Örücü et al. BMC Sports Science, Medicine and Rehabilitation (2025) 17:75
https://doi.org/10.1186/s13102-025-01129-y

BMC Sports Science, Medicine and Rehabilitation

RESEARCH

Open Access

Kinect-based anthropometric measurements: a comparative analysis of traditional methods in youth female weightlifters

Serkan Örücü[1], Bülent Işık[2*], Kenan Erdağı[3], Usame Ömer Osmanoğlu[4] and Erkan Özbay[5]

Abstract

Background The importance of anthropometric measurements for monitoring the physical development of athletes and optimizing training programs is well known. Considering the limitations of traditional methods in terms of accuracy and consistency, the aim of this study is to investigate the potential of Kinect V2 as an alternative.

Methods This study wasperformed on 12 youth female weightlifters who won medals in the Youth European Weightlifting Championship. Humerus length, forearm length, hand length, trochanter-tibiale laterale length, tibial length and shoulder width measurements were performed with both Kinect V2 and manual methods. Statistical differences between groups were evaluated using the Mann–Whitney U test. The consistencies of the measurement methods were analyzed with Bland-Altman plots, correlations were determined with Pearson correlation coefficients, and reliability were evaluated with Intraclass Correlation Coefficient (ICC) values.

Results Kinect V2 provided accuracy and consistency comparable to manual methods in measurements of humerus (ICC = 0.532), forearm (ICC = 0.600), and hand length (ICC = 0.760). While medium-level concordance was observed in trochanter-tibiale lateral length measurements (ICC = 0.749), high-level concordance and reliability were found in tibial length (ICC = 0.914) and shoulder width (ICC = 0.869) measurements.

Conclusions There were significant differences between the results of humerus length, forearm length and trochanter-tibiale laterale length obtained with both measurement methods. Therefore, measurements of these parameters require significant care. Findings of this study suggest that Kinect V2 can be a reliable tool for rapid and practical anthropometric assessments in sports settings, but highlight the importance of careful calibration and adjustments for specific measurements. Future studies should examine the use of this device more comprehensively across different sports and populations.

Highlights

- Anthropometric measurements are important for monitoring the physical development of athletes and optimizing their training programs. Considering the limitations of traditional methods in terms of accuracy and consistency. Kinect analyzes the movements of athletes during sports education and training processes, making it possible to organize training programs according to individual needs.

*Correspondence:
Bülent Işık
bulentisik@kmu.edu.tr

Full list of author information is available at the end of the article

- Kinect V2, which has a high potential for use, especially in medical exercise and clinical applications, also finds a wide range of applications in sports sciences.
- In this study, a comparative analysis of certain lower and upper extremity anthropometric measurements such as humerus length, forearm length, hand length, trochanter-tibiale laterale length, tibial length and shoulder width of female weightlifting athletes in the youth age category were performed using Kinect V2 and manual methods.

Keywords Microsoft kinect, 3D imaging technology, Anthropometry, Olympic style weightlifting, Youth age category

Introduction

Anthropometry is a discipline that studies the dimensions, proportions and physical characteristics of the human body [1]. This discipline evaluates the body composition of individuals, helping to monitor their medical conditions and optimize their sports performance [2]. Anthropometric measurements are an important tool in sports sciences, especially for organizing the training programs of young and developing athletes according to their individual needs. The effects of physical structure on sports performance are more pronounced in power sports such as weightlifting; accurate and reliable anthropometric measurements play a critical role in determining athletes' training and competition strategies [3]. Traditionally, anthropometric measurements were performed by manual methods. These measurements performed using tools such as calipers, measuring tapes and goniometers, have long been preferred due to their accuracy and minimal equipment requirements [4]. However, manual measurements depend on the operator's experience and measurement accuracy, which can negatively impact repeatability and accuracy [5]. Additionally, manual measurement processes are time-consuming and impractical for large-scale data collection efforts [4]. Such limitations have increased the need for the development of more rapid and effective methods in sports sciences.

Technological advances have offered new possibilities for anthropometric measurements, and computer vision systems, especially devices with 3D, depth sensing and motion capture technologies, have become remarkable [6].

These devices stand out with their ability to perform both static and dynamic analyses by monitoring users' movements and body positions in real time [7, 8]. These developments have made data collection and analysis processes more efficient in the fields of sports sciences and medical exercise application. Kinect technology, one of the existing digital anthropometric assessment methods, has been increasingly used in sports sciences and clinical applications. Kinect V2, in particular, stands out as a device that can perform users' body measurements with high accuracy. This device allows for the rapid collection of large data sets, while also facilitating use thanks to the ability to collect data independently of the operator [9]. Kinect V2, which has a high potential for use, especially in medical exercise and clinical applications, also finds a wide range of applications in sports sciences. However, Kinect's accuracy and reliability may change depending on the position measured, the used algorithms, and the calibration of the device [9, 10]. Therefore, comparing data obtained with Kinect with manual measurements is important to evaluate the accuracy of the device and its potential for application in sports science. A study by Naufal et al. (2022) showed that Kinect V2 could produce results with similar accuracy compared to manual methods for different anthropometric measurements [11]. These findings suggest that Kinect stood out not only for its rapid data collection capacity, but also for its ability to deliver repeatable results. Another study by Adikari et al. (2017) focused on the accurate measurement of body dimensions by Kinect and the usability of this data in virtual dressing rooms [12]. The potential of data obtained using Kinect to minimize operator errors and provide reproducibility is seen as a great advantage in large-scale research and clinical applications [11, 12]. These advantages provided by Kinect indicate its potential for widespread use in areas such as medical exercise, sports training and clinical physiological applications [6, 13]. This technology allows athletes to improve their technique and optimize their performance by monitoring their movements in real time. In sports training, it provides a scientific approach to training processes by precisely analyzing the movements of athletes and provides valuable feedback for individual performance improvements [6]. Especially in the field of exercise therapy for medical purposes, it is possible for patients to exercise on their own at home and to monitor the accuracy and effectiveness of these exercises remotely by using Kinect [9]. This both supports the treatment processes and increases the independence of the patients. Kinect analyzes the movements of athletes during sports education and training processes, make it possible to organize training programs according to individual needs [6].

In this context, comparing anthropometric measurements performed with Kinect V2 with anthropometric measurements performed with manual methods is of critical importance in terms of evaluating the accuracy and applicability of the device in both sports sciences and clinical applications. In terms of accurate, fast and precise measurement, using Kinect V2 instead of the manual measurement method in anthropometric measurements of participants with different characteristics such as patients, elite athletes and healthy individuals may result in different. Available literature shows that comparisons between Kinect V2 and manual measurement methods are limited; this study aimed to fill this gap and better understand the potential of the device in anthropometric measurements through a study conducted with weightlifting athletes. This study specifically focused on youth female weightlifters, as this group represents a restricted accessible sample of athletes who regularly train and achieve international success, such as participation in the Youth European Weightlifting Championship. This selection enables the evaluation of Kinect V2's potential in a highly disciplined and consistent athletic population, while providing focused insights into its applicability in sports science. With the current study, we chose to use a method that could partially avoid varying measurement results among manual measurement practitioners in regular anthropometric evaluations of high-level athletes, such as elite female weightlifters. Furthermore, we wanted to emphasize speed in terms of time in anthropometric assessments of elite athletes as an alternative to manual measurement methods. Therefore, this study aims to conduct a comparative analysis of certain lower and upper extremity anthropometric measurements such as humerus length, forearm length, hand length, trochanter-tibiale laterale length, tibial length and shoulder width of female weightlifting athletes in the youth age category using Kinect V2 and manual methods. The hypothesis is that anthropometric measurements performed with the Kinect V2 would produce similarly accurate and repeatable results compared to manual measurement methods. It is anticipated that Kinect V2's advantages, such as rapid data collection and operator independence, would provide data that were compatible with results obtained with manual methods, especially for measurements such as shoulder width, humerus length, forearm length, hand length, trochanter-tibiale laterale length and tibial length.

Methods

Participants and data collection

This study included anthropometric measurements of 12 youth female weightlifters who won medals at the Youth European Weightlifting Championship held in Thessaloniki, Greece between 15 and 23 June 2024. The participants, whose body weight ranges were between 45 and 81 kg (Q1-Q3), were Turkish Youth Women's National Weightlifting Team athletes. The athletes participating in the study were selected from athletes who prepared for international competitions by training twice a day, six days a week, had no health problems, and were free of orthopedic injuries that would prevent weightlifting training in the last 6 months. Demographic data, physical measurements and weightlifting performances of the participants with an average age of 16–17 years (Q1-Q3) were shown in Table 1. Athletes with a history of serious trauma to their lower and upper extremities or any structural or systemic diseases that cause joint and movement limitation were excluded from the study. Inclusion and exclusion criteria were determined through detailed examination and questioning by a medical doctor experienced in sports. Before participating in the study, all athletes informed about the purpose and procedures of the study and their informed consent was obtained.

Our research was performed in accordance with the principles of the 2013 Helsinki Declaration, and approval was obtained from the Faculty of Medicine Local Scientific Research Ethics Committee (Date: 04.07.2024, approval number: 08-2024/10).

In the study, participants informed about the study and a signed informed consent form was obtained from the participants. Additionally, the necessary written and signed informed consents for the participants whose personal or clinical details along with any identifying images were included to be taken and published were obtained from them and their parent/legal guardian.

Anthropometric measurements were performed according to the techniques described by Norton et al. (1996) [14]. In order to increase the accuracy of the measurements, each participant's body measurements were measured three times using both traditional manual

Table 1 Demographic, anthropometric, and weightlifting performance metrics of youth female weightlifters

Youth female weightlifting athletes *n* = 12	Parameters	Mean	Standard Deviation	Median	Q1-Q3
	Age (year)	16.50	0.53	16.50	16.00–17.00
	Height (cm)	159.10	8.27	161.00	154.75–165.00
	Body weight (kg)	63.90	17.05	65.00	45.00–81.00
	BMI (kg/m^2)	24.90	4.94	24.30	20.05–30.08
	Training age (year)	4.10	1.10	4.00	3.75-5.00
	Max snatch (kg)	77.60	9.12	78.50	71.25-85.00
	Max clean and jerk (kg)	94.70	11.91	97.50	85.50-103.75

BMI: Body mass index (kg/m^2), Max snatch: maximum snatch weightlifting performance (kg), Max clean and jerk: maximum clean and jerk weightlifting performance (kg), Q: quartile methods and the Microsoft Kinect V2 device, and the average values were used for analysis [14]. Athletes wore appropriate clothing during the measurement and were required to stand in a certain position and not move during the measurement process. For manual measurements, the areas to be measured were marked in advance and participants were asked to maintain a stable standing position.

Sample size calculation

The sample size computation was based on the study by Krzeszowski et al. [15]. The automatic direct method available in G*Power software 3.1.9.7 version was used, with a medium effect size of 1.06, the significance level of α = 0.05, power = 0.80. The sample size obtained was calculated to be at least 10 weightlifters. In addition, 20% of participants were added to compensate for the possible problem. Thus, the sample size to be studied was determined as 12 weightlifters.

Kinect V2 features and system design

The designed system consists of three parts. In the first part, the data collected from the athletes using Kinect V2 is transferred to the computer. The Kinect V2 sensor used in the system contains a 1920 × 1080 pixel RGB (red-green-blue) camera, a 512 × 424 pixel infrared CMOS depth sensor, and a microphone array. The depth sensor uses a technology called TOF (Time of Flight) to measure depth by reflecting back the IR (infrared) rays (860 nm) it sends onto a surface [16, 17]. As a result, the depth sensor creates a 3D depth map by determining the distances to the surfaces where the IR rays are reflected [18–20]. This depth map provides the depth and density values for each pixel to be used. In addition, Kinect V2 provides the 3D coordinates of any anthropometric point (Joint_X, Joint_Y and Joint_Z) tracked through its own skeleton tracking algorithm. The pixel positions in the resulting depth map are converted to real-world coordinates using camera calibration parameters [21]. These transformations are performed by considering the coordinates of the optical center of the camera and its focal lengths. Subsequent to this process, the skeleton was extracted and the 3D joint positions were accessed. Then, the 3D positions of the joints to be processed in the system were selected from these joints.

Noise has been observed in depth data from Kinect V2 due to various factors such as sensor limitations and environmental conditions [20, 22]. Reducing these noises is necessary to increase the accuracy and reliability of the data [23, 24].

This data was first passed through an Exponential Moving Average (EMA) filter in order to reduce the noise they contained. EMA Filter is an infinite impulse response filter that uses exponentially decreasing weighting [25]. With this feature, the weighting used for each old data decreases exponentially and never reaches zero [26]. Thus, EMA filter provides smoothing on old data while at the same time working sensitively to recent changes. In our system, while applying EMA filter to 3D joint coordinates, each joint point is considered independently as done in [27]. Then, the filtering process was applied separately to X, Y and Z components of joint coordinates as expressed in Eq. 1 as shown in Fig. 2.b.

$$
\begin{aligned}
S_{x,t} &= \alpha.\mathrm{X}_t + (1-\alpha).S_{x,t-1} \\
S_{y,t} &= \alpha.\mathrm{Y}_t + (1-\alpha).S_{y,t-1} \\
S_{z,t} &= \alpha.\mathrm{Z}_t + (1-\alpha).S_{z,t-1}
\end{aligned}
\tag{1}
$$

In 1, $S_{x,\,t}$, $S_{y,\,t,}$ ve $S_{z,\,t,}$" respectively, represent the corrected values for the X, Y, and Z coordinates at time t, α is the smoothing factor, "X_t, Y_t, *and* Z_t," are the measured values of the joint coordinates at time t, and "$S_{x,\,t-1}$, $S_{y,-1,}$ and $S_{z,\,t-1}$," are the corrected values at the previous time step t-1.

The most important feature to consider in the EMA filter is the smoothing factor indicated by α. This factor is a parameter that controls the weighting of new and old measurements. The value of this parameter usually takes a value between 0 and 1. If α is selected close to one, the EMA filter gives more weight to the latest measurements, making it more sensitive to changes in the data, and if it is selected close to zero, it gives more weight to old data, making it less sensitive to recent changes [25, 26, 28, 29]. In our study, the α factor was selected as 0.6, as in the study performed by Del Bimbo et al. [30].

After reducing the noise of 3D joint coordinates in R^3 using the EMA filter, vectors were created for the joints tracked in the study. In this process, the nonzero A vector formed between the wrist and elbow and the nonzero B vector formed between the elbow and shoulder are defined in the R^3 as $A = a_1i + a_2j + a_3k$ and $B = b_1i + b_2j + b_3k$. These vectors were presented in Eqs. 2 and 3, with $\| \vec{\mathrm{A}} \|$ denoting the length of vector A and $\| \vec{\mathrm{B}} \|$ denoting the length of vector B.

$$
\| \vec{\mathrm{A}} \| = \sqrt{\begin{array}{l}(Shoulder_{Left}.x - Elbow_{Left}.x)^2 \\ +(Shoulder_{Left}.y - Elbow_{Left}.y)^2 \\ +(Shoulder_{Left}.z - Elbow_{Left}.z)^2\end{array}} \tag{2}
$$

$$
\| \vec{\mathrm{B}} \| = \sqrt{\begin{array}{l}(Elbow_{Left}.x - Wrist_{Left}.x)^2 \\ +(Elbow_{Left}.y - Wrist_{Left}.y)^2 \\ +(Elbow_{Left}.z - Wrist_{Left}.z)^2\end{array}} \tag{3}
$$

Following this process, with the data obtained for each joint coordinate using 2 and 3, the distance between the joints, "d", is calculated as shown in Eq. 4 [27].

$$d = \sqrt{\sum_{i=1}^{N} (A_i - B_i)^2} \tag{4}$$

In the third step of the system, the lengths measured above were recorded for subsequent statistical analyses.

Experimental study

This research was performed through a two-stage experimental study. In the first stage, the lower and upper extremity lengths and shoulder width of youth female weightlifters were measured manually by traditional methods using a Harpender digital caliper (Fig. 1). Anthropometric measurements were performed three times by an experienced medical doctor, standing and in a comfortable position, for both sides of the athletes, and the measurement results were recorded in centimeters The body weights of the athletes were measured

Fig. 1 Manual anthropometric measurement

using the Tanita bioimpedance device (Tanita-MC 580, Japan) in the morning on an empty stomach, barefoot and wearing light clothing [31]. Body mass index (BMI) was calculated using weight and height. Height measurements were performed barefoot by a Seca height meter (213 portable mechanic, Germany) [14]. The highest lift values achieved by athletes in the snatch and clean & jerk techniques in the Youth European Championship were obtained from the official website of the European Weightlifting Federation [32].

Humerus (acromiale-radiale) length measurement: Humerus length was measured as the distance between the acromiale and radial points using a caliper.

Forearm length measurement: Forearm length was measured from the radiale to the stylion using a caliper.

Hand length measurement: Hand length was measured as the distance from the midstylion to the dactylion with a caliper.

Trochanter-tibiale laterale length measurement: Trochanter-tibiale laterale length was measured as the distance from the trochanter to the tibiae laterale using a caliper.

Tibial length measurement: Tibial length was measured from the lateral point of the tibia to the most distal point of the lateral malleolus using a caliper.

Shoulder width measurement: Shoulder width was measured as the distance between the outermost points of the acromion processes using a caliper.

Iliospina-tibiale laterale length measurement: Iliospina-tibiale laterale length was measured as the distance from the iliospinale to the tibiale laterale using a caliper.

Crista iliaca-tibiale laterale length measurement: Crista iliaca-tibiale laterale length was measured as the distance from the upper border of the crista iliaca to the lateral point of the tibia using a caliper [33, 34].

In the second stage, the lower and upper extremity lengths (right and left) and shoulder width of the weightlifting athletes were measured under the supervision of an expert weightlifting coach using a Kinect V2-based system shown in Fig. 2, and the results were recorded in centimeters.

In this system, the Kinect V2 is positioned 1.5 m above the ground and the athletes are positioned 2.5 m away from the device (Fig. 2a). This arrangement was performed as suggested in the work of Naufal et al., (2022) [11]. The raw depth data collected by the Kinect V2 was transferred via a USB 3.1 port to a computer with an Intel (R) Core (TM) i7 processor, 16 GB of RAM and an 8 GB graphics card (Fig. 2b). The joints to be utilized were selected by extracting the skeletal structure from the data, and then an EMA filter was applied to the 3D joint coordinates of these selected joints to reduce the noise they contain. The filtered 3D joint coordinates were used to calculate the limb lengths of weightlifters. Thus, using perspective geometry and camera features, 3D coordinates of any point were obtained as shown in Fig. 3. Finally, these anthropometric data were both saved in the database and made available for viewing on the screen simultaneously (Fig. 2c).

Statistical analysis

Statistical analyses were performed using IBM SPSS Statistics 25.0 (Chicago, IL) software. Mean, standard deviation, median, first and third quartile values were calculated for all variables. Test-retest reliability was assessed using Intraclass Correlation Coefficient (ICC) values, and the precision and repeatability of measurements were evaluated using Coefficient of Variance (CV) and Coefficient of Repeatability (CR). Mann–Whitney U test was used to evaluate statistical differences between groups. The consistencies of the measurement methods

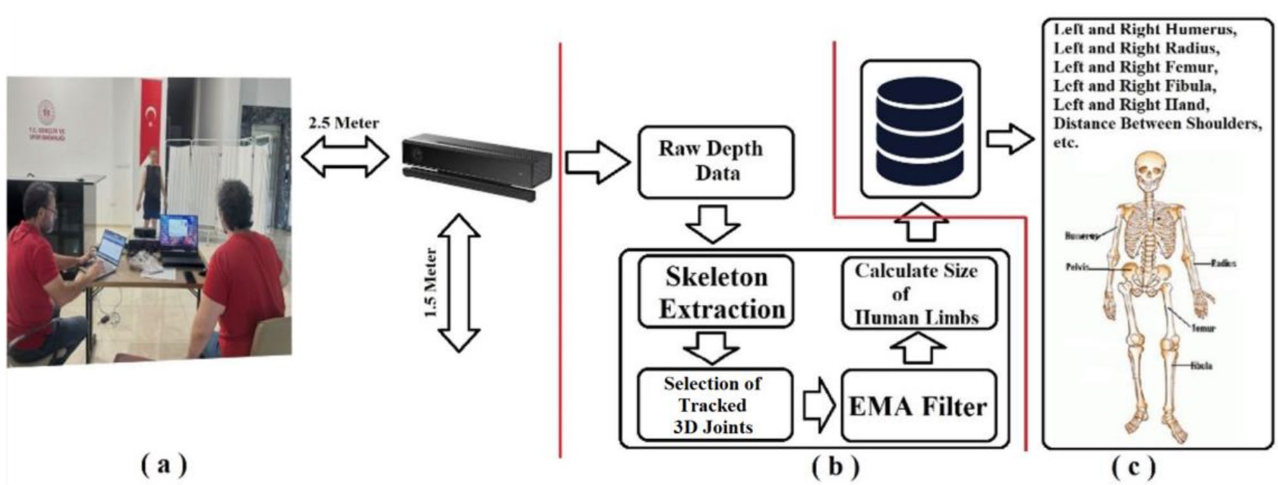

Fig. 2 Functioning principle of the system designed with Kinect V2

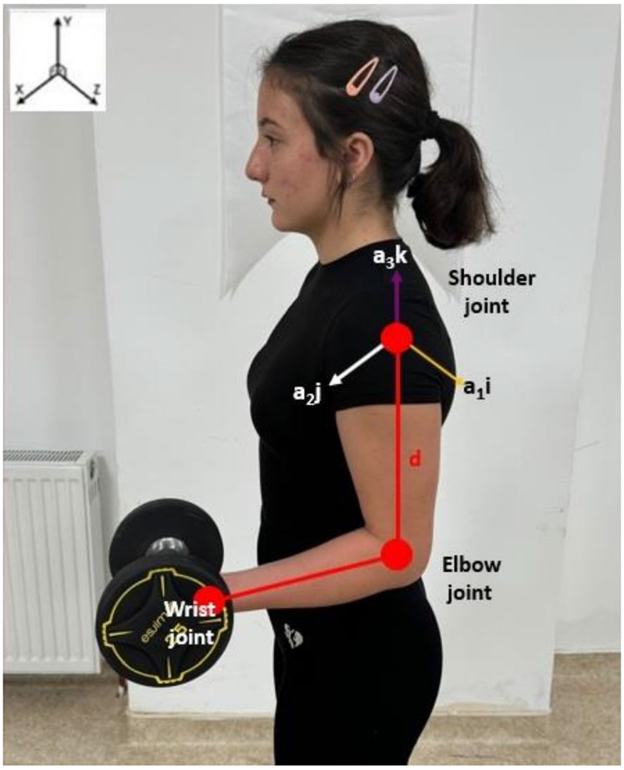

Fig. 3 Distance between joints

were analyzed with Bland-Altman plots using Python 3.7.9 (Delaware, USA). In order to determine the correlations between measurements, Pearson correlation coefficients were calculated, and repeatability and inter-rater reliability coefficients were evaluated. ICC values below 0.5 were considered as poor reliability, values between 0.5 and 0.75 as moderate reliability, values between 0.75 and 0.9 as good reliability, and values above 0.9 as excellent reliability [35]. The threshold for statistical significance was determined as $p < 0.05$.

Results

Values regarding demographic, anthropometric and weightlifting performances of youth female weightlifters are shown in Table 1.

A statistically significant difference found between Kinect and manual measurements in humerus length measurements ($p < 0.001$, Table 2). Kinect provided lower variation (CV: 6.36% vs. 7.40%) and higher consistency (CR: 4.57 vs. 5.77) compared to manual measurements. However, the ICC value (0.532) and the correlation coefficient ($r = 0.667$) showed moderate concordance between the two methods. Bland-Altman Analysis revealed that the mean measurement difference was + 2.26 cm and the 95% confidence interval was between − 0.70 and + 5.23 cm (Fig. 4; Table 3).

A statistically significant difference found between Kinect and manual measurements in forearm length measurements ($p < 0.001$, Table 2). Kinect provided lower variation and higher coherency compared to manual measurements (CV: 6.83% vs. 7.94%; CR: 4.21 vs. 5.32). However, the ICC value (0.600) and the correlation coefficient ($r = 0.704$) showed moderate concordance between the two methods. Bland-Altman Analysis revealed that the mean measurement difference was + 1.92 cm and the 95% confidence interval was between − 0.70 and + 4.55 cm (Fig. 4; Table 3).

There was no statistically significant difference between Kinect and manual measurements in hand length measurements ($p = 0.096$, Table 2). Measurements performed by both methods generally gave similar results. Kinect provided lower variation (CV: 7.22% vs. 9.13%) and higher coherency (CR: 2.97 vs. 3.94) than manual measurements. The CC value (0.760) and Pearson correlation coefficient ($r = 0.738$) indicated a good level of concordance and a strong relationship between the two methods. Bland-Altman Analysis revealed that the mean measurement difference was + 0.74 cm and the 95% confidence interval ranged from − 1.09 to + 2.58 cm (Fig. 4; Table 3).

A significant difference was found between Kinect and manual measurements in Trochanter-tibiale laterale length measurements ($p = 0.014$, Table 2). Kinect provided similar variation and consistency as manual measurements (CV: 6.69% vs. 6.47%; CR: 6.13 vs. 6.24). The CC value (0.749) and correlation coefficient ($r = 0.782$)

Table 2 Comparison of anthropometric measurements in youth female weightlifters: Microsoft kinect vs. manual methods

Length and width measurements	Manually Measured Value (cm)				Microsoft Kinect Measured Value (cm)				*p* Value
	Mean	SD	Median	Q1-Q3	Mean	SD	Median	Q1-Q3	
Humerus length (right/left)	28.10	2.08	28.00	27.30–29.00	25.95	1.65	26.00	24.80–27.20	**< 0.001**
Forearm length (right/left)	24.18	1.92	24.10	22.20–26.00	22.26	1.52	21.61	21.20–23.30	**< 0.001**
Hand length (right/left)	15.55	1.42	15.50	14.60–16.20	14.81	1.07	14.85	13.80–15.70	0.096
Trochanter-Tibiale laterale length (right/left)	34.80	2.25	35.20	32.00-36.90	33.02	2.21	33.00	31.01–35.50	**0.014**
Tibial length (right/left)	33.09	1.70	32.95	31.40–34.70	33.23	1.96	33.65	32.80–34.50	0.718
Shoulder width	31.27	2.46	31.05	29.58–33.13	31.38	2.06	31.50	29.35–33.60	0.853

SD: Standard deviation, Q: quartile

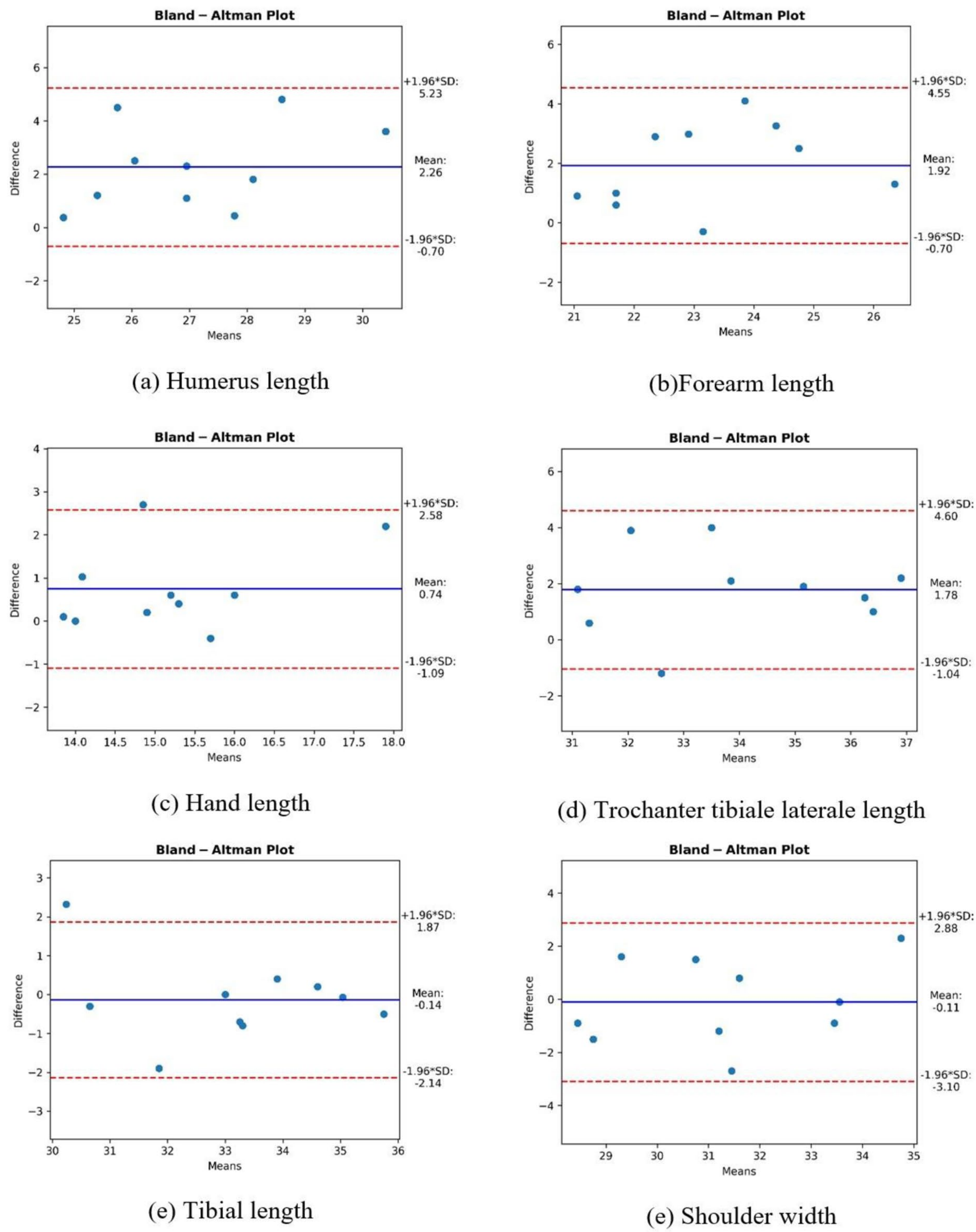

Fig. 4 Bland-altman plots illustrating the agreement between kinect V2 and manual measurements for anthropometric variables in youth female weightlifters

Table 3 Correlation and bland–altman analysis of anthropometric measurements in youth female weightlifters: a comparative study of manual and Microsoft kinect methods

Parameter	Manually Measured Value (cm)				Microsoft Kinect Measured Value (cm)				ICC	*r*	Bland–Altman plot	
	Mean	SD	CV	CR	Mean	SD	CV	CR			Bias	95% CI (%)
Humerus length (right/left)	28.10	2.08	7.40	5.77	25.95	1.65	6.36	4.57	0.532	0.667	+ 2.26	-0.70 to + 5.23
Forearm length (right/left)	24.18	1.92	7.94	5.32	22.26	1.52	6.83	4.21	0.600	0.704	+ 1.92	-0.70 to + 4.55
Hand length (right/left)	15.55	1.42	9.13	3.94	14.81	1.07	7.22	2.97	0.760	0.738	+ 0.74	-1.09 to + 2.58
Trochanter-Tibiale laterale length (right/left)	34.80	2.25	6.47	6.24	33.02	2.21	6.69	6.13	0.749	0.782	+ 1.78	-1.04 to + 4.60
Tibial length (right/left)	33.09	1.70	5,14	4,71	33.23	1.96	5.9	5.43	0.914	0.845	-0.14	-2.14 to + 1.87
Shoulder width	31.27	2.46	7,87	6,82	31.38	2.06	6.56	5.71	0.869	0.762	-0.11	-3.10 to + 2.88

SD: Standard Deviation; CV: Coefficient of Variance; CR: Coefficient of Repeatability; ICC: Intraclass Correlation Coefficient

indicated a moderate level of concordance and a strong relationship between the two methods. Bland-Altman Analysis showed that the mean measurement difference was + 1.78 cm and the 95% confidence interval ranged from − 1.04 to + 4.60 cm (Fig. 4; Table 3).

There was no statistically significant difference in Tibial length measurements between Kinect and manual measurements ($p = 0.718$, Table 2), indicating that both methods provide similar results. Kinect provided lower variation (CV: 5.9% vs. 5.14%) and higher coherency (CR: 5.43 vs. 4.71) compared to manual measurements. The ICC value (0.914) and correlation coefficient ($r = 0.845$) indicated high concordance and reliability between the two methods, confirming the test-retest reliability of Kinect V2 for tibial length measurements. Bland-Altman Analysis indicated that the mean measurement difference was − 0.14 cm and the 95% confidence interval ranged from − 2.14 to + 1.87 cm.

There was no statistically significant difference between Kinect and manual measurements in Shoulder Width measurements ($p = 0.853$, Table 2), indicating that both methods yield similar results. Kinect provided lower variation (CV: 6.56% vs. 7.87%) and higher coherency (CR: 5.71 vs. 6.82) compared to manual measurements. The high ICC value (0.869) and correlation coefficient ($r = 0.762$) indicated high concordance and reliability between the two methods. Bland-Altman Analysis showed that the average measurement difference was − 0.11 cm and the 95% confidence interval ranged from − 3.10 to + 2.88 cm (Table 3).

Discussion

In this prospective study, anthropometric measurements of youth female weightlifters were compared using Kinect V2 and manual measurement methods. The findings reveal that Kinect V2 provided lower variation and higher coherency than manual methods in some measurements. It has been observed that Kinect V2 exhibited superior performance in terms of both accuracy and repeatability, especially in humerus length, forearm length and hand length measurements. Although manual measurements were used as a reference in this study, they were not considered the absolute golden standard. Both methods have inherent limitations that could influence the interpretation of the results. For instance, manual measurements are susceptible to operator-dependent variability, while Kinect V2's performance can be affected by calibration and environmental factors. These factors should be carefully considered when comparing the methods, to ensure that significant differences were interpreted cautiously and in context. These results show that Kinect V2 had significant potential as a tool that meets the need for fast and practical data collection in the field. On the other hand, while both methods provided similar results in

Trochanter-tibiale laterale length and tibial length measurements, shoulder width measurements showed high concordance and reliability in both methods. This suggests that Kinect V2 could be an alternative to manual methods in certain measurements, but both methods could have their own advantages and limitations.

Overall, our findings support the potential use of Kinect V2 in sports science and clinical applications and suggest that this technology could be an effective tool in athlete performance assessments. This study specifically focuses on youth female weightlifters, a group selected due to their regular training schedules and high level of consistency, as well as their international competitive experience. Unlike previous studies that often included general populations, this research provides insights into the applicability of Kinect V2 in a highly disciplined athletic population, directly comparing its results with manual methods. However, the importance of future studies that examined in more depth the effectiveness and reliability of different methods in various application areas is also highlighted. Future research should explore the applicability of Kinect V2 in diverse athletic populations to clarify its broader potential and limitations. Nowadays, the developments of digital technologies and depth sensors have revolutionized anthropometric measurement methods. Depth sensors such as the Microsoft Kinect offer many advantages over manual measurement methods. In their studies, Krzeszowski et al., (2023) and Jamil et al., (2020) showed that Kinect offered high accuracy and repeatability [15, 36]. The results of these studies indicate that Kinect produces result with similar accuracy to manual methods in anthropometric measurements. Our study also supports these findings; it has been observed that Kinect V2 exhibited low variation and high coherency, especially in humerus length, forearm length and hand length measurements. This shows that Kinect V2 could be a suitable tool for large-scale field studies. Our findings show that there was a significant difference between the Kinect V2 and manual methods in trochanter-tibiale laterale length measurements, while there was no statistically significant difference between the two methods in tibial length measurements. According to our hypothesis, Kinect V2 is expected to provide results with similar accuracy to manual methods. These results are consistent with a study by Jamil et al., (2020) reporting that Kinect-based systems provide low error rates and acceptable accuracy in common lower extremity measurements such as leg length [36]. Additionally, Wang et al., (2024) stated that Kinect-based measurement systems offered high accuracy and repeatability in lower extremity measurements [29]. The findings obtained from our study show that Kinect V2 could be a suitable alternative to manual methods in tibial length measurements, however, it should be taken into consideration that there might be some differences in trochanter-tibiale laterale length measurements with manual methods. The fact that both methods showed high concordance and reliability in shoulder width measurements supports our hypothesis and indicates that Kinect V2 could be a good alternative to manual methods. It should be noted, however, that Kinect V2 might not be the best choice for every measurement. In light of these data, further research is needed to better understand the performance of Kinect V2 on different anthropometric measurements. In particular, studies examining the effectiveness of this technology in populations of different age groups and sports branches will determine better the usage areas and limits of Kinect V2.

In our study, significant findings were obtained between Kinect V2 and manual methods in humerus and forearm length measurements. Statistically significant differences were found between the measurement methods in terms of humerus and forearm length. On the other hand, the statistical significance of the consistency of the measurement methods and the correlation between them supported our hypothesis. In line with our hypothesis, Kinect V2 has been shown to exhibit lower variation and higher coherency compared to manual methods in both humeral and forearm length measurements. Particularly in humeral length measurements, Kinect V2 provided lower variation and higher coherency than manual measurements. Similarly, in forearm length measurements, Kinect V2 showed lower variation and higher coherency compared to manual methods (Table 3). These results suggest that Kinect V2 could be a reliable alternative for both humerus and forearm length measurements. Additionally, the advantages that Kinect V2 provided in terms of coherency and repeatability in its measurements may make the device more attractive to use, especially in situations where coherency and practicality were important. These findings are consistent with results reported by Jamil et al. (2020) regarding the high accuracy and coherency in forearm length measurements of RGB-D sensors [36]. In Jamil et al., (2020)'s study, low error rates and high accuracy were achieved in forearm measurements using RGB-D sensors [36]. This is in line with the low variation and high coherency rates offered by Kinect V2 in our study. Wang et al., (2024)'s study demonstrated that Azure Kinect provided high accuracy and consistency in limb length measurements on both children and adults [29]. Kinect showed strong correlation ($r = 0.850–0.985$) and excellent concordance ($ICC = 0.829–0.977$) compared to DXA. Overall, these findings demonstrate the potential of Azure Kinect as a measurement tool. However, in our study, the correlation and concordance values obtained between Kinect V2 and manual measurements ($r = 0.667$ and $ICC = 0.532$ for humerus length; $r = 0.704$ and $ICC = 0.600$ for forearm length) were at a moderate level and differ from Wang et al. (2024)'s finding [29]. These differences may be due to the fact that Azure Kinect has more advanced technology and can make more precise measurements. Azure Kinect's advanced sensor technology and high-resolution depth sensing capabilities increase measurement accuracy, which may explain differences in results. This shows that the differences in technological innovations and sensor sensitivities used between Kinect V2 and Azure Kinect might affect the measurement results. Therefore, it should be emphasized that Kinect V2 might require more careful evaluation for certain populations or measurement scenarios.

As a result, Kinect V2 can be used as a practical and reliable measurement tool, particularly in areas where coherency and repeatability were critical. However, one should be aware of the technological limitations and algorithm of the device that assumes fixed rates, and researchers should take these limitations into account when using the device. Research by Sinha et al. (2016) has also shown that Kinect provided comparable accuracy to manual methods in body segment length measurements and offers advantages in dynamic measurements such as joint angles [9]. This is another finding that supports our hypothesis and shows that Kinect V2 could be a suitable alternative for situations that require fast and practical data collection, especially in field studies and non-laboratory applications. Kinect V2 can be used as an alternative to manual methods by demonstrating low variation and high coherency in humerus and forearm length measurements. These characteristics of the device reveal its potential as a reliable measurement tool in sports science applications. Additionally, it is considered as a suitable alternative for field studies and non-laboratory applications that required rapid and practical data collection. However, more comprehensive research is needed to evaluate the accuracy and reliability of this technology in different age groups and sports. Future studies should further identify such uses.

It has been observed that Kinect V2 offers lower variation and higher coherency than manual methods in hand length measurements. These findings suggest that Kinect V2 might be a reliable alternative for hand length measurements (Table 3). These results are in concordance with those reported by Jamil et al. (2020) and Tarabini et al. (2018) [36, 37]. Jamil et al., (2020) reported that Kinect V2 offered low error rates (2.16%) and high correlation values (0.91) in hand length measurements [36]. It was stated in their study that the error rate between manual and sensor-based measurements was at an acceptable level and the correlation coefficient was 0.91. This high concordance supports our hypothesis and reveals that Kinect V2 is comparable to manual methods in terms of accuracy and reliability in hand length measurements. Similarly, Tarabini et al., (2018) stated that Kinect V2 offered high accuracy in specific anthropometric measurements such as hand length [37]. The study showed that measurements made with Kinect V2 were of similar accuracy to measurements obtained with optical systems. This finding is consistent with our hypothesis and highlights the portability and cost-effectiveness advantages of Kinect V2, especially for field studies and large-scale research. In this context, the low variation and high coherency provided by Kinect V2 in hand length measurements indicate that the device could be a suitable option for field studies and sports science applications. However, it should be taken into account that measurement accuracy might not always match manual methods and therefore the use of the device must be evaluated according to the specific application areas. For our hypothesis to be fully confirmed, the advantages provided by Kinect V2 must be optimally used in accordance with specific measurement types and needs. Future studies should focus on broader testing and evaluation of this technology in various populations and sports.

In our study, a statistically significant difference was detected between Kinect V2 and manual methods in Trochanter-tibial laterale length measurements ($p = 0.014$). Kinect V2 provided different results compared to manual measurements. This finding partially contradicts our hypothesis and suggests that Kinect V2 might differ in some lower extremity measurements when compared to manual methods. On the other hand, the fact that there was no statistically significant difference between Kinect V2 and manual methods in tibial length measurements ($p = 0.718$) shows that both methods offered results with similar accuracy and supported our hypothesis. Additionally, it has been stated in the literature that Kinect records lower values in knee height measurements compared to traditional methods [38]. This result shows that Kinect offered less precision in knee height measurements compared to traditional methods. Because, in our study, statistical differences were shown between the measurement methods regarding the Trochanter-Tibiale laterale values. However, there was moderate agreement and a strong relationship between the methods in terms of consistency and variation. This showed that Kinect performed similarly to manual measurements in terms of consistency, while manual measurements might be more reliable in terms of accuracy. Nonetheless, Kinect stands out as a viable alternative in terms of reproducibility and practicality. These findings, in line with our study, have shown that Kinect-based systems offered a certain accuracy and coherency in lower extremity measurements, regardless of the type of clothing, in a study conducted by Park et al. (2024) [39]. While Kinect-based systems gave results close to manual measurements in buttock-knee length and popliteal height measurements, larger deviations were observed in maximum hip breadth measurements due to the effects of clothing and other factors. Adikari et al. (2017)'s study noted that Kinect-based systems offered a certain level of accuracy and coherency, especially in measurements such as hip-to-leg length [12]. These findings are consistent with a study by Jamil et al. (2020), which reported that Kinect-based systems provided low error rates and high accuracy in lower extremity measurements [36]. Similarly, Wang et al. (2024) emphasized that Kinect-based measurement systems offered high accuracy and repeatability in lower extremity measurements [29]. These findings suggest that Kinect V2 could be a viable alternative to manual methods for tibial length measurements; however, it should be taken into consideration that there might be some differences in the measurements of the Trochanter-tibiale laterale length with manual methods. The findings in the literature are also in concurrence with the data obtained in our study. Our research reveals that Kinect provided coherence results with manual measurement methods and supported findings in the literature in this context. Wang et al. (2024) studied lower extremity measurements of children in younger age groups and observed a certain parallelism with the Trochanter-tibial laterale and tibial length data of the youth athletes in our study [29]. On the other hand, the upper leg measurements that we determined by manual methods from different anatomical points in our study (iliospina tibia laterale: 45.79 cm and crista iliaca tibiale laterale: 50.87 cm) showed significant differences from both the data in our own study and the data reported by Wang et al. (2024) [29]. These differences are likely due to Microsoft Kinect not being able to provide the full accuracy required for certain measurements. In this context, in order to fully evaluate the accuracy of our hypothesis, future studies need to better understand the reasons for these differences and investigate the necessary improvements to increase the accuracy of the Kinect V2 in these measurements. Additionally, the performance of this technology in practical applications should be further examined in various populations and sports.

The hypothesis of our study was that Kinect V2 would provide similar accuracy and coherency to manual methods in shoulder width measurements. Our results showed that there was no statistically significant difference in shoulder width measurements between the Kinect V2 and manual methods ($p = 0.853$). This shows that both methods provided similar accuracy and coherency. Kinect V2 provided low variation and high coherency compared to manual measurements. These findings support that Kinect V2 could be a compatible and reliable alternative to manual methods for shoulder width measurements. These results are coherent with the findings reported by Jamil et al. (2020) and Espitia-Contreras et al. (2014) that RGB-D sensors provided reliable results for measurements such as shoulder width [36, 38]. In addition, it was stated in the study of Park et al., (2024) that shoulder width measurements obtained with Kinect V2 were concordant with manual measurements [39]. This indicates that Kinect V2 could be a reliable tool in sports science applications. On the other hand, in the study of Bragança et al. (2017), a significant difference was found between Kinect-based and manual measurements for shoulder width measurements [10]. This difference may result from incompatibilities between the methods and devices used. The fact that there was no significant difference between manual and Kinect V2 measurements in our study show that this device could be a reliable alternative with correct calibration and appropriate use. As a result, the fact that Kinect V2 provided accuracy and coherency similar to manual methods in shoulder width measurements supports our hypothesis and shows that this device could be used as a practical tool in sports science and clinical applications. However, care must be taken in the application of the methods and the calibration of the device. Future studies should further investigate the accuracy and reliability of Kinect V2 under different populations and measurement conditions.

Limitations

This study has some limitations. First, the measurement accuracy of Microsoft Kinect V2 can be affected by device positioning, calibration, and environmental conditions. Although a controlled laboratory environment was used, instrument accuracy may vary under actual field conditions, which may limit the generalized ability of results. Second, although athletes were kept still during the measurement, involuntary movements may affect measurement coherency. Third, the sample size of this study was limited and included only elite female weightlifters in the youth category, which may limit the generalize ability of the findings to other populations and sports. It is recommended that future research be conducted with larger and more diverse samples.

Conclusion

This study compared the performance of Kinect V2 and manual measurement methods in anthropometric measurements of youth female weightlifters and revealed the differences between the two methods in terms of accuracy and coherency. Findings show that Kinect V2 demonstrated comparable accuracy and coherency to manual methods in humeral, forearm, and hand length measurements, making it an effective alternative for situations that require fast and practical data collection in the field. Some differences were observed in trochanter-tibiale laterale length measurements, but high concordance and reliability were found between the two methods in tibial length and shoulder width measurements. As a result, it supports the usability of Kinect V2 in sports and medical science applications; however, it also points out that it might not be an ideal option for every type of measurement. Future research should further examine the use of Kinect V2 across various sports and population groups to more clearly identify the strengths and weaknesses of the device. In this way, the potential and limitations of Kinect V2 can be better understood and more solid results can be obtained about the effectiveness of this technology in different application areas.

Practical applications

This study has shown that Microsoft Kinect V2 is a useful tool for anthropometric measurements in youth female weightlifters. Thanks to the fast and practical data collection capabilities of Kinect V2, it can be used as an alternative to manual methods in sports science and training programs. This technology can be easily applied in the field or laboratory environment by coaches and sports scientists to monitor the development of athletes and obtain measurement data quickly. In addition, the easy portability and use of Kinect V2 also provides advantages for field studies and training programs with large participation. In the future, broader evaluation of Kinect V2 across different sports branches and populations may further expand the potential use of the device in the field of sports science.

Author contributions

Conceptualization, K.E., B.I. and S.Ö.; methodology, K.E., B.I., E.Ö., and S.Ö. software, S.Ö.; formal analysis, U.Ö.O., K.E., B.I. and E.Ö.; investigation, K.E., B.I., E.Ö. and S.Ö.; resources, K.E., B.I., E.Ö. and S.Ö.; data curation, K.E., B.I., E.Ö. and S.Ö.; writing—original draft preparation, K.E., E.Ö. and B.I. writing—review and editing, K.E., B.I., E.Ö. and S.Ö.; visualization, K.E., B.I., E.Ö. and S.Ö.; funding acquisition, K.E., B.I. and S.Ö. All authors have read and agreed to the published version of the manuscript.

Funding

Karamanoğlu Mehmetbey University Scientific Research Projects Coordination Unit, Project No: 14-M-24.

Data availability

Data available on request from the authors (The data that support the findings of this study are available from the corresponding author upon reasonable request).

Declarations

Ethics approval and consent to participate

This research was performed in accordance with the principles of the 2013 Helsinki Declaration, and approval was obtained from Karamanoğlu Mehmetbey University Faculty of Medicine Local Scientific Research Ethics Committee (Date: 04.07.2024, approval number: 08-2024/10). In the study, participants were informed about the study and a signed informed consent form was obtained from the participants. Additionally, the necessary written and signed informed consents for the participants whose personal or clinical details along with any identifying images were included to be taken and published were obtained from them and their parent/legal guardian.

Consent for publication

Written consents for publication were obtained from the participants and their parent/legal guardian shown in Figs. 1, 2 and 3, separately. Additionally, the necessary written and signed informed consents for the participants whose personal or clinical details along with any identifying images were included to be taken and published were obtained from them and their parent/legal guardian.

Competing interests

The authors declare no competing interests.

Author details

[1]Computer Technologies Program, Vocational School of Technical Sciences, Karamanoğlu Mehmetbey University, Karaman 70200, Turkey
[2]Departments of Physiology, Medical School, University of Karamanoğlu Mehmetbey, Karaman 70200, Turkey
[3]Departments of Physical Education and Sports, Ahmet Keleşoğlu Faculty of Education, Necmettin Erbakan University, Konya 42090, Turkey
[4]Departments of Biostatistics, Medical School, University of Karamanoğlu Mehmetbey, Karaman 70200, Turkey
[5]Karamanoğlu Mehmetbey University Vocational School of Health, Karaman 70200, Turkey

Received: 23 January 2025 / Accepted: 24 March 2025
Published online: 09 April 2025

References

1. Marfell-Jones M, Olds T, Stewart A, Carter L. International Standards for Anthropometric Assessment. ISAK. 2006.
2. Fosbøl MO, Zerahn B. Contemporary methods of body composition measurement. Clin Physiol Funct Imaging. 2015;35:81–97. https://doi.org/10.1111/cpf.12152.
3. Storey A, Smith HK. Unique aspects of competitive weightlifting: performance, training and physiology. Sports Med. 2012;42(9):769. https://doi.org/10.1007/BF03262294.– 90.
4. Ulijaszek SJ, Kerr D. Anthropometric measurement error and the assessment of nutritional status. Br J Nutr. 1999;82(3):165–77. https://doi.org/10.1017/s0007114599001348.
5. Glock F, Vogel M, Naumann S, Kuehnapfel A, Scholz M, et al. Validity and intraobserver reliability of three-dimensional scanning compared with conventional anthropometry for children and adolescents from a population-based cohort study. Pediatr Res. 2017;81:736–44. https://doi.org/10.1038/pr.2016.274.
6. Che YL, Lu ZJ. The key technology research of kinect application in sport training. AMR. 2014;945:1890–3. https://doi.org/10.4028/www.scientific.net/amr.945-949.1890.
7. Bougourd J, Dekker L, Grant Ross P, Ward J. A comparison of women's sizing by 3D electronic scanning and traditional anthropometry. J Text Inst. 2000;91(2):163–73. https://doi.org/10.1080/00405000008659536.
8. Yu CY, Lo YH, Chiou WK. The 3D scanner for measuring body surface area: A simplified calculation in the Chinese adult. Appl Ergon. 2003;34(3):273–8. https://doi.org/10.1016/S0003-6870(03)00007-3.
9. Sinha S, Bhowmick B, Chakravarty K, Sinha A, Das A. Accurate upper body rehabilitation system using kinect. Annu Int Conf IEEE Eng Med Biol Soc. 2016;2016:4605–9. https://doi.org/10.1109/EMBC.2016.7591753.
10. Bragança S, Arezes P, Carvalho M, Ashdown SP, Xu B, Castellucci I. Validation study of a kinect based body imaging system. Work. 2017;57(1):9–21. https://doi.org/10.3233/WOR-172532.
11. Naufal A, Anam C, Widodo CE, Dougherty G. Automated calculation of height and area of human body for estimating body weight using a Matlab-based kinect camera. Smart Sci. 2022;10(1):68–75. https://doi.org/10.1080/23080477.2021.1983940.
12. Adikari AMSB, Ganegoda NGC, Wanniarachchi WKIL. Non contact human body parameter measurement based on kinect sensor. IOSR-JCE. 2017;19(3):80–5. https://doi.org/10.9790/0661-1903028085.
13. Haas D, Phommahavong S, Yu J, Krüger-Ziolek S, Möller K, Kretschmer J. Kinect based physiotherapy system for home use. Curr Dir Biomedical Eng. 2015;1(1):180–3. https://doi.org/10.1515/cdbme-2015-0045.
14. Norton K, Olds T, Olive S, Craig N. In: Norton K, Olds T, Anthropometrica, editors. Anthropometry and sports performance. A textbook of body

measurement for sports and health courses. Sydney, Australia: UNSW; 1996. pp. 287–364.
15. Krzeszowski T, Dziadek B, França C, Martins F, Gouveia ÉR, et al. System for Estimation of human anthropometric parameters based on data from kinect v2 depth camera. Sensors. 2023;23(7):3459. https://doi.org/10.3390/s23073459.
16. Li L. Time-of-flight camera–an introduction. In: Technical white paper, no. SLOA190B, 2014. https://docs.ampnuts.ru/ti.com.datasheet/OPT8241/White_paper_SLOA190B.PDF. Accessed 19 Dec 2024.
17. Sarbolandi H, Lefloch D, Kolb A. Kinect range sensing: Structured-light versus Time-of-Flight kinect. Comput Vis Image Underst. 2015;139:1–20. https://doi.org/10.1016/j.cviu.2015.05.006.
18. Romacho CB, Hermoso MD, Cintas HP. Automatic Estimation System of Dynamic Knee Alignment Based on Depth Video. (PhD), Üniversidad de Granada, Granada. 2016:88.
19. Morozov MN, Shubin AA, Naidenov KM, Derbenev AA. Physical bases of a ToF Camera–Based optical tracking system for surgical instruments. Bull Russ Acad Sci Phys. 2018;82(12):1525–8. https://doi.org/10.3103/S1062873818120158.
20. Yang L, Zhang L, Dong H, Alelaiwi A, Saddik AE. Evaluating and improving the depth accuracy of kinect for windows v2. IEEE Sens J. 2015;15(8):4275–85. https://doi.org/10.1109/JSEN.2015.2416651.
21. Naeemabadi M, Dinesen B, Andersen OK, Hansen J. Influence of a Marker-Based motion capture system on the performance of Microsoft kinect v2 skeleton algorithm. IEEE Sens J. 2019;19(1):171–9. https://doi.org/10.1109/JSEN.2018.2876624.
22. Wasenmüller O, Ansari MD, Stricker D. DNA-SLAM: Dense noise aware SLAM for TOF RGB-D cameras. In Computer Vision–ACCV 2016 Workshops: ACCV 2016 International Workshops, Taipei, Taiwan, November 20–24, 2016, Revised Selected Papers, Part I 13 (pp. 613–629). Springer International Publishing. https://doi.org/10.1007/978-3-319-54407-6_42
23. Tölgyessy M, Dekan M, Chovanec Ľ. Skeleton tracking accuracy and precision evaluation of kinect V1, kinect V2, and the Azure kinect. Appl Sci. 2021;11(12):5756. https://doi.org/10.3390/app11125756.
24. Ma M, Proffitt R, Skubic M. Validation of a kinect V2 based rehabilitation game. PLoS ONE. 2018;13(8):e0202338. https://doi.org/10.1371/journal.pone.0202338.
25. Yang S, Lei X, Liu Z, Sui G. An efficient local stereo matching method based on an adaptive exponentially weighted moving average filter in SLIC space. IET Image Proc. 2021;15(8):1722–32. https://doi.org/10.1049/ipr2.12140.
26. Sbrana G, Pelagatti M. Optimal hierarchical EWMA forecasting. Int J Forecast. 2024;40(2):616–25. https://doi.org/10.1016/j.ijforecast.2022.12.008.
27. Örücü S, Selek M. Design and validation of Rule-Based expert system by using kinect V2 for Real-Time athlete support. Appl Sci. 2020;10(2):611. https://doi.org/10.3390/app10020611.
28. Chavan YL. Portable Motion Lab for Diagnostic and Rehabilitation Processes (Master's thesis, Wright State University) 2017. http://rave.ohiolink.edu/etdc/view?acc_num=wright1513089313160899
29. Wang SA, Lu MH, Lee AT, Chen CY, Lee LW. Performance of Microsoft Azure kinect DK as a tool for estimating human body segment lengths. Sci Rep. 2024;14(1):15811. https://doi.org/10.1038/s41598-024-66798-0.
30. Del Bimbo A, Ferracani A, Pezzatini D, Seidenari L. Computer vision for natural interfaces. Natural interaction in medical training. Human–Computer Interaction Series. Cham: Springer; 2017. https://doi.org/10.1007/978-3-319-61036-8_3.
31. Long KZ, Beckmann J, Lang C, Seelig H, Nqweniso S, Probst-Hensch N, et al. Impact of a school-based health intervention program on body composition among South African primary schoolchildren: results from the KaziAfya cluster-randomized controlled trial. BMC Med. 2022;20(1):27. https://doi.org/10.1186/s12916-021-02223-x.
32. Ewf sport, European Weightlifting Federation. (2024). https://ewf.sport/european-championships-results/. Accessed 28 Dec 2024.
33. Norton K, Whittingham N, Carter L, Kerr D, Gore C, Marfell-Jones M. In: Norton K, Olds T, editors. Measurement techniques in anthropometry. Sydney, Australia: Anthropometria, University of New South Wales; 1996. pp. 20–73.
34. Norton K, Marfell-Jones M, Whittingham N, Kerr D, Carter L, et al. Anthropometric assessment protocols. In: Gore C, editor. Physiological tests for elite athletes. Champaign, IL.: Human Kinetics; 2000. pp. 66–85.
35. Koo TK, Li MY. A guideline of selecting and reporting intraclass correlation coefficients for reliability research. J Chiropr Med. 2016;15(2):155–63. https://doi.org/10.1016/j.jcm.2016.02.012.
36. Jamil A, Herodian S, Saulia L. RGB-D sensor application for static anthropometry measurement. IOP Conf Ser Earth Environ Sci. 2020;542(1):012036. https://doi.org/10.1088/1755-1315/542/1/012036.
37. Tarabini M, Marchisotti D, Sala R, Marzaroli P, Giberti H et al. A prototype for the automatic measurement of the hand dimensions using the Microsoft Kinect V2. MeMeA. 2018;1–6; https://doi.org/10.1109/MeMeA.2018.8438789
38. Espitia-Contreras A, Sanchez-Caiman P, Uribe-Quevedo A. Development of a Kinect-based anthropometric measurement application. IEEE VR. 2014;71–2. https://doi.org/10.1109/VR.2014.6802056.
39. Park BKD, Jung H, Ebert SM, Corner BD, Reed MP. Efficient Model-Based anthropometry under clothing using Low-Cost depth sensors. Sensors. 2024;24(5):1350. https://doi.org/10.3390/s24051350.

Publisher's note