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Evaluating agreement between a high-g and low-g accelerometer for measuring tibial acceleration across a range of running velocities

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ABSTRACT

Modern inertial measurement units house multiple accelerometers with differing specifications. Previous studies have used both high-g and low-g accelerometers to measure peak tibial acceleration (TA) during running. This dual approach may introduce inconsistencies with data processing due to the different specifications. The purpose of this study was to evaluate the agreement between the high-g and low-g accelerometers in measuring peak axial and resultant TA across a range of running velocities. One hundred recreational runners ran on an athletics track at five self-selected velocities, ranging from very slow to very fast based on their comfortable training pace. Results indicated the difference in agreement between the high-g and low-g accelerometers was curvilinear, with bias shifting towards the high-g accelerometer at higher TA magnitudes. However, the predicted difference was small, only exceeding ±1 g when measuring axial TA approaching its maximum range (16 g). Based on the comparable performance of the high-g and low-g accelerometers, and the relatively high frequency of data clipping in the low-g accelerometer (209 of 495 trials; 42%), it is recommended to use the high-g accelerometer exclusively for measuring TA during running, simplifying data collection and processing requirements.

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wearable sensors; load monitoring; sports technology; operating range; running kinematics

Introduction

During running, external ground reaction forces (GRFs) are generated during each foot-to-ground contact, causing internal loading in the lower limbs. The resulting transient impact shock is transmitted up through the body, with local segment peak accelerations occurring at successively later times as the acceleration is

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attenuated (Derrick, 2004). Although peak tibial acceleration (TA) does not directly reflect tibial bone loading (Zandbergen et al., 2023), it is commonly used as a surrogate measure of impact forces in the tibia, showing a strong positive correlation with vertical force loading rate when measured using bone-mounted accelerometers ($r = 0.87$) (Hennig & Lafortune, 1991). Acceleration signal accuracy decreases with skin-mounted accelerometers, although reasonable estimates of TA are still produced, with significant, moderate positive correlations observed between peak TA and peak instantaneous vertical loading rate ($r = 0.469$) (Greenhalgh et al., 2012). TA occurs in each of the axial, anterior-posterior, and medio-lateral planes, which can be combined to calculate the resultant TA. While axial TA is currently the only parameter linked to running related injury (RRI) (Milner et al., 2006), resultant TA provides a more complete representation of acceleration passing through the tibia and should also be considered in relation to impact loads and RRI (Sheerin et al., 2019). Using the resultant TA also mitigates potential errors from sensor misalignment in the tibia, which can affect accuracy of axial TA measurements. However, while TA offers insight into the impact forces at the tibia, it does not capture the full complexity of tibial bone loading, which is caused by both internal muscle compressive forces and external GRFs (Zandbergen et al., 2023). As such, TA should be interpreted as one of several factors contributing to tibial loading and RRI risk. Although internal forces are difficult to measure in a real-world environment, TA can be measured using wearable accelerometers, contributing to a broader understanding of how external impact forces interact with individual running biomechanics and training habits to inform cumulative loading.

Different accelerometer devices, with varying sampling frequencies and operating ranges, may produce differing acceleration measurements, highlighting the importance of understanding accelerometer device specifications when assessing dynamic forces (Mitschke et al., 2018). Early accelerometers were developed with lower sampling frequencies ranging between 20–800 Hz, and operating ranges capable of measuring up to ±3–10 g, limiting their sensitivity and ability to measure higher magnitude accelerations (Fong & Chan, 2010). Additionally, hard-wired systems limited the practicality of measuring dynamic activities in outdoor environments (Fong & Chan, 2010). Advancements in technology have led to the development of wireless inertial measurement units (IMUs) with inbuilt tri-axial accelerometer, gyroscope, and magnetometer capabilities. Research-grade accelerometers can now store data in internal memory, with higher sampling frequencies ranging 30–1667 Hz and an operating range between ±20–200 g, with the most common sampling configuration in running gait analysis being 1000 Hz, ±16 g (Mason et al., 2023). The improved data fidelity and portability of current systems increase the feasibility of measuring load parameters in natural environments, allowing for monitoring during actual training rather than being constrained to a controlled laboratory. This is especially valuable considering TA measurements differ between laboratory-based and real-world collection, consequently offering a more valid understanding of the relative contributions of TA to running injury risk (DeJong Lempke et al., 2021; Milner et al., 2020).

Recent findings suggest lower accelerometer operating ranges of less than ±16 g may lead to an underestimation of stride length, running velocity and peak TA (Mitschke et al., 2018). Peak axial TA during overground running has been reported to reach up to 24.6 ± 10.8 g, therefore accelerometers with an operating range of ±16 g are unable to accurately measure peak TA above or below this range, with data clipping at 16 g potentially resulting in incorrect conclusions of TA (García-Pérez et al., 2014). Estimating peak TA exceeding 16 g is possible using a restoration algorithm, however the restored signals have been shown to underestimate the true value when compared to a ±200 g accelerometer, suggesting the low-g accelerometer may be unsuitable for measuring TA in running involving high magnitude tibial impacts (Chan et al., 2023). Given these limitations, a minimum operating range of ±32 g is recommended to avoid inaccurate measurements of TA (Mitschke et al., 2018), though a direct comparison using empirical data to support this recommendation is yet to be undertaken.

The Blue Trident IMU (Vicon, Oxford, United Kingdom) has two accelerometers, capable of sampling at both low-g (±16 g, 1125 Hz, 16-bit) and high-g (±200 g, 1600 Hz, 13-bit) ranges. The fidelity of the high-g accelerometer for measuring lower ranges of TA should be considered, due to its higher sampling frequency and increased sensitivity to noise (Doyle, 2024). Previous studies have opted to use the low-g accelerometer for measuring accelerations below ±16 g, and the high-g accelerometer for measuring accelerations above ±16 g, effectively combining separate data streams into one compiled from accelerometers with different specifications (Doyle, 2024). However, this approach could introduce inconsistencies during data processing, as different filter cut-off frequencies may be needed depending on the accelerometer specifications (Day et al., 2021). TA can fluctuate due to running velocity and surface (Sheerin et al., 2019), potentially ranging both below and above 16 g within the same running session. This variability could complicate the interpretation of TA if there is a need to switch between the high-g and low-g accelerometers to analyse different portions of the run. If high-g and low-g accelerometer measurements are comparable at lower TA magnitudes between 0–16 g, using the high-g accelerometer to capture both low and high magnitude ranges would be preferable to avoid inconsistencies with the data. To date, the agreement between the Blue Trident high-g and low-g accelerometers between 0–16 g has not been reported, and it remains unclear whether the degree of agreement varies with TA magnitude or running velocity.

Therefore, the primary aim of this study was to evaluate the agreement between the Blue Trident IMU high-g and low-g accelerometers, during the measurement of peak axial and resultant TA, between 0–16 g, across a range of running velocities. We hypothesised good agreement of less than ±1 g mean difference between the high-g and low-g accelerometers for both axial and resultant TA. The second aim was to evaluate whether the degree of agreement between the high-g and low-g accelerometers was influenced by running velocity. We hypothesised that the degree of agreement between the high-g and low-g accelerometer would not change significantly across different velocities.

Materials and methods

Participants

The participants in this study were part of an ongoing prospective investigation of runners. A group of 100 injury-free recreational runners (65 males, 35 females; mean age: 42.4 ± 10.8 years) participated. Participants were included in the study if they were aged between 20–65 years, ran at least 30 km per week on three or more days per week, and had been running regularly for at least one year (Winter et al., 2020). Participants were required to be injury-free at the time of starting data collection and have the intention of continuing their running for the next 6 months. Therefore, for this study, participants were considered injury-free if they did not have any physical complaints that affected the way they ran, or that caused them to reduce their training volume and intensity from their normal levels for at least 7 days prior to starting data collection (Yamato et al., 2015). Ethical approval was obtained from the Auckland University of Technology Ethics Committee (#22/120), and all participants provided written informed consent.

Study procedure

Overground running data were collected over a 120 m length outdoor tartan athletics track. Participants wore their own running shoes and were provided with a GPS smartwatch (Forerunner 235, Garmin, Kansas, USA) to monitor and record their running velocity for each trial. Tibial acceleration was collected using a tri-axial IMU (Blue Trident, Vicon, Oxford, United Kingdom) attached to the antero-medial aspect of the left distal tibia using double-sided tape and an elastic adhesive bandage (Sheerin et al., 2019). The x-axis of the accelerometer was oriented with the long axis of the tibia bone. The default sampling frequencies of the in-built low- and high-g accelerometers are 1125 Hz and 1600 Hz respectively, hence these were the sampling frequencies used for direct comparison of agreement between the two accelerometers. Data were stored directly to the onboard memory.

Participants were required to complete runs within five velocity bands, which were based on typical running velocities in running biomechanics research (Sheerin et al., 2020). The slowest velocity band was set between 7:55–8:55 min/km (1.9–2.1 m/s), which is suggested to be the preferred walk-to-run transition velocity (Chase et al., 2023; Tseh et al., 2002). Subsequent velocity bands increased by increments of 0.3 m/s. Participants were placed in a baseline 'normal' velocity band corresponding to their self-selected comfortable training velocity, with two bands below (slow and very slow), and two bands above (fast and very fast). Any participant with a velocity band slower than 7:55–8:55 min/km was excluded from this study. Each participant completed two successful trials in each velocity band, using the provided smart-watch to monitor running velocity and stay within the target velocity band. This spread ensured participants ran at a range of velocities they were accustomed to as part of their typical training, to minimise any effects of running at unfamiliar velocities on running technique or TA.

Data processing

To maximise external validity, running velocity was not actively controlled by the researcher, and therefore was not always consistent throughout each run. Smartwatch data were extracted and manually trimmed using the Garmin Connect portal so that the average velocity aligned with the target velocity band. Trimmed trials ranged between 15–38 s long.

Trimmed acceleration data were processed using a custom MATLAB script (R2024a, Mathworks, Massachusetts, USA), to align the accelerometry data to the GPS-determined velocity for each trial. Residual analysis showed that 70 Hz was the most optimal cut-off frequency for both the low-g and high-g signals, therefore data were filtered using a fourth-order, 70 Hz Butterworth low-pass filter with zero phase lag. Resultant TA (a_r) was calculated based on the relationship $a_r^2 = a_x^2 + a_y^2 + a_z^2$, where a_x, a_y and a_z represent accelerations in the axial, anterior-posterior, and medial-lateral directions, respectively. Peak detection was performed on the filtered acceleration signals using MATLAB's *findpeaks* function to identify individual peaks for each of the traces. Mean axial and resultant TA were then calculated within the trimmed period.

Data clipping occurs when the magnitude of acceleration exceeds the accelerometer operating range, resulting in loss of data or inaccurate estimation of TA. For the low-g accelerometer, clipping occurs when accelerations exceed 16 g. As the study was comparing agreement between the low-g and high-g accelerometers, any trials with data clipping (in any axis) were removed for both accelerometers (209 out of 495 trials). To investigate the influence of velocity on accelerometer agreement, each trial was first categorised into the corresponding velocity band. There were a total of 9 velocity bands, with the slowest being 7:55–8:55 min/km (1.9–2.1 m/s) and the fastest being 3:45–4:00 min/km (4.2–4.4 m/s).

Statistical analysis

All statistical analyses were conducted using *R* (v4.3.1, R Core Team, Vienna, Austria). *Tidyverse* was used for data wrangling and visualisation (Wickham et al., 2019), rmba for the Bland Altman analysis (Parker et al., 2016), *robustlmm* (rlmer) for modelling (Koller, 2016), the *easystats* framework (notably *performance*) for comparing models and testing assumptions (Lüdecke et al., 2025), and *sjPlot* and *ggeffects* for estimating model parameters and marginal means, respectively (Lüdecke, 2018; Lüdecke et al., 2024).

To address the first aim, a repeated-measures Bland Altman analysis was performed to visualise the bias between the high-g and low-g accelerometers at differing mean values. Accordingly, the bias and 95% limits of agreement (LOA) were extracted directly from the model to quantify systematic error and variability between accelerometers, with the repeated measures design used to adjust for within-subject correlation (i.e., multiple data points for participants from different velocity bands). Separate models were used to compare the agreement for axial and resultant TA. To expand these analyses, and to address the second aim, linear mixed effects models were performed. The difference between the units was specified as the outcome, with the mean of the units and the velocity bands as predictors, and each participant modelled with a random intercept to account for individual variability. As above, a separate model was built for axial and resultant TA. Visual observation of the residuals and agreement via the previous Bland Altman analysis suggested a non-linear bias between agreement at higher acceleration magnitudes. Subsequently, a non-linear term was added into the model (second-order polynomial fit) which improved model fit and precision of estimates via sensitivity analysis. A robust model alternative was also adopted due to non-normal residuals and performing better than the standard alternative (*lmer*) in comparison to fit indices (e.g., marginal/conditional R^2 and RMSE). For each model, raw and standardised coefficients are presented (the latter via fully refitting models) in tandem to 95% confidence intervals, and p-values. For the velocity variable, the slowest band (7:55–8:55 min/km) was used as the reference category. Estimated marginal means (with associated confidence intervals) for the TA differences were computed at predefined TA levels (3–16 g), to assess variability in agreement across TA magnitudes. The p-value threshold was set at $p = 0.05$.

Results

The mean, range, and number of trials per velocity band for axial and resultant TA are reported in Table 1. In total, 209 out of 495 trials (42%) were excluded due to clipping in the axial or anterior-posterior axes.

Table 1. Mean, range, and number of trials per velocity band for axial and resultant TA from the high-g and low-g accelerometers.

		Mean TA (range) (g)			
Velocity band (min/km)	Number of trials	Axial (high-g)	Axial (low-g)	Resultant (high-g)	Resultant (low-g)
7:55–8:55	10	4.97 (2.77–7.46)	5.25 (3.13–7.3)	6.51 (3.54–11.73)	6.60 (3.66–11.24)
6:55–7:55	33	6.15 (3.45–8.95)	6.33 (3.84–8.71)	8.39 (4.23–14.55)	8.40 (4.39–13.93)
6:10–6:55	58	6.24 (3.34–10.37)	6.42 (3.69–10.33)	9.22 (4.34–17.54)	9.02 (4.56–14.98)
5:35–6:10	58	6.83 (3.2–11.36)	7.05 (3.40–10.99)	9.86 (4.78–19.98)	9.72 (4.99–15.99)
5:05–5:35	59	7.59 (3.56–11.83)	7.74 (3.69–10.68)	10.89 (5.39–17.46)	10.65 (5.62–15.03)
4:40–5:05	41	8.00 (3.58–11.01)	8.12 (3.91–11.07)	11.40 (5.39–19.44)	11.09 (5.47–15.88)
4:15–4:40	22	7.78 (4.01–11.23)	7.98 (4.32–11.08)	11.93 (6.91–21.73)	11.40 (7.05–16.32)
4:00–4:15	5	9.45 (7.55–12.00)	9.61 (7.56–12.04)	11.53 (9.71–13.49)	11.68 (9.73–13.71)
3:45–4:00	0	–	–	–	–

Abbreviations: TA, tibial acceleration.

For axial TA, there was an overall bias of 0.17 g towards the low-g accelerometer, with upper and lower LOA of 0.77 and −0.44 g (Figure 1). For resultant TA, there was a bias of −0.23 g towards the high-g accelerometer, with upper and lower LOA of 1.11 and −1.57 g.

However, the spread of data within the Bland-Altman plots indicates a bias shift towards the high-g accelerometer as the TA magnitude increases. This shift was well-described by a non-linear fit in subsequent analysis, as described below.

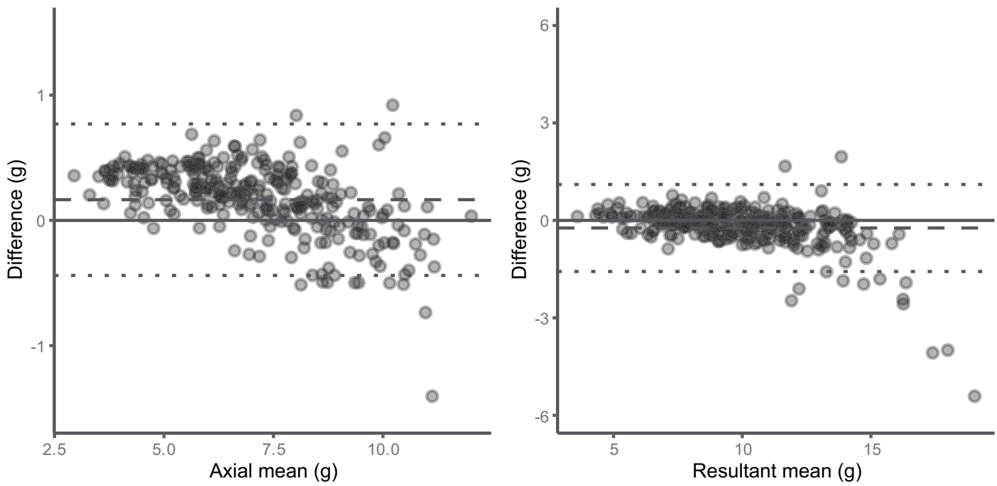

Figure 1. Repeated measures Bland-Altman plots showing differences and 95% LOA between the high-g and low-g accelerometers in measuring mean axial TA (left) and resultant TA (right). Note positive values indicate bias towards the low-g sensor.

The linear terms for vertical and resultant TA were both significant, indicating a strong negative relationship with the difference in accelerometer agreement, where bias shifts towards the high-g accelerometer as TA magnitude increases (Table 2). Notably, the second-degree polynomial term was also significant, suggesting a non-linear relationship, where the difference in agreement between the high-g and low-g accelerometers tended to increase at higher magnitudes of TA. Differences in agreement between velocity bands were not statistically significant ($p > 0.05$).

The estimated marginal means (mean predicted difference) confirm that the difference in agreement between the high-g and low-g accelerometer for both axial and resultant TA follows a curvilinear pattern (Table 3). For axial TA, the low-g accelerometer initially measures slightly higher than the high-g accelerometer at magnitudes up to 10 g, with the highest predicted difference of 0.41 g occurring at magnitudes of 2–3 g. After this point, the bias shifts towards the high-g accelerometer, increasing exponentially as the magnitude of TA approaches 16 g, where the mean predicted difference reaches 1.2 g. In contrast, the mean predicted differences for resultant TA also follows a curvilinear nature, but the high-g accelerometer is predicted to measure higher than the low-g accelerometer across the entire 0–16 g range, with the largest difference of 0.67 g occurring at 16 g.

Table 2. Effect estimates, standard beta, 95% confidence intervals, and significance levels for all fixed effects.

	Axial TA					Resultant TA				
Predictors	Estimates	Std. Beta	CI	Standardised CI	Statistical Significance (p)	Estimates	Std. Beta	CI	Standardised CI	Statistical Significance (p)
(Intercept)	0.18	0.02	0.10 – 0.26	−0.26 – 0.30	< .001*	−0.20	−0.01	−0.35 – −0.05	−0.23 – 0.21	.011*
1st degree term	−2.76	−9.69	−3.18 – −2.33	−11.18 – −8.19	< .001*	−2.54	−3.66	−3.34 – −1.75	−4.81 – −2.51	< .001*
2nd degree term	−0.63	−2.21	−0.84 – −0.42	−2.96 – −1.46	< .001*	−1.35	−1.95	−1.87 – −0.84	−2.69 – −1.21	< .001*
Velocity bands (min/km)										
7:55–8:55	–	–	–	–	–	–	–	–	–	–
6:55–7:55	−0.02	−0.08	−0.09 – 0.04	−0.30 – 0.13	.44	0.05	0.08	−0.07 – 0.17	−0.10 – 0.25	.38
6:10–6:55	−0.02	−0.07	−008 – 0.04	−0.29 – 0.15	.55	0.05	0.07	−0.08 – 0.17	−0.11 – 0.25	.45
5:35–6:10	−0.01	−0.02	−0.07 – 0.06	−0.26 – 0.22	.87	0.04	0.05	−0.10 – 0.17	−0.14 – 0.25	.59
5:05–5:35	−0.00	−0.01	−0.08 – 0.07	−0.27 – 0.25	.91	−0.01	−0.02	−0.16 – 0.13	−0.23 – 0.19	.85
4:40–5:05	0.00	0.01	−0.08 – 0.08	−0.28 – 0.29	.97	0.03	0.04	−0.12 – 0.18	−0.18 – 0.26	.70
4:15–4:40	0.04	0.14	−0.05 – 0.13	−0.17 – 0.46	.38	0.02	0.02	−0.16 – 0.19	−0.22 – 0.27	.85
4:00–4:15	0.08	0.29	−0.03 – 0.19	−0.10 – 0.68	.15	0.12	0.17	−0.10 – 0.34	−0.14 – 0.49	.27

Abbreviations: TA, tibial acceleration; Std. Beta, standard beta; CI, confidence intervals. *Indicates $p < 0.05$.

Table 3. Mean predicted difference between the high-g and low-g accelerometers across 3–16 g.

Mean TA (axial)	Mean predicted difference (g) (95% CI)	Mean TA (resultant)	Mean predicted difference (g) (95% CI)
3	0.41 (0.32, 0.50)	3	−0.15 (−0.37, 0.07)
4	0.39 (0.32, 0.46)	4	−0.10 (−0.28, 0.08)
5	0.36 (0.30, 0.41)	5	−0.06 (−0.21, 0.09)
6	0.30 (0.25, 0.35)	6	−0.04 (−0.16, 0.09)
7	0.23 (0.18, 0.28)	7	−0.03 (−0.14, 0.08)
8	0.14 (0.09, 0.19)	8	−0.04 (−0.14, 0.06)
9	0.03 (−0.02, 0.09)	9	−0.06 (−0.16, 0.03)
10	−0.09 (−0.15, −0.03)	10	−0.11 (−0.20, −0.01)
11	−0.24 (−0.30, −0.17)	11	−0.16 (−0.26, −0.06)
12	−0.40 (−0.48, −0.32)	12	−0.23 (−0.33, −0.13)
13	−0.57 (−0.68, −0.47)	13	−0.32 (−0.42, −0.22)
14	−0.77 (−0.90, −0.64)	14	−0.42 (−0.53, −0.31)
15	−0.99 (−1.15, −0.82)	15	−0.54 (−0.66, −0.42)
16	−1.22 (−1.43, −1.01)	16	−0.67 (−0.081, −0.53)

Note: positive values indicate a bias towards the low-g sensor.

Discussion

This study evaluated the agreement between the high-g and low-g accelerometers for measuring peak axial and resultant TA within the 0–16 g range, across different running velocities. The results indicate the high-g accelerometer provides comparable data to the low-g accelerometer and is appropriate for measuring accelerations during running within the 0–16 g range. Additionally, the degree of agreement was not significantly affected by running velocity, suggesting that acceleration magnitude was the primary factor influencing accelerometer agreement.

The repeated measures Bland Altman analyses indicated an overall bias towards the low-g accelerometer for axial TA, and an overall bias towards the high-g accelerometer for resultant TA. The biases were small, with tight LOAs reported (axial TA: 0.165 g [−0.44 g, 0.77 g]; resultant TA: −0.23 g [−1.57 g, 1.11 g]). However, subsequent analyses suggested the difference in agreement between the two accelerometers was curvilinear, where bias shifted towards the high-g accelerometer at higher TA magnitudes. Both the Bland Altman plots and estimated marginal means indicate that these discrepancies increase as TA magnitude approached 16 g. The magnitude of absolute bias was small in practical terms, with mean predicted differences in agreement not exceeding ±1 g when measuring resultant TA. For axial TA the mean predicted difference exceeded 1 g, but only at magnitudes approaching 15–16 g (mean difference = 1.2 g). This finding was similar to previous research suggesting the low-g accelerometer underestimates peak TA compared to the high-g accelerometer near the upper limit of its ±16 g operating range (Chan et al., 2023). Nonetheless, while absolute differences were generally small, relative bias was more evident at lower TA magnitudes. For example, relative bias was 14.0% at 2.77 g and −3.2% at 3.54 g for axial and resultant TA, respectively—representing the lowest observations in the dataset. Across the interquartile range of observed TA magnitudes, relative bias was more modest: 1.1 to 5.6% for axial TA and −1.84 to −0.47% for resultant TA. Although small, these relative errors may still hold practical relevance depending on the application context. Considering both accelerometers are integrated into the same IMU, with identical alignment, placement and securement, differences in agreement are likely due to differences in hardware specifications.

Given the generally small mean predicted differences between the high-g and low-g accelerometers at lower magnitudes of TA, the results suggest there is no need to switch between accelerometers based on acceleration magnitude thresholds. For research settings where measurement accuracy is essential, the high-g accelerometer would be the recommended choice due to its ability to measure both lower and high TA magnitudes without the risk of data clipping. For real-world monitoring of TA in runners, battery life, data storage capacity, accessibility, and cost should be considered alongside the intended use of wearable sensors. Given their comparable performance within the 0–16 g range, the low-g accelerometer could be a viable option for monitoring TA in runners where TA magnitude is not expected to exceed this threshold. However, a practical consideration is the occurrence of data clipping, which happens when accelerations exceed the accelerometer operating range, resulting in loss of data or inaccurate measurements of TA. Clipping can occur in any of the three axes and can therefore result in inaccurate measurements of resultant TA. In this study, 209 out of 495 trials (42%) showed clipping in either the axial or anterior-posterior axes. Peak TA during overground running has been reported to reach up to 24.6 ± 10.8 g, hence using the low-g accelerometer would result in the exclusion of any trials that exceed its upper limit of ±16 g (García-Pérez et al., 2014). Given that the magnitude of TA may vary depending on a range of factors including velocity, fatigue, footwear, and running surface (Sheerin et al., 2019), using the high-g accelerometer alone may be preferable to capture the full spectrum of accelerations while maintaining data integrity and consistency, rather than using a combination of both the high-g and low-g accelerometers. Future research on individual training habits, including frequency and duration, could provide more insight into appropriate sensor selection depending on the intended use and runners' TA profiles.

It should be noted that this study compared differences in agreement using mean axial and resultant TA over a portion of the trial, rather than comparing differences in agreement between each individual peak. Additionally, the results are limited to running activities on a flat surface. Running surface and inclination angle may influence TA magnitude, and its impact on accelerometer agreement is currently unknown. Future research should also consider analyses of other sports or activities, as different dynamic movements may affect accelerometer agreement. Finally, the IMUs were attached to all participants by a single researcher. While this helps maintain intra-tester reliability, it is possible that different placements or method of securement by other researchers may influence accelerometer agreement.

Conclusion

This study evaluated the agreement between the high-g and low-g accelerometers in the Blue Trident IMU for measuring peak axial and resultant TA within the 0–16 g range. Although the low-g accelerometer recorded impacts from running steps at marginally smaller magnitudes than the high-g accelerometer as magnitude of TA increased, mean predicted differences were within ±1 g when measuring resultant TA, and only exceed ±1 g (1.2 g difference) when measuring higher magnitudes of axial TA. Proportionally, bias was higher at low values, but more modest within the bulk of the observed data. Running velocity was found to have no significant effect on accelerometer agreement. Based on the comparable performance of the two accelerometers at low TA magnitudes, as well as the relatively high clipping rate of the low-g accelerometer, it is recommended to use the high-g accelerometer exclusively for measuring TA during running, simplifying data collection by eliminating the need for both high- and low-g accelerometers irrespective of TA magnitude.

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