# Trunk Motion Measurement

## Towards Evidence-Based Classification in Wheelchair Sports: A Study on Trunk Kinematics and Mobility Performance


Aag de Bruijn

Delft University of Technology

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## Towards Evidence-Based Classification in Wheelchair Sports: A Study on Trunk Kinematics and Mobility Performance

by

A.J.A.C. de Bruijn

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|---|---|
| Student number: | 4677226 |
| Thesis advisors: | H.E.J. Veeger |
| | R.M. van der Slikke |
| Thesis committee: | H.E.J. Veeger (chair) |
| | R.M. van der Slikke |
| | A.H.A. Stienen |
| Faculty: | Mechanical Engineering (ME) |

TU Delft

# Towards Evidence-Based Classification in Wheelchair Sports: A Study on Trunk Kinematics and Mobility Performance

*Abstract*—**Objective: This study aimed to validate the use of Inertial Measurement Units (IMUs) for quantifying trunk motion in wheelchair sports and explore the relationship between trunk motion, wheelchair mobility performance, and classification level in elite wheelchair basketball athletes.**
**Methods: Fourteen participants (seven elite wheelchair athletes and seven non-WC users) completed eight standardized wheelchair mobility tests. Trunk motion was measured using IMUs and compared with a 3D motion capture (MOCAP) system. Trunk kinematics and wheelchair performance metrics were derived and analysed for correlation in the elite wheelchair group.**
**Results: IMUs, especially those mounted on the upper back, showed excellent agreement with 3D motion capture data (ICCs $>$ 0.90; RMSE $<$ 8%). Mean trunk angle correlated with wheelchair linear velocity during manoeuvring and sprinting tasks (r $>$ 0.75), highlighting the role of dynamic trunk use in enhancing propulsion. Additionally, trunk kinematics, particularly range of motion, mean tilt angle, and forward lean time, showed strong correlations with classification level (r $>$ 0.79), especially during the straight push test. Performance metrics demonstrated weaker correlation with classification (r $<$ 0.47), suggesting that impairment may not directly translate into measurable differences in mobility performance in this sample.**
**Conclusion: Trunk rotation angles derived from IMUs provide a valid and practical tool for measuring trunk motion. Their integration could support more transparent and impairment-focussed classification frameworks.**

*Index Terms*—**Wheelchair sports, trunk kinematics, wheelchair mobility performance, inertial measurement units, evidence-based classification**

## I. Introduction

In wheelchair sports, athletes are classified into categories to ensure fair and equitable competition. Paralympic athletes present with diverse types and degrees of physical impairments, and classification is used to group them based on the extent to which their impairment affects sports performance. This levels the playing field, allowing skill, fitness, endurance, and mental focus to determine success, instead of the degree of impairment. For this system to be effective and trusted, classification must be objective and reliable. An evidence-based classification process enhances transparency, minimizes errors in class allocation, and reduces the risk of athletes deliberately underperforming during classification assessments [1]–[4].

Current wheelchair classification methods typically follow a three-step procedure. First, the athlete is assessed against a list of eligible impairments and minimum impairment criteria using standard medical tests, such as manual muscle testing or spasticity grading scales. These minimum impairment criteria are usually a quantitive limit, such as a minimum leg length difference of 6 cm for wheelchair basketball. Second, classifiers evaluate how the impairment impacts sport-specific performance, often through functional tests conducted in controlled setting. For instance, wheelchair tennis classifiers observe athletes during pushing, turning, stopping, and ball strokes. In some sports, trunk control is reviewed during this step, though it is often assessed subjectively, with limited use of standardized scoring rubrics or objective measurements. Finally, athletes are optionally observed during in-field competition to verify initial classification [5]–[9]. This entire process remains heavily reliant on expert judgment and lacks the empirical rigor needed to ensure consistency, which can lead to misclassification and unfair advantages.

Recognizing these limitations, recent efforts have aimed to anchor classification decisions in objective performance data. Notably, Van Der Slikke, Bregman, Berger, *et al.* [10] found a significant difference between wheelchair performance and classification level between low classes and middle-high classes in wheelchair basketball athletes. Additionally, Van Der Slikke, Berger, Bregman, *et al.* [11] showed that impairment level and sport type affect wheelchair mobility performance, expressed through metrics such as speed and acceleration. While these findings highlight that impairment can influence performance, they also underscore the limitations of using performance metrics alone for classification, since performance is affected by many non-impairment factors. This has motivated the search for objective measures that more directly reflect impairment, such as trunk motion during match play.

The ability of a wheelchair athlete to leverage their trunk plays a significant role in wheelchair propulsion and, consequently, athletic performance [12], [13]. Being able to move the trunk forward can increase the ability to transfer power from the trunk to the pushrim of the wheelchair, resulting in more speed [14]–[17]. In addition, not only the forward lean of the trunk increases the range of motion and thus duration of the hands on the handrims of the wheelchair, but also the backward motion of the trunk towards the neutral position during the recovery phase results in forward propulsion of the wheelchair [18]. Trunk movement, particularly the ability to shift body weight effectively, can also enhance turning speed, providing a further advantage in manoeuvrability. Furthermore, trunk control enhances agility and postural stability, which are critical elements in wheelchair sports such as basketball, rugby, and tennis. Despite its importance, trunk motion is often under-assessed or evaluated only subjectively in classification. For example, in elite wheelchair tennis trunk control accounts for only 14% of the classification level, while arm control accounts for 86%. This raises the question: could quantifying trunk motion more objectively improve evidence-based classification?

In this study, wheelchair sports performance is defined using velocity-based metrics derived from wheelchair kinematics. Although velocity performance metrics do not cover the full range of skills (such as ball handling or recovery from perturbation), they serve as proxies for mobility-related performance. Trunk motion is characterized using angular metrics, including range of motion. These metrics are captured across seven functional wheelchair tests, designed to reflect key movements seen in competition, such as sprinting, turning, and stopping. To ensure generalizability across wheelchair sports, no ball handling is included.

Capturing trunk motion accurately is key. While 3D motion capture systems are considered the gold standard, they are impractical for use outside a laboratory setting due to spatial constraints, occlusion, and high costs. Inertial Measurement Units (IMUs), on the other hand, offer a portable and cost effective alternative suitable for in-field data collection, though they can suffer from drift and accuracy limitations, especially at high speeds [19].

This study had two primary objectives:

1) To validate the use of inertial measurement units (IMUs) for measuring trunk motion in functional mobility wheelchair tests, by comparing them with an optokinetic motion capture system.
2) To explore the relationship between trunk motion, athletic performance, and classification level among elite wheelchair basketball athletes.

By examining these questions, this research contributes to the development of more objective impairment-based tools that can inform fairer and more transparent classification in wheelchair sports.

## II. Methods

### A. Participants

Fourteen participants were recruited: seven elite youth wheelchair basketball athletes from the Dutch national team and seven individuals without prior experience in wheelchair sports. Non-experienced participants were allowed time to become comfortable with wheelchair propulsion and agility before testing. Each test was introduced with verbal instructions and a demonstration to ensure understanding. Participant characteristics are presented in Table I.

### B. Equipment and Measurement Systems

Non-experienced participants used a standardized sports wheelchair (Quickie RGK All Court), while elite athletes used their personal sports wheelchair, including any straps or support systems. Each wheelchair was equipped with two Inertial Measurement Units (x-IMU3, x-io Technologies), one mounted on the right wheel axis and one in the centre of the backrest of the wheelchair frame. This configuration was previously validated for capturing wheelchair kinematics by Van Dijk, Van Der Slikke, Rupf, *et al.* [20].

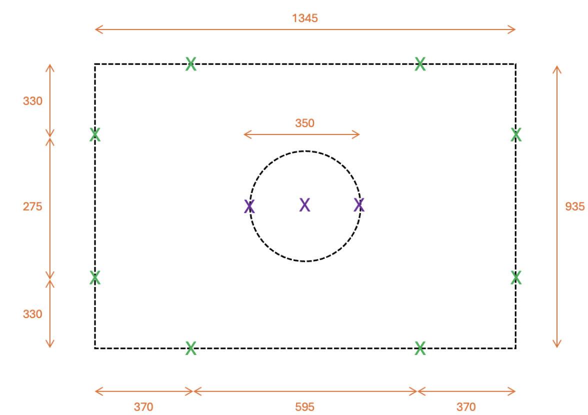



Fig. 1: MOCAP measuring area, with optimal measuring circle in the middle. Green X = camera; orange arrow = distance (cm); purple X = cone used during mobility tests 5 and 6.

To measure trunk motion, two additional IMUs were placed at spinal levels T3-T4 (upper back) and T11-T12 (lower back) to capture representative upper and lower trunk motion. T11-T12 was selected as the lowest possible location on the back still visible by the 3D motion capture (MOCAP) system, avoiding occlusion from the wheelchair backrest. T3-T4 was chosen to allow stable attachment to the racer-back vest worn by the participants. Biomechanically, these locations capture segmental motion dynamics of the upper trunk and pelvis. The use of two IMUs allowed for the assessment of the effect of IMU placement on measurement accuracy, providing insight into optimal sensor location for trunk motion measurement.

Each IMU captured 3D acceleration, angular velocity, and magnetic orientation at 100 Hz. Orientation data with respect to the earth's global frame was fused using the Madgwick filter on the sensor firmware [21]. Subsequently, the orientation of the IMU over time was downloaded as quaternions.

Each trunk-mounted IMU was also rigidly connected to a cluster of three reflective markers. These were tracked by an eight-camera motion capture system (Prime$^{x}$ 13 Optitrack v2.3, Natural Point) operating at 120 Hz. The cameras were placed within a 13.5 by 9.35 m rectangular area to ensure optimal visibility, as shown in Figure 1. A central circle was designated as the optimal measurement area, where marker visibility was the highest.

### C. Wheelchair Mobility Tests

Eight wheelchair mobility tests, adapted from Van Der Slikke, Berger, Bregman, *et al.* [22], were used to simulate real-world wheelchair sports manoeuvrers. Tests were modified to suit the measurement environment and are outlined in Table II and Figure 2. Each test was executed twice by each participant, once at normal speed and once at maximum effort.

| Subjects | N | Age | Sex (m/f) | Weight (kg) | Height (cm) | Class |
|---|---|---|---|---|---|---|
| non WC athlete | 7 | 26.4 (10.5) | 2/5 | 69.0 (10.5) | 177.3 (9.9) | - |
| WC athlete | 7 | 18.7 (2.4) | 5/2 | 64.2 (12,9) | 171 (10.7) | 3.0 (1.4) |

TABLE I: Subject characteristics, mean (standard deviation)

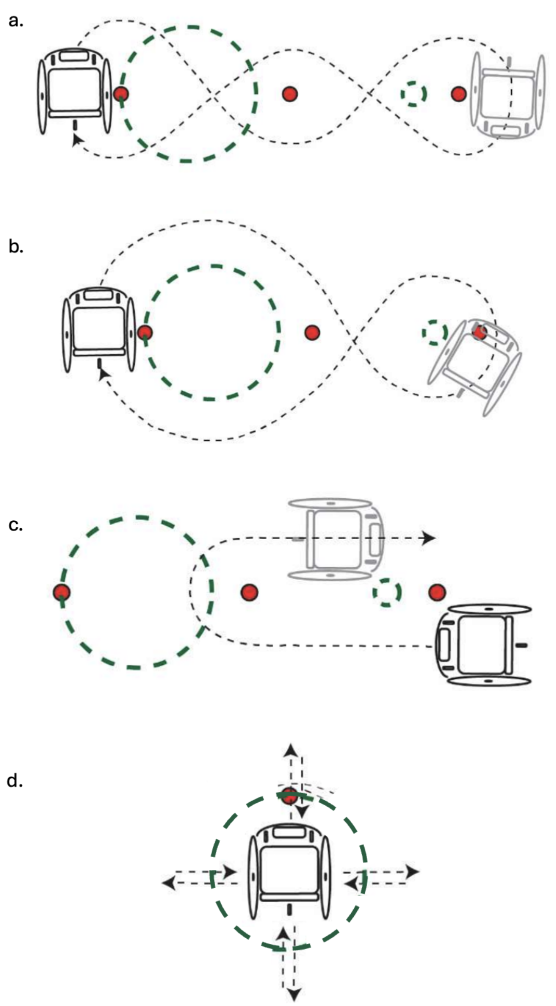



Fig. 2: Four wheelchair mobility tests: a. slalom, b. figure 8, c. u-turn, and d. starmove; figure modified from Van Der Slikke, Berger, Bregman, *et al.* [22]

| Test | Name | Description |
|---|---|---|
| 1 | Trunk movement | Perform maximal trunk flexion and extension in the frontal plane, maximal flexion in both directions in the sagittal plane, and maximal trunk exorotation to both sides |
| 2 | Straight push | Sprint across the entire measurement area |
| 3 | Intermittent sprint | Sprint across the measurement area and come to a complete stop at its centre |
| 4 | Pivot | Rotate 180 degrees around the z-axis in both clockwise and counter-clockwise directions |
| 5 | Slalom | Ride around the cones as shown in Figure 2.a |
| 6 | Figure 8 | Ride around the cones to make a figure 8 as shown in Figure 2.b |
| 7 | U-turn | Perform a u-turn around the cone as shown in Figure 2.c |
| 8 | Starmove | Star wise bi-directional rotation combined with back-and-forth movement as shown in Figure 2.d |

TABLE II: Wheelchair mobility tests with descriptions of the movement

### D. Trunk Motion and Validation

IMU and MOCAP orientations were converted to rotation matrices in Python. The IMU data was resampled to 120 Hz using spherical linear interpolation (SLERP), to match the MOCAP sampling frequency. Rotation matrices were then converted to Euler angles using an XYZ decomposition sequence. Temporal alignment was achieved by computing the cross-correlation of the Euler angles around the z-axis for the whole measurement to determine the time lag. This is based on the assumption that the global z-axis of both the IMU and 3D MOCAP system are oriented vertically.

To account for the spatial misalignment between the IMU and 3D motion capture local coordinate frames, all rotation matrices were normalized using Equation 1. For each test, the orientation at $t = 0$, denoted $\mathbf{R}(0)$, was used as the reference matrix. This approach removes the influence of the initial sensor orientation by expressing all subsequent rotations relative to the starting position, which was consistently upright across tests. The transformation follows the identity property of rotation matrices: $\mathbf{R} \cdot \mathbf{R}^{-1} = \mathbf{I}$.

$$\mathbf{R}_{\text{rel}}(t) = \mathbf{R}(t) \cdot \mathbf{R}(0)^{-1} \tag{1}$$

Trunk orientation was simplified into a single tilt angle ($\beta$), representing the deviation of the trunk from the vertical axis, as shown in Figure 3. The reason and limitations of this approach are discussed in Section IV-D. The formulated trunk tilt angle describes frontal and sagittal flexion and extension, where each movement results in a positive angle, which is calculated using Equation 2.

$$\beta = \cos^{-1}(\mathbf{R}_z \cdot \mathbf{e}_z), \qquad \text{where } \mathbf{e}_z = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \tag{2}$$

From the trunk tilt angle, the following trunk motion metrics were derived for each test and speed combination:

- Range of Motion (ROM) (º)
- Mean Tilt Angle (º)
- Mean Angular Velocity (º/s)
- Time Spent Leaning Forward $> 25$º (s)

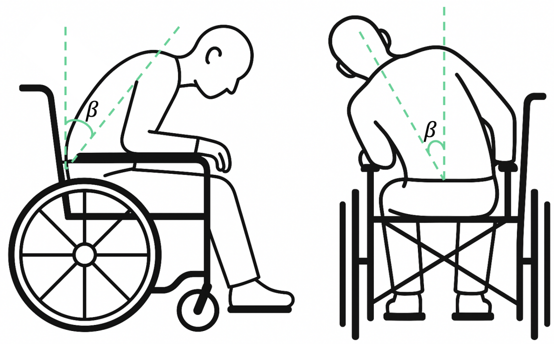



Fig. 3: Trunk tilt angle $\beta$

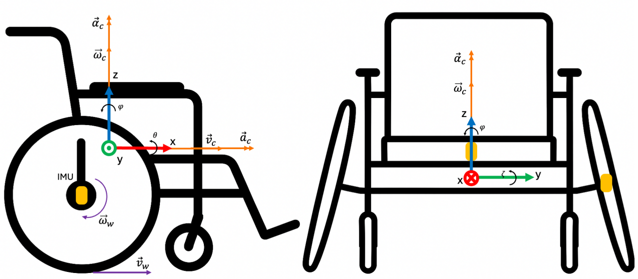



Fig. 4: Diagram of the wheelchair including all mobility performance measures (orange arrows): $\omega_c$, $v_c$, $a_c$, $\alpha_c$. The global frame of the wheelchair is shown (red, green, blue arrows) with its decomposed Euler angles: $\varphi$, $\zeta$, $\theta$. Additional terms used to determine the performance metrics, such as the angular velocity of the wheel $\omega_w$ and the linear velocity of the wheel $v_w$, are visualized in purple arrows. The IMU sensors mounted in the right wheel and backrest are shown in yellow.

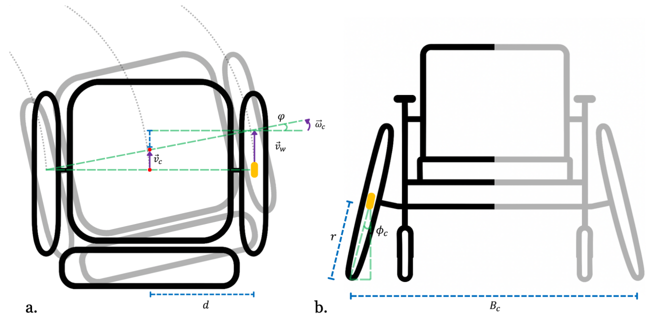



Fig. 5: a. Top view of the wheelchair showing the calculation of the linear velocity of the wheelchair frame ($v_c$), taking the linear velocity of the wheel ($v_w$) and the angular velocity of the chair frame ($\omega_c$) into account. b. Back-view of the wheelchair showing the geometry of the cambered wheel and the determination of the distance of the IMU to the centre of the wheelchair frame ($d$).

The selected trunk motion metrics were included based on their ability to capture distinct aspects of dynamic trunk use and movement strategy. The range of motion reflects the extent to which an athlete is able to utilize the trunk during a given task, providing an indication of available mobility. The mean trunk tilt angle represents the athlete's habitual trunk posture throughout the movement, not only offering insight in trunk motion ability but also strategy and overall forward lean tendency during propulsion. The mean angular velocity characterizes the speed at which the trunk is actively rotated, which may relate to the athlete's ability to generate propulsion power through dynamic trunk use. Lastly, the time spent leaning forward beyond 25º captures the duration of sustained forward engagement, which may reflect temporal endurance and could be relevant in contexts involving prolonged effort. The 25º cutoff was determined by calculating approximately two standard deviations above the mean of all recorded trunk tilt angles, capturing substantial trunk rotation. Although the range of motion and mean angle showed a high correlation (r = 0.81), both were included as they provide complementary information regarding movement capacity and postural control, resulting in a complete assessment of trunk function.

To assess the distribution of trunk tilt angles over time, derived from both the trunk-mounted IMUs and the 3D motion capture system, normality was evaluated using the Shapiro–Wilk test. A p-value greater than 0.05 was considered indicative of a normally distributed dataset. In addition, histograms of the trunk tilt angles were generated to visually assess their distribution. To investigate the relationship between the IMU-derived and MOCAP-derived trunk tilt angles, a correlation plot was constructed. Agreement between the two measurement systems was further examined using a Bland–Altman plot, by examining the mean bias and limits of agreement between the two systems derived angles. The differences between the IMU- and MOCAP-derived trunk tilt angles (i.e., the residuals) were also tested for normality using the Shapiro–Wilk test. Potential outlier behaviour was taken into consideration throughout this analysis.

Validation of the IMU-derived trunk metrics against the MOCAP data included computation of the mean bias, root mean square error (RMSE) and the two-way mixed model intra-correlation coefficient (ICC[3,1]). The mean bias and RMSE shows how much the IMU trunk metrics are over or underestimated in comparison to the 3D MOCAP trunk metrics, where the RMSE penalizes outliers more. The ICC is calculated to compare the time series trunk tilt angles of the IMUs against the MOCAP system. The ICC considers consistency, but not perfect agreement, so this validation metric indicates how well the IMU trunk tilt angles are consistent with the 3D MOCAP trunk tilt angles over time relative to the total variability. ICC scores were interpreted as [23]:

- Excellent (ICC $> 0.90$)
- Good ($0.75 <$ ICC $\leq 0.90$)
- Moderate ($0.50 <$ ICC $\leq 0.75$)
- Poor (ICC $\leq 0.50$)

### *E. Performance Metrics*

To investigate the relationship between trunk motion and wheelchair performance, four performance metrics were calculated from the wheel- and frame-mounted IMUs capturing wheelchair kinematics, as shown in Figure 4:

- Chair linear velocity ($v_c$, m/s)
- Chair angular velocity ($\omega_c$, deg/s)
- Chair linear acceleration ($a_c$, m/s$^2$)
- Chair angular acceleration ($\alpha_c$, deg/s$^2$)

The performance metrics were selected because they reflect fundamental components of wheelchair movement relevant to sports performance and trunk contribution. Chair linear velocity represents the forward propulsion speed of the wheelchair and is closely linked to the athlete's ability to generate sustained forward motion. The angular velocity of the wheelchair captures rotational movements, such as those occurring during turning tasks, and may depend heavily on trunk contribution to initiate and control directional changes and weight shifts. Including both linear and angular velocity allows for a comprehensive assessment of the two primary movement axes in wheelchair sports: straight propulsion and directional manoeuvring. Furthermore, the accelerations of both velocity metrics were included to quantify how rapidly athletes are able to initiate or change motion. These acceleration metrics reflect explosive power and responsiveness. These four wheelchair frame metrics offer a direct measure of the athlete-wheelchair system's performance and are sensitive to contribution of trunk motion during propulsion and directional changes.

The linear and angular velocities and accelerations of the wheelchair were calculated for each of the eight wheelchair mobility tests, which were all performed at two speeds. Only the seven elite wheelchair basketball athletes were considered in the trunk and performance analysis, because the performance of non-experienced participants is significantly different from the elite athletes, creating outliers in the data. To calculate the four performance metrics, the performance metric equations were adapted from methodologies described in Van Der Slikke, Berger, Bregman, *et al.* [22] and Van Dijk, Van Der Slikke, Rupf, *et al.* [20].

Wheelchair motion was determined by decomposing the orientation data from the IMUs, mounted on the wheel axis and wheelchair frame, into Euler angles: pivot ($\varphi_w$ & $\varphi_c$), roll ($\zeta_w$ & $\zeta_c$), and pitch ($\theta_w$ & $\theta_c$) angles, as shown in Figure 4. The wheel angular velocity $\omega_w$ reflects how the wheel rotates, which is needed to determine the linear velocity of the wheelchair frame $v_c$. Although the wheel of a sports wheelchair is typically cambered, i.e. tilted inward at the top, no correction for camber angle is necessary when using the IMU orientation with respect to the global frame. This is because the rotation around the wheel's roll axis remains consistent and the angular velocity of the wheelchair frame $\omega_c$ does not show up in the roll angles. Therefore, the wheel angular velocity is determined using: $\omega_w = \Delta\zeta_w \cdot f_s^{IMU}$.

To determine the linear velocity of the wheelchair frame centre $v_c$, both the linear velocity of the wheel ($v_w = \omega_w \cdot r$) and the turning motion of the chair must be considered. When the chair turns, the velocity of the wheel-mounted IMU deviates from the true centre-of-mass velocity of the chair. To correct for this, a geometric correction using the wheelchair frame pivot angle ($\varphi_c$) and the lateral distance ($d$) between the IMU and the wheelchair's centre is applied by using Equation 3. The geometry of the correction term is shown in Figure 5.a.

$$v_c = (\omega_w \cdot r) \pm [\tan(\varphi_c) \cdot d] \cdot f_s^{IMU} \quad (3)$$

The lateral distance $d$ is a function of the total chair width $B_c$, camber angle $\phi_c$, and wheel radius $r$, as shown in Equation 4. The geometry of the lateral distance is visualized in Figure 5.b.

$$d = \frac{B_c}{2} - \sin(\phi_c) \cdot r \quad (4)$$

Furthermore, the chair angular velocity $\omega_c$ captured the wheelchair's rotation about the vertical axis and is obtained from the frame-mounted IMU pivot angle, as shown in Equation 5.

$$\omega_c = \Delta\varphi_c \cdot f_s^{IMU} \quad (5)$$

Finally, linear and angular accelerations are derived from their respective velocities using Equation 6 and Equation 7.

$$a_c = \Delta v_c \cdot f_s^{IMU} \quad (6)$$

$$\alpha_c = \Delta\omega_c \cdot f_s^{IMU} \quad (7)$$

The speeds and accelerations over time are simplified to the maximum speed and acceleration of each test performed by the participants. Each test was performed by participants at a normal speed and a high speed, which should result in significantly different mobility performance metrics. It is assumed that these speed conditions will also yield significantly different trunk motion, because trunk will be leveraged more when higher speeds are realized. To evaluate whether the instructed speed conditions (high speed vs. normal speed) resulted in measurable differences in movement behaviour, paired sample t-tests were conducted for the trunk and performance metrics across each wheelchair mobility test.

The relationship between the trunk motion metrics and the wheelchair mobility performance is investigated by computing Pearson correlation values for each combination of trunk versus performance metric. Furthermore, the Pearson correlation between trunk motion, performance and classification level are investigated. However, based on the validation results (Section III-A), only range of motion and mean tilt angle were included in subsequent analyses of the relationship between trunk motion, performance, and classification level. Mean angular velocity and time spent leaning forward showed large errors relative to the 3D MOCAP reference (Table III), and were therefore excluded to ensure valid interpretation of results. Additionally, only the trunk tilt angles measured by the IMU mounted on the upper back are included in the following analyses, due to higher accuracy results from the validation study.

TABLE III: Mean bias and RMSE results of the validation of both trunk IMUs when compared to the 3D MOCAP data. Both validation metrics are also represented as the percentage of mean bias and RMSE relative to the IMU-derived trunk metric.

| | | **Lower trunk (T11-T12) IMU** | | **Upper trunk IMU (T3-T4)** | |
|---|---|---|---|---|---|
| | Speed | mean bias (%) | RMSE (%) | mean bias (%) | RMSE (%) |
| Range of motion (º) | Normal | 0.52 (1.51) | 6.84 (19.70) | -0.54 (1.50) | 1.49 (4.11) |
| | High | -1.02 (2.30) | 10.23 (23.14) | -0.61 (1.22) | 4.35 (8.79) |
| Mean tilt angle (º) | Normal | -0.84 (6.37) | 6.29 (47.87) | -0.04 (0.27) | 1.05 (8.18) |
| | High | -0.36 (2.10) | 7.87 (45.99) | -0.05 (0.28) | 1.32 (7.54) |
| Mean angular velocity (º/s) | Normal | -0.10 (13.43) | 1.16 (149.03) | -0.02 (1.14) | 0.77 (44.64) |
| | High | -0.23 (11.12) | 2.14 (105.66) | 0.16 (6.26) | 1.40 (55.40) |
| Time leaning forward (s) | Normal | -0.46 (10.82) | 2.29 (54.31) | 0.06 (1.27) | 1.97 (41.37) |
| | High | -0.08 (1.52) | 1.35 (24.39) | -0.09 (1.50) | 0.83 (13.18) |

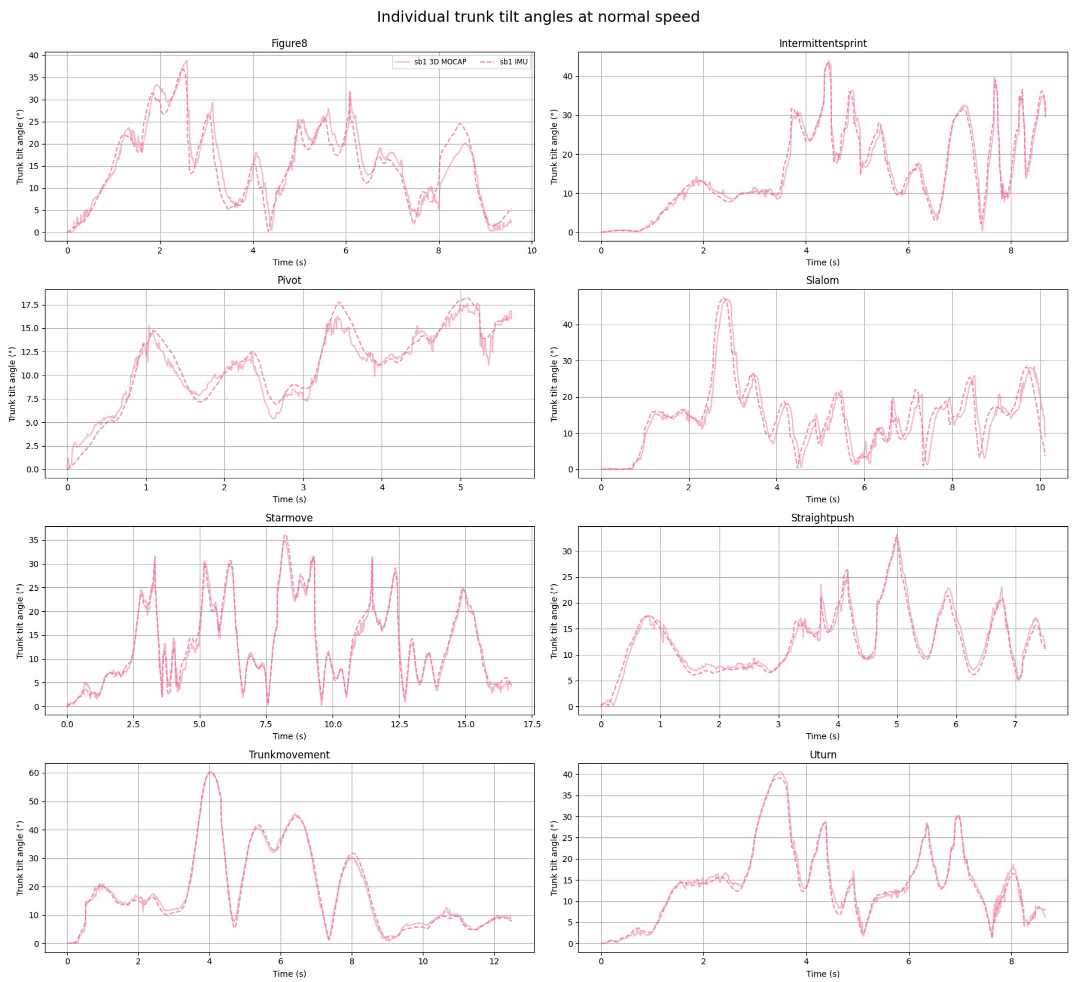



Fig. 6: IMU and 3D MOCAP-derived trunk tilt angles (º) of each test of one elite wheelchair athlete at normal speed, measured using the upper-back mounted IMU

## III. Results

### A. Validation

Normality test results are summarized in Appendix A. Although IMU-derived trunk tilt angles showed excellent agreement with the 3D MOCAP data (Pearson's r = 0.99 for the upper back and r = 0.87 for the lower back). Normality tests revealed that neither the IMU nor MOCAP-derived angles followed a normal distribution. Shapiro-Wilk tests yielded p-values below 0.0001, with positive skewness ($> 1.4$) and moderate kurtosis ($< 3$), reflecting the inherently positive tilt angle values. The residuals (MOCAP - IMU) also deviated strongly from normality, showing extreme skewness (–2.74 for the upper back, –2.11 for the lower back) and high kurtosis (77.60 and 32.16), indicating the presence of significant outliers, particularly for the lower back sensor. IMU and 3D MOCAP-derived trunk tilt angles of one elite wheelchair athlete for all eight tests are shown in Figure 6, indicating a good visual match between the trunk tilt angles derived by both systems over time.

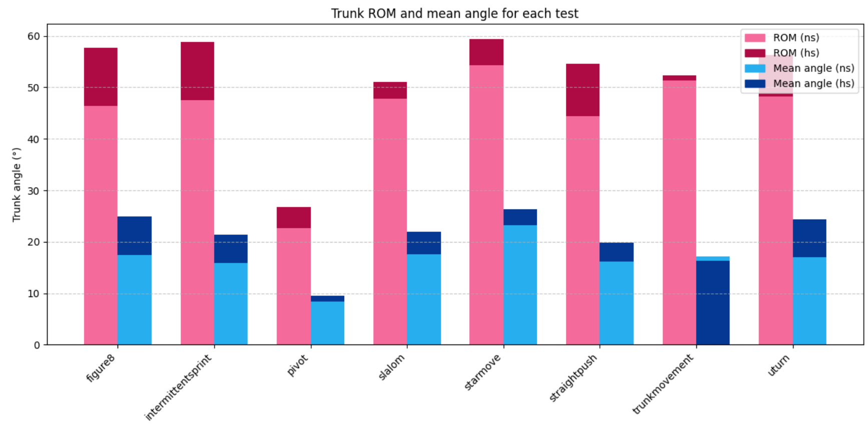



Fig. 7: Trunk range of motion and mean angle of all elite athletes measured during the eight wheelchair mobility tests at two speed conditions, where hs = high speed, and ns = normal speed

Table III summarizes the overall agreement between the trunk-mounted IMUs and the 3D MOCAP system across all tests performed by the fourteen participants. For both the lower back (T11-T12) and the upper back (T3-T4) IMUs, the mean bias and RMSE were calculated for the trunk motion metrics. Additionally, the mean biases and RMSEs are presented as a percentage of the absolute IMU-derived trunk metrics values.

The validation results demonstrate that both the lower back and upper back IMUs show that agreement with the 3D MOCAP reference system varies by trunk metric and IMU placement. Overall, the upper back IMU consistently showed lower mean bias and RMSE values compared to the lower back IMU, indicating higher accuracy, particularly for range of motion and mean tilt angle (RMSE = 4.11-8.79% for upper back vs. 19.70-47.87% for lower back). However, trunk mean angular velocity and time leaning forward showed significantly higher RMSE values (up to 149%) than the other two trunk motion metrics for both back-mounted IMUs. Notably, the validation metrics were not consistently higher for high speed conditions, as was expected.

In addition, intraclass correlation coefficients (ICCs) were computed based on the full time series of the trunk tilt angles. ICCs ranges from the 0.91 to 0.99 across most tasks for the upper back IMU, indicating excellent consistency with the MOCAP system. The lower back IMU also showed generally high ICC values (mostly $> 0.90$), though lower ICCs were observed in some tests such as the Slalom and Figure 8 (ICC = 0.49-0.72).

Full tables with task-specific comparisons, including mean IMU values, mean MOCAP values, bias, RMSE and ICCs for each test and speed condition, are provided in Appendix B.

### *B. Trunk Motion and Performance*

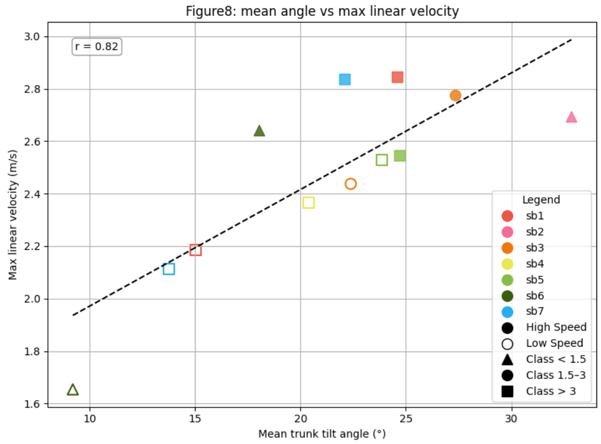
Although four trunk motion metrics were initially measured using the upper-back IMU, only range of motion and mean tilt angle were included in the analysis of trunk motion and its relationship with performance and classification level. The other two metrics were excluded based on poor validation results (see Table III). The mean range of motion and mean angles of all elite wheelchair athletes during each test are shown in Figure 7. To capture wheelchair mobility performance, four maximum speed and acceleration metrics are determined for each test: the linear velocity of the chair $v_c$, the angular velocity of the chair $\omega_c$, the linear acceleration of the chair $a_c$, and the angular acceleration of the chair $\alpha_c$.

To investigate the relationship between the trunk metrics and performance metrics, Pearson correlation for each combination of metrics is determined. Full results of these correlation analyses are shown in Table VIII in Appendix D. The combinations of trunk and performance metrics that yielded a Pearson r-value $\geq 0.75$ are shown in Figure 8.

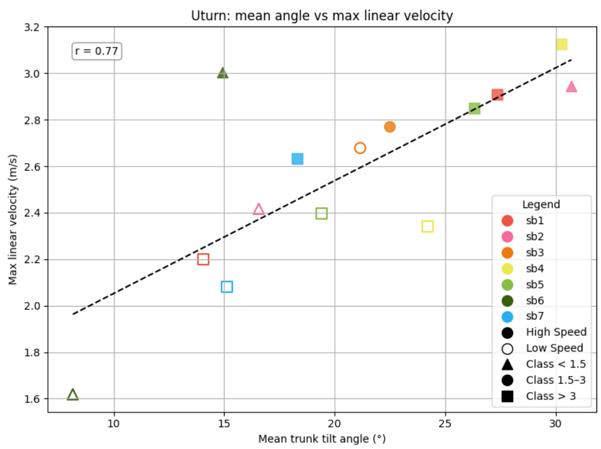
As shown in Figure 8, the mean trunk tilt angle and maximal linear velocity of the wheelchair show a significant correlation (r $\geq$ 0.75) when measured during three different tests: the figure 8, the u-turn, and the intermittent sprint test.

The paired t-tests results investigating the difference between the trunk motion and performance metrics, shown in Appendix C, revealed several noteworthy trends. Wheelchair performance metrics showed significant differences between speed conditions for most tests, although this pattern was not uniform across all metrics and tasks. As expected, the angular velocity of the wheelchair demonstrated statistically significant increases in the high-speed conditions for nearly all test, except the straight push and trunk movement tests. The absence of significant differences in these two tasks aligns with their nature: the trunk movement test involves static trunk motion, and the straight push test involves linear propulsion without directional changes, reducing the opportunity to generate angular velocity. Surprisingly, the linear velocity of the wheelchair did not show significant differences between speed conditions for the slalom, starmove, and straight push tests.

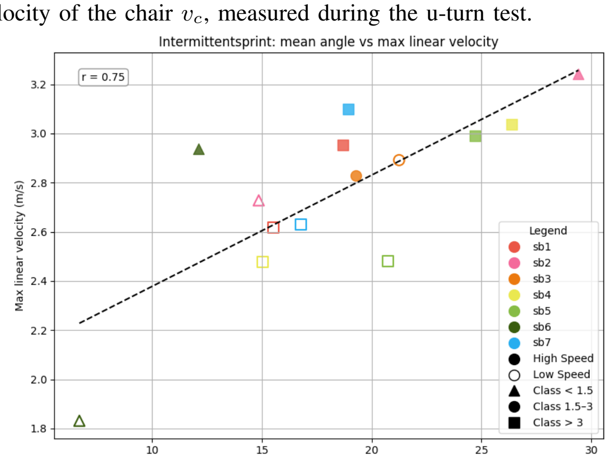
Regarding trunk motion metrics, the range of motion did not result in significant differences between speed conditions for any of the wheelchair mobility tests. The mean angle demonstrated a significant difference during the figure 8, intermittent sprint, slalom and u-turn tests.




(a) Trunk metric mean angle and the performance metric max linear velocity of the chair $v_c$, measured during the figure 8 test.




(b) Trunk metric mean angle and the performance metric max linear velocity of the chair $v_c$, measured during the u-turn test.




(c) Trunk metric mean angle and the performance metric max linear velocity of the chair $v_c$, measured during the intermittent sprint test.

Fig. 8: Plots of trunk metrics and performance metrics where the correlation was $\geq$ 0.75. Subjects are anonymously indicated in different colours. Speed conditions are indicated with a filled or hollow marker. Classification level is grouped in three groups ($<$ 1.5, 1.5-3, $>$ 3) indicated with a triangular, circular and square marker.

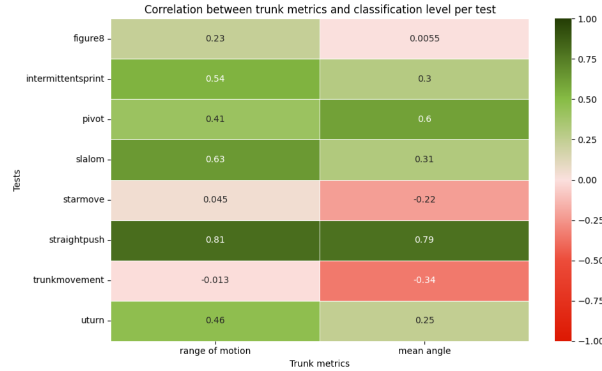



Fig. 9: Correlation between trunk motion metrics and classification level per test


Fig. 10: Correlation between performance metrics and classification level per test

### C. Classification

To investigate the relationship between trunk motion during the wheelchair mobility tests and classification level of the athletes, the correlation between each trunk metric and classification level is determined per test, which is shown in Figure 9. Highest Pearson correlations were found between the range of motion (r-value = 0.81), and mean trunk tilt angle (r-value = 0.79) and classification level, both measured during the straight push test.

To research the effect of classification on wheelchair mobility test performance, Pearson correlation between each performance metric and classification level was calculated, as shown in Figure 10. There were no r-values found above 0.47, indicating poor correlation between all performance metrics and classification level for each test.

Figure 11 and 12 present the trunk movement and wheelchair performance metrics, grouped by classification level into three groups, during the intermittent sprint and straight push tests. The trunk metrics (Figure 11) of the medium and high classification groups are almost the same during the intermittent sprint test, indicating that there is no distinction possible between these groups based on trunk motion. However, during the straight push test, distinction between all three groups is possible.

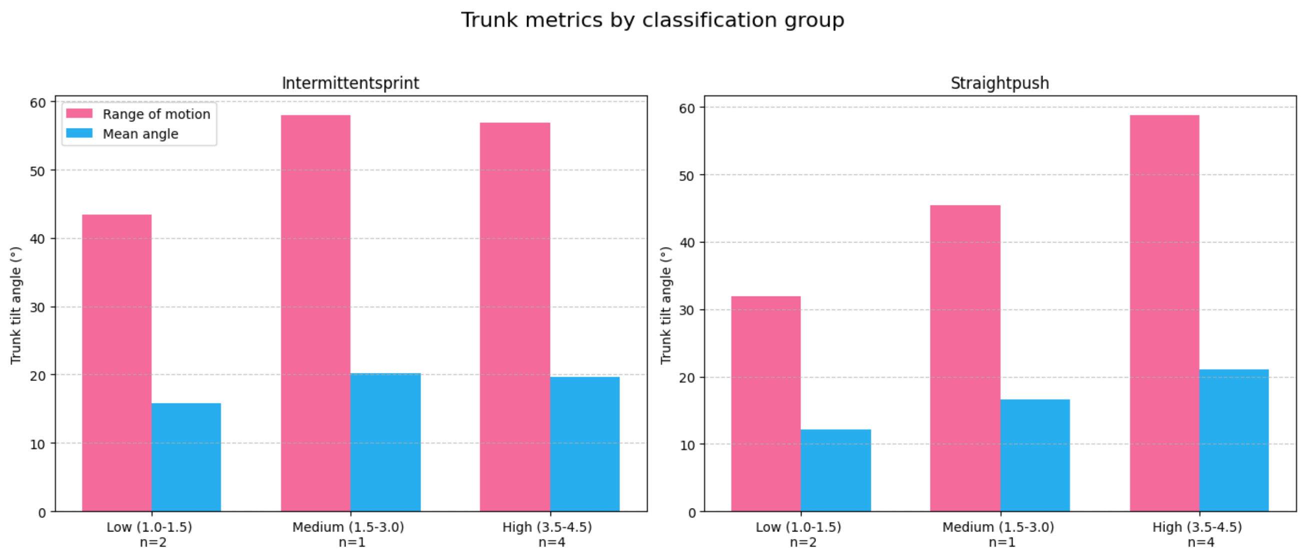



Fig. 11: Trunk motion metrics for three classification level groups: low represents class 1.0 - 1.5, medium represents class 2.0 - 3.0, and high represents class 3.5 - 4.5, measured during the intermittent sprint and straight push tests. The number of subjects per group is indicated with n.

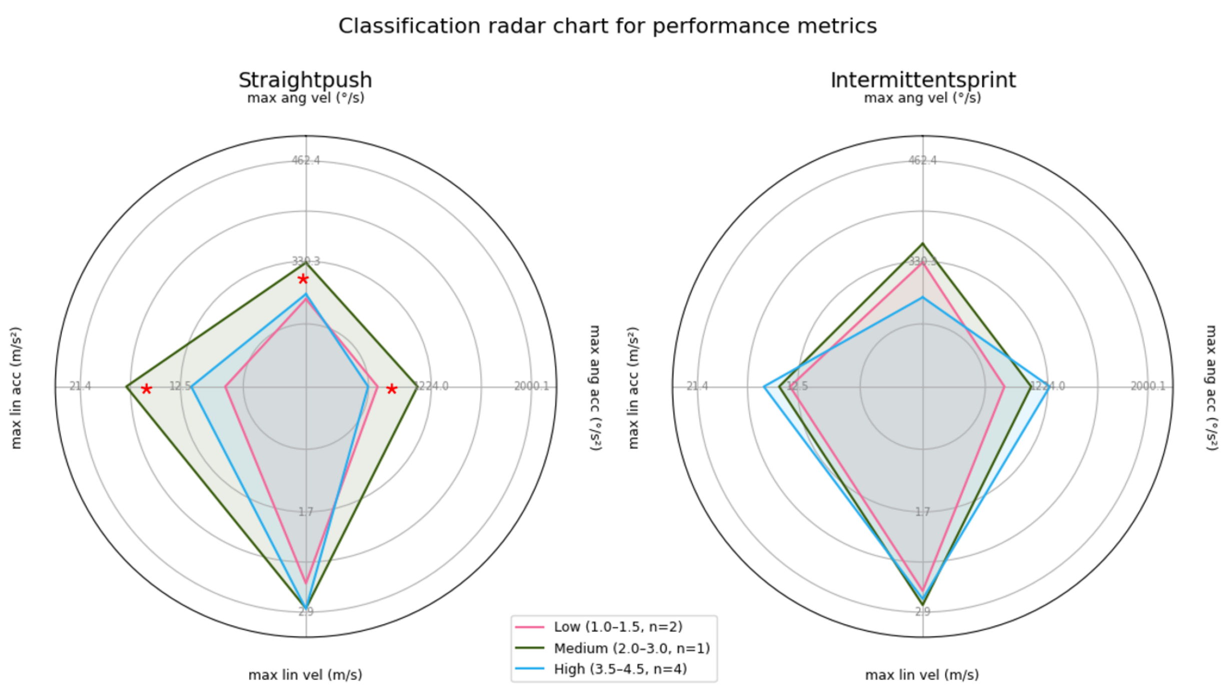



Fig. 12: Wheelchair mobility performance metrics for three classification level groups: low represents class 1.0 - 1.5, medium represents class 2.0 - 3.0, and high represents class 3.5 - 4.5, measured during the intermittent sprint and straight push tests. Significant ($p < 0.05$) differences are indicated with a *. The number of subjects per group is indicated with n.

Additionally, the performance metrics measured during the intermittent sprint and straight push tests (Figure 12) show that the medium class group outperforms the high and low classification groups on multiple performance metrics, even showing significant differences. A distinction between classification groups cannot be made based on the performance metrics. Bar charts and radar charts of trunk metrics and performance metrics when grouping the athletes in classification groups from all tests are shown in Figure 14 in Appendix E.

## IV. Discussion

This study set out to validate the use of inertial measurement units (IMUs) for quantifying trunk motion during wheelchair mobility tasks and to examine how trunk motion correlates with performance and athlete classification in elite wheelchair basketball. The findings support the use of upper-back-mounted IMUs as a reliable and practical tool, and indicate that trunk kinematics are closely linked to both performance and classification level, with implications for evidence-based classification.

### A. Validation

Trunk tilt angles derived from IMUs showed high agreement with 3D motion capture data, especially when the IMU was placed on the upper back (Pearson r = 0.99, ICC $>$ 0.90), indicating excellent temporal consistency. In contrast, the lower back sensor produced more variable results, with some ICC values dropping as low as 0.49, possibly due to sensor instability. Furthermore, the sensor position on the lower back was increasingly susceptible to occlusion from the wheelchair backrest, which may have degraded marker visibility and introduced noise into the MOCAP signal. As a result, while the upper back appears to be a promising location for trunk motion assessment using IMUs, this study does not provide sufficient evidence to conclusively recommend an optimal marker placement.

Comparison of trunk motion metrics further confirmed better performance of the upper back IMU. Mean biases and RMSE values were consistently lower than those from the lower back sensor. Interestingly, two of the four initial trunk motion metrics, the mean angular velocity and the time spent leaning forward, were excluded from subsequent analysis due to poor validation results, with RMSEs reaching up to 149%. The lower validity of the mean angular velocity metric can be explained by the fact that it is derived by taking the time derivative of the trunk tilt angles. Differentiation is inherently sensitive to high-frequency noise and small misalignments, which are often present in IMU-based orientation estimates due to drift or magnetic disturbances. These errors are amplified during differentiation, which may explain the large deviations between the IMU and MOCAP-derived mean angular velocity.

Similarly, the time leaning forward metric is based on a binary threshold of 25º, making it particularly vulnerable to minor angular misestimations. Even small errors in trunk angle estimation, due to drift, noise or time alignments, can result in over or underestimation of the time spent above the threshold, reducing the reliability of the metric. This vulnerability is also present in the 3D motion capture-derived version of the metric, where fluctuations around the threshold due to noise can significantly distort the outcome. These results highlight the importance of metric-specific validation before IMU data is used for quantitative assessment or classification decisions.

In contrast, the remaining trunk metrics, range of motion and mean tilt angle, demonstrated excellent accuracy when compared to the 3D motion capture system. For these two metrics, small mean biases and acceptable RMSEs confirm that IMUs can serve as a viable alternative to laboratory-based 3D MOCAP systems for measuring trunk tilt angle and range of motion in field settings. As mentioned before, the 3D MOCAP system itself was subject to limitations such as marker occlusion and tracking errors, particularly for the lower back sensor, which may have affected its accuracy as a reference standard. These issues are further discussed in Section IV-D, and should be considered when interpreting the validation results.

### B. Trunk Motion and Performance

A strong relationship was found between trunk motion and wheelchair mobility performance, particularly between the mean trunk angle and the maximal linear velocity of the wheelchair during the figure 8, u-turn, and intermittent sprint tests (r $\geq$ 0.75). These findings indicate that dynamic trunk use plays an important role in facilitating propulsion and manoeuvrability. In tests requiring both propulsion and turning, such as the figure 8 and u-turn, effective trunk engagement appears to aid in power transfer and postural stability, supporting better performance outcomes. However, no significant correlation was observed between angular velocity of the wheelchair and trunk motion in these tests, suggesting that trunk involvement is more critical for linear propulsion than for turning speed. In the intermittent sprint test, which primarily involves forward propulsion and an abrupt stop, the strong correlation between linear velocity and trunk mean angle underscores this importance of trunk use during high-speed propulsion.

It is important to note, however, that the mean trunk angle does not solely reflect impairment-related limitations. Rather, it is a composite measure that also captures an athlete's propulsion strategy, where higher mean angles may reflect intentional forward leaning to optimize sprint performance. This dual nature of the metric highlights the need for careful interpretation when using it as an indicator of impairment.

Other research support the notion that trunk motion is a substantial contributor to wheelchair propulsion performance. Dijk, Slikke, Berger, *et al.* [18] quantified the role of trunk movement during the recovery phase of the push cycle, revealing that 25-30% of total forward propulsion was generated after the hands released the pushrim, solely through trunk-induced motion. This highlights that trunk movement plays a critical role in accelerating the wheelchair. Additionally, they found that mean trunk angle increased significantly with sprint intensity. These insights closely align with the present findings, where mean trunk angle was strongly correlated with maximum linear velocity of the wheelchair, reinforcing that athletes who utilize more trunk motion achieve higher performance outputs.

### *C. Classification*

Trunk motion metrics were strongly associated with athlete classification, especially during the straight push test. Range of motion and mean angle were both highly correlated with classification level (r = 0.81, 0.79, respectively). Since this test isolates linear propulsion, these metrics likely reflect the athlete's ability to generate force with their trunk, which is a key determinant for trunk control capacity and thus impairment level.

Conversely, mobility performance metrics showed weak correlations with classification ($r < 0.47$). This discrepancy suggests that performance alone is not a suitable proxy for classification, as athletes may compensate for impairments with skill, training, or strategy. The data highlights that impairment, not performance, should be the basis of classification, reinforcing the potention of trunk motion analysis as a more specific indicator.

The charts shown in Figure 11 and Figure 12 further illustrate that trunk motion metrics could distinguish between classification groups, while performance metrics could not. For example, the medium-classified group outperformed the high-classified group on several performance metrics, even though classification level is lower. This shows that high performance does not necessarily reflect low impairment. However, athletes were measured in their own sports wheelchair, which might have different functions. Some wheelchairs are adjusted to achieve maximum speed, while others might have a higher seating position to promote reaching for the ball. These differences might undermine the performance results that were acquired from the seven elite wheelchair athletes.

In contrast to the findings in this study, Van Der Slikke, Bregman, Berger, *et al.* [10] reported a significant relationship between classification level and wheelchair mobility performance during match play in a sample of 29 wheelchair basketball athletes. Their study aimed to evaluate the necessity of the eight existing classification levels used in elite wheelchair basketball. They observed significant differences in IMU-derived mobility performance between low and medium classified athletes, but not between medium and high classifications. This indicates that the relationship between wheelchair mobility performance and classification is not linear, and athletes might plateau in wheelchair performance from middle to high classification levels. Any statistical correlation between classification and performance inherently assumes a linear relationship that may not accurately reflect these non-uniform trends. This should be considered when interpreting the weaker correlations observed in this study between classification and wheelchair mobility performance metrics. It is worth noting, however, that Van Der Slikke, Bregman, Berger, *et al.* [10] also concluded that mobility performance alone may not serve as a sufficient basis for classification. This reinforces the potential value of incorporating additional measures, such as trunk motion analysis, into performance assessments or classification frameworks.

### *D. Limitations*

Despite promising results, several limitations must be acknowledged. First, IMU and 3D MOCAP-derived trunk tilt angle distributions, as well as their differences (residuals), deviated significantly from normality. This is problematic because the intraclass correlation coefficient (ICC), used to validate temporal consistency, assumes normality based on ANOVA. Therefore, while the ICC values of the upper back were excellent, these findings should be interpreted cautiously due to the violation of these statistical assumptions.

Second, errors in the reference system (3D MOCAP) were present: some datasets showed dubious marker trajectories due to occlusion or overly sensitive tracking settings. Because of the large measurement area, the camera settings were set to be more sensitive to reflections. Visual inspection of the motion capture data confirmed marker flipping within marker clusters, especially for the lower back sensor. Although many of these artifacts were manually corrected through visual observation, not all were resolved. These limitations in the MOCAP system affect the interpretation of the validation results. Since the motion capture system served as the reference, tracking errors may have contributed to the observed discrepancies between the IMU and MOCAP-derived trunk motion metrics. This implies that some of the validation errors may be due to the inaccuracies in the gold standard itself, potentially underestimating the true performance of the IMUs, especially for the lower back. Therefore, the reported validation results should be interpreted with nuance.

When validating the two trunk-mounted IMUs, trunk orientation angles were simplified to a the trunk tilt angle, representing the deviation from the vertical without distinguishing between frontal and sagittal plane movements, nor between flexion and extension. This simplification, which results in only positive values regardless of motion direction, was chosen because accurate 3D spatial alignment between the IMU and MOCAP coordinate frames could not be achieved, likely due to the 3D MOCAP marker flipping and IMU magnetic inaccuracies. The horizontal orientation estimates from the IMUs are particularly prone to drift and distortion due to magnetic interference, especially in indoor environments. Since both the trunk and the wheelchair frame IMUs rely on magnetometer data for horizontal orientation, many inaccuracies are compounded when computing the relative trunk motion. Even small deviations in the horizontal orientation of either sensor can have large effects on the decomposition of trunk motion into pitch and roll angles. This is because frontal flexion can project onto lateral axes, depending on yaw misalignment. Inspection of raw magnetometer data acquired by the IMU sensors showed a fluctuating magnetic field magnitude, indicating that magnetic interference sources were present in the measurement area.

As a result, the simplification to a single trunk tilt angle reduces the biomechanical resolution of the measurement. Movements occurring in different anatomical places, such as forward flexion for propulsion and sagittal rotation for turning, are merged into a single value, limiting the interpretability of the movement strategy. The conflation of frontal and sagittal trunk movements may be acceptable when examining the relationship between trunk motion and impairment, as the ability to move in these directions is likely highly correlated. However, the inability to distinguish between trunk flexion and extension may be a more significant limitation. Because the trunk tilt angle is always positive, trunk motion metrics can be underestimated, particularly the range of motion. This lack of directionality limits the ability to identify whether an athlete's impairment restricts flexion, extension, or both.

Furthermore, the two-IMU configuration used to measure wheelchair kinematics in this study was adopted from Van Dijk, Van Der Slikke, Rupf, *et al.* [20]. In contrast, Van Der Slikke, Berger, Bregman, *et al.* [22] proposed a three-IMU approach, comprising two IMUs mounted on the wheel axles and one on the wheelchair frame. This setup enables the implementation of a wheel skidding correction algorithm, which identifies discrepancies between the wheel-derived velocities and the actual motion of the wheelchair frame. When a wheel skids, it rotates without causing the wheelchair to move forward. This leads to an overestimation of the wheelchair's linear velocity if uncorrected. Since the two-IMU configuration lacks a second wheel-mounted sensor, skidding correction cannot be applied. Validation of the two-IMU approach by Van Dijk, Van Der Slikke, Rupf, *et al.* [20] showed increased root mean squared errors (RMSE) in both linear and angular velocity estimates compared to the three-IMU configuration. Additionally, visual observations during the wheelchair mobility tests in the present study, especially during the starmove test, revealed instances of skidding. As no correction for skidding was implemented, it is likely that some wheelchair mobility performance metrics were overestimated.

The study's small sample size (n = 7 elite athletes) limits generalizability of the results. The classification distribution was non uniform, with no athletes in the 1.5 or 2.0 class, resulting in a signle subject in the middle classification group (2.0 - 3.0 range). This under-representation reduces statistical power and complicates group comparisons, especially when interpreting classification trends. Lastly, when analysing the effects of the two speed conditions on trunk motion and performance metrics, no significant differences were found in several metrics. This may indicate that athletes did not fully reach their maximum effort in the high-speed trial during certain tests, which can introduce variability that is not related to impairment. It is also possible that some trunk metrics are not sensitive to speed-induced differences, because athlete's change their trunk motion strategy, for example by exhibiting faster but smaller trunk movements.

### E. Recommendations for Classification

Strong correlations between trunk motion and performance in agility-demanding tests (e.g. figure 8, u-turn) suggest that effective trunk use contributed substantially to wheelchair manoeuvrability and speed. These tests simulate sport-specific scenarios that require coordinated trunk motion for optimal performance. Furthermore, high correlation between trunk motion and propulsion-focussed tests (e.g. intermittent sprint) highlights the importance of trunk use for propulsion speed. However, since performance is influenced by factors beyond impairment, such as training, skill, and strategy, it should not solely be used to determine classification.

Instead, results showed that the straight push test offers a more controlled and direct evaluation of impairment. This test isolates the athlete's ability to generate forward propulsion without requiring agility or decision-making. The high correlation between trunk motion during this test and classification levels suggests it captures physical limitation more accurately. However, the straight push test might not be the most reliable indicator for classification when used in isolation, because athletes may consciously or unconsciously manipulate their trunk use when aware that the test will be used for classification purposes, potentially compromising its objectivity. Furthermore, this study found that trunk motion and performance metrics did not always show significant differences during low and high effort trials, indicating that athletes may not consistently perform at maximal effort when intrinsic motivation is lacking. In contrast, competitive match setting naturally induce high motivations due to the desire to win, reducing the likelihood of deliberate underperformance.

Therefore, future classification systems could benefit from incorporating trunk motion assessment during actual match play. Using an IMU op the upper back to measure trunk kinematics, such as the range of motion or mean trunk tilt angle, during sprint-like movements within competition offers a more reliable representation of the athlete's functional trunk motion ability. These metrics could serve as objective indicators to support or verify class allocation decisions.

This approach aligns with the broader goal of classification: to assess impairment, not performance. Including a biomechanically meaningful and objective measured task like forward propulsion would strengthen the evidence base of classification and reduce the reliance on subjective judgment.

### F. Future Research

Future studies should focus on achieving accurate 3D validation of IMU-derived trunk motion. This requires resolving spatial alignment between IMU and MOCAP systems across all three rotational axes. In the current study, a trunk tilt angle was used due to the difficulty of achieving consisted 3D spatial alignment, especially in the presence of magnetic interference affecting the IMU's heading estimation. This could be improved by computing IMU orientation using only 6 degrees of freedom (accelerometer and gyroscope) and exclude magnetometer data, which is often distorted by environmental magnetic interference. While using 6 DOF increases the risk of drift over time due to integration errors in dynamic measurement conditions, it may enable more accurate 3D spatial alignment with MOCAP in short-duration tests. Mitigating magnetometer errors can also be achieved by mapping the magnetic distortions in the test environment. By creating this distortion field, one could correct magnetometer readings and improve IMU orientation estimation using the full 9 DOF sensor data, although this process is time-consuming. Recent developments in magnetometer calibration algorithms may offer a more practical solution to this issue by improving heading accuracy and possibly resolve spatial alignment issues [24]. Additionally, data-driven improvements to sensor fusion algorithms, such as modifications to the Madgwick filter [25], could enhance IMU orientation estimation during high-speed trunk movements. Finally, data-driven optimization approaches can be used to minimize the difference between IMU and MOCAP orientation data [26].

In parallel, further research should also adress the reliability of the MOCAP system itself, particularly regarding noise and tracking instability. 3D motion capture systems are widely regarded as the gold standard for motion measurement. However, in the present study marker flipping and dropout of markers were frequently observed, resulting in noisy and questionable marker trajectories. Future work could investigate optimized camera configurations or improved sensitivity settings to mitigate these issues. Additionally, advanced algorithms could detect and correct marker flipping automatically during post-processing. Enhancing robustness of the reference is critical to ensure that validation results accurately reflect the performance of the IMUs, rather than errors in the gold standard.

Improved spatial alignment and orientation accuracy of both motion measurement systems would enable true 3D validation. This, in turn, would provide deeper insight into the accuracy of IMU-based trunk motion measurement by ensuring complete confidence in the reference system. Additionally, 3D trunk assessment would allow for differentiation between movement directions and types, such as flexion versus extensions and sagittal versus frontal trunk motion. This is particularly relevant in the context of classification, as impairments may affect specific trunk muscle groups asymmetrically, particularly the back and stomach muscles responsible for flexion and extension. A more detailed understanding of how athletes perform distinct trunk movement could contribute to a more impairment-specific classification decision.

Another promising direction for future research is the development of a machine learning model to predict classification level using a combination of trunk motion data, wheelchair performance metrics, and athlete specific features, such as impairment specifics. Such a model could be trained using supervised learning methods, since current classification labels are available for a large dataset. Temporal IMU signals and summary metrics could be engineered into a large set of informative features. Feature reduction techniques such as principal component analysis (PCA) or clustering could identify the most relevant predictors. Firstly, a more interpretable model like a single decision tree could help visualize decision rules and threshold values. More complex models like random forests could be used to enhance prediction accuracy, while compromising on interpretability. Developing such a data-driven, evidence-based system has the potential to make classification less dependent on subjective observation.

## V. Conclusion

This study demonstrated the feasibility and validity of using upper-back-mounted inertial measurement units (IMUs) to quantify trunk motion during wheelchair sports performance tasks. Compared to 3D motion capture, IMUs offered excellent agreement, making them a viable tool for in-field assessment at high speeds. Furthermore, the relationship between trunk motion, performance metrics, and athlete classification was explored. This analysis revealed that trunk motion metrics were strongly correlated with athlete classification, whereas wheelchair mobility performance metrics showed only weak correlations. This contrast highlights that classification should be driven by impairment rather than performance. These findings support the integration of objective trunk motion metrics into evidence-based classification systems for wheelchair sports, offering a more consistent and transparent framework than current subjective practices.

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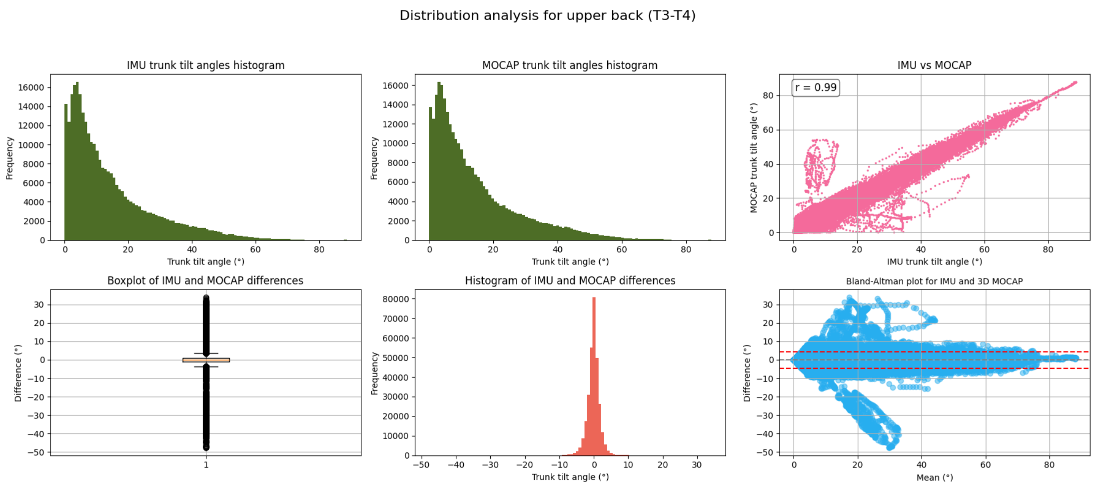
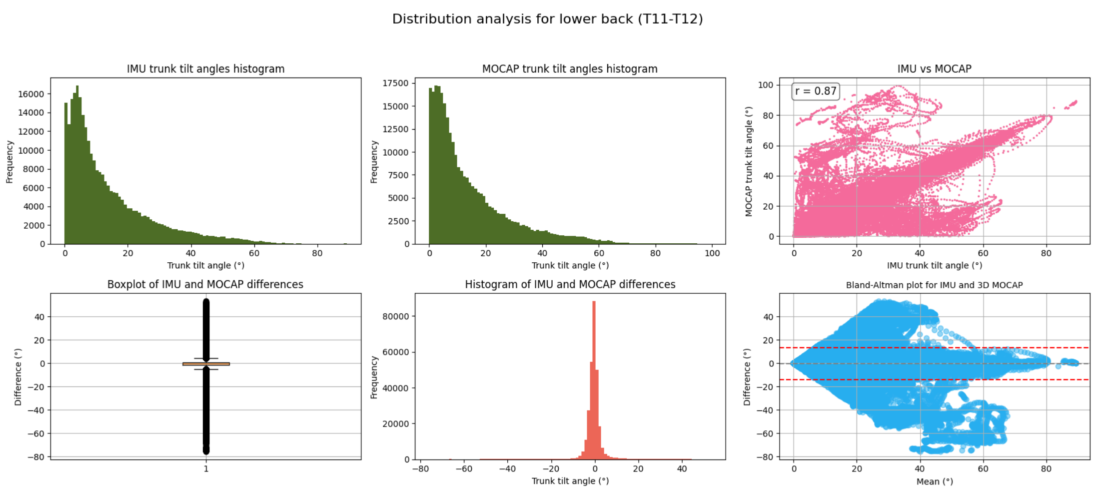
## Appendix A
## Normal distribution

TABLE IV: Summary of distribution characteristics and agreement analysis for trunk tilt angles of the IMUs mounted on the upper back and lower back. The Shapiro statistic is indicated with the corresponding p-value. Skewness and kurtosis values are shown. Whether the distribution follows a normal distribution is answered. Finally, Bland-Altman results are indicated.

| Sensor | Data Type | Shapiro Stat. | p-value | Skewness | Kurtosis | Normal distribution | Bland-Altman (bias/LoA/std) |
|---|---|---|---|---|---|---|---|
| Upper back | IMU | 71880.28 | $< 0.0001$ | 1.43 | 1.88 | No | – |
| | MOCAP | 71106.98 | $< 0.0001$ | 1.42 | 1.84 | No | – |
| | Residuals | 235029.94 | $< 0.0001$ | $-2.74$ | 77.60 | No | $-0.081$ / $\pm 4.35$ / $2.26$ |
| Lower back | IMU | 72477.08 | $< 0.0001$ | 1.50 | 2.02 | No | – |
| | MOCAP | 84592.99 | $< 0.0001$ | 1.62 | 2.84 | No | – |
| | Residuals | 171479.08 | $< 0.0001$ | $-2.11$ | 32.16 | No | $-0.549$ / $\pm 13.31$ / $7.07$ |




(a) Data distribution of the IMU and MOCAP trunk tilt angles and differences for the upper back IMU (T3-T4)




(b) Data distribution of the IMU and MOCAP trunk tilt angles and differences for the lower back IMU (T11-T12)

Fig. 13: Visual comparison of IMU-derived and 3D MOCAP-derived trunk tilt angles for the back sensors. Top row (left to right): histograms of trunk tilt angles from the IMU and MOCAP, and a scatter plot showing the correlation between the two modalities. Bottom row (left to right): boxplot of the differences between IMU and MOCAP measurements, histogram of the residuals, and Bland–Altman plot indicating the bias (gray dashed line) and 95% limits of agreement (red dashed lines).

# Appendix B
# Validation

TABLE V: Comparison of trunk kinematics from the upper back-mounted IMU (T3-T4) and motion capture across wheelchair mobility tests. The mean IMU and MOCAP-derived values of the trunk metrics are shown. The validation metrics, mean bias and RMSE, are shown. Finally, the ICC[3,1] of the time series trunk tilt angles of each test is indicated.

| | | **Range of motion (º)** | | | | **Mean tilt angle (º)** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Speed | IMU | MOCAP | Bias | RMSE | IMU | MOCAP | Bias | RMSE | |
| Trunk movement | High | 57.81 | 57.12 | 0.69 | 3.77 | 14.30 | 13.54 | 0.76 | 2.24 | |
| | Normal | 39.46 | 39.70 | -0.25 | 1.43 | 13.52 | 13.55 | -0.03 | 0.48 | |
| Straight push | High | 50.13 | 54.14 | -4.01 | 11.70 | 15.06 | 15.84 | -0.79 | 2.78 | |
| | Normal | 33.36 | 34.17 | -0.81 | 2.10 | 12.41 | 12.69 | -0.28 | 1.29 | |
| Intermittent sprint | High | 55.02 | 55.75 | -0.73 | 1.70 | 18.33 | 18.61 | -0.28 | 0.65 | |
| | Normal | 39.46 | 39.70 | -0.25 | 1.43 | 13.52 | 13.55 | -0.03 | 0.48 | |
| Pivot | High | 21.90 | 22.43 | -0.53 | 1.01 | 7.04 | 7.11 | -0.07 | 0.42 | |
| | Normal | 18.89 | 19.08 | -0.19 | 0.73 | 6.19 | 6.22 | -0.02 | 0.20 | |
| Slalom | High | 44.95 | 45.47 | -0.53 | 0.96 | 17.64 | 17.74 | -0.11 | 0.31 | |
| | Normal | 34.23 | 34.75 | -0.52 | 0.84 | 13.55 | 13.56 | -0.01 | 0.23 | |
| Figure 8 | High | 52.60 | 52.22 | 0.38 | 1.22 | 20.65 | 20.75 | -0.10 | 0.63 | |
| | Normal | 33.36 | 34.17 | -0.81 | 2.10 | 12.41 | 12.69 | -0.28 | 1.29 | |
| U-turn | High | 53.42 | 53.40 | 0.02 | 1.79 | 21.82 | 21.56 | 0.25 | 0.51 | |
| | Normal | 39.66 | 39.44 | 0.22 | 1.21 | 14.61 | 14.68 | -0.07 | 0.47 | |
| Starmove | High | 57.61 | 58.07 | -0.46 | 1.18 | 23.70 | 23.84 | -0.14 | 0.66 | |
| | Normal | 42.74 | 42.94 | -0.20 | 0.91 | 15.89 | 16.11 | -0.22 | 0.51 | |
| | | **Mean angular velocity (º/s)** | | | | **Time spent leaning forward (s)** | | | | **ICC** |
| | Speed | IMU | MOCAP | Bias | RMSE | IMU | MOCAP | Bias | RMSE | |
| Trunk movement | High | -0.22 | -0.09 | -0.13 | 0.57 | 3.61 | 3.36 | 0.25 | 0.53 | 0.97 |
| | Normal | 2.59 | 3.07 | -0.48 | 0.78 | 6.83 | 7.98 | -1.15 | 3.08 | 0.96 |
| Straight push | High | 4.19 | 3.50 | 0.69 | 2.64 | 5.56 | 5.64 | -0.07 | 1.52 | 0.91 |
| | Normal | 1.28 | 0.94 | 0.34 | 0.57 | 3.87 | 4.03 | -0.16 | 1.33 | 0.97 |
| Intermittent sprint | High | 3.25 | 3.02 | 0.23 | 1.29 | 7.63 | 8.25 | -0.62 | 1.67 | 0.99 |
| | Normal | 2.59 | 3.07 | -0.48 | 0.78 | 6.83 | 7.98 | -1.15 | 3.08 | 0.98 |
| Pivot | High | 0.48 | 0.60 | -0.12 | 0.33 | 0.65 | 0.74 | -0.09 | 0.33 | 0.98 |
| | Normal | 0.53 | 0.61 | -0.08 | 0.27 | 0.62 | 0.69 | -0.07 | 0.30 | 0.95 |
| Slalom | High | 2.80 | 2.89 | -0.09 | 0.82 | 7.21 | 7.39 | -0.18 | 0.31 | 0.98 |
| | Normal | 1.96 | 2.15 | -0.18 | 0.52 | 6.59 | 6.63 | -0.04 | 0.19 | 0.96 |
| Figure 8 | High | 2.13 | 2.36 | -0.23 | 0.67 | 6.75 | 6.77 | -0.01 | 0.22 | 0.99 |
| | Normal | 1.28 | 0.94 | 0.34 | 0.57 | 3.87 | 4.03 | -0.16 | 1.33 | 0.96 |
| U-turn | High | 4.99 | 4.21 | 0.77 | 2.34 | 5.61 | 5.57 | 0.04 | 0.15 | 0.99 |
| | Normal | 2.34 | 2.21 | 0.12 | 0.41 | 4.69 | 4.68 | 0.01 | 0.16 | 0.94 |
| Starmove | High | 2.41 | 2.30 | 0.11 | 0.38 | 12.40 | 12.48 | -0.08 | 0.22 | 0.99 |
| | Normal | 1.69 | 1.78 | -0.09 | 0.27 | 9.27 | 9.35 | -0.08 | 0.30 | 0.97 |

TABLE VI: Comparison of trunk kinematics from the upper back-mounted IMU (T11-T12) and motion capture across wheelchair mobility tests. The mean IMU and MOCAP-derived values of the trunk metrics are shown. The validation metrics, mean bias and RMSE, are shown. Finally, the ICC[3,1] of the time series trunk tilt angles of each test is indicated.

| | | **Range of motion (º)** | | | | **Mean tilt angle (º)** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Speed | IMU | MOCAP | Bias | RMSE | IMU | MOCAP | Bias | RMSE | |
| Trunk movement | High | 55.04 | 56.33 | -1.29 | 3.27 | 13.34 | 13.22 | 0.12 | 0.80 | |
| | Normal | 56.06 | 56.24 | -0.18 | 1.81 | 16.69 | 16.54 | 0.15 | 1.20 | |
| Straight push | High | 44.99 | 49.36 | -4.37 | 9.33 | 15.38 | 17.29 | -1.91 | 4.00 | |
| | Normal | 34.09 | 35.02 | -0.94 | 1.65 | 13.48 | 14.28 | -0.80 | 0.97 | |
| Intermittent sprint | High | 50.42 | 56.66 | -6.23 | 16.82 | 19.10 | 21.58 | -2.48 | 5.43 | |
| | Normal | 38.49 | 39.58 | -1.08 | 2.28 | 14.53 | 16.15 | -1.63 | 3.18 | |
| Pivot | High | 18.11 | 19.55 | -1.44 | 2.27 | 6.85 | 7.38 | -0.53 | 0.89 | |
| | Normal | 17.42 | 18.62 | -1.20 | 1.61 | 6.76 | 6.96 | -0.21 | 0.79 | |
| Slalom | High | 37.30 | 34.83 | 2.47 | 15.71 | 17.45 | 19.74 | -2.29 | 17.78 | |
| | Normal | 29.52 | 23.72 | 5.80 | 11.77 | 12.83 | 13.84 | -1.01 | 14.29 | |
| Figure 8 | High | 44.66 | 40.61 | 4.05 | 14.30 | 20.08 | 15.01 | 5.07 | 11.43 | |
| | Normal | 29.73 | 23.10 | 6.64 | 14.21 | 12.61 | 14.55 | -1.93 | 11.60 | |
| U-turn | High | 48.61 | 49.18 | -0.57 | 2.08 | 21.53 | 21.97 | -0.45 | 1.53 | |
| | Normal | 33.43 | 35.91 | -2.47 | 6.57 | 12.90 | 14.02 | -1.12 | 2.90 | |
| Starmove | High | 51.65 | 52.71 | -1.07 | 1.56 | 21.59 | 22.11 | -0.52 | 0.78 | |
| | Normal | 38.74 | 39.54 | -0.80 | 1.19 | 15.68 | 15.93 | -0.25 | 0.48 | |
| | | **Mean angular velocity (º/s)** | | | | **Time spent leaning forward (s)** | | | | **ICC** |
| | Speed | IMU | MOCAP | Bias | RMSE | IMU | MOCAP | Bias | RMSE | |
| Trunk movement | High | 1.03 | 1.00 | 0.03 | 0.64 | 3.18 | 3.06 | 0.12 | 0.52 | 0.98 |
| | Normal | 0.66 | 0.72 | -0.05 | 0.29 | 5.49 | 5.62 | -0.13 | 0.35 | 0.99 |
| Straight push | High | 2.61 | 2.78 | -0.17 | 0.82 | 5.30 | 6.12 | -0.82 | 1.42 | 0.91 |
| | Normal | 0.56 | 0.51 | 0.05 | 0.43 | 4.75 | 6.43 | -1.68 | 4.80 | 0.96 |
| Intermittent sprint | High | 3.43 | 4.78 | -1.36 | 4.59 | 6.20 | 7.01 | -0.81 | 1.22 | 0.93 |
| | Normal | 1.79 | 2.20 | -0.41 | 0.93 | 6.30 | 7.21 | -0.91 | 1.46 | 0.93 |
| Pivot | High | 1.59 | 1.63 | -0.03 | 0.33 | 0.61 | 0.74 | -0.13 | 0.34 | 0.96 |
| | Normal | 2.14 | 2.18 | -0.04 | 0.41 | 0.45 | 0.56 | -0.10 | 0.26 | 0.94 |
| Slalom | High | 0.14 | 0.54 | -0.40 | 1.06 | 5.61 | 5.60 | 0.01 | 1.96 | 0.72 |
| | Normal | -0.12 | 0.35 | -0.47 | 1.15 | 3.62 | 3.23 | 0.39 | 3.99 | 0.49 |
| Figure 8 | High | 1.72 | 1.49 | 0.23 | 3.57 | 6.07 | 4.92 | 1.16 | 2.62 | 0.61 |
| | Normal | -0.89 | -0.15 | -0.74 | 2.40 | 2.98 | 3.33 | -0.34 | 2.05 | 0.55 |
| U-turn | High | 2.96 | 2.90 | 0.05 | 0.57 | 5.26 | 5.32 | -0.06 | 0.31 | 0.99 |
| | Normal | -0.25 | -0.97 | 0.72 | 1.50 | 2.81 | 3.19 | -0.37 | 0.97 | 0.86 |
| Starmove | High | 2.62 | 2.77 | -0.16 | 0.39 | 11.34 | 11.53 | -0.19 | 0.30 | 0.99 |
| | Normal | 1.98 | 2.00 | -0.03 | 0.27 | 7.38 | 7.81 | -0.43 | 0.68 | 0.96 |

## Appendix C
## Speed significant difference

TABLE VII: Paired t-test results comparing high speed (HS) and normal speed (NS) conditions per test for trunk and performance metrics. Statistically significant differences ($p < 0.05$) are bold.

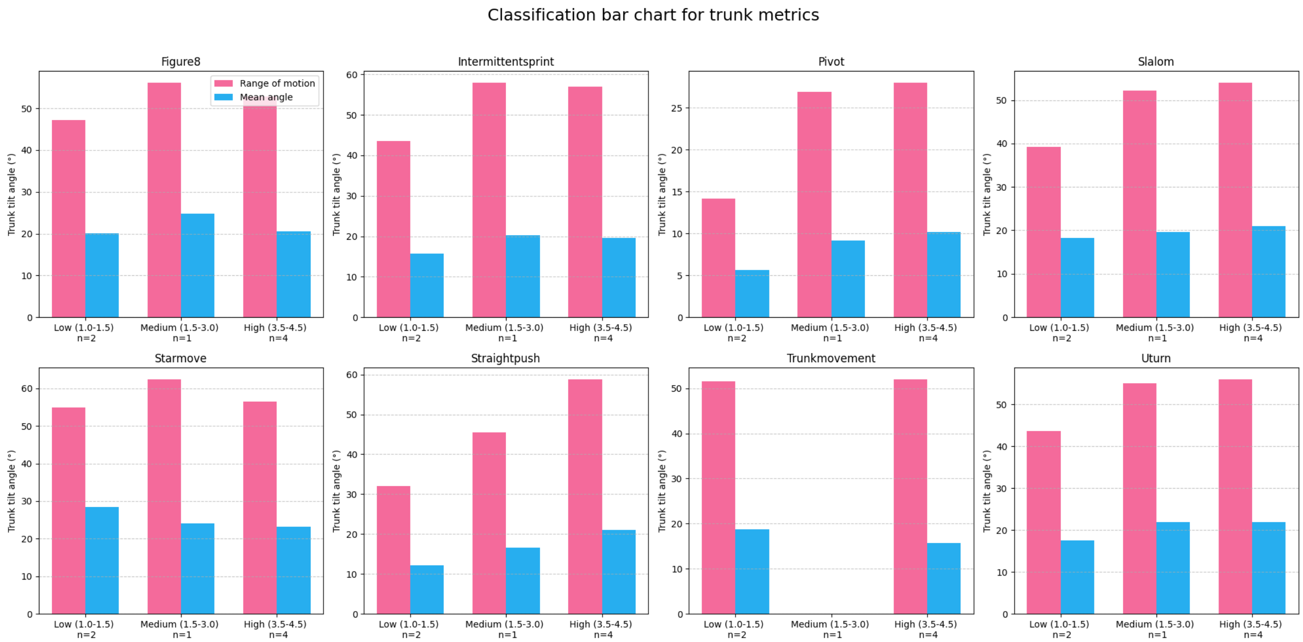
| Test | Metric | Mean HS | Mean NS | Mean Diff | t-Statistic | p-Value |
|---|---|---|---|---|---|---|
| Figure 8 | ROM (º) | 55.55 | 45.00 | 10.54 | 2.63 | 0.0584 |
| | Mean angle (º) | 23.35 | 16.84 | 6.50 | 4.00 | **0.0161** |
| | Ang vel chair (º/s) | 581.15 | 509.53 | 71.62 | 2.85 | **0.0465** |
| | Ang acc chair (º/$s^2$) | 1182.52 | 1193.75 | -11.24 | -0.07 | 0.9460 |
| | Lin vel chair (m/s) | 3.26 | 2.66 | 0.60 | 3.96 | **0.0166** |
| | Lin acc chair (m/$s^2$) | 25.71 | 11.33 | 14.38 | 2.42 | 0.0730 |
| Intermittent sprint | ROM (º) | 58.88 | 47.55 | 11.33 | 2.43 | 0.0510 |
| | Mean angle (º) | 21.36 | 15.84 | 5.52 | 2.59 | **0.0413** |
| | Ang vel chair (º/s) | 587.26 | 506.11 | 81.15 | 2.69 | **0.0361** |
| | Ang acc chair (º/$s^2$) | 1753.01 | 1644.15 | 108.86 | 0.52 | 0.6197 |
| | Lin vel chair (m/s) | 3.80 | 3.17 | 0.62 | 3.39 | **0.0146** |
| | Lin acc chair (m/$s^2$) | 28.05 | 18.43 | 9.62 | 3.55 | **0.0121** |
| Pivot | ROM (º) | 26.78 | 24.84 | 1.94 | 0.34 | 0.7490 |
| | Mean angle (º) | 9.47 | 8.42 | 1.05 | 1.87 | 0.1356 |
| | Ang vel chair (º/s) | 534.74 | 384.91 | 149.83 | 6.37 | **0.0031** |
| | Ang acc chair (º/$s^2$) | 1976.76 | 1259.93 | 716.83 | 1.90 | 0.1304 |
| | Lin vel chair (m/s) | 1.71 | 1.28 | 0.43 | 1.60 | 0.1852 |
| | Lin acc chair (m/$s^2$) | 12.23 | 6.80 | 5.43 | 1.39 | 0.2367 |
| Slalom | ROM (º) | 51.71 | 48.05 | 3.66 | 1.16 | 0.3311 |
| | Mean angle (º) | 20.85 | 17.12 | 3.73 | 3.84 | **0.0312** |
| | Ang vel chair (º/s) | 572.35 | 481.95 | 90.41 | 3.86 | **0.0307** |
| | Ang acc chair (º/$s^2$) | 1357.27 | 1085.85 | 271.42 | 2.77 | 0.0698 |
| | Lin vel chair (m/s) | 3.01 | 2.56 | 0.45 | 1.94 | 0.1471 |
| | Lin acc chair (m/$s^2$) | 18.76 | 8.35 | 10.41 | 2.86 | 0.0647 |
| Starmove | ROM (º) | 59.35 | 54.36 | 4.99 | 0.97 | 0.3700 |
| | Mean angle (º) | 26.28 | 23.27 | 3.01 | 1.27 | 0.2526 |
| | Ang vel chair (º/s) | 468.41 | 379.81 | 88.60 | 4.89 | **0.0027** |
| | Ang acc chair (º/$s^2$) | 1869.66 | 1224.60 | 645.06 | 2.59 | **0.0411** |
| | Lin vel chair (m/s) | 2.44 | 2.12 | 0.32 | 2.37 | 0.0557 |
| | Lin acc chair (m/$s^2$) | 20.17 | 10.49 | 9.68 | 6.84 | **0.0005** |
| Straight push | ROM (º) | 52.77 | 48.28 | 4.49 | 0.59 | 0.5944 |
| | Mean angle (º) | 19.86 | 16.92 | 2.94 | 1.65 | 0.1984 |
| | Ang vel chair (º/s) | 592.38 | 523.50 | 68.88 | 1.67 | 0.1940 |
| | Ang acc chair (º/$s^2$) | 1852.13 | 1077.57 | 774.56 | 2.26 | 0.1088 |
| | Lin vel chair (m/s) | 3.69 | 3.40 | 0.29 | 0.96 | 0.4070 |
| | Lin acc chair (m/$s^2$) | 26.37 | 18.73 | 7.64 | 1.36 | 0.2663 |
| Trunk movement | ROM (º) | 52.34 | 51.36 | 0.98 | 0.51 | 0.6293 |
| | Mean angle (º) | 16.26 | 17.13 | -0.87 | -0.53 | 0.6173 |
| | Ang vel chair (º/s) | 367.74 | 350.32 | 17.42 | 0.70 | 0.5169 |
| | Ang acc chair (º/$s^2$) | 723.10 | 891.71 | -168.61 | -0.87 | 0.4254 |
| | Lin vel chair (m/s) | 0.97 | 0.89 | 0.08 | 1.02 | 0.3525 |
| | Lin acc chair (m/$s^2$) | 5.42 | 4.86 | 0.55 | 0.29 | 0.7818 |
| U-turn | ROM (º) | 56.35 | 48.17 | 8.18 | 1.74 | 0.1322 |
| | Mean angle (º) | 24.34 | 16.95 | 7.39 | 4.09 | **0.0064** |
| | Ang vel chair (º/s) | 555.27 | 450.67 | 104.59 | 3.55 | **0.0121** |
| | Ang acc chair (º/$s^2$) | 1488.11 | 956.12 | 531.99 | 2.85 | **0.0294** |
| | Lin vel chair (m/s) | 3.63 | 2.81 | 0.82 | 4.49 | **0.0041** |
| | Lin acc chair (m/$s^2$) | 20.20 | 7.57 | 12.63 | 4.67 | **0.0034** |

## Appendix D
## Trunk VS performance correlation

TABLE VIII: Correlation between trunk metrics and performance metrics per test. Values are Pearson's r with associated p-values in parentheses. Statistically significant differences ($p < 0.05$) are bold.

| **Test** | **Trunk Metric** | **Max ang vel chair** | **Max ang acc chair** | **Max lin vel chair** | **Max lin acc chair** |
|---|---|---|---|---|---|
| Figure 8 | ROM | 0.68 (p=0.0149) | 0.46 (p=0.1366) | 0.75 (p=0.0053) | 0.47 (p=0.1225) |
| | Mean angle | 0.62 (p=0.0328) | 0.41 (p=0.1902) | **0.82 (p=0.0012)** | 0.52 (p=0.0798) |
| Intermittent sprint | ROM | 0.02 (p=0.9405) | 0.45 (p=0.1089) | 0.65 (p=0.0125) | 0.65 (p=0.0121) |
| | Mean angle | 0.26 (p=0.3686) | 0.35 (p=0.2267) | **0.75 (p=0.0018)** | 0.64 (p=0.0136) |
| Pivot | ROM | 0.60 (p=0.0389) | -0.01 (p=0.9743) | **0.88 (p=0.0002)** | 0.31 (p=0.3323) |
| | Mean angle | 0.47 (p=0.1223) | 0.06 (p=0.8626) | 0.65 (p=0.0225) | 0.59 (p=0.0450) |
| Slalom | ROM | 0.19 (p=0.5703) | 0.03 (p=0.9292) | 0.41 (p=0.2102) | 0.27 (p=0.4177) |
| | Mean angle | 0.49 (p=0.1235) | 0.44 (p=0.1805) | 0.47 (p=0.1470) | 0.61 (p=0.0455) |
| Starmove | ROM | 0.61 (p=0.0205) | 0.39 (p=0.1633) | 0.52 (p=0.0544) | 0.57 (p=0.0321) |
| | Mean angle | 0.58 (p=0.0282) | 0.24 (p=0.4047) | 0.18 (p=0.5348) | 0.49 (p=0.0727) |
| Straight push | ROM | 0.29 (p=0.3802) | -0.00 (p=0.9922) | 0.51 (p=0.1051) | 0.35 (p=0.2904) |
| | Mean angle | 0.33 (p=0.3212) | 0.06 (p=0.8609) | 0.65 (p=0.0300) | 0.34 (p=0.3113) |
| Trunk movement | ROM | -0.48 (p=0.1133) | -0.17 (p=0.6008) | -0.39 (p=0.2144) | -0.40 (p=0.2002) |
| | Mean angle | 0.42 (p=0.1686) | 0.69 (p=0.0125) | 0.50 (p=0.0981) | 0.22 (p=0.4920) |
| U-turn | ROM | 0.56 (p=0.0360) | -0.08 (p=0.7862) | 0.50 (p=0.0714) | 0.38 (p=0.1811) |
| | Mean angle | 0.51 (p=0.0646) | 0.23 (p=0.4213) | **0.77 (p=0.0013)** | 0.54 (p=0.0466) |

# APPENDIX E
# CLASSIFICATION GROUPS




(a) Bar chart with trunk motion metrics: range of motion and mean trunk tilt angle. No trunk movement test data was available for the single participant of the middle classification group, due to complications with the IMU measurement.


(b) Radar chart with wheelchair mobility performance metrics: wheelchair linear velocity $v_c$, wheelchair angular velocity $\omega_c$, wheelchair linear acceleration $a_c$, and wheelchair angular acceleration $\alpha_c$.

Fig. 14: Trunk motion and wheelchair mobility performance metrics for different classification groups per test: low classification ($< 1.5$), medium classification (2.0-3.0), and high classification ($> 3.5$). The number of participants present in each classification group is indicated with n.

*AI Statement*

During the writing process of this thesis, I made use of AI tools (specifically ChatGPT) to support tasks such as rewriting and improving text clarity, structuring and organising text to ensure logical flow, providing feedback on drafts and grammar and spelling correction. These tools were used as supplementary aids.