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Calibration and metrological characterization of a wearable inertial device for jump height measurement in professional athletes

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ABSTRACT
The countermovement jump is a recognized indicator of neuromuscular function and lower-limb explosive power, with applications in both sport performance assessment and rehabilitation. Gold-standard measurement systems, such as force platforms and motion capture, are accurate but are limited by high costs, lack of portability, and constrained applicability in field settings. Wearable inertial measurement units (IMUs) have emerged as a promising alternative, enabling the unobtrusive monitoring of athletes in real-world conditions; however, their reliability strongly depends on metrological performance. This study presents an application-oriented metrological characterization of a commercially available inertial device (K-AI, K-Sport, Italy) for jump height estimation in professional athletes. A total of 31 elite basketball and volleyball players performed sport-specific jumps at varying intensities and distances. Jump height estimated by the IMU using the flight-time method was compared against a non-invasive markerless video-based reference system (MediaPipe Pose). Results revealed a systematic underestimation by the IMU (mean residual: –0.12 m; 95 % CI: [–0.20, –0.03] m), although a strong linear correlation with the reference was observed (ρ = 0.95). A calibration function was derived to correct systematic bias, and the combined expanded uncertainty (k = 2) was quantified at 0.10 m. The study demonstrates that properly calibrating the K-AI device is a practical, field-deployable solution that supports reliable athlete monitoring in real-world environments.

Section: RESEARCH PAPER

Keywords: jump height estimation; sport performance; wearable sensors; IMU; metrological characterization

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1. INTRODUCTION

The evaluation of countermovement vertical jump and squat jump is a widely recognized indicator of lower limb explosive power and neuromuscular performance, playing a crucial role in sports (e.g. basketball, volleyball, track and field, and strength and conditioning programs) [1] and rehabilitation [2]. The significance of this indicator lies in evaluating performance, monitoring training, and preventing injuries [3].

Traditional methods for analysing jumps include force platforms [4], marker-based motion capture systems (MoCap) [5], contact mats [6], and photoelectric cells [7], which are considered the gold standard technologies in the biomechanical field. Force platforms are used to assess vertical jump heights by measuring the time of flight (TOF) or evaluating ground reaction forces during take-off and landing [8], [9]. Xu et al. [10] in their research examine the different calculation methods to estimate jump height during countermovement jump and drop jump. When comparing force platform and motion capture systems, they found that the impulse momentum method implemented with a force platform achieved high reliability with a coefficient of variation (CV) ranging from 0.10 % to 11.34 % and an intraclass correlation coefficient (ICC) between 0.88 and 0.97, for measuring jump height from take-off to the apex of the jump. Although motion capture systems showed very low variability (CV: 0.13 %; ICC: 0.90), the force platform remains the reference standard due to its ability to directly measure ground reaction forces and accurately determine the take-off instant, thus reducing potential biases associated with other approaches. Although more accessible and portable options for field acquisition are emerging, they are often limited in measurement area, allowing only a few steps or jumps, and typically require multiple installations.

Similarly, MoCap systems enable the detailed kinematic tracking of body segments, allowing for three-dimensional analysis of movement mechanics [11]. Platforms such as Vicon (Oxford Metrics Group Ltd., Oxford, UK), Qualisys (Qualisys AB, Gothenburg, Sweden), and OptiTrack (NaturalPoint, Corvallis, OR, USA) can deliver sub-millimetre precision when

used in well-controlled and calibrated laboratory conditions [12]. However, despite their accuracy, these technologies have several limitations [13] that hinder their practical application in real-world sports environments. In particular, they require controlled laboratory conditions, involve complex setup and calibration procedures, and depend on specialized personnel for data acquisition and processing [14]. Moreover, the high cost and bulkiness of the equipment significantly restrict their accessibility and portability, making them impractical for field-based or longitudinal monitoring of athletes.

An alternative method is markerless photogrammetry, which uses computer vision tools such as MediaPipe [15] or OpenPose [16] to accurately infer body landmarks from video sequences, thus removing the requirement for physical markers. This is a non-invasive approach, suitable for field-based applications using standard video cameras or smartphones [17]. These tools enable the tracking of multiple joints and the reconstruction of the trajectory. OpenPose with multiple cameras achieves mean absolute errors (MAE) below 30 mm in about 80 % of cases, although errors greater than 40 mm have been reported in frames affected by tracking issues [18]. OpenCap, a smartphone-based markerless platform, recently showed strong agreement with marker-based systems in cycling, with strong agreement ($r > 0.9$) for hip (flexion/extension), knee (flexion/extension), and ankle (dorsiflexion/plantarflexion) joint angles [19]. Conversely, in real competition scenarios, such as long jump analysis, OpenPose exhibited poor reliability, with an ICC of 0.17 [20]. Moreover, in gait analysis, MediaPipe showed ICC ranging from 0.75 to 0.90 with Vicon for most temporal parameters [21].

In response to the above-mentioned challenges, wearable inertial measurement units (IMUs) have emerged as a promising alternative [22], [23]. IMUs are compact, lightweight devices that integrate triaxial accelerometers, gyroscopes, and magnetometers to record dynamic motion data [24]. Their miniaturized design and wireless capabilities allow for unobtrusive integration into garments or sport equipment, facilitating performance tracking in natural training conditions [25], [26]. Moreover, in the sports environment, the advantages of IMU-based systems lie in their portability and lightweight design [27], which make them accessible for a widespread use across diverse training contexts, allowing athletes to perform freely without interference as well as trainers to gather relevant data in real-time. Their user-friendly design and minimal setup requirements enable coaches and athletes to easily obtain performance data without needing advanced technical skills. These devices are also ideal for long-term monitoring, thanks to their battery-powered design and wireless data transmission, which enables the tracking of the athlete's performance over time and in various environments. Despite their potential, the accuracy of jump height estimation using inertial sensors can be influenced by several factors, including the positioning of the sensor on the body [28], movement artifacts (e.g. soft tissue motion), and variations in individual jumping techniques. Wearable solutions based on inertial sensors have been validated for estimating jump height in field settings [29], [30], [31]. Recent evidence indicates that ankle [32] or single sacrum-mounted IMU [33] combined with appropriate algorithms can yield good agreement with laboratory gold standards (motion capture system and force platforms) with a low-sampling-rate IMU positioned at L5; the numerical double integration method showed $r = 0.87$ and a bias = 2.5 cm in double-leg vertical jumps [34]. Studies show that placement matters; positioning near the sacrum/segmental centre of mass (COM) improves the accuracy of vertical acceleration and derived jump height and is also the best location to estimate ground reaction force during jumping [35]. Otherwise, de Ruiter et al. [36] found that validity compared with a force platform was excellent for IMUs positioned on the feet, while the IMU applied to the chest showed the greatest bias (−6.35 cm), while maintaining limits of agreement and correlation values comparable to those of other positions. The IMU attached to the waistband showed the lowest validity. In another study with adolescents [37], validity comparisons between torso- and hip-mounted IMUs for jump height assessment showed promise relative to contact mats. Mean hip-mounted IMU overestimated jump height by 5.5 cm (26 %), with excellent agreement (ICC = 0.89). Torso-mounted IMU also exceeded contact mat values by 4.9 cm (23 %) with similarly high agreement (ICC = 0.87). While both IMU placements systematically overestimated jump height, they showed strong concurrent validity with contact mats, and are feasible tools for adolescent jump height assessments. Many studies have utilized IMUs positioned at the lumbar region, given its proximity to the body's COM [38], [39]. In a recent study of external load in professional volleyball male athletes, jumps made according to playing position varied [40]. However, in certain team sports, athletes wear tracking systems integrated into torso equipment, which often includes IMUs [41], [42]. This placement may be less cumbersome and more seamlessly integrated into sports practice, as it aligns with equipment already commonly used by athletes.

Given this technological landscape, existing literature has investigated the validity of IMU-based jump assessment highlighting a substantial lack of standardized, application-driven metrological procedures (particularly calibration) for evaluating commercial devices directly in their real operational context, making it challenging to ensure comparability and reliability across studies and applications.

In this study, the performance of a commercially available wearable IMU (K-AI, K-Sport, Fano, Italy) was evaluated for jump height estimation in real-world conditions, using a practical and easy to realise markerless video-based approach as the reference system. The experimental protocol was used on a cohort involving 31 professional athletes from basketball and volleyball teams in realistic application contexts, and the metrological performance of the device was assessed across various jump types. Markerless photogrammetry, based on the MediaPipe Pose library [43] was originally implemented as a reference system to provide non-invasive, video-based estimates of jump height. The analysis included the assessment of trueness, precision, 95 % confidence interval, and Pearson's correlation coefficient. Finally, a calibration function was derived to describe the relationship between IMU-based and reference measurements. The objective is therefore to provide a replicable metrological characterisation procedure for commercial wearable devices, directly applicable in real sports scenarios for the sake of training effectiveness and sport performance optimization.

2. MATERIALS AND METHODS

This section describes the test population, the experimental procedures, the devices used, and the data analysis techniques.

2.1. Measurement devices

Two measurement devices were used in this study: the wearable inertial sensor K-AI (K-Sport, Fano, Italy) [44] and a digital camera (Nikon D7200, Nikon Corporation, Tokyo, Japan), serving as the reference system.

The K-AI system is a compact, professional-grade inertial device. The device is embedded within a specially designed sport bib that ensures secure placement on the athlete's upper back, allowing for stable data acquisition without interfering with movement or performance. The sensor was positioned in a dedicated pocket located in the upper thoracic region (approximately between T1 and T3) of the athlete's back (Figure 1), fabricated by the producer itself. The K-AI unit incorporates a triaxial accelerometer and a triaxial gyroscope, which together enable six-degree-of-freedom motion tracking, and a triaxial magnetometer for orientation estimation. The device is compact and lightweight, measuring (79 × 42 × 18.6) mm³ and weighing 61 g. The sampling frequency is 238 Hz for inertial measurements (accelerometer and gyroscope) and 40 Hz for magnetometer data, providing adequate temporal resolution for the analysis of dynamic sports movements. According to the manufacturer's specifications, the measurement ranges are ± 16 g for the accelerometer, ± 2000 °/s for the gyroscope, and ± 16 Gauss for the magnetometer. The internal lithium-polymer battery provides up to 8 hours of continuous use, complemented by a 32 MB memory card, making the device ideal for full training sessions or match-play data collection.

The Nikon D7200 was equipped with an 18–105 mm lens, with aperture settings between f/3.5 and f/5.6. ISO values ranged from 600 to 800, and shutter speed was fixed at 1/125 s. The camera was mounted on a tripod at pelvis height and positioned directly in front of the subject. Exposure settings were adjusted for each environment to ensure optimal image quality.

2.2. Test population and test protocol

The experimental campaign involved 31 professional athletes (16 female volleyball players and 15 male basketball players), recruited from two Italian first-division teams. The average age of the participants was (24 ± 4) years, with a mean body mass index (BMI) of (21.8 ± 2.1) kg/m² (values reported as mean ± standard deviation). All participants were healthy, free from recent lower limb injuries, and engaged in regular competitive training.

Before data collection, each subject was informed about the study procedures and main objectives and signed an informed consent form. The study protocol complied with the ethical standards outlined in the World Medical Association Declaration of Helsinki [45] and was approved by the Research Ethics Committee of the Università Politecnica delle Marche. Data collection was carried out in compliance with the General Data Protection Regulation (GDPR – EU Regulation 2016/679).

Each participant was instructed to position herself/himself in front of the camera wearing the K-Sport sport bib with the IMU device. Figure 1 illustrates the experimental setup. Before data acquisition, participants were required to remain stationary, as the initial video frames would be utilized to establish a reference threshold. The test protocol included various types of jumps performed at three different distances from the camera (i.e. 4 m, 5 m, 6 m) to evaluate the effect of subject-camera distance. Each subject was asked to perform five repetitions per jump type at each distance, resulting in a total of 15 jumps per condition.

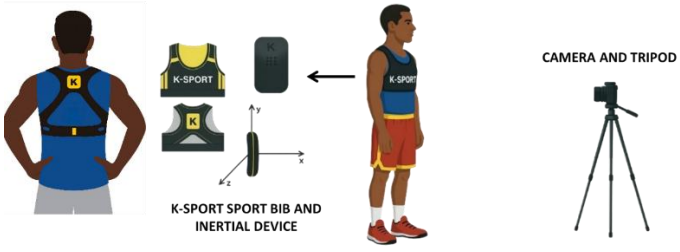

Figure 1. Experimental setup showing the athlete wearing the K-AI device integrated into the sports bib and positioned in front of the camera. The local reference frame of the sensor, positioned in the upper thoracic region, is also shown.

Table 1. Overview of the experimental protocol phases.

Phase	Distance (m)	Jump Type	Sport	Repetitions
Main test	4, 5, 6	Squat Jump (SJ)	All participants	5
Main test	4, 5, 6	Block Jump (BJ)	Volleyball only	5
Main test	4, 5, 6	Jump Shot Simulation (JS)	Basketball only	5
Variability test	5	Low, medium, high-intensity jumps	All participants	5 per intensity

The jump types were selected based on the athlete's sport discipline and included:

- Squat jumps: starting from a static squatting position, the participant performs an explosive vertical jump.
- Block jumps (performed by volleyball athletes): executed from a preparatory stance, this jump involves a vertical extension combined with a synchronized arm movement to simulate a block.
- Jump shot simulations (performed by basketball athletes): this movement mimics a basketball jump shot, combining explosive lower-limb extension with an upward arm motion.

Finally, to evaluate the variability of the results related to the jump amplitude, the participant performed an additional set of jumps at 5 m, varying the intensity of the effort: 5 low-intensity jumps, 5 medium-intensity jumps, and 5 high-intensity jumps. The experimental protocol is summarized in Table 1.

2.3. Data analysis

The analysis of the acquired data, comprising both video recordings and inertial signals, was carried out in a Python environment. This processing pipeline aimed to estimate jump height from each device and subsequently evaluate the agreement between the two measurement approaches.

To estimate jump height from video recordings, a markerless tracking approach was adopted using MediaPipe Pose [15], [46], an open-source library developed by Google for real-time human pose estimation (Figure 2). This framework utilizes BlazePose, a Machine Learning (ML) model that can detect 33 anatomical landmarks from 2D video input. Key body joints, including shoulders, hips, knees, and ankles, are identified frame by frame, enabling the reconstruction of motor trajectories.

Before data processing, a static calibration phase was conducted to assess the accuracy of the landmark detection algorithm. This involved acquiring videos of subjects in a stationary condition at various distances (from 4 to 9 m) from the camera, and comparing the 2D landmark distances detected by MediaPipe with actual measurements obtained manually with a tape measure, with a resolution of 1 mm. This validation was essential for quantifying the measurement uncertainty associated with the video system under static conditions. The Authors have previously presented a detailed description of the procedure [47].

In this study, the hip landmarks (points 23 and 24 in Figure 2) were extracted from each frame. Their midpoint was computed to represent the approximate

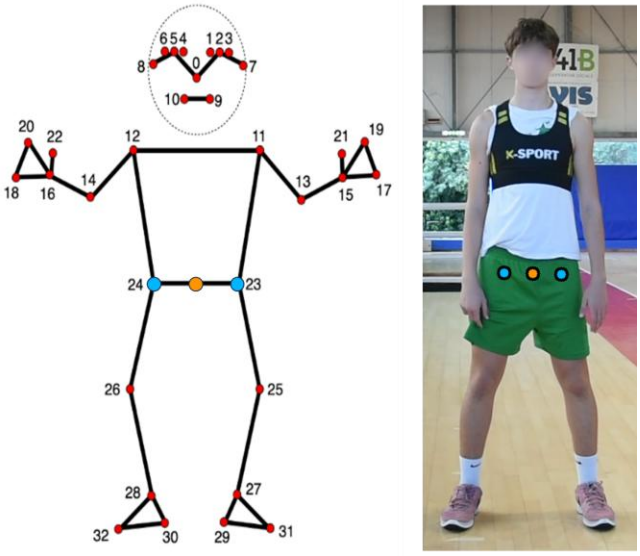

Figure 2. MediaPipe Pose model with 33 landmarks; in blue: left and right hip (24, 23), in orange: their midpoint. On the right, the identified landmarks are shown on the test subject.

vertical position of the subject's centre of mass (Figure 2). The resulting *y*-coordinate signal, initially in pixel units, was converted to metric units using a calibration curve derived from a checkerboard-based photogrammetric procedure [47]. The calibration curve determines the conversion factor from pixels to cm as a function of subject–camera distance. This conversion allowed the tracking of vertical displacement during each jump.

To establish a reference threshold, subjects were instructed to remain still at the beginning of each trial. The vertical coordinate of the hip centre in this initial phase was used as a reference threshold. The maximum peak in the signal corresponding to the vertical displacement of the pelvis midpoint was then identified. The jump height was calculated as the difference between this peak value and the initial threshold. An example of the analysed signal is reported in Figure 3.

From the K-AI device, positioned on the athlete's back, only the vertical component of acceleration was analysed. The signal underwent a 7 Hz low-pass Butterworth filtering process. A cutoff frequency of 7 Hz was selected empirically after preliminary trials, as it provides the effective attenuation of high-frequency noise while preserving the main motion-related features of the vertical acceleration signal. Although slightly lower than standard biomechanical cutoffs (10–12 Hz), this frequency provided effective attenuation of high-frequency impact noise upon landing, while preserving the main motion-related features of the vertical acceleration signal during the push-off and flight phases. Jumps were segmented based on prominent negative peaks in the signal, which correspond

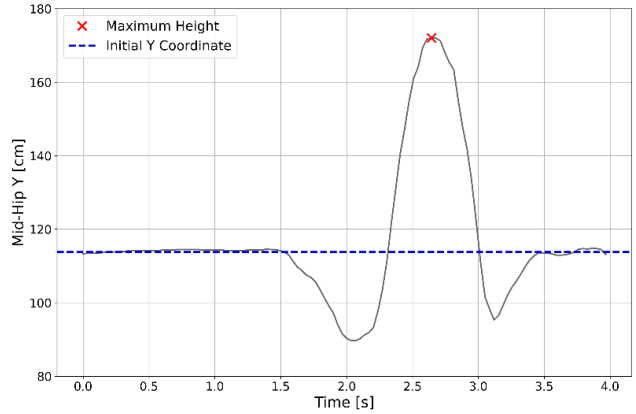

Figure 3. Vertical pelvis displacement during a jump is measured from the initial standing posture (baseline) to the maximum peak of elevation. Jump height is the difference between these two points.

to the impact phases of landing. Within each segment, two key local minima were identified, representing the loading (squat phase) and landing phases of the jump [48].

A threshold was established at $y = 0$, representing the phase at which the subject reaches zero acceleration during the flight phase. Between the local minima points, the zero-crossings of the acceleration curve were detected. These intersections indicate the time during which the subject is airborne, as acceleration approaches zero in the flight phase. The TOF was computed as the time interval between the two zero-crossings. Figure 4 shows the filtered signal with annotated minima and zero-crossings used for TOF computation, along with the corresponding movement phases: erect position, squat, push-off, flight, landing, erect position. Under the assumption of ideal projectile motion and negligible air resistance, jump height h was calculated using equation (1):

$$h = \frac{g}{8} TOF^2 , \tag{1}$$

where:

- h = jump height in m,
- g = gravitational acceleration, i.e. $9.81\ \mathrm{m/s^2}$,
- TOF = time of flight in s.

1. Erect position (start)
2. Squat – lowering phase, muscles loaded.
3. Push-off – explosive extension, feet leaving the ground.
4. Flight phase –no ground contact.
5. Landing – eccentric phase, muscles absorb impact.
6. Erect position (end)

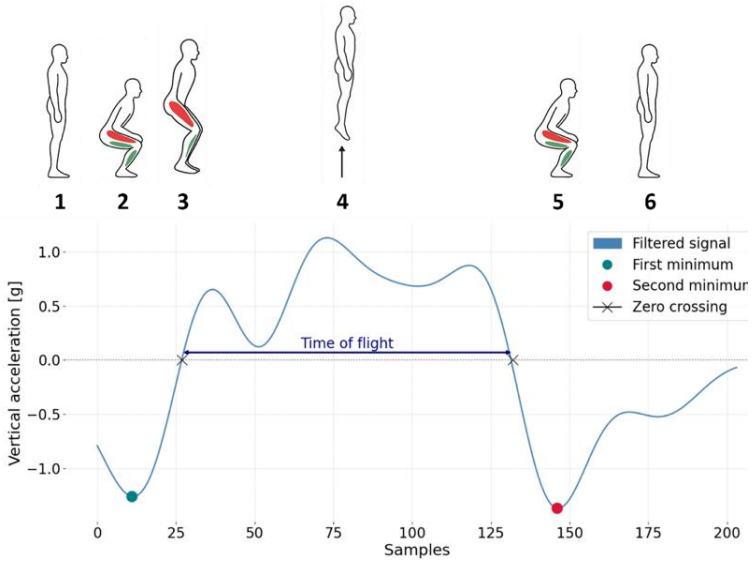

Figure 4. Example of jump segmentation based on vertical acceleration. The filtered signal is shown with the two key local minima (loading and landing phases) and the zero-crossings used to compute the time of flight (TOF).

The difference between the two jump height measurements (i.e. measurement residuals) was analysed to assess the trueness and precision of the IMU-based estimation. In particular, the mean and standard deviation of the residuals were calculated. Agreement between methods was further evaluated using a Bland–Altman plot, incorporating the 95 % confidence interval (CI95%) for limits of agreement. To assess the strength of the linear relationship between the two methods, the Pearson's correlation coefficient was computed, with values interpreted as follows: weak ($\varrho < 0.30$), moderate ($0.30 < \varrho < 0.70$), and strong ($\varrho > 0.70$) [49]. The linearity error was calculated as the maximum deviation from the regression line, expressed as a percentage of the measured value. The calibration curve of the K-AI device was obtained by fitting the experimental data with a linear regression line, which provides the relationship between test and reference values.

The combined measurement uncertainty $u(h)$ was estimated as the root sum square of two components (2):

$$u(h) = \sqrt{u_1^2 + u_2^2} \quad , u \text{ in m}, \tag{2}$$

with

- u_1: uncertainty related to the video system, considering the contributions of interfering sources, such as calibration errors, lighting conditions, and variations in landmark detection with MediaPipe in static conditions;
- u_2: variability caused by the measurement differences between the IMU data and the estimates derived from video analysis.

The relative measurement uncertainty was then computed according to equation (3):

$$u_{\text{rel}}(\%) = \frac{u(h)}{\bar{y}_{\text{pred}}} \cdot 100\ \%\,, \tag{3}$$

where $\bar{y}_{\text{pred}}$ is the mean value predicted by the regression model. This relative uncertainty was used to define the uncertainty bands in the correlation plots, corresponding to $\pm\, u(h)$ around the regression line, thus providing a data-driven estimate of the expected variability without imposing an a priori threshold.

3. RESULTS

This section reports the K-AI device validation results. The checkerboard-based photogrammetric calibration and the static validation of the video system had already been conducted and reported in [47]. Static measurements demonstrated the lowest measurement variability at 4–6 m from the camera, with standard deviations of 1.50 cm (4 m), 1.08 cm (5 m), and 1.08 cm (6 m), respectively. Beyond 6 m, a marked increase in variability was observed, with standard deviations of 1.40 cm (7 m), 3.55 cm (8 m), and 3.45 cm (9 m). This progressive rise in dispersion indicates reduced measurement precision with increasing distance. Therefore, the measurements were conducted on professional athletes at 4, 5, and 6 m from the camera. From this static calibration, the uncertainty associated with the video-based measurement system, referred to as u_1, was quantified. By averaging the results across all distances, an overall mean error of 0.47 cm and a standard deviation of 1.81 cm were obtained, leading to an estimated value of u_1 equal to 0.0181 m. Considering a coverage factor $k = 2$ (95 % confidence level), the expanded uncertainty is 0.0362 m.

Figure 5 shows the distribution of the residuals in estimated jump height between the test device (K-AI) and the reference (camera). The mean residual was -0.12 m, with a standard deviation of 0.04 m. This result indicates that the test device tends to underestimate the reference value. This standard deviation, denoted as u_2, represents the uncertainty due to the disagreement between the two measurement systems under dynamic conditions. With a coverage factor $k = 2$, the corresponding expanded uncertainty is 0.08 m.

The Bland–Altman plot (Figure 6) indicates a CI95% of [-0.20, -0.03] m. The interpolating line was also calculated, correlating the average jump heights with the residuals for both cases. In particular, the negative slope suggests that the greater the jump height, the larger the (absolute) difference between the test and the reference device. Furthermore, a scatter plot with the fitting line between the reference device measurements and the test device measurements, and Pearson's correlation coefficient ϱ was used to perform the correlation analysis. Results indicate a strong positive correlation with ϱ equal to 0.95 (Figure 7). The figure also shows uncertainty bands corresponding to the calculated combined measurement uncertainty $u(h)$. The combined uncertainty $u(h)$, calculated as the squared sum of the uncertainties related to the camera parameters (u_1), and the uncertainty from the comparison between the K-AI sensor and the camera (u_2) is 0.05 m. Considering a coverage factor $k = 2$, the expanded uncertainty is 0.10 m. These bands, plotted as $\pm\, u(h)$ around the regression line, provide a visual representation of the expected variability between the two methods.

The calculated interpolation line of the data represents the calibration curve of the K-AI device, which needs to be integrated to correct the jump height measurement of the inertial sensor according to equation (4):

$$h_{\text{test}} = 0.66 \cdot h_{\text{ref}} + 0.01\,, \tag{4}$$

where

- h_{test} is the jump height in m measured by the K-AI device;
- h_{ref} is the reference jump height in m measured by the video-based system.

4. DISCUSSION

This research is an application-oriented metrological study. The contribution is to demonstrate that a commercially available wearable device can be rigorously characterised and calibrated using an accessible, markerless reference system, and that this methodology is feasible in real-world team sports contexts. The ability to validate and integrate the sensor into the athletes' usual training environment is a key practical advantage, supporting longitudinal monitoring, ecological data acquisition, and scalable integration into professional workflows.

The study aimed to characterize the metrological performance of the K-AI wearable IMU by comparing its jump-height estimates with those obtained via markerless video analysis using MediaPipe. The results demonstrate the significant potential of the K-AI wearable device for estimating jump height. As a valid alternative to traditional video-based systems, it offers several practical advantages, including autonomous data acquisition in real-world field conditions, enhanced comfort and freedom of movement for athletes, reduced setup and operational costs, and increased flexibility in data collection and analysis. These features make the K-AI device a promising solution for coaches and

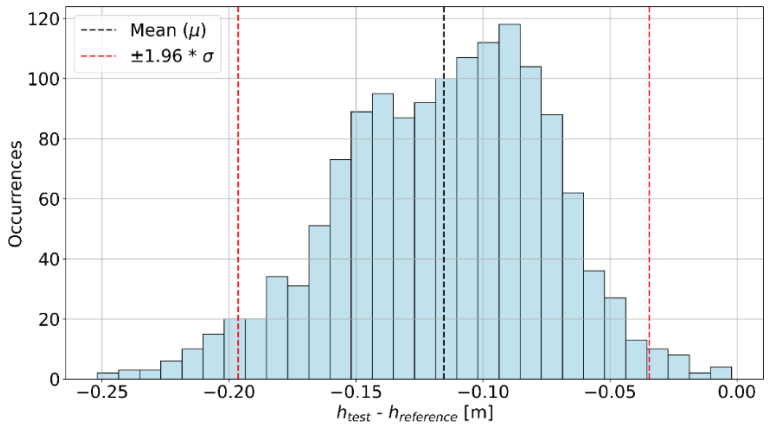

Figure 5. Distribution of residuals in jump height estimation between the K-AI device and the video-based reference system. The black line indicates the mean residual, while the red lines represent the CI95% around the mean.

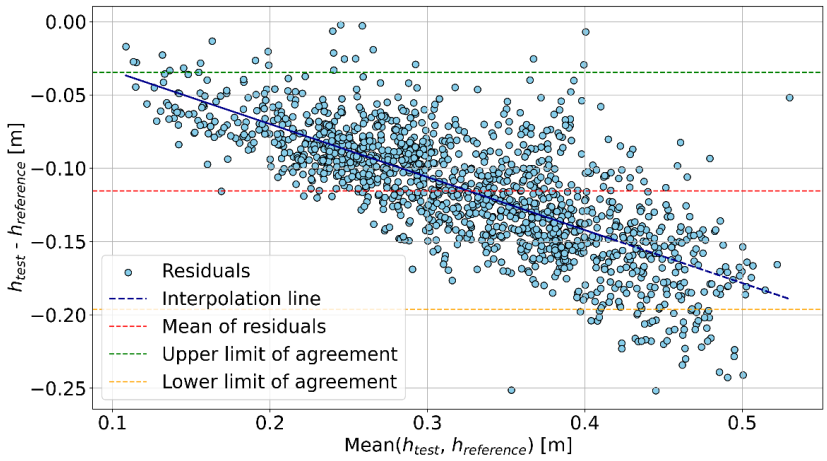

Figure 6. Bland–Altman plot comparing jump height estimates from the K-AI device and the reference video system. The blue line represents the interpolation of the residuals, showing the trend of systematic deviation between the two methods.

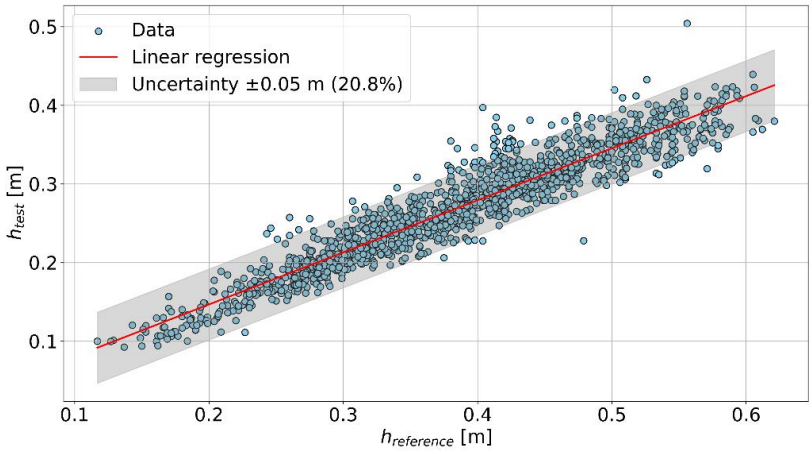

Figure 7. Correlation analysis between K-AI and video-based jump height estimates. The scatter plot includes the linear regression line, Pearson's correlation coefficient (ρ = 0.95) and uncertainty bands.

sports practitioners seeking efficient and unobtrusive measurement tools. While the markerless video-based system (i.e. MediaPipe) provides a fast, low-cost, and field-deployable reference, it is important to acknowledge that it has not been benchmarked against gold standards like force platforms or 3D optical motion capture (e.g. MoCap system). Indeed, using a single-camera 2D tracking system introduces potential uncontrolled systematic uncertainty into the reference baseline. Specifically, perspective and depth limitations can affect the video baseline accuracy, as 2D projections may not fully capture out-of-plane motions. Nevertheless, the static calibration demonstrated a variability of about 1–2 cm, confirming its suitability as a practical baseline for this application-oriented assessment. The advantage of this measurement system lies in the sensor placement within a specially designed sport bib. This configuration ensures a secure and consistent positioning of the IMU on the athlete's back, minimizing motion artifacts, while avoiding discomfort or interference with natural movement. Unlike traditional MoCap systems, the sport bib allows for unconstrained motion, making it particularly suitable for high-intensity, sport-specific tasks. Moreover, this setup enables autonomous data acquisition in real-world training environments without requiring a controlled laboratory setting or constant operator supervision. This study involved professional athletes performing sport-specific jump types at various distances and intensities from a camera. The comparative analysis with the markerless video reference system based on MediaPipe revealed a systematic bias, with the K-AI device consistently underestimating jump height. Specifically, the mean residual was -0.12 m, with a standard deviation of 0.04 m. Bland–Altman analysis further confirmed this discrepancy, showing a 95 % confidence interval of [-0.20, -0.03] m. Additionally, the negative slope of the residuals relative to the mean values indicates that the underestimation increases (in modulus) with the reading (i.e. higher jump heights). From a practical standpoint, a mean bias of 12 cm is substantial and could be not acceptable for coaches relying on absolute jump height for performance assessment. However, despite this bias, a strong linear relationship is evident between IMU-based and reference measurements, with a Pearson's correlation coefficient of 0.95. This indicates that the calibration function can effectively compensate for the systematic error in real applications, allowing the device to mathematically adjust the estimates and provide accurate tracking of the athlete's performance over time. -This high level of correlation suggests that the K-AI device can reliably capture variations in jump performance, although the output must be adjusted for accurate absolute values. To address this issue, a calibration function was derived through linear regression, yielding equation (4), which aligns the IMU measurements more closely with the reference data (mainly correcting the systematic error). This correction enhances the usability of the device in contexts where the measurement

precision is critical, such as performance monitoring or injury risk assessment. The expanded combined measurement uncertainty ($k = 2$), estimated at 0.10 m, incorporates both the intrinsic measurement uncertainty of the video-based system and the measurement differences between IMU and reference measurements. It is worth noting that the Bland–Altman plot suggests a proportional bias, indicating that the (absolute) measurement error increases with jump height. While a linear regression model was selected for its simplicity and to avoid overfitting, a non-linear calibration model might better capture this proportional error. Future studies will explore non-linear adjustments to further improve the accuracy across different jump intensities. In comparison, Rantalainen et al. [42] reported ICC values > 0.90 and small biases in jump height estimates derived from flight time using a torso-worn IMU.

5. CONCLUSIONS, LIMITATIONS, AND FUTURE WORKS

The results of this study highlight both the strengths and current limitations of the K-AI system for jump height estimation in real-world sport environments. Although the device systematically underestimates jump height, it exhibits a strong linear relationship with the reference system, thereby enabling accurate trend capture. The calibration function derived in this work, together with the quantification of measurement uncertainty, supports the use of the device for field-based monitoring, provided that a calibration step is included.

Despite the relevance of the findings, several considerations should be taken into account when interpreting the results. A first limitation concerns the definition of jump intensity in the test protocol. The categorization of jumps into low-, medium-, and high-intensity is inherently subjective and does not guarantee consistent classification across different individuals or testing sessions. To reduce this variability, jump intensity should be classified using objective, reproducible metrics.

A notable limitation of this study is the method used to estimate jump height from IMU data, which relied on the flight-time method. Although widely adopted due to its simplicity and computational efficiency, this method assumes a symmetric parabolic flight due to gravity [50] and does not account for sport-specific dynamics. For instance, it overlooks the effects of asymmetric motion, arm swing variability, and running starts, which introduce additional horizontal accelerations and affect flight characteristics. Future research should address these limitations by incorporating biomechanical modelling that accounts for complex movement patterns, including contributions from the loading phase and upper-body motion. A further limitation concerns the calibration procedure and the interpretation of uncertainty. The linear calibration adopted here provides a first-order correction of systematic distortion, but its generalisability to different populations, movement types, or acquisition conditions has not yet been evaluated. Similarly, although the combined measurement uncertainty was quantified, it was not contextualised relative to the measurement uncertainty values typically reported for gold-standard systems, such as force plates or optical motion capture. A broader comparison would allow a clearer understanding of the practical accuracy of the device.

Additionally, the IMU device was positioned on the upper back, a location not generally recommended in the literature for jump-height estimation. Although sites such as the sacrum or L5 vertebra (located in the lower back) offer better proximity to the centre of mass, they are challenging to implement in high-intensity sport settings, because belts or straps tend to shift during dynamic movements, introducing soft-tissue artefacts and reducing measurement stability. The upper-back placement of the commercial bib reflects the actual operating conditions under which athletes use the device. Nevertheless, this choice may affect the accuracy of the raw measurement and necessitate calibration. In this study, no systematic comparison was made between upper back positioning and the positions recommended in the literature. Future studies should focus on this analysis, which would allow quantification of the extent to which the observed distortion is attributable to positioning rather than to sensor performance or the time-of-flight estimation method.

Furthermore, the integration of ML techniques could enable subject-specific calibration, allowing for adaptive correction based on individual athletic profiles and improving measurement accuracy across different sports contexts. For example, thanks to the possibility of fine-tuning personal data, it has been observed that a model can significantly improve the classification of an individual athlete's running style by adding just 5 % of subject-specific data [51]. Artificial intelligence (AI) plays a crucial part in managing and preventing injuries by analysing biomechanical data and muscle fatigue in real-time [52]. By providing early intervention strategies, AI can help prevent injuries before they happen.

AUTHORS' CONTRIBUTION

Luna Panni: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

Gloria Cosoli: Conceptualization, Data curation, Methodology, Supervision, Validation, Visualization, Writing – review & editing.

Marco Arnesano: Conceptualization, Data curation, Funding acquisition, Methodology, Project Administration, Resources, Supervision, Validation, Writing – review & editing.

Lorenzo Scalise: Conceptualization, Funding acquisition, Methodology, Project Administration, Resources, Writing – review & editing.

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