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Validity of the Enode Sensor and My Jump 3 App for Assessing Countermovement Jump Performance

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Abstract: Countermovement jump (CMJ) performance analysis is vital in sports science for assessing lower-body strength and neuromuscular efficiency. This study evaluated the validity of the Enode Sensor and My Jump 3 App for measuring vertical jump heights, comparing them to those measured using the established Force Plate. Twenty-nine participants performed CMJs measured using each device. Descriptive statistics indicated mean jump heights of 48.4 ± 4.18 cm (for the Enode Sensor), 47.3 ± 4.05 cm (for My Jump 3), and 46.1 ± 4.03 cm (for the Force Plate). Reliability was confirmed via Intraclass Correlation Coefficients (ICCs), with the Enode Sensor at 0.914 and My Jump 3 at 0.968, demonstrating excellent reliability. Bland–Altman analysis showed mean biases of 2.281 cm (for the Enode Sensor) and 1.297 cm (for My Jump 3) against the Force Plate, with limits of agreement suggesting close alignment. Strong positive correlations were observed (for the Enode Sensor, $r = 0.972$ and for My Jump 3, $r = 0.987$; $p < 0.001$), and linear regression analysis produced R^2 values of 0.945 and 0.973, respectively, confirming both tools' accuracy for vertical jump measurement. These findings indicate that although both tools are suitable for CMJ assessment, My Jump 3 demonstrated slightly superior accuracy, underscoring the potential for accessible, reliable performance monitoring in sports contexts.

Keywords: CMJ; explosive lower-body power test; measurement accuracy; wearables; video-based assessment tool; force platform; elite-level team athletes; consistency; athletic output; vertical displacement

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1. Introduction

Countermovement jump (CMJ) assessment serves as a cornerstone in sports science, widely recognized for evaluating lower-body power, neuromuscular performance, and overall athleticism [1]. This assessment method holds particular importance in sports, such as basketball, where explosive strength is essential for performance in movements, like jumping, sprinting, and changing directions [2]. The CMJ involves a rapid downward movement followed by an explosive upward jump, effectively utilizing the stretching–shortening cycle to maximize power output [3]. Given their role in assessing explosive performance, CMJ metrics can inform training choices and load management, helping coaches and practitioners to maximize training effectiveness and minimize overtraining risks [4,5].

Research indicates that CMJ assessments can help to identify athletic talent and track performance changes over time, with notable studies investigating its utility across sports and populations. For instance, Haugen et al. [6] analyzed CMJ performance in female soccer players, finding that CMJ assessments could help to identify athletes with superior neuromuscular function and jumping ability. Similarly, Pociūnas [7] emphasized the importance of consistent pre-test protocols for accurate CMJ results, highlighting a strong association between pre- and post-warmup CMJ performance in basketball players. Additionally, research on the interaction between the human body and surfaces of varying stiffness, such as that by Arampatzis et al. [7], reveals that softer surfaces can enhance jump performance by increasing the ratio of the positive-to-negative mechanical work, with adjustments influenced by both surface stiffness and movement intensity. Moreover, studies show that short-duration static stretching may not significantly affect jump performance or alter neuromuscular parameters, such as the maximum voluntary contraction, strain, or stiffness [8], underscoring the complexity of factors that impact CMJ performance and its broader applicability in sports assessment.

CMJ assessments can derive numerous kinetic and kinematic variables—including jump height, peak power, the rate of force development, and peak velocity—offering comprehensive insights into an athlete's explosive capabilities and overall neuromuscular health [9,10]. Claudino et al. [1] further validated CMJ height as a reliable measure for tracking neuromuscular status in athletes, underscoring its relevance for monitoring fatigue and recovery.

Traditional CMJ measurement methods, such as Force Platforms and motion capture systems, are often viewed as gold standards because of their precision in capturing ground reaction forces and detailed kinematic data [11]. Force Platforms, for instance, accurately quantify jump metrics, like vertical jump height, peak force, and the rate of force development [12]. Despite their accuracy, these tools are often expensive, require extensive setup, and are typically confined to laboratory settings, limiting their practicality in routine field assessments [1,13].

Recent technological advancements have aimed to address these limitations by introducing more accessible alternatives, notably, wearable sensors and mobile applications [14]. Devices like the Enode Sensor leverage accelerometers and gyroscopes to capture motion data during jumps, offering a portable and cost-effective option for performance monitoring [15]. Likewise, mobile applications, such as My Jump, utilize smartphone cameras and advanced video analysis algorithms to estimate jump height and other CMJ metrics, thus making performance assessment more accessible and practical for day-to-day use by athletes and coaches [16]. Although these tools offer convenience, they may also face challenges in accuracy, especially in uncontrolled environments, where factors such as surface variations and user positioning can impact data reliability [15,17].

A considerable body of research has explored the accuracy and reliability of the My Jump application and various wearable devices in jumping assessments [17–31]. Validity, which measures how well a tool assesses its intended construct, and reliability, which concerns the consistency of repeated measurements, are central to evaluating these tools [32,33]. Several studies have mentioned that My Jump can provide valid, reliable jump height measurements comparable to those from Force Plates in controlled environments, making it a practical alternative for settings beyond the lab [17,34–36]. Wearable devices, such as accelerometers and inertial measurement units, have also demonstrated promising accuracy, though factors like sensor placement and calibration can affect data quality [4,37]. Research on the Enode Plus (formerly VmaxPro) for measuring vertical jump height remains comparatively limited, with no studies to date directly assessing its validity against both the My Jump 3 Application and the Force Plate standard.

The aim of this study is to evaluate and compare the accuracy and reliability of CMJ data obtained from the Enode Sensor and My Jump 3 Application against those obtained from a gold-standard Force Plate. Specifically, this study sought to answer (1) how CMJ data from the Enode Sensor compare to Force Plate data in terms of accuracy and reliability, (2) how CMJ data from the My Jump 3 App compare to Force Plate data, and (3) how the validity and reliability of the Enode Sensor compare directly to those of My Jump 3.

2. Materials and Methods

2.1. Participants

A total of 29 male professional basketball players (M_{age}: 23.0 ± 4.5 years, range: 18–31; body mass: 92.0 ± 13.0 kg; body height: 193 ± 8.5 cm) were recruited as volunteers from a first-division National Championship basketball club in Hungary. The group consisted of six point-guards (20.69%), five shooting guards (17.24%), six small forwards (20.69%), seven power forwards (24.14%), and five centers (17.24%). The players had an average of 11.76 ± 3.58 years of experience in competitive events. Their training experience at the amateur level averaged 9.10 ± 1.68 years, while their elite-level training experience averaged 2.66 ± 2.64 years. All the participants were healthy and actively engaged in competitive basketball. Each participant attended one testing session, with a total duration of 30 min.

Inclusion criteria included active participation in competitive basketball (>5 years), experience with countermovement jump testing, and no history of lower extremity injuries within the past six months, which could impact the jump performance. Exclusion criteria included participants with recent lower extremity injuries or surgeries within the past year, as these conditions may impair neuromuscular function, strength, and coordination. Such impairments could potentially skew CMJ performance data and lead to inaccurate conclusions about baseline jump abilities in healthy athletes. Additionally, participants were required to refrain from high-intensity physical activity for 48 h prior to testing to ensure that fatigue did not influence their jump performance. The study was approved by the ethics committee (approval number: RES2024/011). It was a non-interventional study and conducted in accordance with the Declaration of Helsinki. Informed consent was obtained from each participant and the basketball club, after being thoroughly informed about the study's purpose, procedures, and potential implications.

2.2. Data Collection and Analysis Procedures

This study employs a cross-sectional observational design to compare measurements obtained from the Enode Sensor and My Jump 3 App against those obtained from a Force Platform, which serves as the gold standard. Cross-sectional studies are well suited for comparing different measurement tools within a single time frame, enabling efficient data collection and analysis [38]. A power analysis was conducted to ensure an adequate sample size for detecting a large effect [39,40], following Cohen's criteria [41], which determined the appropriate number of participants required for this study. Thus, a sample size of 29 participants is deemed as sufficient for validity studies in cross-sectional designs that compare measurement tools [41].

Countermovement jump assessments were conducted in a controlled team setting using laboratory-grade equipment within a S&C environment in a single session from 15:00 to 16:30, on a stable and level floor surface under consistent artificial lighting, with the laboratory temperature maintained at 21 ± 2 °C. The participants completed an 8-min treadmill warmup, followed by a 4-min dynamic stretching session that included quadriceps stretches, front stretch kicks, forward lunges, bodyweight squats, and low-intensity countermovement jumps. Clear instructions were provided on performing the countermovement jump without an arm swing. Given that prior experience with countermovement jump assessments was an inclusion criterion, all the participants were already familiar with the protocol. The participants stood with their hands positioned at their hips, performed a countermovement to a depth of their choice, and then jumped as high as they could when ready. Each participant completed three maximum-effort CMJs, with a 2-min rest between attempts, and the highest jump was selected for analysis, as in similar studies [31]. Jump heights were recorded simultaneously on all the devices. The participants performed the jumps on a Force Platform while wearing an Enode Hip Belt with the Enode Sensor secured inside, and each jump was video-recorded using a smartphone for analysis in the My Jump 3 Application.

2.3. Research Tools

2.3.1. Enode Sensor

The Enode Sensor (formerly known as VmaxPro) is a wearable inertial measurement unit (IMU) equipped with an accelerometer and gyroscope, specifically designed for sports performance monitoring and programming. It tracks various aspects of athletic movements, particularly those involving explosive power, such as jumps, sprints, and lifts [42].

The Enode Sensor is a small, lightweight, and portable device with dimensions of 44 × 27 × 13 mm and a weight of 16 g, making it easy to attach to the body or sports equipment. It features a 12-h battery life, a wireless connectivity range of 15 m, and a measuring range of >0.15 m/s, enabling the accurate measurement of rapid movements. The sensor connects to a smartphone or tablet via Bluetooth, allowing for real-time data transfer and analysis through the Enode application, which provides detailed visualizations and performance metrics. In this study, the Enode app was operated on an iPhone 14 Pro. After establishing a Bluetooth connection, the application displayed a real-time 3D representation with six marked sides for proper sensor orientation. The sensor was briefly placed on each side for precise calibration, ensuring accurate measurements. Triaxial acceleration data were collected by the sensor's inertial measurement unit (IMU) at a sampling rate of 1000 Hz and transmitted via Bluetooth (~65 Hz) to the iPhone 14 Pro. These features, combined with its compact design and ability to operate within a temperature range of 0–40 °C, ensured the device's reliable performance under standard testing conditions [42].

The Enode Sensor measures parameters, such as jump height, flight time, peak power, and force production, during movements, like the countermovement jump. It can also track metrics, such as acceleration and top speed, during sprints and monitor lift velocity and force to optimize training loads and techniques. Furthermore, it analyzes jump biomechanics, including eccentric and concentric phases, to enhance technique and performance [42].

For countermovement jump assessments, the Enode Sensor must be attached close to the center of mass. This placement minimizes measurement errors by capturing the athlete's total body movement during the jump. Ideally, the sensor is positioned on the side above the hip of each participant, following a standardized protocol to ensure consistent placement and minimize variability. This setup was achieved with the Enode Hip Strap, which has a quick-release buckle, allowing for secure attachment of the sensor and quick changes between athletes [42].

2.3.2. My Jump Lab App (My Jump 3)

The My Jump 3 App (formerly My Jump 2) is a mobile application available for iOS and Android smartphones. For jump assessments, My Jump 3 uses the smartphone's camera and video analysis algorithms to estimate jump heights based on flight times. Users record jumps with the smartphone camera, and the app analyzes the video to calculate key metrics. It supports various jump types, including the countermovement jump (CMJ), squat jump (SJ), and drop jump (DJ). Designed with an intuitive interface, the app is accessible to coaches, athletes, and sports scientists without requiring extensive technical expertise. It allows for data storage within the app, with options for exporting data for additional analysis or recordkeeping. The app also provides immediate feedback on jump performance, enabling users to make quick adjustments during training (My Jump Lab Pro). Specifically, the My Jump Lab App (My Jump 3) employs the same methodology as that of My Jump 2, where jump analysis involves marking the takeoff and landing moments on the time axis. According to the manufacturer, the new AI feature in My Jump Lab enhances this process, using computer vision (image recognition) to create a bounding box around the subject captured in the video and calculates their position in pixels during the jump. These pixel data are then converted to centimeters, using the user's body height as a calibration factor. Preliminary testing of the app against a Force Plate showed excellent validity, 0.93 between instruments, highlighting the app's reliability for measuring vertical jump heights [43]. In this study, My Jump 3 was used on an iPhone 14 Pro, which offers a video-recording capacity of 240 frames per second (FPS). The smartphone was positioned on a stand 1.5 m from the participant, at a height of approximately 30 cm, following the app's recommended guidelines [17], which resulted in an observation angle of about 11.5° from the ground, to ensure stability and minimize recording errors [44]. The app was operated by an experienced observer with expertise as a strength and conditioning (S&C) coach, ensuring adherence to the app's guidelines.

2.3.3. Force Platform

Force Platforms, also known as Force Plates, are sophisticated measurement devices used in sports science, biomechanics, and clinical settings to assess ground reaction forces during various movements, including jumps, gaits, and balance tasks. These devices provide detailed information about the forces exerted by the feet on the ground, which can be used to analyze movement mechanics and performance [45].

Force Platforms measure three-dimensional ground reaction forces (vertical, anterior–posterior, and medial–lateral) exerted by the feet during different movements. With high sampling rates, they capture rapid force changes during explosive movements, like jumps. Known for their high degrees of accuracy and precision, Force Platforms are considered as the gold standard for biomechanical analyses. They measure forces along multiple axes, providing comprehensive data on force directions and magnitudes [46].

In this study, a high-quality PJS-4P60S Force Platform with MVJ v.4.0 software ("JBA" Zb. Staniak, Warsaw, Poland) and a 400 Hz sampling rate will serve as the reference standard for CMJ measurements. The Force Platform connects through an analog-to-digital converter (ADC) to a Dell Inspiron i7 laptop operating the MVJ v.4.0 software. This setup enables precise measurements of ground reaction forces during CMJs, providing accurate data on jump heights. The platform will be calibrated according to the manufacturer's specifications before data collection to ensure accuracy and reliability. Despite their accuracy, Force Platforms require a controlled environment, limiting their application in everyday training settings.

2.4. Statistical Analysis

Descriptive statistics were used to summarize the data, calculating means and standard deviations for the highest vertical jump measurements recorded for each participant across all the methods. The Shapiro–Wilk test was used to evaluate the data distribution normality, while Levene's test assessed the homogeneity of the variances. Reliability was assessed through the Intraclass Correlation Coefficient (ICC), which measures the consistency or reproducibility of quantitative measurements by different observers assessing the same quantity [47]. Following the recommendations of Shrout and Fleiss, the intra-rater reliability ICC was used to illustrate absolute agreement across multiple measurements. Reliability was categorized as poor (ICC < 0.5), moderate ($0.5 \leq$ ICC < 0.75), good ($0.75 \leq$ ICC < 0.9), or excellent (ICC ≥ 0.9) [48].

Agreement between the Enode Sensor, My Jump 3, and the Force Plate was assessed with Bland–Altman analysis, which provides a visual representation of the differences between methods. This analysis calculates the mean bias (the average difference between methods) and limits of agreement (mean difference $\pm$ 1.96 times the standard deviation of the differences) [49].

Correlation analysis was conducted to evaluate the strength and direction of relationships between measurements from different methods, with both Pearson's and Spearman's correlation coefficients calculated). Linear regression analysis was also performed to assess how well measurements from the Enode Sensor and My Jump 3 could predict Force Plate measurements. The coefficient of determination (R^2) was used to quantify the proportion of the variance in Force Plate measurements explained by the other methods [50].

This comprehensive data analysis approach involved multiple statistical methods to rigorously evaluate the reliability and validity of the Enode Sensor and My Jump 3 against those of the Force Plate. Combining descriptive statistics, reliability analysis, Bland–Altman analysis, correlation analysis, and linear regression allowed for a robust understanding of the performances of these tools. These methods provided a detailed evaluation of CMJ performance data, summarizing trends (descriptive statistics), assessing consistency (reliability analysis), evaluating agreement (Bland–Altman analysis), examining relationships (correlation analysis), and predicting outcomes (linear regression). Statistical analyses were conducted using Jamovi (version 2.3.28) [51–54] and SPSS (version 29.0.2.0) [55].

3. Results

The descriptive statistics for vertical jump heights measured using the Enode Sensor, My Jump 3, and Force Plate are presented in Table 1. The Enode Sensor recorded the highest mean vertical jump height (48.4 cm), followed by My Jump 3 (47.3 cm), with the Force Plate recording the lowest mean vertical jump height (46.1 cm).

Table 1. Descriptive statistics (cm).

Device	M ± SD	SEM	Min	Max
EN	48.4 ± 4.18	0.77	39.0	54.3
MJ	47.4 ± 4.05	0.75	38.2	53.0
FP	46.1 ± 4.03	0.74	37.8	52.4

Notes: EN—Enode Sensor; MJ—My Jump 3; FP—Force Plate; M ± SD—Mean ± Standard Deviation; SEM—Standard Error of the Mean; Min—Minimum; Max—Maximum. All the values are presented in centimeters (cm).

The results, presented in Tables 2 and 3, provide ICC values for both Single Measures and Average Measures, along with their respective 95% Confidence Intervals (CIs) and Significance Levels. Both the Enode Sensor and My Jump 3 demonstrated excellent reliability when compared to the Force Plate, with ICC values of 0.914 and 0.968, respectively, both of which were statistically significant ($p < 0.001$).

Table 2. Reliability analysis of Enode Sensor compared to Force Plate measurements.

Intraclass Correlation Type	ICC Value	95% CI	F Test	df1	df2	Sig.
Single Measures	0.842	−0.042 to 0.963	69.351	28	28	0.00 *
Average Measures	0.914	−0.087 to 0.981	69.351	28	28	0.001 *

Notes: ICC—Intraclass Correlation Coefficient; CI—Confidence Interval; F—F-statistic for the reliability test; df—degrees of freedom, Sig.—Significance Level. * $p < 0.05$.

Table 3. Reliability analysis of My Jump 3 compared to Force Plate measurements.

Intraclass Correlation Type	ICC Value	95% CI	F Test	df1	df2	Sig.
Single Measures	0.938	0.065 to 0.986	144.923	28	28	0.001 *
Average Measures	0.968	0.122 to 0.993	144.923	28	28	0.001 *

Notes: ICC—Intraclass Correlation Coefficient; CI—Confidence Interval; F—F-statistic for the reliability test; df—degrees of freedom; Sig.—Significance Level. * $p < 0.05$.

The Bland–Altman analysis was conducted to evaluate the agreement between the Enode Sensor and My Jump 3 against the Force Plate in measuring vertical jump heights. The mean bias and limits of agreement for each comparison are presented in Tables 4 and 5, with the corresponding scatterplots in Figures 1 and 2. The results indicated that both the Enode Sensor and My Jump 3 tend to overestimate vertical jump heights compared to the Force Plate.

Table 4. Bland–Altman analysis of Enode Sensor compared to Force Plate measurements.

Bland–Altman	95% Confidence Interval		
	Estimate	Lower	Upper
Bias (n = 29)	2.281	1.908	2.65
Lower limit of agreement	0.362	−0.281	1.01
Upper limit of agreement	4.199	3.555	4.84

Table 5. Bland–Altman analysis: My Jump 3 vs. Force Plate.

Bland–Altman	95% Confidence Interval		
	Estimate	Lower	Upper
Bias (n = 29)	1.2968	1.042	1.551
Lower limit of agreement	−0.0141	−0.454	0.426
Upper limit of agreement	2.6077	2.168	3.048

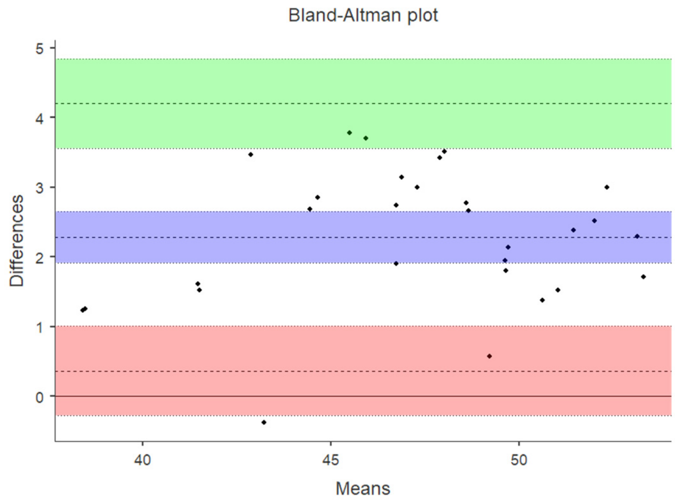

Figure 1. Bland–Altman scatterplot: Enode Sensor vs. Force Plate. Notes: Green Area (Upper Limit of Agreement): Indicates the upper bound of the agreement interval. Purple Area (Mean Difference): Represents the average difference between the two methods, showing any systematic bias. Red Area (Lower Limit of Agreement): Indicates the lower bound of the agreement interval. Points within these limits demonstrate consistency between the methods, while outliers highlight discrepancies.

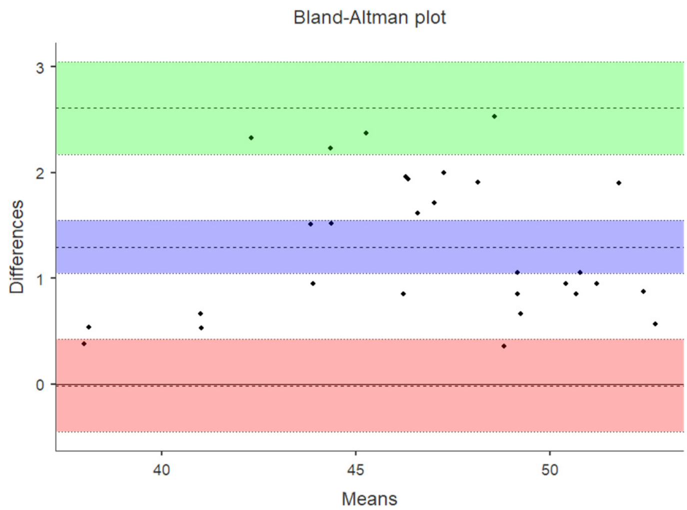

Figure 2. Bland–Altman scatterplot: My Jump 3 vs. Force Plate. Notes: Green Area (Upper Limit of Agreement): Indicates the upper bound of the agreement interval. Purple Area (Mean Difference): Represents the average difference between the two methods, showing any systematic bias. Red Area (Lower Limit of Agreement): Indicates the lower bound of the agreement interval. Points within these limits demonstrate consistency between the methods, while outliers highlight discrepancies.

Specifically, in comparing the Enode Sensor to the Force Plate, the mean bias was 2.281 cm, indicating that the Enode Sensor generally overestimated vertical jump heights by 2.281 cm relative to the Force Plate. The limits of agreement ranged from −0.281 cm to 4.84 cm, suggesting some variability in individual measurements.

For My Jump 3 versus the Force Plate, the mean bias was 1.297 cm, with My Jump 3 overestimating jump heights by 1.297 cm on average. The limits of agreement, ranging from −0.014 cm to 3.048 cm, suggest that My Jump 3 is closer to the Force Plate's measurements, indicating better agreement with the Force Plate compared to the Enode Sensor.

The correlation analysis (Table 6) between the Enode Sensor and the Force Plate revealed an extremely strong positive relationship (Figure 3), with a Pearson correlation coefficient of 0.972 and a Spearman correlation coefficient of 0.977. Similarly, the My Jump 3 App demonstrated a very strong positive relationship with the Force Plate (Figure 4), showing a Pearson correlation coefficient of 0.987 and a Spearman correlation coefficient of 0.988. These results underscore the high levels of agreement between both the Enode Sensor and My Jump 3 App with the Force Plate, supporting their use as reliable alternatives for measuring vertical jump heights.

Table 6. Correlation analysis: Enode Sensor, My Jump 3, and Force Plate.

Correlation Analysis	EN vs. FP	MJ vs. FP
Pearson's r	0.972	0.986
Spearman's rho	0.977	0.988

Notes: EN—Enode Sensor; MJ—My Jump 3; FP—Force Plate.

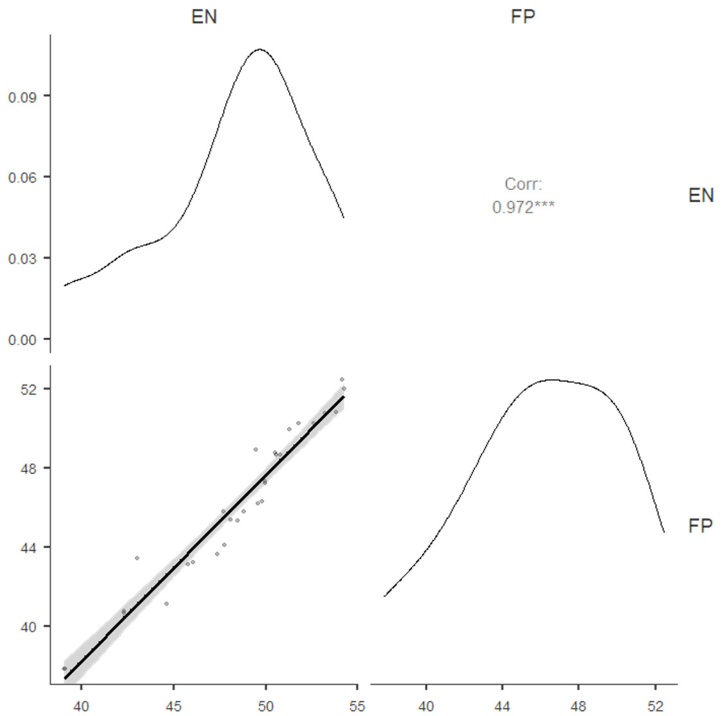

Figure 3. Correlation and density distribution of vertical jump measurements: Enode Sensor vs. Force Plate. Notes: Corr—Pearson correlation coefficient; EN—Enode Sensor; FP—Force Plate; *** denotes significant correlation at the level of $p < 0.001$.

The linear regression analysis between the Enode Sensor (EN) and the Force Plate (FP) demonstrates a strong predictive relationship, suggesting that the Enode Sensor closely approximates measurements from the Force Plate. The model fit results reveal a high degree of correlation, with an R value = 0.972 and an R^2 = 0.945, indicating that approximately 94.5% of the variance in Enode Sensor measurements can be explained by Force Plate values. The overall model is statistically significant, as indicated by the F-statistic ($F(1, 27) = 466$, $p < 0.001$), affirming the strength and reliability of the predictive model (Table 7).

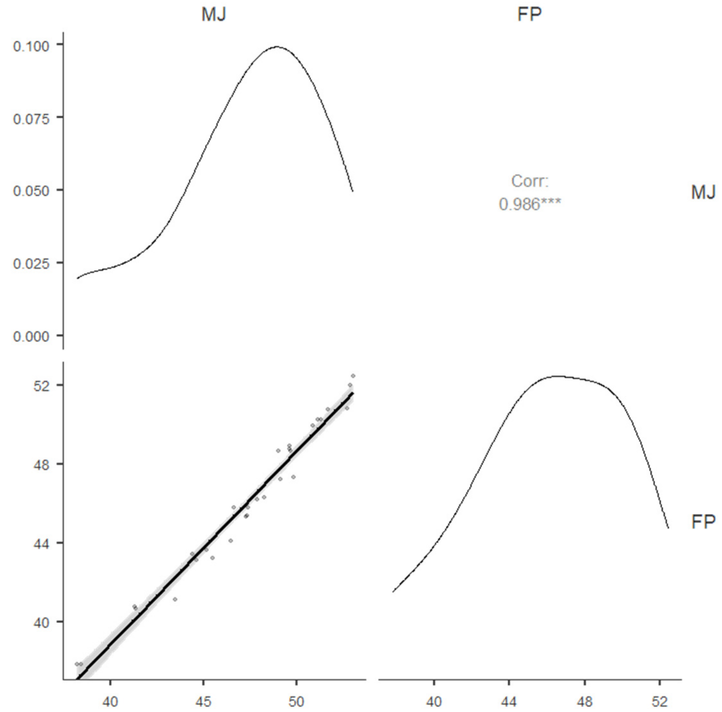

Figure 4. Correlation and density distribution of vertical jump measurements: My Jump vs. Force Plate. Notes: Corr—Pearson correlation coefficient; MJ—My Jump 3; FP—Force Plate; *** denotes significant correlation at the level of $p < 0.001$.

Table 7. Regression analysis of Enode Sensor and My Jump 3 App against Force Plate measurements.

Device	R	R^2	F Statistic	Sig.	Model Coefficients		
					Intercept (Estimate ± SE)	Slope for Predictor (Estimate ± SE)	95% Confidence Interval for Slope
Enode vs. Force Plate	0.972	0.945	466	0.001 *	1.85 ± 2.161	1.01 ± 0.047	from0.913 to 1.11
My Jump 3 vs. Force Plate	0.986	0.973	966	0.001 *	1.64 ± 1.476	0.992 ± 0.031	from 0.927 to 1.06

Notes: R—Pearson correlation coefficient; R^2—Coefficient of determination; F—F-statistic for model significance; Sig.—Significance level; *denotes significant correlation at the level of $p < 0.001$; Intercept (Estimate ± SE)—Baseline measurement with standard error; Slope for Predictor (Estimate ± SE)—Rate of change in device measurement per unit of change in Force Plate; 95% Confidence Interval for Slope—Precision range for slope estimates.

An examination of the model coefficients further supports this strong relationship. The intercept is 1.85 (SE = 2.161, $p = 0.398$), indicating that the baseline difference between the two methods is minor. The slope for the Force Plate predictor is 1.01 (SE = 0.047, $p < 0.001$), which is close to 1, suggesting a nearly one-to-one relationship between Force Plate and Enode Sensor measurements. The 95% confidence interval for the slope (from 0.913 to 1.11) further reinforces this strong agreement, highlighting the Enode Sensor's reliability in measuring vertical jump heights in comparison to the gold-standard Force Plate. These findings underscore the Enode Sensor's potential as an accurate and cost-effective alternative for vertical jump assessment, providing robust data closely aligned with traditional laboratory-based Force Plate measurements.

The linear regression analysis between the My Jump 3 App and the Force Plate also demonstrates a remarkably strong predictive relationship, indicating that My Jump 3 provides measurements closely aligned with those from the Force Plate. The model fit statistics show an exceptionally high degree of correlation, with an R value of 0.986 and an R^2 value of 0.973, meaning that 97.3% of the variance in My Jump 3 measurements can be explained by Force Plate values. The overall model is statistically significant, with an F-statistic of 966 ($F(1, 27) = 966$, $p < 0.001$), confirming the robustness and reliability of this predictive model.

4. Discussion

The current study reinforces the validity and reliability of both the Enode Sensor and My Jump 3 App as tools for measuring vertical jump heights, establishing them as accessible alternatives to traditional Force Plates. Both the Enode Sensor (mean bias: 2.3 cm; ICC: 0.914; R^2: 0.945; Pearson's r: 0.972; Spearman's rho: 0.977) and My Jump 3 (mean bias: 1.3 cm; ICC: 0.968; R^2: 0.973; Pearson's r: 0.987; Spearman's rho: 0.988) demonstrated strong accuracy relative to that of the Force Plate, with My Jump 3 exhibiting closer agreement, as indicated by its lower bias and higher proportion of explained variance. Consistent with previous research that highlights the utility of CMJ assessments for evaluating lower-body power and neuromuscular function in athletes [1,56], measurements with both devices demonstrated high degrees of correlation with Force Plate measurements, indicating these devices' potentials for accurate performance tracking in sports settings.

The reliability analysis revealed that both devices had excellent Intraclass Correlation Coefficients (ICCs), with values of 0.914 for the Enode Sensor and 0.968 for My Jump 3, both statistically significant. High ICC values affirm the stability of these devices for repeated measurements over time, making them feasible for longitudinal monitoring in training contexts [32,33]. This finding is particularly significant in sports, where practitioners require reliable tools to track performance changes and adjust training loads based on accurate feedback [4].

Moreover, the strong positive relationships observed between each device and the Force Plate, as indicated by Pearson and Spearman correlation coefficients (r = 0.972–0.988), align with previous studies on the My Jump App's validity for jump height assessment [17–20,34,44]. This high degree of correlation validates the suitability of both the Enode Sensor and My Jump 3 App for assessing jump performance in both controlled and field environments, especially given their cost effectiveness and portability compared to those of conventional Force Plates [14,19].

The Bland–Altman analysis further revealed that both devices slightly overestimated jump heights compared to those measured using the Force Plate, with mean biases of 2.281 cm and 1.297 cm for the Enode Sensor and My Jump 3, respectively. The My Jump 3 App showed closer agreement with the Force Plate, as evidenced by narrower limits of agreement (My Jump 3: from −0.014 to 3.048 cm; Enode Sensor: from −0.281 to 4.84 cm), indicating that My Jump 3 may offer greater precision. This finding aligns with studies that have reported near-perfect agreement between My Jump and Force Plate measurements [17,57]. The higher precision of My Jump 3 could be advantageous for practitioners who require detailed performance analysis, such as in competitive environments or for elite athlete monitoring [14,58].

The regression analysis results further substantiate the reliability of these devices. R^2 values of 0.945 for the Enode Sensor and 0.973 for My Jump 3 indicate that a large proportion of the variance in Force Plate measurements can be explained by these alternative tools. These findings echo prior studies that have validated wearable devices and mobile applications for CMJ assessment, as they provide an accessible means to collect reliable jump data without the logistical constraints of laboratory settings [15,19,29]. The high R^2 values in the regression analyses suggest that both the Enode Sensor and My Jump 3 App can accurately predict jump heights, supporting their potential application across different athletic levels and training contexts.

These results underscore the My Jump 3 App's accuracy as a measurement tool for vertical jump heights, suggesting it performs comparably to the Force Plate, which is widely regarded as the gold standard. The high R^2 value and significance level indicate that My Jump 3 could serve as a practical and accessible alternative for performance monitoring in athletic settings, providing reliable data that align closely with laboratory-based Force Plate measurements. An R^2 value near 1, observed for both the Enode Sensor and My Jump 3 App, demonstrated that a substantial proportion of the variance in Force Plate measurements can be accounted for by these tools, highlighting their strength as predictors of jump heights. These results suggest that both the Enode Sensor and My Jump 3 App offer reliable estimates of jump heights, with minimal accuracy loss relative to Force Plate measurements, making them suitable for both training and competitive settings.

Despite these promising results, it is crucial to acknowledge limitations. The controlled conditions under which measurements were taken may limit the generalizability of these findings. Previous research suggests that environmental variability, such as surface conditions and lighting, can impact measurement accuracy in real-world settings [59,60]. Thus, future studies should validate these devices in field-based scenarios with a more diverse sample to enhance the robustness of the results. Additionally, although three jumps were performed per participant, only the best jump was selected for analysis, which prevented the further calculation of absolute reliability measures (standard error of measurement—SEM—and minimal detectable change—MDC). Incorporating multiple testing sessions or additional trials in future research would enable these indices to be determined, providing a more comprehensive interpretation of the data. Furthermore, despite the app being operated by an experienced observer with expertise as a strength and conditioning (S&C) coach—ensuring adherence to the app's guidelines and utilizing the highest available recording frequency—errors may still have occurred because of inaccuracies in marking the jump/landing moments or frame omissions in the recording frequency. Nevertheless, the app's flexibility, cost effectiveness, and practical applications in training environments make it a valuable tool, with future studies potentially enhancing its accuracy through automated frame detection or higher-frequency cameras.

Lastly, the Enode Sensor and My Jump 3 App demonstrated excellent reliability and validity in measuring vertical jump heights when compared to the Force Plate measurements, offering practical, cost-effective solutions for sports performance monitoring. These tools have the potential to democratize access to performance data, allowing for continuous, real-time athlete monitoring that can support individualized training adjustments and load management without requiring expensive laboratory equipment. The implications of this study suggest that as technology advances, wearable sensors and mobile applications will continue to play integral roles in sports science, offering versatile tools for assessing and optimizing athletic performance in dynamic, real-world environments. Future studies should extend beyond the current controlled laboratory setting by evaluating these tools across diverse athletic populations and under more dynamic, field-based conditions to enhance their generalizability and practical relevance.

5. Conclusions

This study confirmed the Enode Sensor and My Jump 3 App as reliable, valid alternatives to traditional Force Plates for assessing vertical jump height when tested on this study's participants, with both devices demonstrating high agreement and significant Intraclass Correlation Coefficient (ICC) values in comparison to those for Force Plate measurements. Although minor overestimations were noted for both tools, as shown by Bland–Altman analyses, these deviations were within acceptable limits, reinforcing the suitability of both tools for practical use in diverse training contexts. The portability and real-time monitoring capabilities of these devices make them particularly advantageous for training sessions, offering a flexible and accurate option across various athletic settings. These findings underscore the potential for accessible, portable technologies to facilitate regular performance monitoring outside laboratory environments, empowering coaches and athletes to make data-informed adjustments to training intensity and strategy.

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