Between-system agreement of K-AI wearable tech (K-sport) and vector S7 global navigation satellite systems for measuring distance, velocity, and acceleration metrics

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Abstract

This study evaluated the agreement between K-AI Wearable Tech and the previously validated Vector S7 during an Australian football training session. Thirty sub-elite Australian football male players (21.6 ± 2.8 years) took part in the study. The K-AI Wearable Tech demonstrated mean absolute error (MAE) and root mean square error (RMSE) values of 74.1 m (1.00%) and 133.9 m (1.68%) for total distance, 52.6 m (6.46%) and 64.7 m (10.42%) for combined high-speed running-sprinting distance (> 19 km · h^{-1}), 6.5 m (4.66%) and 9.8 m (6.51%) for sprinting distance (> 25 km · h^{-1}). Acceleration and deceleration counts were 5.9 (13.92%) and 7.6 (17.04%), and 2.3 (10.07%) and 3.0 (13.66%), respectively. Peak and instantaneous velocity showed MAE and RMSE of 0.35 km · h^{-1} (1.20%) and 0.39 km · h^{-1} (1.35%), and 0.11 km · h^{-1} (2.26%) and 0.15 km · h^{-1} (3.03%), respectively. Mean biases (95% limits of agreement) were 64.2 m (−170.0 to 298.4) for total distance, 48.6 m (−36.6 to 133.8) for combined high-speed running-sprinting distance (> 19 km · h^{-1}), and −4.0 m (−21.9 to 13.9) for sprinting distance (> 25 km · h^{-1}). Acceleration and deceleration counts showed biases of −3.1 (−17.0 to 10.7) and 1.0 (−4.6 to 6.7), while peak and instantaneous velocity were 0.34 km · h^{-1}(−0.05 to 0.73) and 0.11 km · h^{-1}(−0.09 to 0.32), respectively. The intraclass correlation coefficient (ICC) ranged from very large to nearly perfect across all metrics assessed. Collectively, these findings demonstrate that the K-AI Wearable Tech produced distance-, velocity-, and acceleration-based outputs comparable to those obtained from Vector S7. However, the magnitudes of both absolute and proportional differences should be considered when interpreting agreement between systems.

Keywords

Athlete monitoring, Australian football, global navigation satellite systems, tracking technology

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Introduction

Understanding the physical demands of training and competition represents a fundamental component of training prescription, performance evaluation, and athlete monitoring processes in team sports environments.[1,2] The use of electronic tracking technologies to quantify and measure player movement has become common practice across most professional sporting organisations.[3] Technologies including optical tracking systems, radio-frequency-based Local Positioning Systems (LPS), and Global Navigation

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Satellite Systems (GNSS), such as the Global Positioning System (GPS), Galileo, Globalnaya Navigatsionnaya Sputnikovaya Sistema (GLONASS), and BeiDou, enable the continuous capture of spatiotemporal data, including position, speed, and time, from which a range of metrics can be derived to characterise movement demands.[4,5] These outputs commonly include total distance covered, distance accumulated within predefined speed zones, and the frequency (counts) of high-intensity efforts exceeding specified acceleration thresholds. Collectively, these metrics are operationalised as indicators of external load and are routinely utilised to inform training prescription, guide rehabilitation processes, and support decision-making to manage training loads and mitigate injury risk.[2,6] While these outputs provide valuable applied insights, it is important to consider the methodological processes implemented by technology manufacturers that underpin the derivation of these outputs. Specifically, the manner in which these systems acquire, process, and filter raw data, along with their inherent technological specifications (e.g., sampling frequency, signal noise, and positional accuracy), can meaningfully influence the magnitude and interpretation of the resulting outputs.[5,7] As such, differences in device specifications and data-processing approaches may affect the comparability of external load metrics across technologies in applied contexts.

Previous research has demonstrated that GPS devices provide valid estimates of total distance; however, measurement accuracy varies across movement tasks and between device manufacturers.[3,8,9] More specifically, accuracy tends to decline as movement intensity increases, with metrics such as peak velocity and high-intensity running exhibiting greater error compared to total distance.[3,8–10] While increases in sampling frequency (e.g., from 1 Hz to 10 Hz) have been shown to improve the measurement of high-speed activities, limitations in both validity and reliability persist during sport-specific movements, particularly those involving rapid changes of direction and accelerative-decelerative efforts.[11,12] Furthermore, discrepancies between manufacturers have been reported for commonly used metrics, including peak velocity and acceleration counts.[13,14] These differences are likely attributable to variations in signal quality, data processing algorithms, and sampling frequency.[7] Higher-frequency GNSS technologies may offer greater temporal resolution and thereby improve sensitivity to rapid changes in velocity and short-duration movements. This is particularly pertinent to Australian football, where movement demands are highly intermittent and characterised by frequent accelerative, decelerative, and multidirectional actions, placing substantial demands on measurement systems.[15] Nevertheless, such theoretical advantages are contingent upon signal quality and data-processing approaches, as increased sampling frequency does not inherently translate to improved measurement accuracy.[14] Compounding this issue, the current regulatory landscape for sports technologies lacks formal standardisation, meaning manufacturers are not required to disclose or independently verify the accuracy of their systems.[1] Consequently, the systematic evaluation of measurement quality across devices, alongside the development of industry standards, is essential to support practitioners and researchers in accurately interpreting and applying technology-derived metrics.

The recently developed Sports Technology Quality Framework provides a structured approach for the evaluation and comparison of sports technologies.[16] One key component of this framework is concurrent validity, which refers to the extent to which a technology output relates to a previously validated measure when simultaneously assessed.[16] The application of this framework enables a systematic and standardised comparison of tracking technologies, allowing quantification of agreement across their outputs. Accordingly, guided by the Sports Technology Research Network (STRN) framework, this study aims to assess the between-system agreement of K-AI Wearable Tech GNSS (K-Sport World Srl, Pesaro, Italy) and the previously validated Vector S7 GNSS (Catapult Innovations, Melbourne, Australia)[17] for quantifying distance-, velocity-, and acceleration-based metrics during Australian football pre-season training. The findings of this study will provide practitioners with evidence to inform technology selection and interpretation of key performance metrics within applied high-performance settings.

Materials and methods

Participants

Thirty sub-elite male players (21.6 ± 2.8 years) from a Victorian Football League (VFL) club took part in the study. Participants' training regimes ranged from three to five moderate-to-high-intensity training sessions per week, incorporating both on-field running and gym-based strength training. The study was conducted in accordance with the Declaration of Helsinki for research involving human participants and received ethical approval from the university's Human Research Ethics Committee (HRE25-155). Written informed consent was obtained from all participants prior to data collection.

Procedure

Data were collected during an outdoor, on-field preseason training session conducted on natural grass at the team's training facility, under the supervision of the team's high-performance and coaching staff. Data collection was conducted under favourable meteorological conditions to optimise satellite reception, in accordance with recommendations from previous investigations.[18,19] The training session lasted approximately 90 min. During the session, participants were equipped with a Catapult Vector S7 GNSS unit sampling at 10 Hz. Each unit integrated a tri-axial accelerometer ($\pm$16 g; 1000 Hz), a tri-axial gyroscope ($\pm 2000° \cdot s^{-1}$; 100 Hz), and a tri-axial

Figure 1. Placement of GNSS units in the football training jumper and custom sports vest. The Vector S7 unit is marked in red and the K-AI unit in black.

magnetometer (±4900 μT; 100 Hz). Catapult GNSS data were recorded in real time using OpenField software (version 3.13.3; Catapult Sports, Melbourne, Australia). Concurrently, data were also collected using a GNSS K-AI Wearable Tech unit sampling at 50 Hz. This unit incorporates a synchronised inertial system comprising a tri-axial accelerometer (±16 g; 6664 Hz), a tri-axial gyroscope ($\pm 2000° \cdot s^{-1}$; 208 Hz), and a tri-axial magnetometer (40 Hz). The Catapult device was positioned in the manufacturer-specified pocket within the Australian football training jumper, while the K-AI unit was secured in the back pocket of a custom sports vest worn underneath the training jumper. Both units were positioned between the scapulae near one another (Figure 1). GNSS units from both manufacturers were activated 30 min prior to the commencement of the training session to ensure adequate satellite lock.[20]

Data processing

Prior to data extraction, Vector S7 datasets were trimmed using OpenField software to delineate the start and end of each participant's training session. The resulting timestamps were then applied to trim the corresponding K-AI datasets using K-Fitness software (version 1.0.3.232; K-Sport World Srl, Pesaro, Italy). The trimmed K-AI data were subsequently uploaded to Dynamix (K-Sport World Srl, Pesaro, Italy), a cloud-hosted web application for athlete performance management and analytics that centralises, processes, and visualises data collected from K-AI units. Discrete variables of interest from both technologies were then downloaded and imported into customised Microsoft Excel™ (version 2301, Microsoft Corporation, Santa Rosa, CA, USA) spreadsheets, with processing and synchronisation executed using RStudio® statistical computing software (version 2024.09.1; RStudio, Boston, MA, USA). Discrete variables included total distance, running distance ($15\text{–}19\ km \cdot h^{-1}$), high-speed running (HSR) distance ($19\text{–}25\ km \cdot h^{-1}$), combined HSR-sprinting distance ($> 19\ km \cdot h^{-1}$), sprinting distance ($> 25\ km \cdot h^{-1}$), peak velocity, acceleration and deceleration counts. More specifically, acceleration and deceleration counts were derived from sustained changes in GNSS-based instantaneous velocity exceeding defined positive or negative acceleration thresholds for a minimum duration. Threshold magnitudes and temporal criteria were defined according to each manufacturer's specifications; for both technologies, acceleration and deceleration counts were identified as changes greater than or less than $3\ m \cdot s^{-2}$ with a minimum duration threshold of 0.4 s.

Instantaneous velocity was also examined in this study. Prior to data synchronisation, the K-AI velocity traces were down-sampled from 50 Hz to 10 Hz to match the Catapult system's sampling frequency. This procedure was performed within the K-Sport data-processing environment using the proprietary raw data converter application provided by the manufacturer. The exported files included reported instantaneous velocity using epoch-based Coordinated Universal Time (UTC) timestamps, which were subsequently converted to local time using the dplyr, readr, tidyr, and lubridate R packages.[21–24] Synchronisation of the velocity time-series between the two technologies was achieved using timestamp alignment. Subsequently, a sample-level shift was applied to account for systematic device latency arising from differences in internal signal processing across systems. The magnitude of the shift was determined by identifying the temporal offset that minimised the root mean square error (RMSE) between paired signals within a predefined lag window.[25] This process was conducted using shiny, ggplot2, plotly, data.table, and tidyverse R packages.[26–30]

Statistical analysis

A total of 30 paired GNSS traces were available for the analysis of discrete variables. However, a GNSS-paired trace was excluded from the instantaneous velocity analysis due to a brief interruption of approximately 6 s in the continuous velocity signal. As waveform-based analyses require uninterrupted and temporally aligned time-series data, this trace was excluded to preserve methodological integrity.[25] Discrete variables were instead retained, as they were unaffected by the transient signal disruption. The distribution of raw measurements for all variables of interest was evaluated using the Shapiro-Wilk test. Total distance for both technologies, running distance ($15\text{–}19\ km \cdot h^{-1}$) for K-AI, and acceleration and deceleration counts for Vector S7 were non-normally distributed, whereas all other variables satisfied the normality assumption. Shapiro-Wilk test was also used to assess the distribution of the paired differences for all variables of interest, along with visual inspection of Q-Q plots to inform the Bland–Altman analysis.[31] Paired differences showed evidence of non-normality for all variables except peak velocity and acceleration count.

Descriptive analyses, mean bias, mean absolute error (MAE), RMSE, and 95% limits of agreement (LoA) were used to assess agreement between K-AI and Vector S7. For each metric, paired differences were calculated as K-AI minus Vector S7, such that positive bias values indicated K-AI overestimation and negative values indicated underestimation relative to Vector S7. Mean bias was calculated as the average paired difference, MAE as the average absolute difference, RMSE as the square root of the average squared difference, and 95% LoA as mean bias $\pm$ 1.96 standard deviation of the paired differences.[16,32] As a sensitivity analysis, non-parametric LoA were also calculated using the 2.5th and 97.5th percentiles of the paired differences, with results indicating broad consistency with the conventional LoA.[31,33] MAE and RMSE were also expressed as percentages relative to the corresponding Vector S7 value. A two-way mixed-effects intraclass correlation coefficient for absolute agreement (ICC [A,1]) with 95% confidence intervals was used to assess the degree of agreement between the two technologies, quantifying the proportion of total observed variance attributable to true between-observation differences relative to the measurement error.[34] The use of this variance-component approach was informed by the assessment of the raw measurement distributions. The criteria for determining the ICC magnitude were established as follows: trivial, 0 to < 0.1; small, 0.1 to < 0.3; moderate, 0.3 to < 0.5; large, 0.5 to < 0.7; very large, 0.7 to < 0.9; nearly perfect, 0.9 to 1.0.[35]

Additionally, Bland–Altman plots with 95% LoA were generated for the discrete measures to visually examine agreement and the distribution of between-system differences across participants. Heteroscedasticity was evaluated by regressing the absolute Bland–Altman differences and the corresponding mean of the two systems, with a significant positive slope ($p < 0.05$) interpreted as evidence of magnitude-dependent error. Heteroscedasticity was observed for sprinting distance and acceleration count. To account for proportional heteroscedasticity and non-normally distributed paired differences, log-transformed Bland–Altman analysis was applied to discrete variables to express agreement on a relative scale. Mean bias and 95% limits of agreement were estimated on the logarithmic scale and subsequently back-transformed and expressed as percentage differences relative to the magnitude of the measurements. Conversely, deceleration count was excluded from this analysis because it contained zero values that violate the assumptions of the log-ratio method.[36] Statistical analyses and plots were computed using readr, dplyr, janitor, purrr, tibble, irr, stringr, ggplot2, and scales.[22,23,27,37–42] No data from the inertial measurement units embedded within either GNSS technology were analysed.

Instantaneous velocity was further analysed using statistical non-parametric mapping (SnPM) to compare K-Ai and Vector S7 across the entire time-series.[43] Each trace was time-normalised and interpolated to 101 nodes, representing 0–100% of the trace. Normality of the paired difference trace was assessed descriptively at each node using Shapiro–Wilk tests, and non-parametric inference was used for the waveform analysis. Paired SnPM{t} tests were performed using permutation-based inference with 10,000 iterations and a two-tailed alpha level of 0.01. The comparison direction was K-AI minus Vector S7, such that positive SnPM{t} values indicated higher instantaneous velocity values for K-AI. Data processing, statistical analysis, and visualisation were conducted using the dplyr, tidyr, readr, reticulate, and ggplot2 R packages.[21–23,27,44]

Results

The results of the between-system agreement analyses are presented in Tables 1 and 2. Nearly perfect ICC values were observed for all the parameters, with peak velocity reporting a very large ICC. This suggests that the two systems ranked participants similarly. However, the 95% CI showed wide ranges for velocity-based metrics. Absolute agreement was further evaluated using mean bias, MAE, RMSE, and Bland–Altman LoA. K-AI consistently reported higher values in all distance- and velocity-based metrics compared to the Vector S7, except sprinting distance and acceleration count. The magnitude error values were generally small between the two GNSS systems, as reflected by low MAE and RMSE across most parameters. Nevertheless, acceleration and deceleration counts exhibited comparatively larger MAE and RMSE values, indicating reduced agreement between devices.

For each variable, Bland–Altman plots with 95% LoA were generated for all discrete variables (Figure 2). Additionally, log-transformed Bland–Altman analysis expressed agreement on a relative scale. Total distance showed proportional bias and 95% LoA of 0.84% (−1.96 to 3.72), running distance (15–19 $km \cdot h^{-1}$) of 6.06% (−2.68 to 15.59), HSR distance (19–25 $km \cdot h^{-1}$) of 6.68% (−9.43 to 25.66), combined HSR-sprinting distance (> 19 $km \cdot h^{-1}$) of 5.40% (−9.02 to 22.11), sprinting distance (> 25 $km \cdot h^{-1}$) of −3.18% (−13.99 to 8.98). Peak velocity and acceleration count were 1.16% (−0.18 to 2.53) and −7.46% (−34.55 to 30.83), respectively. Instantaneous velocity paired SnPM{t} analysis identified significant differences between K-AI and Vector S7 in instantaneous velocity across the time-normalised trace ($\alpha = 0.01$; critical threshold $t^* = 4.04$). Two isolated supra-threshold clusters were detected, spanning 16.5–17.5% and 42.5–43.5% of the time-normalised trace (Figure 3). In both clusters, instantaneous velocity values were higher for K-AI compared with Vector S7.

Discussion

This study aimed to evaluate the agreement between K-AI Wearable Tech GNSS and the previously validated

Table 1. Relative agreement results between K-AI and Vector S7 GNSS units.

Variable	ICC (95% CI)	Interpretation	p-value
Total Distance (m)	0.997 (0.992; 0.999)	Nearly perfect	<0.001
Running Distance 15–19 km $\cdot$ h^{-1} (m)	0.981 (0.641; 0.995)	Nearly perfect	<0.005
HSR Distance 19–25 km $\cdot$ h^{-1} (m)	0.976 (0.636; 0.994)	Nearly perfect	<0.005
Combined HSR-sprinting Distance > 19 km $\cdot$ h^{-1} (m)	0.980 (0.776; 0.994)	Nearly perfect	<0.001
Sprinting Distance > 25 km $\cdot$ h^{-1} (m)	0.964 (0.918; 0.984)	Nearly perfect	<0.001
Acceleration Count (n)	0.908 (0.798; 0.957)	Nearly perfect	<0.001
DecelerationCount (n)	0.979 (0.955; 0.990)	Nearly perfect	<0.001
Peak Velocity (km $\cdot$ h^{-1})	0.899 (0.041; 0.975)	Very Large	<0.05
Instantaneous velocity (km $\cdot$ h^{-1})	0.933 (0.485; 0.980)	Nearly Perfect	<0.005

Abbreviation: ICC = intraclass correlation coefficient, CI = confidence interval, HSR = high-speed running.

Vector S7 GNSS during an Australian football pre-season training, using the principles of the Sports Technology Quality Framework.[16] Overall, the findings suggest that closer agreement was observed for total distance and velocity-based variables, where mean bias and relative errors were generally small, whereas agreement was reduced for velocity-threshold-derived distances and acceleration- and deceleration-count metrics. The nearly perfect ICC values observed across most of the metrics assessed indicate that the K-AI and Vector S7 systems ranked athletes similarly, suggesting comparability in how both systems captured the main features of athletes' movement during training. This is consistent with previous GNSS validation studies that have reported similar relative agreement across devices operating under comparable sampling rates, antenna configurations, and satellite environments.[45] However, agreement was not uniform across all outcomes, as wider 95% confidence intervals were observed for velocity-based metrics. These broader intervals likely reflect the inherent challenges associated with capturing rapid, high-frequency changes in movement, an area where GNSS technologies traditionally exhibit greater variability due to the need for precise positional differentiation over very short time windows.[11] This variability should be interpreted in the context of the known challenges of achieving high agreement in metrics derived from high-intensity, multidirectional movements using GNSS.[11,45] Therefore, while the K-AI system demonstrated outputs comparable to Vector S7 for several key external-load metrics, caution is warranted when interpreting variables that are more sensitive to signal processing, temporal alignment, or event-detection procedures.

Mean bias analyses indicated systematic group-level differences between devices, with the K-AI unit generally reporting greater values across most distance- and velocity-based metrics, except sprinting distance and acceleration count, for which it reported lower values than the Vector S7. These differences were modest in magnitude and mostly consistent in direction, suggesting a stable and predictable pattern rather than random measurement noise. Such systematic offsets are common in GNSS comparisons and often reflect differences in proprietary filtering algorithms, satellite constellations, or signal-processing strategies rather than deficiencies in measurement quality.[11,45] However, the 95% LoA crossed zero for all discrete variables, suggesting variability in both the direction and magnitude of the paired between-system differences. The comparatively low MAE and RMSE values observed for most variables highlighted alignment across devices, indicating that systematic differences may have limited influence in applied context. Nevertheless, the practical impact of these errors should be interpreted relative to the decision thresholds and expected within-athlete changes associated with each monitoring application.[46] Acceleration and deceleration counts exhibited larger errors, reflecting the well-documented challenges of capturing short-duration, high-frequency movement events. These findings are consistent with broader GNSS literature and underscore that event-based metrics remain inherently more sensitive to device-specific processing approaches.

The Bland–Altman analyses provide additional context for interpreting these differences (Figure 2). Although proportional bias was present for several variables, the relative LoA were narrow for key metrics such as total distance and peak velocity, supporting the comparability of these outputs between systems. These results are particularly encouraging given the ecological nature of the training environment, where movement patterns are highly variable and difficult to capture with precision. In contrast, wider LoA were observed for HSR, combined HSR-sprinting distance, sprinting distance, and acceleration count, indicating reduced agreement for these metrics. This pattern is consistent with previous research demonstrating that high-intensity and event-based metrics are more difficult for GNSS devices to quantify consistently and may be more sensitive to device-specific processing procedures.[11,45] Practitioners should therefore exercise greater caution when comparing these outputs across systems.

The SnPM$\{t\}$ analysis revealed two brief but statistically significant periods in which K-AI reported higher instantaneous velocity than the Vector S7. These isolated supra-threshold clusters suggest that, although the overall velocity

Table 2. Descriptive statistics and magnitude of errors measurement results.

Variable	Technology	Mean ± SD	MAE (%)	RMSE (%)	Mean bias (95% LoA)
Total Distance (m)	K-AI	7514.1 ± 1778.7	74.1 (1.00)	133.9 (1.68)	64.2 (−170.0 to 298.4)
	Vector S7	7449.9 ± 1762.0			
Running Distance 15–19 km $\cdot$ h^{-1} (m)	K-AI	1198.9 ± 418.6	65.4 (6.17)	80.4 (7.83)	65.4 (−28.0 to 158.7)
	Vector S7	1133.5 ± 406.6			
HSR Distance 19–25 km $\cdot$ h^{-1} (m)	K-AI	871.2 ± 308.7	56.4 (7.97)	66.1 (12.18)	52.5 (−27.3 to 132.4)
	Vector S7	818.6 ± 293.2			
Combined HSR-sprinting Distance > 19 km $\cdot$ h^{-1} (m)	K-AI	997.2 ± 325.3	52.6 (6.46)	64.7 (10.42)	48.6 (−36.6 to 133.8)
	Vector S7	948.6 ± 313.1			
Sprinting Distance > 25 km $\cdot$ h^{-1} (m)	K-AI	126.0 ± 36.8	6.5 (4.66)	9.8 (6.51)	−4.0 (−21.9 to 13.9)
	Vector S7	130.0 ± 36.5			
Acceleration Count (n)	K-AI	41.0 ± 16.7	5.9 (13.92)	7.6 (17.04)	−3.1 (−17.0 to 10.7)
	Vector S7	44.2 ± 18.6			
DecelerationCount (n)	K-AI	27.8 ± 15.2	2.3 (10.07)	3.0 (13.66)	1.0 (−4.6 to 6.7)
	Vector S7	26.8 ± 14.4			
Peak Velocity (km $\cdot$ h^{-1})	K-AI	29.28 ± 0.85	0.35 (1.20)	0.39 (1.35)	0.34 (−0.05 to 0.73)
	Vector S7	28.94 ± 0.82			
Instantaneous velocity (km $\cdot$ h^{-1})	K-AI	5.14 ± 0.41	0.11 (2.26)	0.15(3.03)	0.11 (−0.09 to 0.32)
	Vector S7	5.03 ± 0.41			

Abbreviation: SD = standard deviation, MAE = mean absolute error, RMSE = root mean square error, LoA = limits of agreement, HSR = high-speed running.

traces were broadly comparable, short sections of the signal may be sensitive to device-specific processing decisions. This interpretation is supported by previous GNSS research showing that manufacturer processing, smoothing, filtering, and algorithmic derivation can influence velocity-related outputs, particularly during high-intensity or transitional movement phases.[25,47] The absence of widespread differences across the trace supports the general comparability between systems, while the detected clusters highlight the sensitivity of instantaneous velocity to subtle variations in signal handling. As such, these findings reinforce the need for caution when interpreting fine-grained velocity profiles across different GNSS technologies, particularly during short, dynamic actions where proprietary processing may amplify small discrepancies.[47]

The authors want to clarify that using timestamps to define corresponding session windows imposes several constraints that affect temporal alignment. In this study, timestamps were used solely to trim each training session within the respective software, whereas sample-level synchronisation was applied only for the instantaneous velocity analysis. Because timestamps depend on device-specific internal clocks, small differences in clock drift, recording onset, or sampling intervals can create subtle misalignments between systems.[48] These offsets may be negligible for gross measures such as total distance. However, they could become problematic for high-frequency metrics, where even millisecond-level discrepancies influence the shape and timing of velocity or acceleration profiles. Additionally, manufacturer-specific processing and export pipelines, including filtering, interpolation, and smoothing routines, can shift the effective timing of recorded samples, meaning that identical timestamps may not correspond to identical movement events across devices.[47,49] As a result, timestamp-based trimming does not guarantee full temporal alignment, and residual offsets may persist for all variables except instantaneous velocity, which was explicitly synchronised.

Limitations and future directions

A limitation of this study is the sample size of 30 athletes. Although this number is consistent with previous validation research in team-sport settings, it may still limit the generalisability of the findings. The sample was drawn from a single semi-professional Australian football squad during a specific phase of the pre-season; therefore, movement patterns, training intensities, and contextual factors may not fully represent other teams, competition levels, or phases of the annual cycle. While the study captured a broad range of ecologically valid movement demands, the absence of controlled, repeatable movement trials prevents a more granular understanding of device behaviour under specific locomotor conditions. In addition, environmental and satellite-related conditions were not directly quantified. Although both systems reported qualitatively adequate satellite connectivity, and precipitation was not present during data collection, favourable meteorological conditions play a decisive role in ensuring stable signal acquisition and reliable performance metrics, particularly in team sport contexts where rapid locomotor actions demand high temporal and spatial precision.[50]

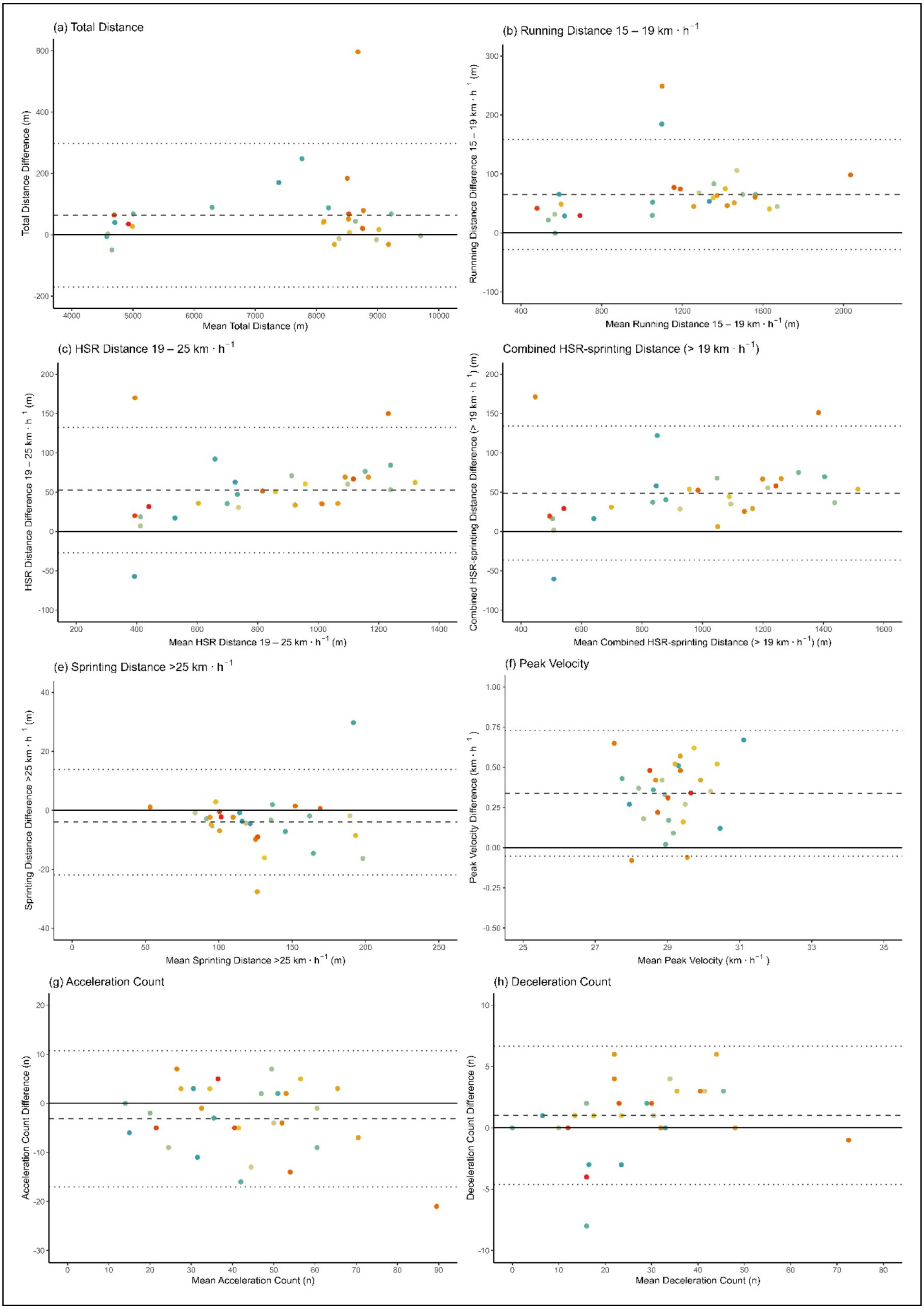

Figure 2. Bland–Altman plots comparing K-AI and Vector S7 discrete variables reporting the mean difference and 95% LoA. Note: Dashed line = mean difference, dotted lines = 95% LoA. Each colour represents a participant.

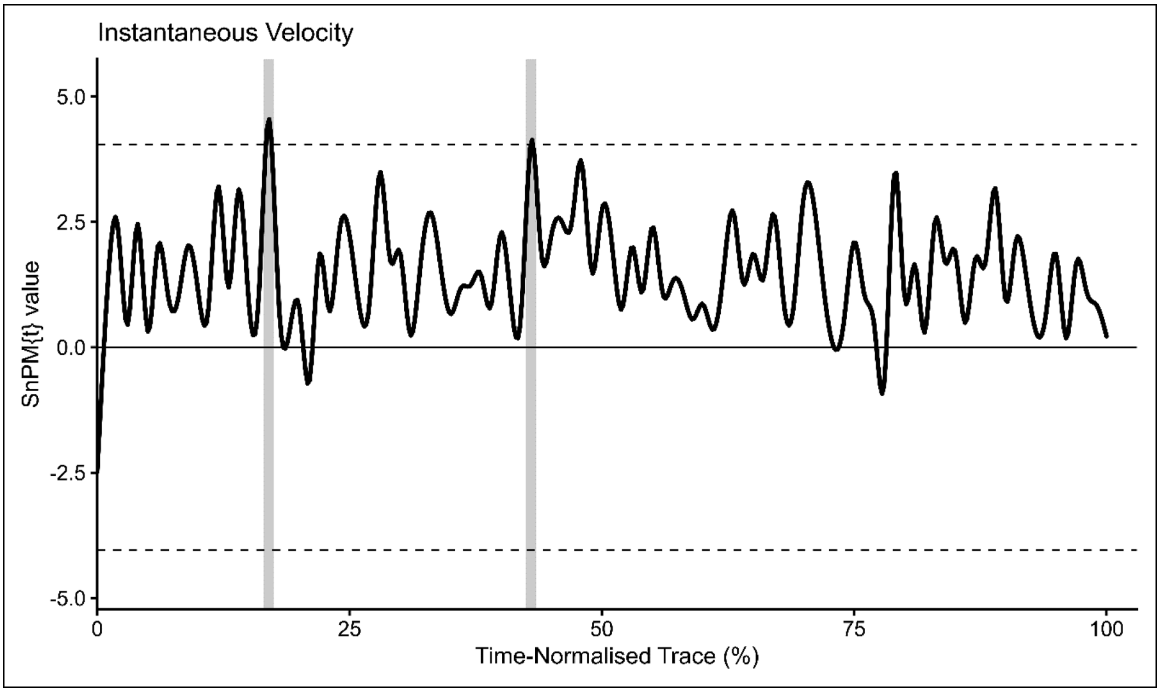

Figure 3. Statistical non-parametric mapping (SnPM) comparisons for instantaneous velocity across the time-normalised trace between K-AI and Vector S7. Note: dashed line = alpha threshold of 0.01; shadow area = region exceeding critical threshold.

Clear skies and dry air enhance atmospheric transparency, reducing signal attenuation and scattering, and supporting higher signal-to-noise ratios and more stable carrier-phase tracking. Conversely, precipitation, dense cloud cover, and elevated humidity introduce water vapour that absorbs and diffuses GNSS signals, increasing the likelihood of transient satellite dropouts and widening the limits of agreement for high-frequency metrics such as instantaneous speed and acceleration. Future research should therefore examine device performance across larger and more diverse cohorts, include controlled movement protocols, and assess how environmental conditions, satellite availability, sampling frequency, and proprietary filtering algorithms influence agreement between GNSS systems. Such investigations would help clarify the contexts in which GNSS technologies may be interpreted interchangeably and where device-specific calibration or interpretation remains necessary.

Practical applications for coaching

From an applied perspective, the present findings suggest that the K-AI Wearable Tech can be used to monitor common external-load metrics such as total distance, running distance, and peak velocity during field-based training. These variables demonstrated agreement with the Vector S7, indicating that practitioners can expect broadly comparable outputs when using the K-AI system for routine load monitoring, session planning, and longitudinal athlete profiling. However, the variability observed in acceleration- and deceleration-based metrics highlights the need for caution when interpreting event-based outputs, particularly in environments where rapid changes in direction and short-duration bursts are central to performance. In such cases, practitioners may consider prioritising distance- and velocity-derived measures for decision-making, or alternatively avoid mixing datasets from different GNSS brands when analysing acceleration-related metrics.

Conclusion

Collectively, the findings of this study demonstrate that the K-AI Wearable Tech provides measurement outputs that are comparable to those of the Vector S7 for most distance and velocity metrics, supporting its use for monitoring general external load in team-sport environments. The agreement across core metrics suggests that the K-AI system can be suitable for applied usage, particularly for metrics that underpin routine load monitoring and longitudinal athlete profiling. At the same time, practitioners should remain mindful of the reduced agreement observed for acceleration- and deceleration-based metrics, especially when comparing data across devices or merging historical datasets collected with different technologies. These insights reinforce the value of applying the Sport Technology Quality Framework when evaluating emerging tracking systems, ensuring that users understand not only the agreement between technologies but also the direction and magnitude of any systematic differences.

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Author contributions

All authors have read and agreed to the published version of the manuscript. Individual contributions included: research concept and study design: MD, SP, CS, JH, MB; literature review: MD, SP; Data collection, data analysis and interpretation: MD, SP, JH, MB; Statistical analyses: MD; Writing of the manuscript or reviewing/editing a draft of the manuscript: MD, SP, CS, JH, MB.

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The study was conducted in accordance with the Declaration of Helsinki and approved by the University Human Research Ethics Committee (HRE25-155).

Informed consent statement

Informed consent was obtained for the subjects involved in the study.

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