©Journal of Sports Science and Medicine (2023) **22,** 310-316
http://www.jssm.org DOI: https://doi.org/10.52082/jssm.2023.310

**Research article**

# Analysis of Motion Characteristics and Metabolic Power in Elite Male Handball Players

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## Abstract

While handball is characterized by repeated sprints and changes of direction, traditional player load models do not consider accelerations and decelerations. The aim of this study was to analyze the differences between metabolic power and speed zones for player load assessment with regard to the player role. Position data from 330 male individuals during 77 games from the 2019/20 German Men's Handball-Bundesliga (HBL) were analyzed, resulting in 2233 individual observations. Players were categorized into wings, backs and pivots. Distance covered in different speed zones, metabolic power, metabolic work, equivalent distance (metabolic work divided by energy cost of running), time spend running, energy spend running, and time over 10 and 20 W were calculated. A 2-by-3 mixed ANOVA was calculated to investigate differences and interactions between groups and player load models. Results showed that total distance was longest in wings (3568 ± 1459 m in 42 ± 17 min), followed by backs (2462 ± 1145 m in 29 ± 14 min), and pivots (2445 ± 1052 m in 30 ± 13 min). Equivalent distance was greatest in wings (4072.50 ± 1644.83 m), followed by backs (2765.23 ± 1252.44 m), and pivots (2697.98 ± 1153.16 m). 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) and a small interaction effect between backs and pivots ($p < .01$, ES = 0.22). The results underline the need for individualized management of training loads and the potential of using information about locomotive accelerations and decelerations to obtain more precise descriptions of player load during 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.

**Key words:** Position data; performance analysis; big data; LPS; player load.

## Introduction

Correctly assessing player load and physiological requirements underlying successful game performance is critical for efficient training regimes to optimize performance and prevent injuries (Akenhead and Nassis, 2016; Bourdon et al., 2017; Miguel et al., 2021). In handball, game performance is characterized by repeated sprints, cutting movements, jumps, tackles, and throws (Karcher and Buchheit, 2014). Recent work has analyzed external player load during official handball matches during different competitions (García-Sánchez et al., 2023). Several player load measures, including time on court, distance covered in different speed zones, maximum speeds, number and magnitudes of accelerations and decelerations have been reported. Generally, wing players cover greater distances, at higher maximum speeds (Cardinale et al., 2017; Büchel et al., 2019; González-Haro et al., 2020; Manchado et al., 2020; 2021), as well as more high intensity accelerations (Karcher and Buchheit, 2014; González-Haro et al., 2020). Overall, most distances were covered at low intensities, either walking or jogging.

Another approach to characterize player load that has not been used in handball is the Metabolic Power (MP) concept (di Prampero and Osgnach, 2018). MP is defined as the energy expenditure per unit of time necessary to move at a certain speed. MP combines distance, speed and acceleration into interpretable measures of instantaneous power, aggregated power over time (i.e., work), or equivalent distance (i.e., work divided by the cost of constant speed running; di Prampero and Osgnach, 2018). The underlying calculations are based on the biomechanical equivalence of accelerated running on flat terrain and constant speed running on an incline, where energy expenditure can be assessed empirically (Minetti and Pavei, 2018).

Both approaches capture specific parts of game demands of handball players but have some limitations. One problem with speed zones stems from the use of different cut-off values across studies (e.g., five zones; Büchel et al., 2019; vs. six zones; Manchado et al., 2021) which makes comparisons difficult (Bradley and Ade, 2018). Additionally, distances covered at certain speeds do not capture handball players' frequent accelerations, decelerations, and changes of direction during which demands for the metabolic and neuro-muscular systems are high (di Prampero et al., 2005; Dos'Santos et al., 2018). In contrast, MP includes instantaneous accelerations and decelerations in the model, but has been critically discussed (Polglaze and Hoppe, 2019) and tested for its methodological and physiological validity (Brochhagen, 2022). Although MP seems to be methodologically valid (Polglaze and Hoppe, 2019; Brochhagen, 2022), several studies show conflicting evidence regarding its physiological validity when compared to the criterion validity oxygen uptake (Manzi et al., 2014; Buchheit et al., 2015; Fuchs et al., 2021).

Conceptually, the assessment of MP faces another problem, as the model frequently involves usage of high-degree polynomials ($4^{th}$ or $5^{th}$) to fit the data. This is the case for both the original model (di Prampero et al., 2005) and the updated model (di Prampero and Osgnach, 2018).

Received: 16 August 2022 / Accepted: 16 May 2023 / Published (online): 01 June 2023

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 results for a large range of accelerations. To the best of our knowledge, the models have not been merged before and a merge has only been briefly discussed in previous work (Savoia et al., 2020). However, as the model itself is modular, the updated models can be merged, which is described in the method section. In summary, using MP to assess player load in handball appears warranted. To circumvent some of the problems of the earlier formulation of the MP approach the new model should be used.

To the best of our knowledge, MP has not been used to characterize player load in elite handball matches and it is unclear whether it is suitable to capture the role specific player load while combining instantaneous distance, speed, and acceleration. Therefore, the aim of this study is to analyze the differences between MP and speed zones for player load assessment with respect to player roles. We report benchmark values for both player load models using a large sample (*N* = 77 games) from the German Handball Bundesliga. Player loads are then compared across different player roles. Based on the related work available, we have the following central hypotheses: (i) wings cover more distances, especially in high-speed zones, confirming established results; (ii) the equivalent distance is generally higher than the distance covered because it includes accelerations and decelerations; (iii) the difference between the equivalent distance and distance of wing is higher than for backs and pivots, because their game is characterized by more high-intensity accelerations (Karcher and Buchheit, 2014; González-Haro et al., 2020).

## Methods

### Subjects

Data from 330 individual male players of 18 teams during 77 games of the 2019/20 German Men's Handball-Bundesliga (HBL) were analyzed, resulting in 2233 observations. 292 observations from 40 goalkeepers were removed from further analysis. A minimum required time on court of five minutes was set, resulting in the exclusion of 312 observations. Additionally, seven observations were identified as outliers due to erroneous sensor data and excluded. In total 1665 observations from 290 players were analyzed. For position-specific differences, the participants were split according to their player role (wings, backs, pivots). Anthropometric data from the players is presented in Table 1. Player data were collected by SportsRadar (St. Gallen, Switzerland) and made available through the HBL. As the data collection is part of the professional season, all players gave their informed consent to the procedure. The institutional review board approved all procedures, in the spirit of the Helsinki Declaration.

### Instruments

Position data were collected using the LPS KINEXON ONE (KINEXON GmbH, Munich, Germany) system at 20 Hz. The accuracy of the system estimated with root mean square errors (RMSE) are around 0.1 m, 0.15 $m \cdot s^{-1}$, and 0.2 $m \cdot s^{-2}$ for position, speed, and acceleration, respectively (for detailed description and validity see Hoppe et al., 2018; Fleureau et al., 2020; Blauberger et al., 2021). Sensors were worn by the players between their shoulders. The system was installed and calibrated by the manufacturer for all matches. Data recording was interrupted by a trained operator when the game clock was inactive during game stoppages (e.g., fouls). Therefore, only net playing time is represented in the data.

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

| Position | n | Height (cm) | Body Mass (kg) | BMI | Age (yrs) |
|---|---|---|---|---|---|
| **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 |

### Data processing

The raw position data was smoothed using a 4th-degree, Butterworth low pass filter with a cut-off frequency of 1 Hz (Winter, 2009). Speed and acceleration for every frame were calculated via central difference method (Winter, 2009). For every player, time on court was determined by the time the sensor was tracked by the LPS, as each sensor was only tracked while on the pitch and when the game clock was running. Percentages of time spent and total distance covered in different speed zones were calculated. The zones were (1) standing (< 1 $m \cdot s^{-1}$); (2) walking (1 - 2 $m \cdot s^{-1}$); (3) jogging (2 - 4 $m \cdot s^{-1}$); running (4 - 5.5 $m \cdot s^{-1}$); high-intensity running (5.5 - 7 $m \cdot s^{-1}$); sprinting (> 7 $m \cdot s^{-1}$) following Manchado et al. (2020; 2021).

MP variables were calculated following di Prampero and Osgnach (2018) using the modified formula from Minetti and Pavei (2018) by exchanging equation (9) in di Prampero and Osgnach (2018) with equations (3) and (4) from Minetti and Pavei (2018) for positive and negative acceleration, respectively. As both equations nearly match inside the stable boundaries of the original equations, this change increases the numerical stability at high accelerations and decelerations without compromising the overall model (Minetti and 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, see Table 2 for definitions. Data were processed with Python 3.8 (Python Software Foundation, Wilmington, Delaware, US). All algorithms for data processing and calculation of metabolic power are available in the Python software package *floodlight* v0.3.2 (Raabe et al., 2022).

### Statistical analysis

The statistical analyses were done using Python 3.8 and *pingouin* v0.5.0 (Vallat, 2018). 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 analyze differences between the roles for every dependent variable. For MP, differences between distance and equivalent distance were analyzed using a two (distance vs. equivalent distance) by three (wings vs. backs vs. pivots) mixed-effects ANOVA. In case of statistically significant effects, post-hoc tests were performed using a Bonferroni adjustment. 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 (Cohen, 2013). Statistical significance was set at α = 0.05.

**Table 2.** **Definitions of variables from the metabolic power concept.**

| Variable | Unit | Definition |
|---|---|---|
| **Metabolic work** | J/kg | Accumulated metabolic power over time |
| **Equivalent distance** | m | Metabolic work divided by the energy cost of constant speed running (3.6 J/m) |
| **Equivalent distance index** | % | Equivalent distance divided by total distance |
| **Time spent running** | % | Time the Metabolic power model detects running divided by time on court |
| **Energy spent running** | % | Metabolic work while the Metabolic power model detects running divided by total metabolic work |
| **Time over 10/20 W** | min | Total time spent while metabolic power is higher than 10/20 W. |

**Table 3.** **Descriptive results and group comparisons for every dependent variable as mean ± standard difference.**

| | | Unit | Wings (n=903) | Backs (n=411) | Pivots (n=351) |
|---|---|---|---|---|---|
| **Time** | **On court** | min | 41.90 ± 17.31bp | 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 (p < 0.05) difference to wings/backs/pivots. Eq = Equivalent; abs = absolute; rel = relative; HI = High intensity; W = Watts

## Results

Descriptive results and group differences for each dependent variable by player role are presented in Table 3. Figure 1 presents the influence of player role on total distance covered. The graph shows the distribution of absolute distances covered separated by speed zones and player roles. On average, wings covered the largest distances in all speed zones. While all player roles covered the largest distances in the low-intensity zones, only wings covered a substantial amount of distance in high-intensity running and sprinting. Figure 2 shows the intensity distribution of running as time spent in speed zones normalized by total playing time. When controlled for playing time, backs covered longer distances walking and jogging. However, wings also covered greater distances per minute running, high-intensity running, and sprinting. The mixed-effects ANOVA for distance and equivalent distance revealed statistically significant group ($F(2, 262) = 16.77$; $p < 0.01$), distance ($F(1, 262) = 932.55$; $p < 0.01$), and interaction ($F(2, 29.82)$; $p < 0.01$) effects. Post-hoc analysis showed a significant group effect between wings vs. backs ($t(689) = 14.04$; $p < 0.01$; $d = 0.92$), wings vs. pivots ($t(737) = 12.99$; $p < .01$; $d = 0.92$), 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 ($t(410) = 29.30$; $p < 0.01$; $d = 0.32$), backs ($t(902) = 39.13$; $p < 0.01$; $d = 0.25$), and pivots ($t(350) = 22.83$; $p < 0.01$; $d = 0.23$). Interaction effect for groups and (equivalent) distance were significant for wings vs. backs ($t(582) = 10.67$; $p < 0.01$; $d = 0.73$), wings vs. pivots ($t(682) = 12.28$; $p < 0.01$; $d = 0.86$), and backs vs. pivots ($t(710) = 3.70$; $p < 0.01$; $d = 0.22$), meaning that differences between distance and equivalent distance were greater for wings than for backs and pivots by moderate to large effect sizes. Figure 3 shows the difference of distribution of distance covered and equivalent distance for wings, backs and pivots.

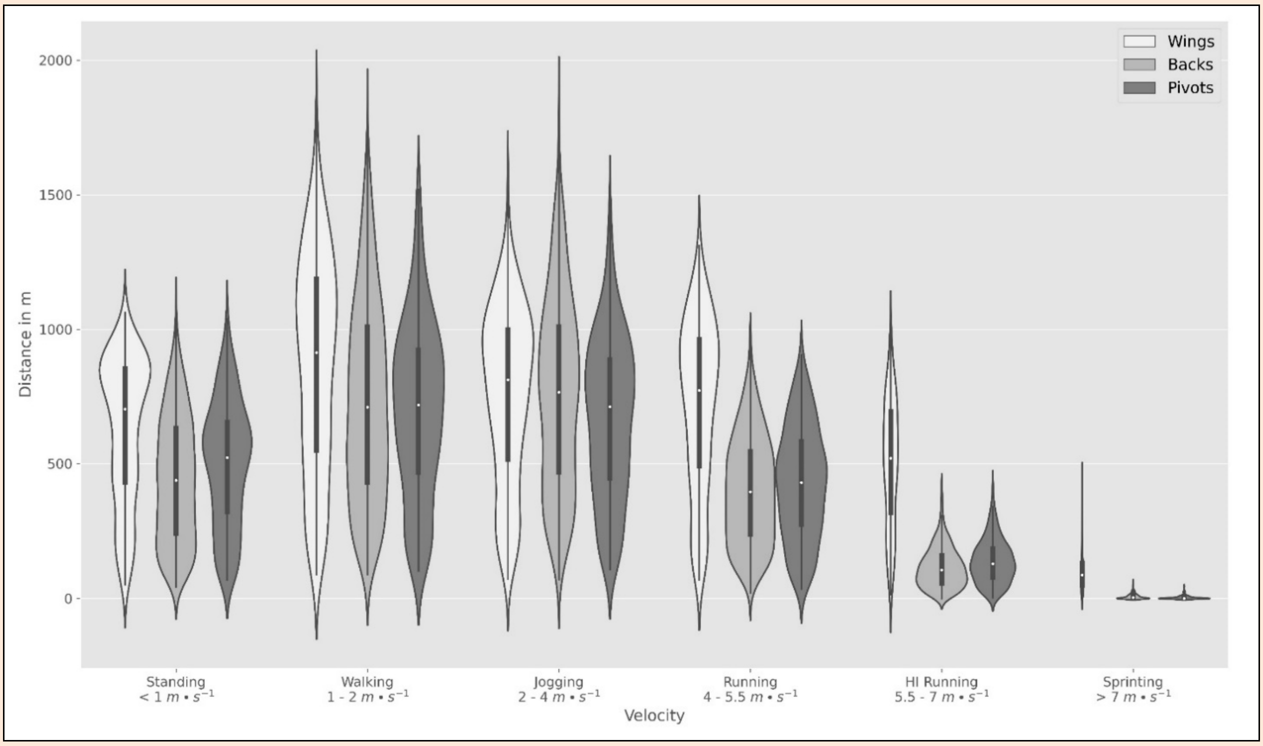


**Figure 1. Violin plots of total distance covered in different speed zones by player roles.**

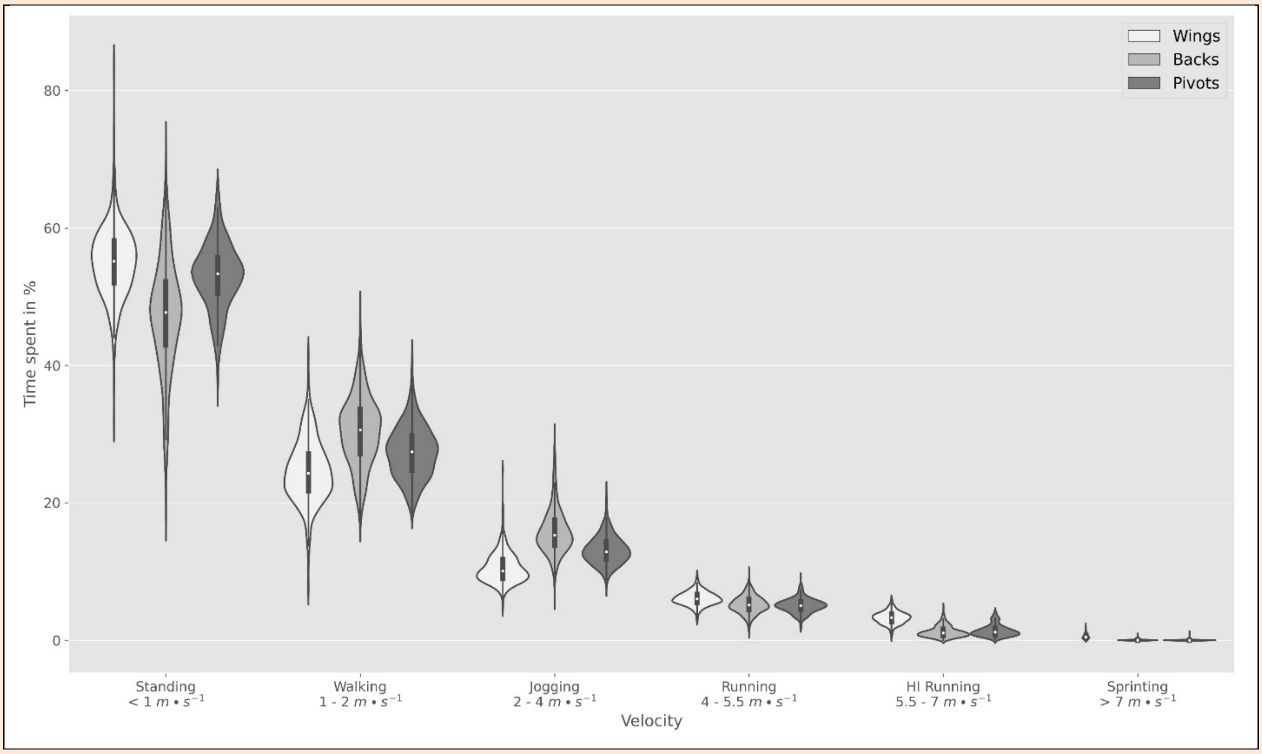


**Figure 2. Violin plots of time spent in different speed zones by player roles as a percentage of total time on court.**

## Discussion

The aim of this study was to compare two different player load models in professional handball league matches with respect to the player role. The results confirmed our first hypothesis, that wings cover the largest distances especially in the highest speed zones (Table 3). Secondly, the equivalent distances are greater for each role by a small effect size. Finally, the discrepancy between distance covered and equivalent distance is significantly greater in wings compared to backs and pivots by moderate to large effect sizes. 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

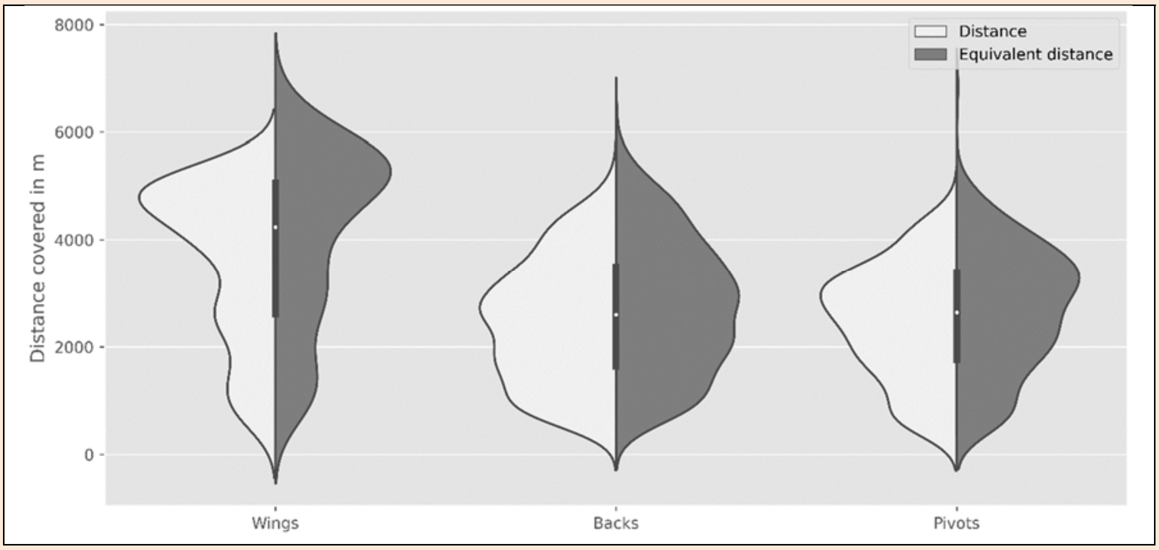


**Figure 3. Split violin plots of total distance covered compared to equivalent distance by player role.**

spent 67% of their 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 speeds. The results further show that their acceleration profiles differ substantially from the other positions. Accordingly, individual player load estimates should include measures of accelerations and deceleration.

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, the present results are similar to the findings by Büchel et al. (2019), who observed 16 home matches of one team in the German Handball Bundesliga. The authors found greater time on court and longer total distances covered for all players. However, similar to the present results, about 80% of time was spent using speeds of under 2 $m \cdot s^{-1}$ 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 the inclusion of game stoppages would lead to a bias and underestimation of real game demands (Mernagh et al., 2021).

The comparison of distance covered 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.

Some limitations of the present study can be identified. During interruptions of the game, e.g., due to fouls, no data was recorded. Therefore, only net playing time is presented in this study. However, considering that players are mostly standing or walking during such breaks, removing them prevents underestimating player load, especially in variables normalized by time on court.

The state of game (active vs. inactive) was assumed to be in line with data recordings. Consequently, time on court and all related variables were computed when position data was 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 being considered off the court. Additionally, only the player role (wing/back/pivot) in the offense formation was available. The influence of individual tactical decisions, like a defense specialist, is not accounted for in this study. However, with respect to the amount of data analyzed in this study, we doubt that this will have a substantial impact on the 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 and Osgnach, 2018). Further, in high body contact sports like handball, energy is spent when blocking opponents from moving (Fuchs et al., 2021). These maximum isometric efforts are not visible in position data and are not accounted for in running distances or the MP concept. Therefore, the load of players who participate in body contact situations more frequently are underestimated even by the MP concept (Gray et al., 2018; Fuchs et al., 2021). Still, the incorporation of acceleration in MP addresses a flaw in the traditional approach and allows for more adequate monitoring of athletes in handball (Polglaze and Hoppe, 2019).

Applying MP to practice requires care as the underlying formulas contain several high-degree ($4^{th}$ and $5^{th}$) polynomials to calculate MP and differentiate between walking and running. Minetti and Parvei's (2018) new approach solves a major part of the problem by remodeling 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. We approach this problem by describing our data processing algorithms in detail and using open source algorithms the reader can verify and reproduce (Raabe et al., 2022).

Despite these limitations, there are some strengths of this study. Previous studies analyzing player load in league play have been limited in sample size and data accuracy (Büchel et al., 2019; González-Haro et al., 2020). The present study presents a large and representative sample size of high-quality position data from elite league play. Further, we used a more robust model of calculating MP from raw position data by merging two existing models (Minetti and Pavei, 2018; di Prampero and Osgnach, 2018). The algorithms used for data processing and player load calculations are available as part of an open source software package for the readers to verify and reproduce (Raabe et al., 2022).

The findings of this study are also important for practitioners. On the one hand, they show representative player load values for elite handball league play. On the other hand, they show that considering only traditional player load models will lead to an underestimation of player load of certain players because their frequent accelerations and decelerations are not included in the analysis. Therefore, we suggest combining both approaches, e.g., by comparing total distance covered and equivalent distance individually to assess the movement profile of the player in comparison to players with similar roles. As the current research suggests (Manzi et al., 2014; Fuchs et al., 2021; Brochhagen, 2022), if implemented correctly, MP has the potential of overcoming the central problems of traditional player load models in team sports.

## Conclusion

The present study indicates the need for more complex player load models than distances covered when analyzing dynamic team sports like handball. To account for those dynamics, the merged MP model appears to be a numerically robust method of integrating accelerations and decelerations into player load estimation and to give researchers and practitioners more detailed insights into players' movement behavior.

Due to the technological advances of player tracking technology, constant collection of position data during training and competition becomes more feasible. This allows future studies to analyze player load from different leagues and competitions. However, as recent studies are mainly focusing on reporting aggregated player load metrics from competitions, future studies should use more (quasi-)experimental approaches, like the influence of team formations on player load.

### Acknowledgements

This project was supported by the German Federal Ministry of Education and Research (BMBF – Bundesministerium für Bildung und Forschung) under Grant 01IS20021A-C. The experiments comply with the current laws of the country in which they were performed. The authors have no conflict of interest to declare. The datasets generated and analyzed during the current study are not publicly available.

## References

Akenhead, R. and Nassis, G.P. (2016) Training load and player monitoring in high-level football: Current practice and perceptions. *International Journal of Sports Physiology and Performance* **11**, 587-593. https://doi.org/10.1123/ijspp.2015-0331

Blauberger, P., Marzilger, R. and Lames, M. (2021) Validation of player and ball tracking with a local positioning system. *Sensors* **21**, 1465. https://doi.org/10.3390/s21041465

Bourdon, P.C., Cardinale, M., Murray, A., Gastin, P., Kellmann, M., Varley, M.C., Gabbet, T.J., Coutts, A.J., Burgess, D.J., Gregson, W. and Cable, N.T. (2017) Monitoring athlete training loads: Consensus statement. *International Journal of Sports Physiology and Performance* **12**, 161-170. https://doi.org/10.1123/IJSPP.2017-0208

Bradley, P.S. and Ade, J.D. (2018) Are current physical match performance metrics in elite soccer fit for purpose or is the adoption of an integrated approach needed? *International Journal of Sports Physiology and Performance* **13**, 656-664. https://doi.org/10.1123/ijspp.2017-0433

Brochhagen, J. (2022) Metabolic Power in Team and Racquet Sports: A Systematic Review with Best-Evidence Synthesis. *Sports Medicine*, 21. https://doi.org/10.1186/s40798-022-00525-9

Büchel, D., Jakobsmeyer, R., Döring, M., Adams, M., Rückert, U. and Baumeister, J. (2019) Effect of playing position and time on-court on activity profiles in german elite team handball. *International Journal of Performance Analysis in Sport* **19**, 832-844. https://doi.org/10.1080/24748668.2019.1663071

Buchheit, M., Manouvrier, C., Cassirame, J. and Morin, J.B. (2015) Monitoring Locomotor Load in Soccer: Is Metabolic Power, Powerful? *International Journal of Sports Medicine* **36**, 1149-1155. https://doi.org/10.1055/s-0035-1555927

Cardinale, M., Whiteley, R., Hosny, A.A. and Popovic, N. (2017) Activity profiles and positional differences of handball players during the World Championships in Qatar 2015. *International Journal of Sports Physiology and Performance* **12**, 908-915. https://doi.org/10.1123/ijspp.2016-0314

Cohen, J. (2013) Statistical Power Analysis for the Behavioral Sciences. Routledge. https://doi.org/10.4324/9780203771587

Dos'Santos, T., Thomas, C., Comfort, P. and Jones, P.A. (2018) The effect of angle and velocity on change of direction biomechanics: An angle-velocity trade-off. *Sports Medicine* **48**, 2235-2253. https://doi.org/10.1007/s40279-018-0968-3

Fleureau, A., Lacome, M., Buchheit, M., Couturier, A. and Rabita, G. (2020) Validity of an ultra-wideband local positioning system to assess specific movements in handball. *Biology of Sport* **37**, 351. https://doi.org/10.5114/biolsport.2020.96850

Fuchs, P., Luteberget, L.S., Fuchs, P.X. and Wagner, H. (2021) Comparative Analysis of the Indirect Calorimetry and the Metabolic Power Method to Calculate Energy Expenditure in Team Handball. *Applied Sciences* **12**, 163. https://doi.org/10.3390/app12010163

García-Sánchez, C., Navarro, R.M., Karcher, C. and de la Rubia, A. (2023) Physical Demands during Official Competitions in Elite Handball: A Systematic Review. *International Journal of Environmental Research and Public Health* **20**, 3353. https://doi.org/10.3390/ijerph20043353

González-Haro, P.J., Gómez-Carmona, C.D., Bastida-Castillo, A., Rojas-Valverde, D., Gómez-López, M. and Pino-Ortega, J. (2020) Analysis of playing position and match statusrelated differences in external load demands on amateur handball: A case study. *Revista Brasileira de Cineantropometria & Desempenho Humano* **22**, e71427. https://doi.org/10.1590/1980-0037.2020v22e71427

Gray, A.J., Shorter, K., Cummins, C., Murphy, A. and Waldron, M. (2018) Modelling movement energetics using global positioning system devices in contact team sports: Limitations and solutions. *Sports Medicine* **48**, 1357-1368. https://doi.org/10.1007/s40279-018-0899-z

Hoppe, M.W., Baumgart, C., Polglaze, T. and Freiwald, J. (2018) Validity and reliability of GPS and LPS for measuring distances covered and sprint mechanical properties in team sports. *Plos One* **13**, 1-21. https://doi.org/10.1371/journal.pone.0192708

Karcher, C. and Buchheit, M. (2014) On-court demands of elite handball, with special reference to playing positions. *Sports Medicine* **44**,

797-814. https://doi.org/10.1007/s40279-014-0164-z
Manchado, C., Pueo, B., Chirosa-Rios, L.J. and Tortosa-Martínez, J. (2021) Time-motion analysis by playing positions of male handball players during the European Championship 2020. *International Journal of Environmental Research and Public Health* **18**, 2787. https://doi.org/10.3390/ijerph18062787
Manchado, C., Tortosa Martínez, J., Pueo, B., Cortell Tormo, J.M., Vila, H., Ferragut, C., Sánchez Sánchez, F., Busquier, S., Amat, S. and Chirosa Ríos, L.J. (2020) High-performance handball player's time-motion analysis by playing positions. *International Journal of Environmental Research and Public Health* **17**, 6768. https://doi.org/10.3390/ijerph17186768
Manzi, V., Impellizzeri, F. and Castagna, C. (2014) Aerobic fitness ecological validity in elite soccer players: A metabolic power appraoch. *Journal of Strength and Conditioning Research* **28**, 6. https://doi.org/10.1519/JSC.0000000000000239
Mernagh, D., Weldon, A., Wass, J., Phillips, J., Parmar, N., Waldron, M. and Turner, A. (2021) A comparison of match demands using ball-in-play versus whole match data in professional soccer players of the English championship. *Sports* **9**, 76. https://doi.org/10.3390/sports9060076
Miguel, M., Oliveira, R., Loureiro, N., García-Rubio, J. and Ibáñez, S.J. (2021) Load measures in training/match monitoring in soccer: A systematic review. *International Journal of Environmental Research and Public Health* **18**, 2721. https://doi.org/10.3390/ijerph18052721
Minetti, A.E. and Pavei, G. (2018) Update and extension of the 'Equivalent Slope' of speed changing level locomotion in humans: A computational model for shuttle running. *Journal of Experimental Biology* **221**, 182303. https://doi.org/10.1242/jeb.182303
Polglaze, T. and Hoppe, M.W. (2019) Metabolic power: A step in the right direction for team sports. *International Journal of Sports Physiology and Performance* **14**, 407-411. https://doi.org/10.1123/ijspp.2018-0661
di Prampero, P.E., Fusi, S., Sepulcri, L., Morin, J.B., Belli, A. and Antonutto, G. (2005) Sprint running: A new energetic approach. *Journal of Experimental Biology* **208**, 2809-2816. https://doi.org/10.1242/jeb.01700
di Prampero, P.E. and Osgnach, C. (2018) Metabolic power in team sports - Part 1: An update. *International Journal of Sports Medicine* **39**, 581-587. https://doi.org/10.1055/a-0592-7660
Raabe, D., Biermann, H., Bassek, M., Wohlan, M., Komitova, R., Rein, R., Kuppens Groot, T. and Memmert, D. (2022) floodlight -- A high-level, data-driven sports analytics framework. **7(76)**, 4588. https://doi.org/10.21105/joss.04588
Savoia, C., Padulo, J., Colli, R., Marra, E., McRobert, A., Chester, N., Azzone, V., Pullinger, S.A. and Doran, D.A. (2020) The Validity of an Updated Metabolic Power Algorithm Based upon di Prampero's Theoretical Model in Elite Soccer Players. *International Journal of Environmental Research and Public Health* **17**, 9554. https://doi.org/10.3390/ijerph17249554
Vallat, R. (2018) Pingouin: Statistics in Python. *Journal of Open Source Software* **3**, 1026. https://doi.org/10.21105/joss.01026
Winter, D.A. (2009) *Biomechanics and Motor Control of Human Movement.* 4th ed. Hoboken, N.J: Wiley. https://doi.org/10.1002/9780470549148

## Key points

- Player load variables should be comparable and interpretable for research and practice
- Assessment of player load in multidirectional team sports, like handball, requires the incorporation of accelerations and decelerations, which is achieved in the Metabolic Power concept
- Analyzing player load in handball with metabolic power shows that wing players' movement behavior is characterized by more frequent accelerations and decelerations than the movement of backcourts and pivots

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