}
Sprinting	%	0.01 ± 0.00 ^{BP}	0.00 ± 0.00 ^{WP}	0.00 ± 0.00 ^{WB}
Distance				
Total	m	3567.89 ± 1458.96 ^{BP}	2462.20 ± 1144.71 ^{W}	2445.01 ± 1052.20 ^{W}
Per minute	m/min	85.73 ± 6.81 ^{BP}	87.36 ± 10.79 ^{WP}	81.26 ± 6.54 ^{WB}
Standing	m	626.60 ± 266.10 ^{BP}	442.73 ± 231.93 ^{W}	499.33 ± 229.88 ^{W}
Walking	m	867.82 ± 399.52 ^{BP}	733.09 ± 366.95 ^{W}	702.13 ± 321.44 ^{W}
Jogging	m	755.89 ± 319.02 ^{P}	760.42 ± 354.64 ^{P}	671.66 ± 295.91 ^{WB}
Running	m	719.20 ± 310.76 ^{BP}	402.19 ± 197.52 ^{W}	429.88 ± 206.43 ^{W}
HI Running	m	502.07 ± 234.54 ^{BP}	115.86 ± 75.43 ^{WP}	138.00 ± 80.67 ^{WB}
Sprinting	m	96.31 ± 66.03 ^{BP}	7.90 ± 10.77 ^{WP}	4.02 ± 7.40 ^{WB}
Metabolic Power				
Metabolic Work abs	J/kg	14661.02 ± 5921.38 ^{BP}	9954.84 ± 4508.80 ^{W}	9712.75 ± 4151.38 ^{W}
Metabolic Work rel	J/kg/min	356.28 ± 52.74 ^{P}	358.31 ± 61.83 ^{P}	325.08 ± 37.78 ^{WB}
Eq Distance abs	m	4072.50 ± 1644.83 ^{BP}	2765.23 ± 1252.44 ^{W}	2697.98 ± 1153.16 ^{W}
Eq Distance rel	m/min	98.97 ± 14.65 ^{P}	99.53 ± 17.17 ^{P}	90.30 ± 10.49 ^{WB}
Eq Distance index	%	1.15 ± 0.11 ^{BP}	1.14 ± 0.10 ^{WP}	1.11 ± 0.08 ^{WB}
Time spent running	%	0.21 ± 0.03 ^{BP}	0.22 ± 0.04 ^{WP}	0.20 ± 0.03 ^{WB}
Energy spent running	%	0.67 ± 0.04 ^{BP}	0.62 ± 0.05 ^{WP}	0.60 ± 0.04 ^{WB}
Time over 10 W	min	6.01 ± 2.43 ^{BP}	4.11 ± 1.86 ^{W}	4.04 ± 1.71 ^{W}
Time over 20 W	min	2.48 ± 1.02 ^{BP}	1.47 ± 0.66 ^{W}	1.41 ± 0.59 ^{W}

W/B/P: Statistically significant difference to Wings/Backs/Pivots. Eq = Equivalent; abs = absolute; rel = relative; HI = High intensity; W = Watts

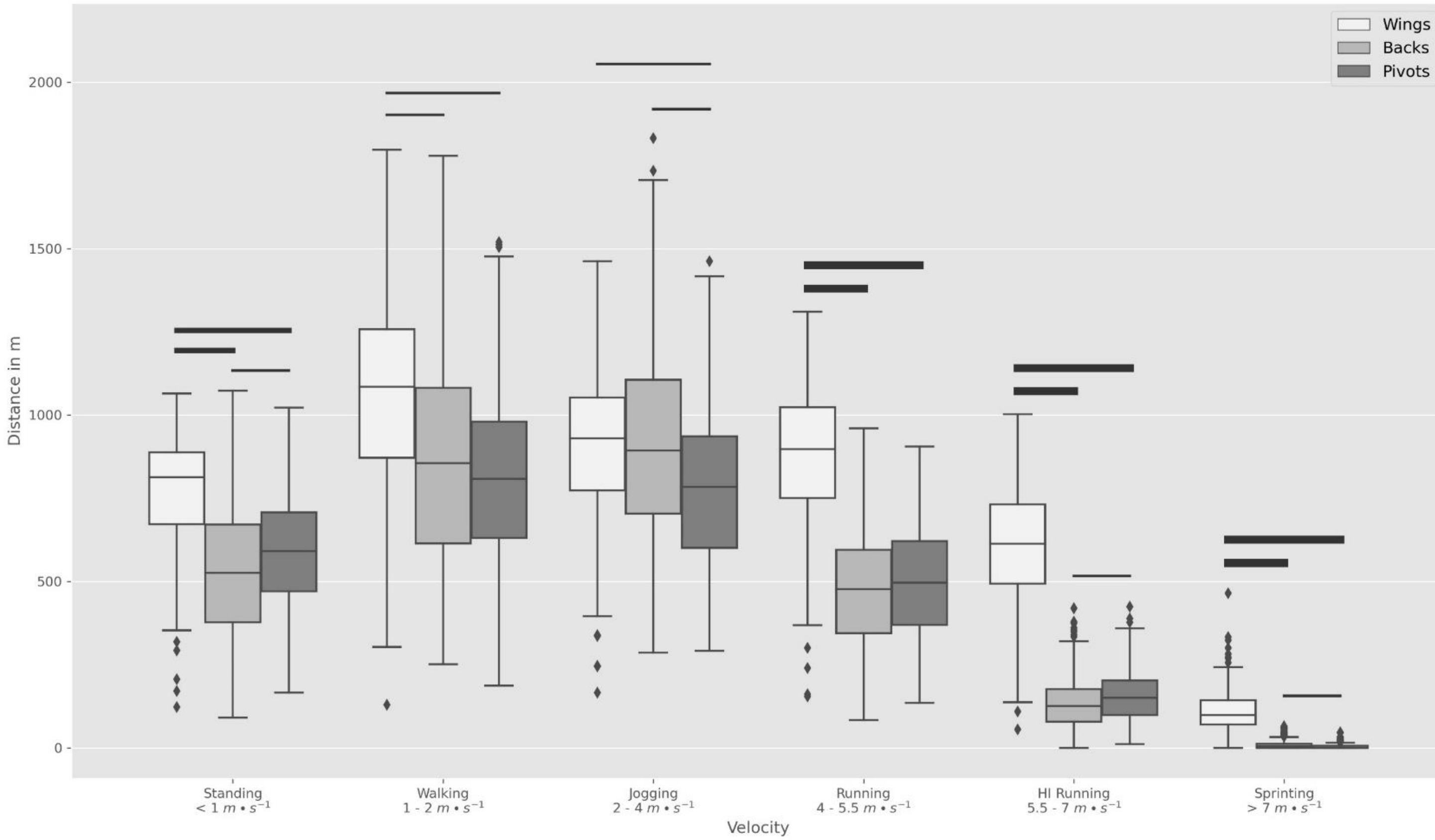

Figure 1: Distance covered in different velocity zones by player roles. Bars indicate statistically significant effect. The thickness of the bar indicates the effect size. Thin line = small effect; medium line = moderate effect, thick line = large effect.

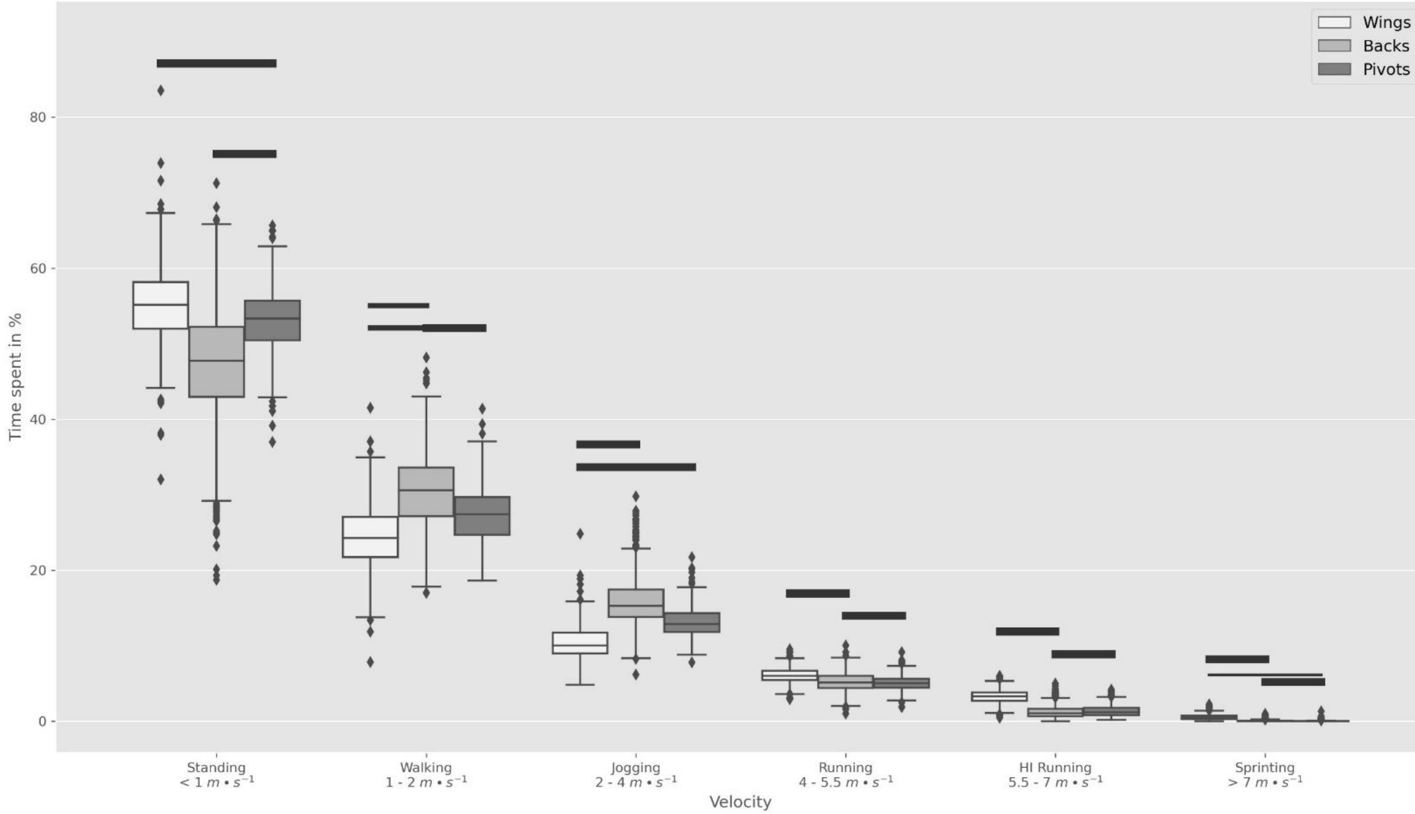

Figure 2: Time spent in different velocity zones by player roles as a percentage of total time on court. Bars indicate statistically significant effect. The thickness of the bar indicates the effect size. Thin line = small effect; medium line = moderate effect, thick line = large effect.

Discussion

The aim of this study was to analyse physiological demands of professional handball league matches and its influence on match outcome. The result confirmed our assumption, that wings cover longest distances and reach highest velocities compared to backs and pivots. However, distance covered still underestimates player load of wings in comparison to equivalent distance.

Compared to the results reported by Manchado et al. (2021), total distance covered is greater for wings (3567 m vs. ~2400 m; 48 %), backs (2462 m vs. ~2000 m; 23%) and pivots (2445 m vs. 1835 m; 33%). Competition specific differences have been observed previously and may be due to different load management strategies depending on match demands and competition density. Although slightly lower, our results are similar to the findings by Büchel et al. (2019), who observed 16 home matches of one team in the German Handball Bundesliga. They found greater time on court and therefore longer total distances covered for all players. However, similar to our result, about 80% of time was spent using velocities of under 2 m·s-1 for all positions. The differences may be due to the different sample sizes. Further, in the present study, time spent and distances covered during game stoppages were excluded from the analysis resulting in 24.3% excluded frames. However, it seems reasonable to assume few high intensity actions were performed during these periods and inclusion of game stoppages would rather lead to a bias and underestimation of real game demands (Mernagh et al., 2021).

The comparison of total distance and equivalent distance showed moderate to large interaction effects between wings vs. pivots and wings vs. backs, while the interaction between pivots vs. backs was trivial. This confirms our expectation that the game intensity of wings compared to backs and pivots is more precisely characterized by the MP model. The comparison of time spent and respective energy spent running leads to similar results. All positions spend about 21% of their time running, however, wings spent 67% energy running, which is substantially more than backs (62%) and pivots (60%). Time spent over 10 and 20 W was longer for wings than pivots and backs but not different between backs and pivots. These findings confirm that wings cover more distance due to longer times on court and cover longer distances at higher velocities, but that their velocity profiles differ substantially from the other positions. Accordingly, individual player load estimates should include measures of accelerations and deceleration.

Related studies in football show a 3-5 times greater distances covered (~ 5000 m per half during professional pre-season matches; Hoppe et al., 2017) and up to 4-5 times greater energy expenditure (~ 47.5 kJ per game during Italian Serie A matches di Prampero & Osgnach, 2018). Di Pramero and Osgnach (2018) report 74.7% energy spent running, which is greater than in handball (60-67%). Osgnach et al. (2010) report Equivalent Distance Indices of 1.15 – 1.35 depending on the player position. This indicates that football may be overall more demanding in terms of movement behaviour. However, no differentiation between running and walking was made (di Prampero & Osgnach, 2018). In summary, MP provides deeper insight in movement behaviour and physiological demands during multidirectional team sports. Nevertheless, more research is needed comparing different games and to get better insight about player's movement behaviour.

The mean physical performance of the team showed no association with match results (score line) supporting recent findings by Manchado et al. (2021) and Cardinale et al. (2017). In the present study, match outcome was modelled as a continuous variable, which increases data granularity. Yet, mean distance covered and equivalent distance were not able to predict score line at match level. Similar results have been found in football (Lepschy et al., 2020), where running performance did not add predictive power on forecasting match results based on team strength, i.e., betting odds (Klemp et al., 2021). Therefore, post-hoc analysis of running performance itself does not seem to be able to determine success in elite hand- and football. At this level of competition, it may be confounded by contextual variables, like score line or team strength, and tactical decisions.

Applying MP to practice requires care as the underlying formulas contain several high-degree (4th and 5th) polynomials to calculate MP and to differentiate between walking and running. Minetti and Parvei's (2018) new approach solves a major part of the problem with remodelling part of the data into a more stable exponential function. We would still encourage optimization of the model to increase robustness and easy application in practice. Further data processing methods should be reported in detail. Especially as different smoothing and differentiation methods may have substantial effects on the signal properties (Winter, 2009). Thus, there is a demand to establish a standardized approach to post processing and smoothing of sports position data.

Some limitations of the present study can be identified. The state of game (active vs. inactive was assumed to be in line with data recordings. Consequently, time on court and all related variables computed based on the position data available. This may lead to discrepancies if non-active players are still recorded due to their spatial proximity to the pitch or missing data due to erroneous sensors was considered as no time on court. Additionally, only the player position in the offense formation was available. The influence of individual tactical decisions, like a defence specialist, are not accounted for in this study. However, with respect to the amount of data analysed in this study, we doubt that this will have a substantial impact on results.

Although all MP parameters are computed relative to body mass, it is unclear if the extreme anthropometrics of handballers, especially pivots, may impact their true energy expenditure during certain movements. More research needs to be conducted to control for inter-individual differences in locomotion costs (di Prampero & Osgnach, 2018). Further, in high body contact sports like handball, energy is spent when blocking opponents from moving. These maximum isometric efforts are not visible in position data and are not accounted for in running distances or the MP concept. Therefore, the internal load of players who participate in body contact situations more frequently will be underestimated by these variables (Gray et al., 2018).

Conclusion

Individual data-driven player load management has become an important part of coaches' work (Akenhead & Nassis, 2016; Bourdon et al., 2017). The constant collection of position data during training and competition does not only allow to control training load, but may also influence technical (Pueo et al., 2021) and tactical decisions in the future. The combined knowledge of players' individual capacities and physiological demands during a competition can support decisions on individual (e.g., substitutions) and team level (e.g., formation) (Rein & Memmert, 2016). Practitioners should investigate how much energy a player is able to spend in a given time period before the physiological demands impact performance and use this information to their advantage during competition. The MP concept proved to be a valuable approach allowing to include accelerations and decelerations information.

Compared to other team sports like football, handball inherently has a higher number of scored goals, which offers the opportunity for researchers to analyse successful game patterns much more directly. So, although no predictive power was found for game success, future studies may focus on different game phases, like ball possession phases to gain further insights on the influence of physical performance patterns on success.

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