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Reliability and validity of lower extremity and trunk kinematics measured with markerless motion capture during sports-related and functional tasks: A systematic review

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ABSTRACT

This study reviewed the literature regarding reliability and validity of markerless motion capture (MMC) for measuring lower extremities and trunk kinematics during sports-related and functional tasks. Articles published until 28 February 2024 were assessed. Studies were included if they assessed walking, squatting, jumping/landing, running, or cutting. After screening, 53 studies were included in the review. Variability across task characteristics, MMC systems, and statistical analyses was observed. The relative reliability of MMC, measured by intraclass correlation coefficient (ICC), ranged from low to excellent, with most variables showing standard error of measurement (SEM) values below 5°. Squats and landing tasks reported the highest reliability, with good to excellent ICC and most joints reporting SEM values < 5°, except for hip flexion (4.0°to 11.1°). Validity studies (compared to marker-based motion capture) showed differences between technologies ranging from 0.2° to 28.6° and correlations negligible (including negative values) to very strong, depending on the task, plane of motion, and joints analysed. Hip angle in frontal plane reported the lowest differences between technologies across tasks. MMC systems provide reliable measurements for most kinematic variables but are not largely comparable to marker-based systems. MMC reliability creates opportunities to develop more ecological valid research outside traditional biomechanical laboratory settings.

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Agreement; motion analysis; pose estimation; deep learning; repeatability; review

Introduction

The frequency and burden of musculoskeletal injuries in sports have not decreased over the last years, significantly affecting both the player and the club (Ekstrand et al., 2021; Torres-Ronda et al., 2022; West et al., 2021). Time lost due to injuries negatively affects team performance, with lower injury rates correlating to greater team success (Hägglund et al., 2013; Podlog et al., 2015; Williams et al., 2017). Additionally, injuries negatively impact clubs' finances through healthcare costs, as well as indirect costs arising from lost productivity (Turnbull et al., 2024). Injury risk mitigation strategies are of utmost importance in sports to maximise athlete availability and impact performance.

Lower limb non-contact injuries (LLNCI) in multidirectional (e.g., football, basketball, rugby) often occur during activities such as landing, running, and cutting (Gill et al., 2023; Vermeulen et al., 2024; Villa et al., 2020, 2021). Repeated screening of modifiable risk factors over time during these activities might be necessary to identify athletes at risk of injury and evaluate treatment effectiveness (Verhagen et al., 2018). One of the key modifiable risk factors for LLNCI is an athlete's movement patterns and the associated internal forces. Reviews have identified kinematic factors associated with and/or predictive of LLNCI such as patellofemoral pain syndrome (PFPS), patellar tendinopathy, groin injuries, exertional medial tibial pain, and anterior cruciate ligament (ACL) during landing (De Bleecker et al., 2020; Harris et al., 2020; Johnston et al., 2018; Tayfur et al., 2022; Waiteman et al., 2022), running (Ceyssens et al., 2019; Vannatta et al., 2020; Willwacher et al., 2022), and cutting (Donelon et al., 2024; Waiteman et al., 2022). Furthermore, impaired kinematics during functional tasks such as single-leg squats (Warner et al., 2019) and walking (Hart et al., 2016; Moore et al., 2020) have been also reported in athletes with LLNCI. Considering this, repeated screening of kinematics during these tasks

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might help to identify injury risk and monitor rehabilitation in athletes.

Three-dimensional (3D) marker-based motion analysis is de facto standard for movement analysis (Needham et al., 2021), but it has limitations such as high cost, time-consuming data collection and analysis, marker placement error, and laboratory-based testing (Wade et al., 2022). As a result of this, new technologies such as markerless motion capture (MMC), which has a lower cost and requires less preparatory time, have been developed to assess athletes and patients outside the laboratory allowing rapid high-volume data collection (Kanko et al., 2021). Recent MMC studies have performed large-scale screening of jump-landing tasks to detect overuse (Little et al., 2023) and acute (Collings et al., 2022) LLNCI. However, effective implementation in sports and clinical settings requires knowledge of its validity – the degree to which an instrument measures what it is intended to measure and how closely the obtained values agree with the true values (Kottner et al., 2011) (i.e., how markerless results compare to 3D marker-based motion capture). Equally important is understanding its reliability. Reliability concerns the extent to which repeated measurements provide similar results over time (de Vet et al., 2006), providing clinicians with the information to differentiate between a real change observed or a measurement error (de Vet et al., 2006). Once the validity and reliability of the biomechanical variables are established, the level of these variables or any changes in them can be confidently viewed in relation to changing injury risk for any given player.

Few reviews have systematically synthesised the reliability and validity of MMC during functional tasks. A review about the evolution of vision-based motion analysis (Colyer et al., 2018) included a brief discussion of MMC validity; however, a systematic search was not performed, a limited number of studies were included, and reliability was not mentioned. A later study (Armitano-Lago et al., 2022) conducted a SWOT analysis (strength, weaknesses, opportunities, threats) of MMC and performed a systematic search (until December 2021) including reliability and validity as keywords. The authors reported 24 validity studies that provided general information about the MMC technology used, tasks performed, validation methods, and kinematic variables. However, the lack of studies on reliability, reporting of results (e.g., statistical parameters), and study quality creates uncertainty about its clinical use.

An updated review of MMC's reliability and validity during sports-related and functional tasks is needed to address these limitations. This would help practitioners assess its applicability for injury risk screening and monitoring in both sports and clinical settings. This systematic review aims to review and synthesise the existing literature regarding the reliability and validity of MMC systems for measuring lower extremities and trunk kinematics during sports-related and functional tasks.

Methods

Reporting of this systematic review was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) (Page et al., 2021). The review protocol was registered on PROSPERO (CRD42024529508).

Study selection

PubMed, Web of Science and CINAHL databases were searched using the following terms: markerless motion capture, validity/reliability, functional tasks (walking, squat, jump/landing, running, and cutting), and kinematics of lower limb and/or trunk. The search strategy is described in Appendix 1. The search was performed from the earliest available to 28 February 2024. Titles, abstracts, and full-text screening were performed independently for eligibility by 2 authors (M.Y. and L.LL.), and a third author (R.J) was available to resolve disagreements. Reference lists from identified articles were also screened to identify other potential articles not identified through this search strategy.

Studies were included if they investigated the reliability and/or validity of MMC of trunk and/or lower extremity (pelvis, hip, knee, and ankle) kinematics (i.e., joint angles) in healthy adults during any of the following tasks: walking, squatting, jumping/landing, running, and cutting. Tasks were selected for their relevance to LLNCI mechanisms and rehabilitation. Landing and cutting are the main injury mechanisms for ACL injuries (Gill et al., 2023; Villa et al., 2020, 2021), while running is the primary mechanism for hamstring strains (Vermeulen et al., 2024). Walking and squatting were included to explore the use of MMC in early rehabilitation, while landing, running, and cutting are more relevant in later rehabilitation stages. For reliability, studies needed to use the same MMC system to calculate the consistency of the results (de Vet et al., 2006). For validity purposes, studies investigating validity with marker-based motion capture as the reference standard were only included (Needham et al., 2021).

MMC technology was considered when the data was captured by two-dimensional technology and was analysed using software to estimate human body segment positions and orientations via visual hull reconstructions (e.g., based on the person's silhouette) or the application of deep learning algorithms based on the detection of anatomical key points (Armitano-Lago et al., 2022). Studies were not included if they employed methods that were not based on kinematic angles (i.e., Landing Error Scoring System) or used other methods to provide markerless data (e.g., Kinovea). Studies including multi-modal approaches such as MMC with inertial sensors were excluded. Studies assessing specifically foot models were excluded. Other exclusion criteria included non-English language, reviews, case studies, and conference papers.

Data extraction

One investigator (M.Y) extracted the following data independently: study population and design, task description, MMC system (technology used for data collection and software used for data analysis), type of reliability, validation method, joint angles and planes of motion, statistics (including discrete or full curve analysis), and results. One additional researcher (L.LL) double-checked the data for discrepancies and quality control. Tables were used to organise and synthesise the data.

For studies comparing two conditions of the same task (e.g., overground vs. treadmill walking), overground walking was chosen due to its ecological validity. Studies assessing walking at different speeds, self-selected, comfortable, or medium speeds were reported. For studies evaluating different speeds during running, the higher speed was reported since this is the main mechanism of hamstring injuries in athletes (Tokutake et al., 2018). For tasks assessed in multiple variations (e.g., normal vs. overhead squat or with vs. without body armour), the primary variation was selected.

For the MMC system, the type of technology used to collect data was sub-grouped into (1) depth-sensing cameras (e.g., Kinect sensor and RGB cameras), (2) video cameras (including high-speed cameras), and (3) tablet/iPhone (Colyer et al., 2018). The technology was also divided according to the number of devices used: single or multiple device systems (more than one device) (Armitano-Lago et al., 2022). Studies on MMC (Núñez et al., 2017; Ryselis et al., 2020) show that multi-camera systems offer superior accuracy and reliability in capturing movement compared to single-camera systems, which are limited by restricted capture volume, self-occlusion, and reliance on camera placement (Armitano-Lago et al., 2022; Wade et al., 2022). In cases where a study compared MMC technology placed at different angles, the conventional or most commonly used positioning was reported. The reliability analysis was divided into (1) within-session (inter-trial) reliability, for studies analysing the results obtained by the same examiner in the same session, and (2) test-retest reliability, for studies analysing the results obtained by the same examiner at different periods, which included within-day and between-day reliability.

Mean values were reported, and individual values, if provided, were averaged for consistency. When studies report values for both the right and left sides, the higher value was included in the table.

Methodological quality assessment

Two independent researchers (MY and L. LL) assessed the quality of the included studies using The Critical Appraisal Tool (CAT) (Brink & Louw, 2012). The initial percentage of agreement between the researchers was calculated. If there was any disagreement, a consensus was reached through discussion. The CAT scale contains 13 evaluation items: five items assess both validity and reliability, four items assess validity only, and the remaining four assess reliability only. Item 4, which assesses interrater reliability, was not considered as MMC data can be collected by different examiners without inter-examiner effects, given that marker placement is not involved. Each study was classified for each item as 'yes' if the information was described in sufficient detail or 'no' if there was not enough information for clarification (Brink & Louw, 2012). A percentage evaluation column was included based on the items that each study achieved [% = (Items marked 'yes' x 100)/total number of items scored]. Studies with a score of 70% or higher were classified as high-quality (Leporace et al., 2023).

Data analysis

Although a meta-analysis was not performed due to the heterogeneity of the included studies, a qualitative analysis was performed. To assess the reliability and validity of MMC, a combination of statistics was analysed as a single measure provides limited information (Kottner et al., 2011). The selection of parameters was guided by reliability and validity guidelines (Brink & Louw, 2012; Kottner et al., 2011), sports literature (Riemann & Lininger, 2018), and the most commonly reported parameters identified in this review to ensure greater representation and inclusion of more studies. Two statistical methods were used to report reliability: relative reliability (i.e., test-retest correlation) and absolute reliability (i.e., repeated-measurement variability) (Kottner et al., 2011; Riemann & Lininger, 2018). For relative reliability, intraclass correlation coefficients (ICC) was reported (i.e., the degree to which individuals maintain their position in a sample) (Lexell & Downham, 2005). ICC was categorised as follows: ≥0.90 (excellent), 0.75–0.89 (good), 0.50–0.74 (moderate), and < 0.50 (low reliability) (Koo & Li, 2016). Absolute reliability (i.e., the degree which repeated measurements vary for individuals) was calculated using the standard error of measurement (SEM). This parameter is easy to interpret as it is expressed in the actual scale of measurement (i.e., joint angles), providing greater clinical value by differentiating between a real change and a measurement error (de Vet et al., 2006; Riemann & Lininger, 2018). The SEM can be interpreted as a reference interval with a coverage probability that approximates to 68% of all true scores in a population (Weir, 2005). Measurement errors were considered acceptable if SEM values are < 5° as this amount of error has been considered clinically acceptable for biomechanical variables (McGinley et al., 2009; Song et al., 2023).

For validity studies, Pearson correlation coefficient strength (r) was used to assess agreement between systems. A Pearson correlation coefficient of ≥ 0.90 was considered very strong, between 0.89 and 0.70 strong, between 0.69 and 0.40 moderate, between 0.39 and 0.10 weak, and < 0.10 negligible (Schober et al., 2018). Additionally, the root-mean-square difference (RMSD) was used to quantify the average difference between systems. This parameter is also expressed in joint angles, increasing clinical relevance. Between-system differences were also considered acceptable if RMSD was < 5°. Data analysis was performed using Microsoft Excel (Microsoft 365 MSO, Version 2501, Build 16.0.18429.20132, 64-bit).

Results

Studies and population characteristics

Electronic databases and manual searches returned a total of 409 articles. Of the 409 articles, 208 duplicates were removed, resulting in 201 articles for initial screening. These articles were assessed by title and abstract to determine whether they met the eligibility criteria. Eighty-two articles were included for full-text appraisal, and 53 were included in the final analysis (Figure 1). The majority of studies (62.9%) were conducted post 2021, reflecting a recent surge in interest in MMC, possibly attributed to its lower cost and greater accessibility. From the included studies, 47 studies (89%) assessed validity and 15 (28%) assessed reliability. Six studies (11%) assessed reliability alone and nine studies (17%) included both reliability and validity. A total of 853 adult participants were included in the validity studies and 291 in the reliability studies. The details of each study can be found in Tables 1 and 2 for validity and Tables 3 and 4 for reliability.

Risk of bias

The agreement between both raters for risk of bias was 89.2% (58 disagreements across 498 questions in 53 studies). For the 15 studies assessing reliability, the average score was 66% (range = 50% to 75%), with five studies (33%) classified as high-quality (>70%). Most studies provided detailed descriptions of the participants, described the MMC technology used, and explained the tasks to allow for replication. Appropriate statistical methods were employed. However, primary sources of bias included that raters were not blinded to prior findings and the lack of many studies to vary the order of assessments (Appendix 2).

For the 47 studies assessing concurrent validity, the average score of the studies was 76% (range = 33% to 100%), with 31 studies (66%) classified as high-quality (>70%). These studies also described the participants and tasks, described markerless and marker-based motion capture technology used, and employed appropriate statistical methods. The risk of bias was generally low for the index test and reference standard domains, as most studies tested markerless and marker-based motion capture simultaneously, which prevents raters from accessing the reference standard's results. However, in two studies, data were not collected simultaneously (Perrott et al., 2017) or this item lacked clarity (Talaa et al., 2023). Like reliability studies, most validity studies did not specify examiner qualifications or competence, therefore, introducing bias.

Characteristics of the tasks

Out of 53 studies, walking was the most commonly reported task in 31 studies (58%), followed by squatting in 16 studies (30%), jump-landing in 11 studies (21%), running in 10 studies (19%), and cutting in one study (2%). Walking was the most frequently reported, likely due to its ecological validity as a universal activity and ease of standardisation compared to the other tasks. Figure 2 shows the tasks performed for the validity and reliability studies separately.

Regarding walking, most studies (23 studies, 74%) performed walking overground, with eight studies (26%) performing the task on a treadmill (Kanko et al., 2021; Macpherson et al., 2016; Ong et al., 2017; Ota et al., 2021; Tamura et al., 2020; Xu et al., 2015; Yang & Park, 2024; Yeung et al., 2021). For overground walking, the majority of the studies (26 studies, 84%) used

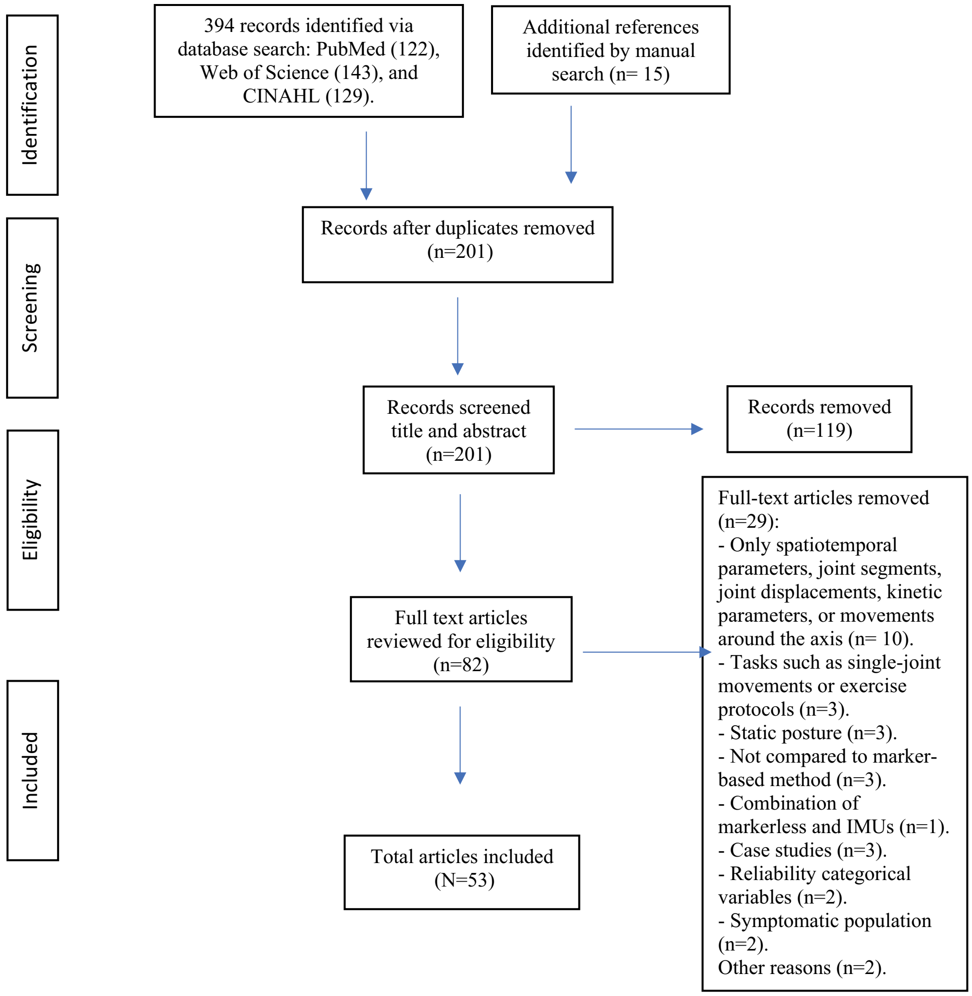

Figure 1. PRISMA flow diagram (Moher et al., 2009) of study selection and inclusion process for validity and reliability studies.

a comfortable or self-selected pace. On the contrary, most studies performed running on a treadmill (8 studies, 80%), except for two studies that performed overground running (Needham et al., 2022; Song et al., 2023). Regarding treadmill running, the most common speed used was standardised (4 studies, 40%) and self-selected (2 studies, 20%). For the cutting task, the only study included reported overground cutting without specifying the speed (Song et al., 2023). For the squats, most studies (11 studies, 69%) assessed double-leg squats, with only five (31%) including single-leg squat tasks (Eltoukhy et al., 2016; Haberkamp et al., 2022; Kotsifaki et al., 2018; Mentiplay et al., 2018; Perrott et al., 2017). Regarding the squat depth, a similar number of studies performed the squat at the maximum depth, restricted knee flexion range of motion, and did not report the depth. The squat duration was reported in only three studies (19%) (Mentiplay et al., 2018; Ota et al., 2020; Schmitz et al., 2015). For jump-landing tasks, most studies (eight studies, 73%) assessed double-leg tasks, with four studies (36%) assessing single-leg tasks (Ito et al., 2022; Kotsifaki et al., 2018; McCarthy et al., 2023; Tipton et al., 2019). The types of jump/landing included drop vertical jumps (6 studies, 55%), countermovement jumps (4 studies, 36%), and hop tasks (2 studies, 18%). Methodologies across studies were inconsistent, differing in box heights and landing targets for drop jumps, required depths for countermovement jumps, and specific parameters for hop tasks such as direction and distance.

Variables and planes of motion

All studies except for one (Macpherson et al., 2016) included the sagittal plane (98%), 32 studies the frontal plane (60%), and 18 studies the transverse plane (34%). Most of the studies including the transverse plane (83%) used a multicamera system. The knee was the most studied joint (51 studies, 96%) included in all studies

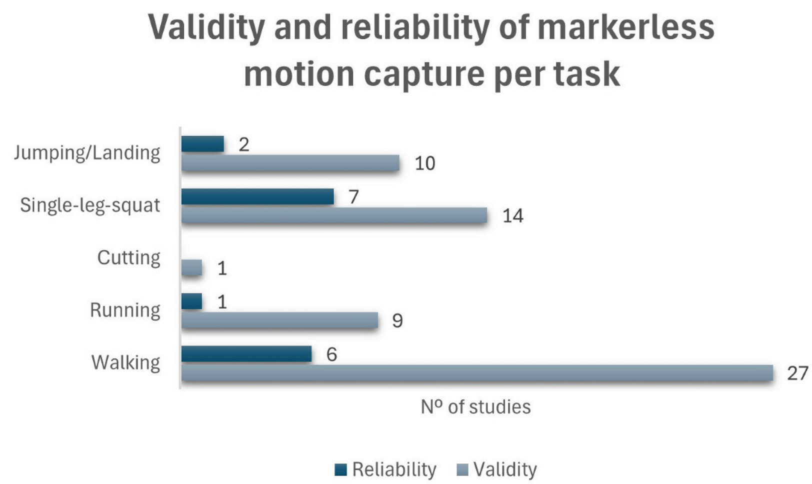

Figure 2. Number of studies per task assessing the validity and reliability of markerless motion capture.

except for two (Andersen et al., 2023; Macpherson et al., 2016). The hip was the second most commonly reported joint in 46 studies (87%), followed by the ankle in 29 studies (55%), the trunk in 10 studies (19%), and the pelvis in 9 studies (17%).

Markerless motion capture methodology

A similar number of studies used either a single-camera (26 studies) or a multi-camera system (27 studies). Multi-camera systems ranged from two to 14 cameras. Regarding the type of technology, the most commonly used were depth-sensing cameras (28 studies, 53%) including Microsoft Kinect sensor, RGB cameras, and a 3D temporal scanner, followed by video cameras (20 studies, 38%), and a tablet/iPhone (five studies, 9%). Tasks such as walking, squats, and landing were often collected using single depth-sensing cameras and at lower capture rates (30 hz). In contrast, running tasks commonly used multiple video cameras and higher capture rates (up to 240 hz). Regarding the software used for data processing, OpenPose was most commonly used (14 studies, 26%), followed by Microsoft Development Kit (10 studies, 19%), and Theia3D (7 studies, 13%).

Analysis and statistical results

There was a trend for studies assessing walking, running, and cutting to use full curve analyses, whereas studies focusing on SLS and landing tasks predominantly used discrete point analyses, including peak or maximum angles, initial contact (IC), maximum knee flexion angle, and joint displacement from IC to peak angle. The results of the studies, along with their categorisation, are presented in Appendix 3.

Reliability

Across tasks, a similar number of studies assessed within-session reliability (8 studies) and test-retest reliability (10 studies). Most test-retest studies measured between-day reliability (9 studies), with fewer measuring within-day reliability (2 studies). The most commonly reported statistics were ICC (11 studies, 73%) and SEM (8 studies, 53%), supporting their use.

Squat

Mean ICC values in the sagittal plane ranged from 0.73 to 0.97 (good to excellent) for the lower limb and trunk (Andersen et al., 2023; Lee et al., 2023; Mentiplay et al., 2018; Ota et al., 2020; Schmitz et al., 2015). SEM values ranged from 2.0° to 10.3° (Andersen et al., 2023; Lee et al., 2023; McCarthy et al., 2023; Mentiplay et al., 2018; Wochatz et al., 2019). At a joint level, the hip showed the highest SEM values in the sagittal plane (4.0° to 10.3°), followed by the knee (2.2° to 8.3°), and the trunk (2.0° to 2.8°). In the frontal plane, the mean ICC ranged from good to excellent (0.84 to 0.96) for the hip and knee (Mentiplay et al., 2018; Schmitz et al., 2015). SEM values of 4.4° were reported for the knee (Mentiplay et al., 2018). In the transverse plane, only one study assessing within-session reliability was included (Schmitz et al., 2015), reporting excellent mean relative reliability and MDC values $< 5°$ for the hip ($ICC = 0.96$; $MDC = 3.7°$) and the knee ($ICC = 0.98$; $MDC = 2.3°$).

Landing

Only one study assessed relative reliability in the sagittal plane, reporting excellent mean values for the hip (ICC =

Table 1. Studies assessing the concurrent validity between markerless and marker-based motion capture during walking, running and cutting.

Author	Participants	Task	Task description	Markerless system method	Validation methods	Joint angles and plane of motion	Statistics and analysis
Sandau et al. (2014)	$N = 10$ (age NR) 0F: 10 M	Walking	Walking overground at preferred speed. Only trials of 1.1 m/s (4.0 km/h) ± 10% were accepted.	Multi-camera. Video camera (eight camera link cameras). Capture rate 75 hz Data processed with Iterative closest point (ICP) algorithm (the patch-based Multiview stereo algorithm).	Ariel Performance Analysis System with 8 cameras Capture rate 75 hz.	Hip, knee, and ankle in the 3 planes.	Full curve (gait cycle) and discrete point (heel strike, mid stance, toe-off, and mid-swing) analysis. RMSD, mean difference with SD, and range of motion. For discrete analysis mean difference, significance level (p-value), and Spearman correlation.
Castelli et al. (2015)	$N = 10$ (33 ± 3 years) 0F: 10 M	Walking	Walking overground at slow, comfortable, and fast speed along an 8-meter walkway.	Single camera Depth-sensing camera (RGB video camera) Capture rate NR Data processed with SEGMARK method	Vicon System with 6 cameras Capture rate NR (interpolation NR)	Pelvis, hip, knee, and ankle in the sagittal plane.	Full curve analysis (gait cycle). RMSD and linear-fit method
Mentiplay et al. (2015)	$N = 30$ (22.87 ± 5.08 years) 15F: 15 M	Walking	Walking overground at a comfortable and fast speed along an 8-meter walkway.	Single camera Depth-sensing camera (Kinect v2) Capture rate 30 hz Data processing with Microsoft SDK	3DMA System with 9 Vicon cameras Capture rate 100 hz (spline interpolation)	Knee in the sagittal and frontal planes. Hip and ankle in the sagittal plane.	Discrete analysis (total range during gait, peak knee angles at the stance, and swing phase). Pearson's correlation coefficients, concordance correlation coefficients, and Bland &Altman plots with LOA.
Xu et al. (2015)	$N = 20$ (25.8 ± 8.2 years) 10F: 10 M	Walking	Walking on a treadmill at 0.85 m/s, 1.07 m/s, and 1.30 m/s.	Single camera Depth-sensing camera (Kinect sensor version NR) Capture rate 60 hz Data processed with Microsoft SDK	Optotrak Certus System (number of cameras NR) Capture rate 60 hz (spline interpolation).	Hip and knee in the sagittal plane.	Full curve (gait cycle) and discrete (maximum angle) analysis. Full curve Pearson correlation coefficient, RMSE, Bland Altman analysis, and ordinary least product regression. Discrete point mean difference.
Macpherson et al. (2016)	$N = 9$ (29.2 ± 4.2 years) 0F: 9 M	Walking and running	Walking on a treadmill at self-selected speed (3.6–5.6 km/h) and running at 70% (10.9–14.0 km/h) and 90% of maximal speed (14.0–18.0 km/h).	Single camera Depth-sensing camera (Kinect v1) Capture rate 30 hz Data processed NR	Vicon System with 6 cameras Capture rate 100 hz (linear interpolation).	Trunk and pelvis in frontal and transverse plane.	Full curve analysis Pearson correlation coefficients and limits of agreement.
Ong et al. (2017)	$N = 10$ (23.1 ± 3.2 years) 0F: 10 M	Walking and running	Walking and running on a treadmill at self-selected speed (approximately 5 km/hour and 10 km/hour respectively).	Multi-camera Video camera (two Point Grey cameras) Capture rate 25 hz. Data processed with a shape-from-silhouette method	Motion Analysis Corp with 8 cameras. Capture rate 100 hz (no interpolation)	Hip, knee, and ankle in the sagittal, frontal, and transverse planes.	Full curve analysis (stance phase). RMSD and ANOVA.
Skals et al. (2017)	$N = 10$ (23.50 ± 1.27 years) 0F: 10 M	Walking	Walking overground at a self-selected pace.	Multi-camera Two Kinect sensor version NR (depth-sensing camera) Capture rate 30 hz Data processed with iPi software Recorder v. 2.2.2.27	Qualisys System with 8 cameras Capture rate 100 hz (interpolation NR).	Hip in the 3 planes. Knee and ankle in the sagittal plane.	Full curve (gait cycle). Pearson correlation and RMSD.
Tanaka et al. (2018)	$N = 51$ (20.9 ± 0.2 years) 16F: 35 M	Walking	Walking overground at a comfortable pace.	Single camera Kinect v2 sensor (depth-sensing camera) Capture rate 30 hz Data processing with Microsoft SDK.	Vicon System with 9 cameras Capture rate 100 hz (spline interpolation).	Hip and knee in the sagittal and frontal planes.	Discrete point analysis (every 10% of gait cycle). Mean difference and Pearson correlation coefficient.

(*Continued*)

Table 1. (Continued).

Author	Participants	Task	Task description	Markerless system method	Validation methods	Joint angles and plane of motion	Statistics and analysis
Haimovich et al. (2021)	$N = 6$ (29.5, range 18–45 years) Gender= NR	Walking	Walking overground at a comfortable speed.	Single camera Kinect v2 (depth-sensing camera) Capture rate 30 hz Data processed with Visual Studio Express as well as Microsoft's Kinect SDK.	Simi Motion System (number of cameras NR) Capture rate 120 hz (interpolation).	Hip and knee in the sagittal and frontal planes.	Full curve analysis (gait cycle). RMSE.
Kanko et al. (2021)	$N = 30$ (23.0 ± 3.5 years) 15F: 15 M	Walking	Walking on a treadmill at a comfortable speed.	Multi camera Eight Qualisys Miqus, cameras. (video camera) Capture rate 85 hz. Data processed with Theia v2021.	Qualisys System with 7 cameras Capture rate 85 hz.	Hip, knee, and ankle in sagittal, frontal, and transverse planes.	Full curve analysis (gait cycle). Average differences and RMSD.
Ota et al. (2021)	$N = 24$ (26.1 ± 4.6 years). 7F: 17 M	Walking and running	Walking on a treadmill at slow (2.5 km/h; 0.69 m/s), moderate (4.0 km/h; 1.11 m/s), and fast speed (5.5 km/h, 1.53 m/s) Running on a treadmill at 8.5 km/h (2.36 m/s).	Multi-camera Two digital cameras (video-camera) Capture rate 60 hz. Data processed with OpenPose.	Vicon System with 8 cameras. Capture rate 60 hz.	Pelvis in the frontal plane. Hip in the sagittal and frontal planes. Knee and ankle in the sagittal plane.	Full curve (cycle) and discrete point analysis (peak angles). Linear regression, coefficients of determination [r^2]), ICC (2,1), and Bland & Altman plots (proportional and fixed bias).
Stenum et al. (2021)	NR	Walking	Walking overground (speed or pace NR).	Multi-camera Four video cameras (video-camera) Capture rate 25 hz. Data processed with OpenPose.	Vicon System (number of cameras NR). Capture rate 100 hz (interpolation NR)	Hip, knee, and ankle in the sagittal plane.	Full curve analysis (gait cycle). Mean absolute error and cross-correlation coefficients during stride cycle
Yeung et al. (2021)	$N = 10$ (27.2 ± 4.7 years) 2F: 8 M	Walking	Walking on a treadmill at 3 different speeds (slow: 0.83 m/s, medium: 1.22 m/s, fast: 1.64 m/s).	Single camera Kinect v2, Orbec Astra Pro v2, and Azure Kinect at 5 different angles (depth-sensing camera) Capture rate 30 hz Data processed with their respective SDK.	Vicon System with 12 cameras Capture rate 100 hz (linear interpolation).	Hip in the sagittal and frontal planes. Knee and ankle in the sagittal plane.	Full curve analysis (gait cycle ROM). RMSE and significant differences.
Ito et al. (2022)	$N = 3$ (28–39 years) 1F: 2 M	Walking	Walking overground (speed or pace NR).	Multi-camera Eight Sony RX0-II cameras (video camera) Capture rate 120 hz Data processed with Theia3D v2021.	Vicon System with 8 cameras Capture rate 120 hz.	Kinematics of hip, knee, and ankle in the three planes of motion.	Full curve analysis. Pearson correlation coefficient and mean difference.
Moro et al. (2022)	$N = 16$ (27.0 ± 2 years). 6F: 10 M	Walking	Walking overground naturally.	Multi-camera Three RGB cameras (depth-sensing camera) Capture rate NR Data processed with AdaFuse.	Optitrack System with 8 cameras Capture rate 100 hz (interpolation NR).	Hip in the sagittal and frontal planes. Knee, ankle, and pelvis in the sagittal plane.	Full curve analysis (gait cycle). SPM.

(*Continued*)

Table 1. (Continued).

Author	Participants	Task	Task description	Markerless system method	Validation methods	Joint angles and plane of motion	Statistics and analysis
Needham et al. (2022)	$N = 15$ (age NR). 8F: 7 M	Walking and running.	Walking and running overground at a self-selected speed.	Multi-camera Nine TTL-pulse synchronised machine (video camera) Capture rate 200 hz Data processed with OpenPose	Qualisys System with 15 cameras Capture rate 200 hz.	Hip in the 3 planes. Knee and ankle in the sagittal plane.	Full curve analysis (gait cycle). RMSE, bland-Altman analyses, linear fit models.
Ruescas-Nicolau et al. (2022)	$N = 12$ (39.1 ± 9.8 years) 5F: 7 M	Walking	Walking overground at a comfortable speed	Multi-camera A 3D Temporal Scanner with sixteen camera modules (Move4D/IBV) (depth-sensing camera) Capture rate 30 hz Data processed with 3D Temporal Scanner.	A MSBP System (Kinescan/IBV) with 16 cameras Capture rate 30 hz	Hip, knee, and pelvis in the 3 planes of motion.	Full curve analysis (gait cycle). Mean difference, RMSD, and Bland & Altman plots.
Washabaugh et al. (2022)	$N = 32$ (age NR). 10F: 22 M	Walking	Walking overground (speed or pace NR).	Single camera. One RGB video camera (depth-sensing camera). Capture rate 25 hz Data processed with 4 open-source estimation methods OpenPose, MoveNet Lightning, MoveNet Thunder, and DeepLabCut.	Vicon System with 10 cameras Capture rate 100 hz (interpolation NR).	Hip and knee in the sagittal plane.	Full curve analysis (gait cycle). Absolute error (mean difference) and SPM.
Yamamoto et al. (2022)	$N = 16$ (22 ± 1 years). 0F: 16 M	Walking	Walking overground at self-selected comfortable and slow speed with normal and large foot progression angle conditions.	Single camera. One RGB video camera (depth-sensing camera). Capture rate 100 hz Data processed with OpenPose.	OptiTrack System with 11 cameras Capture rate 100 hz.	Hip, knee, and ankle in the sagittal plane.	Discrete variable analysis (peak angles). MAE and cross-correlation coefficients.
Horsak et al. (2023)	$N = 21$ (30.2 ± 8.5 years) 12F: 9 M	Walking	Walking overground with 4 different patterns (physiological, crouch, circumduction, and equinus gait). Self-selected speed along a 10 m walkway.	Multi-camera. Two iOS smartphones (tablet/iPhone) Capture rate 60 hz. Data processed with OpenCap	Vicon System with 16 cameras Capture rate 120 hz (interpolation NR).	Pelvis and hip in the 3 planes. Knee in the sagittal plane. Ankle in the sagittal plane. Foot in the frontal plane.	Full curve (gait cycle) and discrete analysis (peak angles) Full curve analysis SPM and RMSE. Discrete analysis of peak differences.
Ino et al. (2023)	$N = 21$ (20.7 ± 1.0 years) 11F: 10 M	Walking	Walking overground at a comfortable pace along a 10 m walkway.	Single camera. Digital video camera (video camera). Capture rate 120 hz. Data processed with Open Pose.	Vicon System with 14 cameras Capture rate 120 hz.	Hip, knee, and ankle in the sagittal plane.	Discrete variable analysis (peak angle and excursion during stance and swing phases). MAE, Pearson correlation coefficient, coefficient of multiple correlation.
Jaén-Carrillo et al. (2023)	$N = 24$ (22.7 ± 2.6 years) 8F: 16 M	Walking and running	Walking (5 km/h) and running on a treadmill (10 and 15 km/h).	Multi-camera. Two Kinect v1 (depth-sensing camera). Capture rate 60 hz Data processed with MotionMetrix system.	Qualisys System with 8 cameras Capture rate 250 hz (interpolation NR).	Trunk, hip, and knee in the sagittal plane.	Spatiotemporal parameters for walking. Discrete point analysis (landing, stance, and swing) for running. Pearson correlation coefficient, ICC (2,1), standard error of estimate, mean difference or bias with 95% CI (LOA) and t-test.
Song et al. (2023)	$N = 10$ (21.9 ± 1.9 years). 5F: 5 M	Walking, running, and cutting.	Walking and running overground (speed or pace NR). Run and cut (speed NR).	Multi-camera. Eight high-resolution video cameras (video camera). Capture rate 100 hz. Data processed with Theia3D v2022.	Motion Analysis Corp with 12 cameras Capture rate 100 hz.	Hip in the 3 planes. Knee and ankle in the sagittal plane.	Full curve analysis. Pearson correlation coefficient and RMSD.

(*Continued*)

Table 1. (Continued).

Author	Participants	Task	Task description	Markerless system method	Validation methods	Joint angles and plane of motion	Statistics and analysis
Talaa et al. (2023)	$N = 32$ (age NR) Gender NR.	Walking	Walking overground normally over a 6.5 m walkway.	Multi-camera. Two video cameras (video camera). Capture rate 25 hz Data processed with OpenPose.	Vicon System With 10 cameras Capture rate 100 hz (interpolation).	Knee in the sagittal plane.	Full curve analysis (gait cycle). Mean absolute error.
Van Hooren et al. (2023)	$N = 40$ (37.8 ± 11.5 years). 19F: 21 M	Running	Running on a treadmill at 2.78 ms and 3.33 ms.	Single camera. (Basler scA640-74 gm, 659 × 494 pixels, Germany) (video camera). Capture rate 50 hz. Data processed with DeepLabCut and OpenPose.	Vicon System With 12 cameras Capture rate 100 hz (cubic interpolation).	Hip, knee, and ankle in the sagittal plane.	Full curve analysis. SPM with Sidak corrections and RMSD.
Wade et al. (2023)	$N = 15$ (26 ± 5 years). 8F: 7 M	Walking	Walking overground at preferred speed (average 1.55 ± 0.23 m/s)	Multi-camera. Two JAI SP5000C machine vision cameras (video camera). Capture rate 200 hz Data processed with OpenPose	Qualisys System with 15 cameras Capture rate 200 hz.	Hip, knee, and ankle in the sagittal and frontal planes.	Full curve analysis (gait cycle). Limits of agreement, bias (mean difference) with SD, and repeated measures correlation coefficient (R2).
Young et al. (2023)	$N = 31$ (34.5 ± 9.7 years) 11F: 20 M	Running	Running on a treadmill between 8 km/h and 14 km/h (selected based upon a pace comparable to their most recent outdoor 5 km pace).	Multi-camera. Two smartphones (tablet/iPhone). Capture rate 240 hz. Data processed with Blazepose.	Vicon System with 14 cameras Capture rate 200 hz (interpolation NR).	Knee in the sagittal plane.	Full curve analysis of cycle. Pearson correlation coefficient and ICC (2,1).
Boldo et al. (2024)	$N = 8$ (28.0 ± 3.7 years) 2F: 6 M	Walking	Walking overground at self-selected pace.	Single camera. RGB-D camera (depth sensing camera). Capture rate 60 hz. Data processed with OpenPose.	Vicon System with 8 cameras Capture rate 120 hz (interpolation).	Hip, knee and ankle in the sagittal plane.	Full curve (gait cycle) and discrete point analysis (ROM of the joints (max-min) and max knee angle in mid-terminal stance and swing; ankle in terminal stance and swing). For full curve Linear Fit Method (linear regression model between a set of curves and a reference curve). For discrete Bland & Altman limits of agreement (bias).
Hu et al. (2024)	$N = 2$ (age NR) Gender NR	Walking	Walking overground to walk at their customary pace along a 3-m-long corridor.	Single camera. iPhone 14 smartphone (tablet/iPhone) Capture rate 30 hz. Data processed: The High-Resolution Network project and Graph MLP-Like.	Vicon System with 12 cameras Capture rate 100 hz (interpolation).	Knee in the sagittal plane.	Full curve analysis (NR phase or complete gait cycle) Pearson correlation coefficient and mean difference.
Kanko et al. (2024)	$N = 30$ (23 ± 3.5 years). 15F: 15 M	Running	Running on a treadmill at each participant's self-selected speed under two clothing conditions (MoCap and sports).	Multi-camera. Eight Qualysis Miqus (video cameras) Capture rate 85 hz Data processed with Theia3D v2022.	Qualisys System with 7 cameras Capture rate 85 hz.	Hip, knee, and ankle in the 3 planes of motion.	Full curve analysis (full cycle). RMSD during the stance and swing phase.
Yang and Park, (2024)	$N = 20$ (24.15 ± 1.8 years). 10F: 10 M	Walking	Walking on a treadmill at the participant preferred speed.	Single camera Five smartphone cameras (at 5 different positions) (tablet/iphone) Capture rate 30 hz Data processed with BlazePose (Mediapipe).	Optitrak System with 9 cameras Capture rate 120 hz (interpolation NR).	Hip, knee, and ankle in the sagittal plane.	Full curve analysis Mean absolute error and Pearson correlation coefficients.

Root mean square error (RMSE); Root mean square difference (RMSD); Standard deviation (SD); Intraclass correlation coefficient (ICC); Not reported (NR); Limits of agreement (LOA); Statistical parametric mapping (SPM); Confidence interval (CI); Software Development Kit (SDK).

0.96; 95% CI: 0.83, 0.96) and knee (ICC = 0.90; CI: 0.78, 0.95), and good mean values for the trunk (ICC = 0.89; 95% CI: 0.77, 0.95) (Mentiplay et al., 2018). For absolute reliability, two studies performed between-day analyses of the hip, knee and trunk in the sagittal plane (McCarthy et al., 2023; Mentiplay et al., 2018) and reported SEM values ranging from 2.4° to 11.1°, with the lowest value for the trunk and the highest for the hip joint. One study also calculated frontal knee kinematics, reporting excellent relative reliability (ICC = 0.96; 95% CI: 0.92, 0.98) and SEM values of 3.6° (Mentiplay et al., 2018). The transverse plane was not assessed in jump-landing tasks.

Walking

In the sagittal plane, the mean ICC ranged from low (−0.15) to excellent (0.99) for the lower limb and trunk (Hu et al., 2024; Ino et al., 2023; Mentiplay et al., 2015; Tamura et al., 2020). In studies assessing between-day reliability, the mean ICC was significantly lower and more variable, ranging from −0.15 to 0.85 (Mentiplay et al., 2015; Tamura et al., 2020), compared to within-session reliability, which ranged from 0.73 to 0.99 (Hu et al., 2024; Ino et al., 2023). Regarding absolute reliability, SEM values ranged from 1.5° to 2.8° for the lower limb, with the highest values reported in the ankle (Riazati et al., 2022). In the frontal plane, relative reliability was only calculated for knee abduction, showing moderate values (ICC = 0.69; 95% CI: 0.48, 0.86) (Mentiplay et al., 2015). SEM values in the frontal plane ranged from 0.9° to 3.0° and in the transverse plane from 2.8° to 5.0°, also showing greater values in the ankle (Riazati et al., 2022).

Running

No studies included in this review reported relative reliability for running. Regarding absolute reliability, one study performing a between-session analysis found low SEM values ranging from 0.4° to 1.3° across all planes for lower limb, pelvis, and trunk kinematics (Moran et al., 2023).

Validity

The most commonly reported statistics were Pearson correlation coefficients, reported in 21 studies (47%), and RMSD, included in 17 studies (36%), supporting their use.

Table 2. Studies assessing the concurrent validity between markerless and marker-based motion capture during single-leg squat and jump-landing tasks.

Author	Participants	Task	Task description	Markerless system method	Validation methods	Joint angles and plane of motion	Statistics and analysis
Schmitz et al. (2015)	*N* = 15 (24 ± 4 years) 7F: 8 M	Squat	Double-leg squat performed to 60° of knee flexion measured with a manual goniometer. The duration was 5 seconds measured with a metronome.	Single camera Kinect (version or model not specified) (depth-sensing camera) Capture rate 30 hz Data processing with Microsoft SDK.	Motion Analysis Corp with 10 cameras Capture rate 200 hz (no interpolation).	Hip and knee in the 3 planes of motion.	Full curve and discrete (peak joint angles) analysis. The average absolute difference for full curve analysis. T-test, Pearson's correlation coefficient, LOA (95% CI) for peak joint angles.
Eltoukhy et al. (2016)	*N* = 10 (22.2 ± 3.4 years) 5F: 5 M	Jump-landing and squat	Double leg drop vertical jump from a 30 cm box with a landing target at a distance equal to 50% of the subject height. Double-leg (overhead squat) and single-leg squat variations. Performed to max depth (duration was NR).	Single camera Kinect v2 (depth-sensing camera) Capture rate NR Data processed with UKinect 1.4 (an in-house custom LabVIEW program).	BTS Bioengineering System with 8 cameras Capture rate 250 hz (interpolation NR).	Hip and knee in sagittal and frontal planes.	Discrete point analysis (peak angle). ICC, LOA, mean difference, Bland Altman plots, and simple linear regression.
Guess et al. (2017)	*N* = 39 (24.6 ± 3.2 years) 20F: 19 M	Jump-landing	Double-leg drop vertical jump from a 31 cm box (distance of landing target NR).	Single camera Kinect v2 sensor (depth-sensing camera) Capture rate 30 hz Data processed with Microsoft SDK.	Vicon System with 8 cameras Capture rate 100 hz (interpolation).	Hip and knee in the sagittal and frontal planes.	Full curve and discrete point (only peak knee and hip flexion) analysis. Full curve Pearson correlation coefficient and RMSD. Discrete analysis mean difference.
Perrott et al. (2017)	*N* = 20 (28.1, range 22–40 years) 10F: 10 M	Squat	Single-leg squat (depth and duration NR).	Multi-camera Fourteen Organic Motion cameras. (video camera) Capture rate 120 hz. Data processed with DARI Vault	Vicon System with 10 cameras Capture rate 100 hz (interpolation NR).	Trunk, pelvis, and knee in the three planes. Hip in the sagittal and frontal planes. Ankle in the sagittal plane.	Discrete variable analysis (change in the angle from the start to max knee flexion and the joint angle at max knee flexion). Pearson correlation coefficient (or Spearman), mean difference, and p-values.
Kotsifaki et al. (2018)	*N* = 34 (26.63 ± 4.23 years) 0F: 20 M	Jump-landing and squat	Single-leg vertical countermovement jump, and modified countermovement jump (double-leg vertical hop and landing on a single leg). Single-leg squat (depth and duration NR).	Multi-camera Two Kinect v2 (depth-sensing camera) Capture rate 30 hz Data processed with iPi software.	BTS Bioengineering System with 13 cameras Capture rate 250 hz (interpolation NR).	Hip, knee, and ankle in the sagittal, frontal, and transverse planes	Discrete point analysis (range of movement of each segment and peak angle). ICC (2, k), SEM, MDC, LOA, and bias using Bland and Altman analysis.

(*Continued*)

Table 2. (Continued).

Author	Participants	Task	Task description	Markerless system method	Validation methods	Joint angles and plane of motion	Statistics and analysis
Mentiplay et al. (2018)	$N = 30$ (23 ± 5 years) 15F: 15 M	Jump-landing and squat	Double-leg drop vertical jump from a 30 cm box (distance of landing target NR). Single-leg squat performed to 60° of knee flexion measured visually. The duration was 4 seconds (not specified how was measured).	Single camera Kinect v2 sensor (depth-sensing camera) Capture rate 30 hz Data processed with a custom written LabVIEW program	Vicon System with 9 cameras Capture rate 100 hz (no interpolation).	Trunk and hip in the sagittal plane. Knee in the sagittal and frontal planes.	Discrete variable analysis (max knee flexion). Pearson's correlation coefficients, concordance correlation coefficients, ICC (2, k), and Bland &Altman plots.
Tipton et al. (2019)	$N = 20$ (30.8 ± years). 6F: 14 M	Jump-landing	Single leg drop landing from a 30 cm box. Double-leg drop jump from a 30 cm box (landing on both feet then pivoting 90° using the test leg to push off to the ipsilateral side). Distance of landing target NR. Single leg hop (direction and distance NR).	Single camera Kinect (version or model not specified) (depth-sensing camera) Capture rate NR Data processed with Brekel Kinect™ software.	Vicon System with 8 cameras Capture rate NR (interpolation NR).	Knee in the sagittal and frontal planes.	Discrete point analysis (peak angle). ICC, mean absolute differences, Bland Altman plots with LOA (95%).
Wochatz et al. (2019)	$N = 21$ (40 ± 14 years) 13F: 8 M	Squat	Double-leg squat performed to 90° of knee flexion (how was measured is NR). Duration of the squat NR.	Single camera Kinect v2 (depth-sensing camera) Capture rate 30 hz Data processed with Microsoft SDK.	Vicon System with 14 cameras Capture rate 500 hz (interpolation NR).	Hip and knee in the sagittal	Discrete variable analysis (at baseline and peak). Pearson's correlation coefficient SEM, and fixed, random, and proportional bias (assessed via Bland&Altman plots and tested with linear regression).
Colombel et al. 2020)	$N = 6$ (32 ± 17 years) 0F: 6 M	Squat	Double-leg deep squat with lateral arm extensions (duration NR).	Single camera Kinect v2 (depth-sensing camera) Capture rate 30 hz Data processed with Microsoft SDK.	Vicon System with 8 cameras Capture rate 100 hz (interpolation NR).	Hip in the 3 planes. Knee in the sagittal plane.	Full curve analysis. Pearson correlation coefficient, RMSD, and SPM.
Ota et al. (2020)	$N = 20$ (26.0 ± 3.4 years) 4F: 16 M	Squat	Double-leg squat performed to maximum depth with a duration of 6 seconds (how duration was measured is NR).	Single camera One digital video camera-equipped tablet (tablet/ iphone) Capture rate 60 hz Data processed with OpenPose.	Vicon System with 8 cameras Capture rate 60 hz.	Trunk, hip, knee, and ankle in the sagittal plane.	Discrete point analysis (peak angles). Linear regression (ML independent variable and Vicon dependent variable), ICC (2,1), and Bland &Altman plots (proportional and fixed bias).
Drazan et al. (2021)	$N = 15$ Age and gender NR	Jump-landing	Double-leg vertical countermovement jump (depth NR).	Multi-camera Two cameras (Sony ICX285, 800 × 600pixels) (video camera) Capture rate 30 hz Data processed with DeepLabCut.	Qualisys System with 15 cameras Capture rate 120 hz (interpolation NR).	Hip, knee, and ankle kinematics in the sagittal plane.	Full curve analysis. RMSE and CMC.

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Table 2. (Continued).

Author	Participants	Task	Task description	Markerless system method	Validation methods	Joint angles and plane of motion	Statistics and analysis
Mauntel et al. (2021)	$N = 20$ (20.50 ± 2.78 years). 10F: 10 M	Jump-landing	Double leg drop vertical jump from a 30 cm box with a landing target at 0.9 m.	Single camera Kinect v2 (depth-sensing camera) Capture rate 30 hz Data processed with PhysiMax software.	Vicon System with 8 cameras Capture rate 200 hz (interpolation NR).	Trunk, hip, and knee in the sagittal and frontal plane.	Discrete variable analysis (IC, max joint angle, and joint displacement from IC to max). ICC (2,1) paired t-test, and Bland & Altman plots.
Haberkamp et al. (2022)	$N = 22$ (16.5 ± 1.2 years) 14F: 8 M	Squat	Single-leg squat to their self-selected maximum depth (duration NR).	Multi-camera Two iPod Touch devices. (tablet/iphone) Capture rate 30 hz Data processed with OpenPose.	Motion Analysis Corp with 12 cameras Capture rate 120 hz (interpolation NR).	Trunk and ankle in the sagittal plane. Hip and knee in the sagittal and frontal plane. Pelvis in the frontal plane.	Full curve and discrete (peak knee flexion angle) analysis. SPM for full curve analysis. Pearson correlation coefficient, average mean difference, LOA, percentage of agreement for discrete point analysis.
Ito et al. (2022)	$N = 3$ (28–39 years) 1F: 2 M	Squat and jump-landing.	Double-leg squat (depth and duration NR). Single-leg forward hop (distance NR).	Multi-camera Eight Sony RX0-II cameras. (video camera) Capture rate 120 hz Data processed with Theia3D v2021.	Vicon System with 8 cameras Capture rate 120 hz.	Kinematics of hip, knee, and ankle in the three planes of motion.	Full curve analysis. Pearson correlation coefficient and mean difference.
Needham et al. (2022)	$N = 15$ (age NR). 8F: 7 M	Jump-landing.	Double-leg countermovement jump (depth NR).	Multi-camera Nine TTL-pulse synchronised machine vision cameras (video cameraa) Capture rate 200 hz Data processed with OpenPose.	Qualisys System with 15 cameras Capture rate 200 hz.	Hip in the 3 planes. Knee and ankle in the sagittal plane.	Full curve analysis. RMSE, bland-Altman analyses, linear fit models.
de Almeida et al. (2023)	$N = 10$ (range 22–55 years) 5F: 5 M	Squat	Double leg squat (depth and duration NR).	Single camera One RGB camera (depth-sensing camera) Capture rate 30 hz Data processed with MOVA3D.	Qualisys System with 7 cameras Capture rate 100 hz (cubic interpolation).	Hip and knee in the sagittal plane.	Full curve and discrete point (max and min values) analysis. For full curve analysis mean value of the difference between systems for all frames. For discrete analysis, Pearson correlation coefficient.
Clemente et al. (2023)	$N = 8$ (range 19–21 years) 7F: 1 M	Squat	Double leg squat (depth and duration NR).	Multi-camera Two Nikon Coolpix A10 camera (video camera) Capture rate 30 hz. Data processed with MediaPipe Pose	Qualisys System with 12 cameras. Capture rate 100 hz (interpolation NR).	Knee in the sagittal plane.	Discrete variable analysis (peak angle and motion amplitudes). Mean Absolute Error, mean absolute Percentage Error, and Pearson correlation.

(*Continued*)

Table 2. (Continued).

Author	Participants	Task	Task description	Markerless system method	Validation methods	Joint angles and plane of motion	Statistics and analysis
Lee et al. (2023)	*N* = 10 (25.4 ± 2.0 years) 0F: 10 M	Squat	Double-leg deep squat (duration NR).	Multi-camera Four RGB cameras (depth-sensing camera) Capture rate 30 hz. Data processed with OpenPose and OpenCV.	Vicon System with 8 cameras Capture rate 100 hz.	Hip and knee in the sagittal plane.	Full curve analysis ICC (3,1), CV (only concurrent).: ICC3,1 (Angle-trajectory validity
Song et al. (2023)	*N* = 10 (21.9 ± 1.9 years). 5F: 5 M	Squat and jump-landing.	Double leg squat (depth and duration NR). Double-leg CMV jump	Multi-camera Eight high-resolution video cameras (video camera) Capture rate 100 hz Data processed with Theia3D v2022.	Motion Analysis Corp with 12 cameras Capture rate 100 hz.	Hip in the 3 planes. Knee and ankle in the sagittal plane.	Full curve analysis. Pearson correlation coefficient and RMSD.

Root mean square difference (RMSD); Intraclass correlation coefficient (ICC); Limits of agreement (LOA); Not reported (NR); Statistical parametric mapping (SPM); Confidence interval (CI); Software Development Kit (SDK); Standard error of measurement (SEM); Minimal detectable change (MDC); Initial contact (IC); coefficient of variation (CV).

Walking

In the sagittal plane, the mean RMSD ranged from 0.5° to 28.6° (Castelli et al., 2015; Haimovich et al., 2021; Horsak et al., 2023; Kanko et al., 2021; Needham et al., 2022; Ruescas-Nicolau et al., 2022; Ong et al., 2017; Sandau et al., 2014; Skals et al., 2017; Song et al., 2023; Xu et al., 2015; Yeung et al., 2021). Regarding the joints, the knee reported the greatest differences (0.5° to 28.6°), followed by the ankle (0.9° to 17.4°), the hip (0.9° to 15.2°), and the pelvis (0.9° to 4.2°). The mean RMSD was lower in the frontal plane, ranging from 0.3° to 8.0° (10 studies). The ankle reported the greatest differences (0.7° to 8.0°), followed by the hip (0.4° to 4.9°), the knee (0.3° to 3.5°), and the pelvis (1.2° to 3.0°). In the transverse plane, the mean RMSD ranged from 0.4° to 13.6° (8 studies). The hip reported the greatest differences (0.4° to 13.6°), followed by the knee (0.4° to 13.2°), the ankle (0.6° to 11.6°), and the pelvis (1.2° to 3.7°). Pearson correlation coefficients for the lower limb, pelvis, and trunk ranged from negligible ($r = -0.30$) to very strong ($r = 0.99$) in the sagittal plane, from weak ($r = 0.14$) to strong ($r = 0.81$) in the frontal plane, and from negligible ($r = -0.63$) to moderate ($r = 0.66$) in the transverse plane (Hu et al., 2024; Ino et al., 2023; Ito et al., 2022; Mentiplay et al., 2015; Skals et al., 2017; Song et al., 2023; Tanaka et al., 2018; Yang & Park, 2024).

Running

In the sagittal plane, the mean RMSD ranged from 0.6° to 13.8° (Kanko et al., 2024; Needham et al., 2022; Ong et al., 2017; Song et al., 2023; Van Hooren et al., 2023). The hip reported the highest differences (0.6° to 13.8°), followed by the knee (0.6° to 10.9°), and the ankle (1.0° to 8.0°). The mean RMSD was lower in the frontal plane, ranging from 0.2° to 7.2° (4 studies). In this plane, the knee reported the highest differences (0.2° to 7.2°), followed by the ankle (0.9° to 6.0°), and the hip (0.3° to 4.5°). Finally, the mean RMSD ranged from 0.5° to 12.8° in the transverse plane (4 studies). The hip reported the highest differences (0.5° to 12.8°), followed by the ankle (0.8° to 8.0°), and the knee (0.5° to 9.4°). Correlations in the frontal plane were the highest, ranging from moderate ($r = 0.61$) to strong ($r = 0.86$) for the lower limb, pelvis, and trunk (Jaén-Carrillo et al., 2023; Macpherson et al., 2016; Song et al., 2023; Young et al., 2023). For the same joints, negligible ($r = 0.02$) to moderate ($r = 0.79$) were found in the transverse plane. In the sagittal plane, correlations ranged from negligible ($r = -0.28$) to very strong ($r = 1.00$) for the lower limb and trunk.

Squats

The mean RMSD was reported in only one study (Song et al., 2023) and ranged from 2.9° to 12.1°. In the sagittal plane, the knee reported the lowest differences (2.9°), followed by the ankle (5.5°), and the hip (12.1°). In the frontal and transverse plane, only the hip was reported with 2.8 and 8.2°, respectively (Song et al., 2023). Correlation coefficients (Clemente et al., 2023; de Almeida et al., 2023; Haberkamp et al., 2022; Ito et al., 2022; Mentiplay et al., 2018; Perrott et al., 2017; Schmitz et al., 2015; Song et al., 2023; Wochatz et al., 2019) ranged from negligible ($r = 0.05$) to very strong ($r = 1.00$) in the sagittal plane, and negligible ($r = 0.00$) to strong ($r = 0.89$) in the frontal plane for the lower limb, pelvis, and trunk. In the transverse plane, ranged from negligible ($r = -0.13$) to strong ($r = 0.79$) for the lower limb.

Landing

In the sagittal plane, the mean RMSD ranged from 1.2° to 12.1° (Drazan et al., 2021; Needham et al., 2022; Song et al., 2023). The hip reported the highest differences (2.0° to 12.1°), followed by the knee (2.7° to 4.4°), and the ankle (1.2° to 5.3°). In the frontal and transverse plane (Needham et al., 2022; Song et al., 2023), the hip was the only joint reported with an RMSD from 2.3° to 11.0°. Correlations in the sagittal plane were the highest, ranging from moderate ($r = 0.51$) to very strong ($r = 1.00$) for the lower limb. In the frontal plane, correlations ranged from weak ($r = 0.28$) to strong ($r = 0.79$), and in the transverse plane, from negligible ($r = 0.09$) to moderate ($r = 0.43$) (Ito et al., 2022; Mentiplay et al., 2018; Song et al., 2023).

Cutting

Only one study assessed cutting (Song et al., 2023). In the sagittal plane, the highest RMSD was found in the hip (13.1°), followed by the knee (5.9°), and ankle (5.7°). The hip was also assessed in the frontal and transverse planes, reporting RMSD of 5.1° and 15.9°, respectively. Correlations in the sagittal plane ranged from moderate ($r = 0.89$) to very strong ($r = 1.0$). Correlations in the frontal plane were strong ($r = 0.79$), and in the transverse plane were weak ($r = 0.60$).

Discussion

This study aimed to review and synthesise the existing literature regarding the reliability and validity of MMC for measuring lower extremities and trunk kinematics during sports-related and functional tasks. The reliability of MMC ranged from low to excellent, with most variables reporting SEM values below 5°, depending on the task, plane of motion, and type of reliability assessed. Validity studies presented high differences between technologies ranging from 0.2° to 28.6° and negligible (including negative values) to very strong correlations, depending on the task, plane of motion, and joints analysed. While MMC provide reliable measurements for most kinematic variables, their results are not generally comparable to those obtained using marker-based motion capture systems.

Markerless technology

One of the most used technologies was depth-sensing cameras (53% of the studies), including the Microsoft Kinect sensor and RGB cameras. In sport-related tasks such as squats and landing this technology was used in approximately 60%. However, depth-sensing cameras have limitations for use in sports biomechanics, such as restricted capture volume, effective only over short range, low framerates (i.e., 30 hz), and inoperability in bright sunlight (Colyer et al., 2018), factors that may impact reliability and validity. In contrast, running tasks were primarily captured using video cameras at higher speeds. Future studies evaluating sports-related tasks such as squats and landing are recommended to use digital video cameras, which offer higher resolution and capture rates (Colyer et al., 2018).

While establishing definitive conclusions about the influence of MMC technology on measurement errors was not possible due to the presence of multiple methodological factors, some trends did emerge. In validity studies, for example, the highest errors were often reported in studies using one or two depth-sensing cameras (e.g., Microsoft Kinect), whereas the lowest errors were commonly observed in studies utilising multiple video cameras (between 2 and 9), despite variations in the software used (see Appendix 3 for more details). In contrast, no clear pattern was observed in reliability studies, which may be attributed to the lower number of studies and additional methodological differences, such as the type of reliability assessed. Although the literature on MMC (Núñez et al., 2017; Ryselis et al., 2020) suggests that multi-camera systems offer superior accuracy and reliability in capturing movement compared to single-camera systems, this review did not find consistent evidence to support that conclusion.

Markerless reliability

For a device or measurement to be considered valid, it must first be reliable (de Vet et al., 2006). In the current study, the relative reliability of MMC for all joints (lower limbs and trunk) ranged from good to excellent for squats and landing irrespective of the plane of motion, with most results presenting a mean ICC higher than 0.90. Additionally, most joints reported absolute reliability values below 5° across all planes of motion. Hip flexion showed the greatest measurement error during these tasks with values ranging between 4.0° to 11.1°, reducing its reliability. These results show that MMC provides low measurement error for most variables when assessing squats and landing tasks, supporting its application in sports settings.

Results for walking showed greater variability, with relative reliability ranging from low (including some negative values) to excellent. Despite this, absolute reliability during walking was lower than 5° for all joints and planes (including hip flexion), providing clinical value (Riazati et al., 2022). Similarly, running reported low SEM values ranging from 0.4° to 1.3° across all planes and joints, including the pelvis and trunk. Overall, between-day analyses showed significantly lower reliability compared to within-session analyses. Within-session reliability captures subject variability, including any systematic noise between trials, whereas between-session variability includes both trial variation and differences between repeated sessions (e.g., variations in gait speed between days, fluctuations due to camera calibration, lighting, and clothing) (Kanko et al., 2021; Moran et al., 2023).

Despite the acceptable reliability obtained in this study, it is important to note that the results for running (in all planes) and for the frontal and transverse planes in the other tasks, such as jump-landing, are based on only one or two studies, making it difficult to draw definitive conclusions. Finally, there is the possibility of bias and overestimation in these results, as none of the studies reported whether raters were blinded to their scores, and it is unclear whether the assessment order varied in most studies. If raters are aware of their previous findings, it may influence the findings of their subsequent measurements and potentially inflate the level of reliability. Additionally, not varying the order of the tests increases the risk of raters recalling the previous test scores. Future research should follow the CAT checklist, with particular emphasis on the neglected criteria, and adhere to the Guidelines for Reporting Reliability and Agreement Studies (Kottner et al., 2011) for reporting purposes.

Table 3. Studies assessing the reliability of markerless motion capture during walking, running and cutting.

Author	Participants	Task	Type of reliability	Task description	Markerless system method	Joint angles and plane of motion	Statistics and analysis
Mentiplay et al. (2015)	$N = 30$ (22.87 ± 5.08 years) 15F: 15 M	Walking	Test-retest reliability (between-day, two sessions with a mean of 7 days apart).	Walking overground at a comfortable and fast speed along an 8-meter walkway.	Single camera Kinect v2 (depth-sensing camera) Capture rate 30 hz Data processing with Microsoft SDK.	Knee in the sagittal and frontal planes. Hip and ankle in the sagittal plane.	Discrete analysis (total range during gait, peak knee angles at the stance, and swing phase). ICC (2,1), Cronbach's alpha, and SEM% of the mean.
Tamura et al. (2020)	$N = 22$ (20.9 ± 0.3 years) 9F: 13 M	Walking	Test-retest reliability (between-day, two sessions 7 days apart).	Walking overground and on a treadmill at 2.0 m/h (3.2 km/h).	Single camera Kinect v2 (depth-sensing camera) Capture rate 30 hz Data processed with Microsoft SDK.	Trunk, hip, and knee joint kinematics in the sagittal plane.	Discrete variable analysis (calculations performed every 10% of the gait cycle of the stance and swing phase). ICC, Pearson correlation coefficient, and MDC.
Kanko et al. (2021)	$N = 8$ (30.5 ± 14.1 years) 2F: 6 M	Walking	Within-session (five trials) and test-retest reliability (between-day, three sessions separated by an average of 8.5 ± 2.0 days).	Walking overground at a comfortable speed.	Multi-camera Eight Sony R×0II cameras (video camera) Capture rate 60 hz Data processed with Theia3D (Version NR).	Hip, knee, and ankle in sagittal, frontal, and transverse plane.	Full curve analysis (gait cycle). Inter-session variability, inter-trial variability, and the ratio between them for curve analysis (based on the SD or variability).
Riazati et al. (2022)	$N = 21$ (37.8 ± 18.8 years) 14F: 7 M	Walking	Test-retest reliability (between-day, two sessions separated by 10 ± 12 days).	Walking overground at a self-selected and fastest comfortable speed.	Multi-camera Eight video cameras (video camera) Capture rate 60 hz Data processed with Theia3D v2021.	Hip, knee, and ankle in the 3 planes.	Full curve (gait cycle) and discrete (initial contact, midstance, and peak angles) analysis. RMSD full curve analysis. SEM for discrete point analysis.
Ino et al. (2023)	$N = 21$ (20.7 ± 1.0 years) 11F: 10 M	Walking	Within-session reliability (three trials).	Walking overground at a comfortable pace along a 10 m walkway.	Single camera One digital video camera (video camera) Capture rate 120 hz Data processed with Open Pose.	Hip, knee, and ankle in the sagittal plane.	Discrete variable analysis (peak angles and angular excursions) ICC (3,1).
Moran et al. (2023)	$N = 21$ (19.5 ± 1.4 years) 14F: 7 M	Running	Within-session and test-retest reliability (between-day, three sessions with at least one day and no more than ten days between visits).	Running on a treadmill at 3 speeds based on individual perception of effort (3, 5, and 7 out of 10 in effort).	Multi-camera Eight Sony R×0II cameras (video camera) Capture rate 120 hz. Data processed Theia3D (version NR).	Trunk, pelvis, hip, knee, and ankle in the sagittal, frontal, and transverse planes.	Full curve and discrete point analysis (IC, toe-off, and peak angles). For full curve analysis inter-session variability, inter-trial variability, and the ratio between them. ICC (3,1), SEM and MDC for discrete variables (intersession 2 v 3).
Hu et al. (2024)	$N = 2$ (age NR) Gender NR	Walking	Within-session reliability (3 trials).	Walking overground to walk at their customary pace along a 3-m-long corridor.	Single camera iPhone 14 smartphone (tablet/iphone) Capture rate 30 hz Data processed: The High-Resolution Network (HRNet) and Graph MLP-Like.	Knee in the sagittal plane.	Discrete point (range of motion) ICC (2,k).

(*Continued*)

Table 3. (Continued).

Author	Participants	Task	Type of reliability	Task description	Markerless system method	Joint angles and plane of motion	Statistics and analysis
Kanko et al. (2024)	N = 30 (23 ± 3.5 years). 15F: 15 M	Running	Within-session reliability (3 trials).	Running on a treadmill at each participant's self-selected speed under two clothing conditions (MoCap and sports).	Multi-camera Eight Qualysis Miqus video cameras (video camera) Capture rate 85 hz Data processed with Theia3D v2022.	Hip, knee, and ankle in the 3 planes of motion.	Full curve analysis (running cycle). Inter-session variability.

Root mean square difference (RMSD); Intraclass correlation coefficient (ICC); Not reported (NR); Software Development Kit (SDK); Standard error of measurement (SEM); Minimal detectable change (MDC); Standard deviation (SD).

Markerless validity

It is more difficult to draw conclusions from validity studies due to the large number of studies (47 in total). Differences between technologies ranged from 0.2° to 28.6°, depending on the task, plane of motion, and joint analysed. Similarly, Pearson correlation coefficients varied from negligible to very strong. Importantly, some negative correlations (mostly weak) were reported across tasks, particularly in the transverse plane. Negative correlations suggest that MMC measures movement in the opposite direction compared to marker-based methods, which could limit its clinical applicability.

Walking reported the largest differences between technologies, probably due to the higher number of studies investigating this task and the diverse methodologies used. Across tasks, the frontal plane reported the smallest differences between technologies (<5°), particularly in the hip. Song et al. (Song et al., 2023) was the only study to report values exceeding 5° for hip adduction during cutting. Bias in validity studies was lower than in reliability studies, with 66% classified as high-quality, increasing confidence in the results. The main source of bias was the lack of detail about the examiners' qualifications or competence. This is important when comparing MMC with marker-based technologies, as experienced evaluators tend to obtain better precision in marker placement and, consequently, more accurate kinematic data (Fonseca et al., 2023).

Clinical application of markerless technology to specific injuries

Understanding the reliability and validity of MMC during sports-related and functional tasks is necessary for identifying injury risk and monitoring athlete rehabilitation (Verhagen et al., 2018). Monitoring changes in performance during high-risk tasks (relative to baseline values) provides valuable insights into injury risks and fatigue-related performance deficits, enabling targeted interventions.

Increased knee abduction and trunk ipsilateral inclination angles during single-leg landing tasks, at initial contact and/or peak values, are associated with future non-contact ACL injuries in elite footballers (Collings et al., 2022; Kolodziej et al., 2022). This review identified that no studies have investigated the reliability and validity of trunk kinematics in the frontal plane during landing tasks. For knee abduction, Mentiplay et al. (Mentiplay et al., 2018) reported excellent reliability with low SEM values (3.6°) during a double-leg drop vertical jump at maximum knee flexion. In contrast, Ito

Table 4. Studies assessing the reliability of markerless motion capture during single-leg squat and jump-landing tasks.

Author	Participants	Task	Type of reliability	Task description	Markerless system method	Joint angles and plane of motion	Statistics and analysis
Schmitz et al. (2015)	$N = 15$ (24 ± 4 years) 7F: 8 M	Squat	Within-session reliability (5 trials).	Double-leg squat performed to 60° of knee flexion measured with a manual goniometer. The duration was 5 seconds measured with a metronome.	Single camera Kinect (version or model not specified) (depth-sensing camera) Capture rate 30 hz Data processing with Microsoft SDK.	Hip and knee in the 3 planes of motion.	Discrete analysis (peak joint angles). ICC (1,k) and MDC.
Mentiplay et al. (2018)	$N = 30$ (23 ± 5 years) 15F: 15 M	Jump-landing and squat	Test-retest reliability (between-day, two sessions with a mean of 7 days apart).	Double-leg drop vertical jump from a 30 cm box (distance of landing target NR). Single-leg squat performed to 60° of knee flexion measured visually. The duration was 4 seconds (not specified how was measured).	Single camera Kinect v2 sensor (depth-sensing camera) Capture rate 30 hz Data processed with a custom written LabVIEW program	Trunk and hip in the sagittal plane. Knee in the sagittal and frontal planes.	Discrete variable analysis (max knee flexion). ICC (2, k) and SEM.
Wochatz et al. (2019)	$N = 21$ (40 ± 14 years) 13F: 8 M	Squat	Between-day reliability (2 sessions with a mean of 7 days apart).	Double-leg squat performed to 90° of knee flexion (how was measured is NR). Duration of the squat NR.	Single camera Kinect v2 (depth-sensing camera) Capture rate 30 hz Data processed with Microsoft SDK.	Hip and knee in the sagittal plane.	Discrete variable analysis (at baseline and peak). SEM and LOA
Ota et al. (2020)	$N = 20$ (26.0 ± 3.4 years) 4F: 16 M	Squat	Within-session reliability (3 trials).	Double-leg squat performed to maximum depth with a duration of 6 seconds (how duration was measured is NR).	Single camera One digital video camera-equipped tablet (tablet/iphone) Capture rate 60 hz Data processed with OpenPose.	Trunk, hip, knee, and ankle in the sagittal plane.	Discrete point analysis (peak angles). ICC (1,3)
Andersen et al. (2023)	$N = 18$ (30.2 ± 0.6 years) 8F: 10 M	Squat	Test-retest reliability. Within-day (session 1 in the morning and 2 in the afternoon) and between-day (sessions 2 and 3 separated by 3 to seven days).	Double-leg squat and overhead squat with and without body armour at maximum depth and to a standardised depth using a plyometric box (45 cm). Duration NR.	Single camera 3D infrared and RGB cameras encased in a single unit (depth-sensing camera) Capture rate 30 hz. Data processed with HumanTrak (VALD, V 2.7.6).	Trunk in the sagittal plane.	Discrete point analysis (peak value). ICC, Pearson correlation coefficients, SEM, and MDC.

(*Continued*)

Table 4. (Continued).

Author	Participants	Task	Type of reliability	Task description	Markerless system method	Joint angles and plane of motion	Statistics and analysis
Lee et al. (2023)	$N = 10$ (25.4 ± 2.0 years)	Squat	Within-session reliability (five trials)	Double-leg deep squat (duration NR).	Multi-camera Four RGB cameras (video camera) Capture rate 30 hz. Data processed with OpenPose and OpenCV.	Hip and knee in the sagittal plane.	Discrete point analysis (phase NR). ICC (3,1), SEM, MDC, and CV.
McCarthy et al. (2023)	$N = 18$ (30.22 ± 0.60 years)	Jump-landing and squat	Test-retest reliability Within-day (session 1 in the morning and 2 in the afternoon with a minimum of 3 hours between each) and between-day reliability (session 2 and 3 with a minimum of 3 days in between),	Single leg drop vertical jump from 45 cm box (landing target placed at a comfortable distance). Double leg squat and overhead squat with fixed (45 cm box) and unrestricted range (maximal depth). Duration NR.	Single camera 3D infrared and RGB cameras encased in a single unit (depth-sensing camera) Capture rate 30 hz. Data processed with HumanTrak (VALD, V 2.7.6).	Hip and knee in the sagittal plane.	Discrete point analysis (peak angle). reliability. ICC (3,1), SEM, MDC, and Person's correlation coefficient.

Root mean square difference (RMSD); Intraclass correlation coefficient (ICC); Not reported (NR); Software Development Kit (SDK); Standard error of measurement (SEM); Minimal detectable change (MDC); Standard deviation (SD); Limits of agreement (LOA); Coefficient of variation (CV).

et al. (Ito et al., 2022) found weak correlations for knee abduction ($r = 0.26$) during a single-leg forward hop (full curve analysis) when compared to marker-based motion capture. Despite the acceptable reliability, discrepancies between systems may limit the use of the MMC as a screening tool for knee abduction. Further research is needed, particularly for single-leg landings, as double-leg landings may not fully represent the biomechanical demands during high-injury risk activities in multidirectional sports (Taylor et al., 2016). IC, the phase where ACL injuries often occur (Villa et al., 2020), should also be prioritised.

Knee disorders such as PFPS and ACLR are associated with increased trunk flexion during single-leg landing and cutting tasks (Waiteman et al., 2022), with ACLR also linked to reduced knee flexion during single-leg landing (Johnston et al., 2018). Mentiplay et al. (Mentiplay et al., 2018) reported good ICC values and an SEM of 2.4° for trunk flexion during double-leg landing, but no validity studies have been reported. Additionally, the reliability and validity of trunk kinematics during cutting have not been investigated. Regarding knee flexion, validity studies showed differences of less than 5° with moderate to very strong correlations during landing (Drazan et al., 2021; Ito et al., 2022; Mentiplay et al., 2018; Needham et al., 2022; Song et al., 2023), with excellent relative reliability and SEM values ranging from 3.8° to 9.3° (McCarthy et al., 2023; Mentiplay et al., 2018). However, all the studies except for Ito et al. (Ito et al., 2022) involved double-leg landing tasks, which may reduce their clinical relevance. Increased hip adduction during landing (initial contact) (De Bleecker et al., 2020) and running (Ceyssens et al., 2019; Vannatta et al., 2020) has also been associated with PFPS in multidirectional sports. The differences between technologies for measuring hip adduction were low, with moderate to strong correlations during both landing (Ito et al., 2022; Song et al., 2023) and running (Song et al., 2023). This finding is clinically relevant and supports the use of this variable in clinical practice. Overall, variables associated with ACL reconstruction (knee flexion) and PFPS (hip adduction) during high risk tasks are both valid and reliable. However, the validity of knee abduction for ACL injury risk and trunk kinematics for both ACL and PFPS is inconclusive due to the limited research.

Limitations

This study presents several strengths and limitations. Among its strengths, it provides reliability and validity results of MMC for a wide range of tasks commonly assessed to identify injury risk and monitor rehabilitation in athletes. Furthermore, it incorporates absolute reliability parameters (expressed in the actual scale of measurement), which enhances its clinical applicability. However, the methodology across the included studies exhibited a high degree of heterogeneity, particularly regarding task characteristics, such as varying speeds for walking or running, and differences in single- vs. double-leg tasks for jumping, landing, and squats. Additionally, the MMC systems used across studies varied in terms of the number and type of technologies for data capture, as well as the software employed for analysis. Therefore, establishing definitive conclusions about the MMC technology used in studies reporting the highest error was challenging, as results may also be affected by other methodological factors. Another limitation was the limited representation of certain tasks, which may affect the generalisation of their results. The reliability of landing and running was examined in a few studies, while cutting was evaluated in one validity study, with no studies assessing its reliability. Furthermore, there was inconsistency in statistical parameters used across studies. Only studies that reported the specified statistics were included in the analysis. As a result, studies using different statistical metrics were excluded from analysis, which could be considered a limitation. However, the parameters were chosen based on literature recommendations and the most commonly reported in this review, and therefore, they are considered representative. Reporting only SEM values for the reliability of MMC may present limitations, as practitioners can be only 68% confident that changes in kinematic variables reflect real change and not measurement error. To achieve 95% confidence, MDC values should be reported, which is considered an extension of SEM. However, due to the limited number of studies (5), this was not possible.

Future research

Future studies should use standardised protocols, assess relevant injury-risk tasks (e.g., single-leg movements relevant to the demands of the sport), include trunk kinematics, and report clinically relevant parameters like SEM and MDC. Additionally, comparisons between MMC methods should be explored to clarify the superiority of one system over another. Regarding validity, since comparisons with the gold standard (bi-planar videoradiography) (Kessler et al., 2019) were not performed, the true accuracy of MMC remains unknown, highlighting the need for future validation studies. Ecological validity of MMC (i.e., real-world data capture) should be prioritised, but caution is needed, as this may compromise internal validity due to the challenge of controlling task performance outside a lab setting. As this study included only healthy individuals, future research should explore MMC reliability and validity in injured populations. Future research should also explore the implementation of machine learning-based error correction methods, which may improve the accuracy and robustness of MMC in complex or real-world environments (Mathis et al., 2020). Additionally, investigating the reliability and validity of multimodal approaches (e.g., MMC with inertial sensors) may be necessary, as these have been proposed to improve accuracy (Shin et al., 2023).

Conclusions

Considerable variability across studies in task characteristics, MMC systems, and statistical analyses employed was observed, affecting comparisons between studies. The reliability of MMC ranged from low to excellent, with most variables showing SEM values below 5°. Validity studies showed differences between technologies ranging from 0.2° to 28.6° and correlations negligible (including negative values) to very strong. Both reliability and validity results depended on the task, plane of motion, and joints analysed, which explains the variability observed. While MMC provide reliable measurements for most kinematic variables, their results are not largely comparable to marker-based motion capture systems. Future studies using more standardised protocols are needed to allow comparison. MMC provides a reliable method which creates opportunities to develop more ecological valid research outside of traditional biomechanical laboratory settings. Moreover, MMC has the potential to democratise access to movement analysis for coaches and athletes, particularly in low-resource environments or contexts where financial and logistical constraints restrict the feasibility of traditional motion capture systems.

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