Quality evaluation of the Theia3D markerless motion capture system for measuring football-specific movements

Mark Bennetts

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Abstract

The evolution of limb-tracking systems in elite football (soccer) has facilitated enhanced player technique analysis, load quantification, injury risk identification, and referee decision-making assistance. Three-dimensional (3D) markerless motion capture systems provide a non-invasive alternative to traditional laboratory-confined 3D marker systems, serving as a feasible tool for assessment of football specific limb kinematics in-game. However, limb-tracking in football has typically focused on officiating support in-game, with the quality of spatiotemporal limb-tracking data captured by markerless motion capture systems for use in training and tactical decision making currently not reported. As such, this study aims to assess the magnitude of difference between the 'gold standard' Vicon motion capture system and a Theia3D markerless motion capture system during football specific movements (i.e., dribbling, kicking, tackling, limb tracking during player-dense phases of play). This builds on previous research by introducing limb kinematics assessment into a football setting, expanding from a traditionally clinical context. This thesis enhances the understanding of markerless motion capture technology in a football specific context to provide guidelines on the integration and use of markerless motion capture systems in elite football environments. Three males and one female, with a mean age of 23 ± 0.7 years, an average height of 179.9 ± 5.7 cm, and a mean weight of 80.1 ± 3.3 kg participated in various football specific movements while being recorded by Theia3D (v2023.1.0.3161) and Vicon (2.15 and 2.13) systems. Acquired movement data was exported as .csv files and run in RStudio v2024.04.2-764 whereby it was cleaned, frame synchronised, aligned, and produced as interpretable data. The Theia3D system produced overall MAE and RMSE values of 0.19 ± 0.06 m and X-axis: 84.8 ± 83.6°, Y-axis: 18.4 ± 15.6°, Z-axis: 42.9 ± 31.6°, respectively. The Theia3D system proved to be effective at analysing isolated movement, with low magnitude of difference between the two systems during shooting, passing, and dribbling. The system produced high magnitude of difference during congested, multi-player trials, with misidentification of players inflating error values, suggesting end-users would most benefit from this technology by applying it to isolated skill assessment for technique analysis, injury identification and prevention, and talent identification, rather than team tactical analysis and officiating assistance in match play. Future research may be directed towards full body analysis, outdoor capture volume, more detailed post-capture filtering, and assessing alternative kinematic metrics (i.e., angular velocity).

Student declaration

I, Mark Bennetts, declare that the Master of Research Practice thesis entitled ‘Quality evaluation of the Theia3D markerless motion capture system for measuring football-specific movements’ is no more than 50,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

I have conducted my research in alignment with the Australian Code for the Responsible Conduct of Research and Victoria University’s Higher Degree by Research Policy and Procedures.

Signature: [redacted] Date: October 31, 2024

Ethics declaration

All research procedures reported in the thesis were approved by the Victoria University Human Research Ethics Committee – HRE24-017.

Signature: [redacted] Date: October 31, 2024

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Abbreviations

2D – Two Dimensional

3D – Three Dimensional

ACL – Anterior Cruciate Ligament

CGI – Computer Generated Image

CI – Confidence Interval

COM – Centre of Mass

DFB – German Football Association

DFL – German Football League

DOF – Degrees of Freedom

EPTS – Electronic Performance and Tracking Systems

FIFA - Fédération Internationale de Football Association

GCVSPL - Generalised Cross-Validatory Spline

GNSS – Global Navigation Satellite System

GPS – Global Positioning System

IFAB – International Football Association Board

LBW – Leg Before Wicket

LED – Light Emitting Diode

LPS – Local Positioning System

MAE - Mean Absolute Error

OCST – Optimum Common Shape Technique

RMSE – Root Mean Square Error

SAOT – Semi Automated Offside Technology

SARA – Symmetrical Axis of Rotation Analysis

SCoRE – Symmetrical Centre of Rotation Estimation

SD – Standard Deviation

VAR – Video Assistant Referee

VOL – Virtual Offside Line

VU – Victoria University

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Chapter 1: Introduction

Three-dimensional (3D) limb-tracking systems are regularly used across a range of sport applications to assess human movement. However, 3D motion capture system use in sporting applications has historically involved the marker-based motion capture systems to provide accurate and reliable assessment measures. However, the invasiveness of applying markers to individuals, and the time consumption of human model reconstruction and analysis have been outlined as key limitations in capture efficiency (Kanko, Laende, Selbie, et al., 2021). Like marker-based 3D motion capture systems, markerless 3D motion capture technology allows the capture of 3D kinematics, but without the need for physical marker placements on individuals and subsequent skeleton reconstruction and calibration for data capture. As such, markerless systems may provide end-users with a more time-efficient and less invasive 3D motion capture system alternative to traditional marker-based systems.

Vicon marker-based motion capture systems are considered the ‘gold standard’ in assessing 3D movement kinematics, as they allow for sub-millimetre accuracy by tracking retro-reflective markers within a 3D capture volume using infrared cameras (Merriaux et al., 2017). Alternatively, markerless motion capture systems utilise optical video cameras, artificial intelligence, and machine learning software to track individuals within a defined 3D capture volume. One such 3D markerless motion capture system is Theia3D markerless motion capture system (Kingston, Canada). Forming in 2018, Theia3D is a machine learning algorithm-based software developed largely for clinical biomechanical assessments (Kanko, Laende, Davis, et al., 2021; Kanko, Laende, Strutzenberger, et al., 2021; Theia Markerless, 2019). The Theia3D algorithm utilises inverse kinematics and rigid body tracking to estimate and produce a 3D skeleton of human subjects within a calibrated test space (Riazati et al., 2022; Theia Markerless, 2019). Previously, Theia3D has been used in clinical settings to assess gait techniques and kinematics, clinical movements, clothing impacts on tracking accuracy, baseball pitching assessment, and boxing kinematics (Dobos et al., 2022; Kanko, Laende, Davis, et al., 2021; Lahkar et al., 2022; Song et al., 2023; Wren et al., 2023). However, to date, previous research using Theia3D has not investigated the accuracy of the system’s ability to track players during football-specific movements. Furthermore, Theia3D offers end-users the ability to track multiple human subjects simultaneously within the capture volume which is ideal for quantifying player kinematics in sporting contexts such as match scenarios. However, previous studies have yet to report the systems accuracy in tracking multiple players within the capture volume.

Markerless motion capture and player tracking technology is regularly used, and easily accessible for most professional football organisations globally. Specifically, since the introduction of player tracking in football in 2015, Fédération Internationale de Football Association (FIFA) has allowed top flight leagues and teams to utilise electronic performance and tracking systems (EPTS) to track player movements within matches for the purposes of match officiation, load management, performance analysis, and fan engagement (Ellens et al., 2022; Robertson et al., 2023). Commonly used EPTS are wearable units, most notably Global Positioning Systems (GPS), Local Positioning Systems (LPS), and Global Navigation Satellite Systems (GNSS), however, the improvements in computer vision has led to an influx in optical tracking systems. These systems offer spatiotemporal data to locate athletes' position and movements relative to the field of play during matches or training. Spatiotemporal data provides insight into important kinematic metrics such as velocity, distance covered, and high-speed running efforts. However, spatiotemporal data does not provide contextual information on the technical movement aspects of player performances such as movement discrepancies that indicate ball possession or fouls. Virtual Offside Line (VOL) is an optical based system that projects a semi-automated offside line onto camera footage to determine if players are offside during a match, with the system also utilising specific player landmarks relative to other players and the goal line. Additionally, Video Assistant Referee (VAR) utilises VOL technology to assist on-field referees with decisions that may be contentious or uncertain. These optical-based technologies aid in match officiating but do not provide information regarding spatiotemporal and kinematic player data for improving performance, injury prevention, or talent identification purposes. The validation and implementation of a 3D tracking system that allows the analysis of players limb and joint kinematics will open many more opportunities for match insights and player performance analytics. For instance, an accurate and reliable 3D markerless system can provide specific joint information that may be decisive in officiating offsides or fouls within a match, which improves officiating quality and maintains fairness and sporting integrity in competition. There is a clear gap in match data regarding player movements, leaving opportunity for investigation into in depth playing data such as joint angles, position, velocities, and accelerations.

Theia3D markerless motion capture system is one system that may provide greater context around football player movements. Theia3D has been predominantly validated in a clinical setting, with few studies assessing the system in a sport specific setting. Furthermore, Theia3D has yet to be validated in a football context (i.e., match scenarios, technique analysis), which may be due to the complex and unpredictable nature of football movements and the variation of capture environments within sport. As such, the aims of this study are to compare the accuracy of the Theia3D markerless motion capture system to the 'gold standard' Vicon marker-based system for the purpose of

1. assessing the capabilities of the Theia3D system to track football-specific movements in isolation (i.e., leg swings, squats, arm swings) and match contexts (i.e., passes, headers, small-sided games, and tackling)
2. to determine specific movement and match scenarios where Theia3D performs best vs poorly to provide system use-case guidelines for football end-users

Chapter 2: Literature review

Research relating to the practical application of limb tracking technology within a football context is limited, with a majority of research pertaining to the assessment of centre of mass (COM) spatiotemporal data of footballers during training or matches (Arjol-Serrano et al., 2021; Ellens et al., 2022; Tierney et al., 2016). Previously, comparing markerless motion capture systems with marker based system in a football specific context has posed challenges, such as the complexity of movements, the systematic and logistical challenges during the early development of markerless systems, and the impracticality of marker-based system utilisation in a 'real world' setting transferrable to football (Palucci Vieira et al., 2022).

As such, Section 2.1 of this literature review outlines the basic concept and physical demands of football. Providing insights on current practices used to officiate and the possibilities for further technology applications. Section 2.2 focus on the types of player tracking systems currently used in football and alternative sports. This section provides information on how established player tracking systems work, and how they are used by teams and officials to effectively track player movements and physical outputs. Following this, Section 2.3 focuses on established and developing limb tracking systems, and their applications in sport. Specifically, this section focuses on how markerless limb tracking systems are being used in sport, including their use-cases such as performance analysis, officiating, injury prevention, load management, and talent identification. Finally, suggestions on how these use-case applications in alternative sports may be applied in a football context, and the current ability of markerless systems to be used in various football scenarios will be explored in Section 2.4.

2.1 Football background

Football (soccer) is often referred to as the world game, with around 265 million people participating in football worldwide (Haugaasen & Jordet, 2012). Football is an invasion game where two teams, consisting of 11 players each attempt to possess and move a ball and score in an opposition net without using their arms. It is classified as a high intensity, intermittent, non-continuous exercise as players typically cover around 10-15 kilometres per game during its allotted 90 minutes plus stoppage time (Ekblom, 1986; Modric et al., 2020). Wide defenders and midfielders are found to travel the furthest overall distance, with attackers and wide defenders also performing the most high-speed movements out of all players on the field

(Griffin et al., 2020; Modric et al., 2020). Resultantly, teams typically implement positional tactics to be organised into various formations to manage players physical abilities, while adhering to coach play style (Arjol-Serrano et al., 2021). Common movement patterns during football matches include various types of kicking, dribbling, tackling, sprinting, and heading. As a result of these movement patterns, impact injuries (i.e., concussions from head contact between players during an aerial challenge) and overexertion injuries (i.e., thigh strains from overexertions when shooting) occur frequently, requiring relevant medical attention, training interventions, and preventative measures (Ekstrand et al., 2011). As such, the ability of player tracking technology to monitor and track players movement patterns is an important tool for football injury prevention stakeholders.

Top flight football leagues are leagues classified as the top level or division in professional sport, either domestically or internationally. Top flight leagues and teams have introduced various technological measures of tracking physical outputs of players to aid in preventing head impact injuries, and musculoskeletal impact and overexertion injuries. Specifically, the introduction of wearable and optical tracking technology has provided opportunities for teams to view players' physical output information with the goal of optimising athlete performance. In game and training wearable technology such as GPS/GNSS, LPS, and accelerometers have largely been used for time-motion analysis, providing contextual information on players tactical positioning and running physical output during matches (Lutz et al., 2020). Official rule changes have been made in recent years to account for optical system technological advancements that assist officials when making key decision during match play. For example, The International Football Association Board (IFAB) introduced goal line technology into law 1.11 of the game in 2012 to assist in accurately verifying when a ball has fully crossed the goal line (International Football Association Board, 2024a). Similarly, EPTS and wearable technologies have been included in laws 4.4 and 5.5 of the game to be used under the organisation of FIFA and overseen by the respective league using this technology (International Football Association Board, 2024b). Both systems aid the referee and officiating staff in making key decisions pertaining to the match. The successful utilisation of wearable technology and optical ball tracking in an officiating context has prompted further investigation of markerless motion capture systems functionality for other use-cases by the football industry during matches and training.

2.2 Electronic performance and tracking systems

Football and other sports have started investing in the use of electronic performance and tracking systems (EPTS) to provide player performance insights, and match officiation assistance. EPTS are typically wearable or video-based systems used for spatiotemporal tracking of COM during matches. Wearable systems may include Global Positioning Systems (GPS), Local Positioning Systems (LPS), Global Navigation Satellite Systems (GNSS), while improvement in computer vision technology have led to more optical tracking systems also emerging as a viable alternative to wearables.

2.2.1 Wearable tracking systems

Global positioning system (GPS) and Global navigation satellite system (GNSS) units are small instruments often worn between the shoulder blades of players during training or matches. The key difference between GPS and GNSS is the satellite system in which they rely on, with GNSS being more compatible in receiving signals from multiple satellite networks, and GPS being a type of GNSS that is limited in its network compatibility (Hegarty & Chatre, 2008). Both types of units pick up radio signals emitted by satellites that orbit the globe. These signals captured by the units are then transferred to the monitoring station where a location of the signals reception are determined and a coordinate position is provide of the GPS/GNSS unit (Rainham et al., 2008). To maximise positional accuracy, several satellite signals, (typically 5 minimum) are received by the GPS/GNSS unit. This ensures unit global positions are discovered with the lowest possibility of error. LPS technology, like GPS, utilise radio frequency emission to wearable units to determine player position (Hasan et al., 2018). However, instead of using global satellites to track player coordinates, mounted stations within a stadium set local coordinates that reflect the layout of the sporting arena (Hoppe et al., 2018). This system allows option for high sample rates and the ability to track players within indoor stadiums without affecting frequency strength, which is a limitation of the GPS and GNSS systems (Serpiello et al., 2018). All wearable systems (i.e., GPS, GNSS, and LPS) provide tracking outputs of a player's COM which can subsequently be used for tactical positioning and athlete fitness training (Modric et al., 2020). Football specific studies have largely utilised wearable technology with the aim of assessing these performance related metrics during training and match play. Wearable technology is often compared with alternative wearables (i.e., GPS vs accelerometers) but have also been compared with marker-based and markerless motion capture systems (Ellens et al., 2022; Makar et al., 2023). For example, 3D markerless motion capture technology performance has been explored in football matches compared to GPS units, however this study's metrics were restricted to COM spatiotemporal data (i.e., velocity, position) (Ellens et al., 2022; Makar et al., 2023). Additionally, GPS units have been used to quantify training loads, providing insight on workload in training, but relying exclusively on velocities, positions, and accelerations (Cummins et al., 2013; Furtado Mesa et al., 2023; Gabbett, 2010; Ravé et al., 2020). These studies assess GPS and optical markerless motion capture systems COM data in a football specific context, unfortunately, the provision of COM data alone does not provide that granular detail on physical performance metrics such as limb positioning, joint angles and movements that provide insight into technical aspects of relevant football skills.

Another wearable technology that has been utilised in the tracking of limb kinematics is accelerometers. Accelerometers are wearable units that measure the of rate of change of velocity at a high frequency, typically used to assess COM agility and limb acceleration during high speed movements (Ward et al., 2005). Accelerometers have largely been used to assess isolated limbs such as legs and arms to capture high speed movements such as kicking and throwing (Boyd et al., 2013; Dinu et al., 2012; Sakata et al., 2023). Accelerometers have been attached to athletes' shanks during Australian football kicking to assess lower leg velocity and acceleration, and determine areas for training focuses regarding kicking effectiveness (Boyd et al., 2013). However, accelerometers, whilst providing contextual info on limb vectors, are limited in providing positional data and visual outputs of the movement (Yang & Hsu, 2010). Furthermore, individuals must wear the device, making it invasive and potentially leading to inhibition of an athletes' natural movement (Verheul et al., 2020). Finally, limitations around the legality of wearing accelerometers during professional football matches also constrain their use during competition environments, as such, football stakeholders may not be able to obtain competition performance data (International Football Association Board, 2024b). Alternatively, advances in the sophistication of optical-based tracking systems can provide full body positional data, joint kinematics (i.e., velocity and angle), and automation of specific movement detection not currently viable with accelerometers alone.

2.2.2 Optical tracking systems

Optical tracking systems provide a non-invasive alternative for player tracking that allows more granular details on limb tracking in combination with COM without the need for devices placement on players (Rico-González et al., 2020). Optical tracking systems can use single or multiple camera setups to capture distinctive visual cues from individuals, allowing the systems to track their movements in a pre-defined two-dimensional (2D) and 3D space (Colyer et al., 2018). Optical cameras are generally mounted in a stationary position, and may utilise various wavelengths of light such as natural, artificial, or infrared light to track moving images (Sherman & Craig, 2003, 2018). Optical tracking has evolved to accurately track human movements beyond COM locational tracking to now include isolated limb movements, and full-body tracking which is becoming more universally available to the sport industry.

2.2.3 Quality assessment of optical tracking systems in football

Player tracking technology in football has continuously evolved since the early 2000s (Mazzeo et al., 2008), with the in-match technology being limited to the assessment of spatiotemporal metrics of performance through tracking COM position and velocities (Rampinini et al., 2007; Schmid & Lames, 2023). In recent years, tracking technologies introduced into the rules of the game have included Virtual Offside Line (VOL), Virtual Assistant Referee (VAR), both of which utilise broadcast footage, and EPTS. VOL utilises optical markerless motion capture to determine player limb position to create a virtual offside line at the furthest point of the relevant attacker and defender. The German Football League (DFL) and German Football Association (DFB) led the trials and implementation of VOL into professional match play during the 2017/18 season of DFL, and found initial uses of this technology to be problematic due to insufficient camera angles (Kolbinger, 2019). After further developments of the system, accuracy improved, and the system became a permanent aspect of the officiating process from the 2018/19 season across the majority of the top football leagues in the world (Kolbinger, 2019). Further research and development of this technology reported acceptable metric capture from various recording positions (Dunn & Allen, 2020). However, a limitation in the study included the static positioning of participants on the field, thus not providing insight into the dynamic nature of players movements during match play.

Another technology implemented to assist football officiating is the VAR system. VAR technology is a process that utilises a combination of VOL and broadcast footage to provide the best insight into ball/player limb positions during a specific play requiring technology assistance in refereeing decision making, thus decreasing on field umpire biases (Holder et al., 2022). VAR has faced criticism over its implementation, as referee decisions in the past, regardless of accuracy, added more excitement to the game. The reduction of referee mistakes and time taken to review decisions poses arguments that it removes emotion from the match (Tamir & Bar-eli, 2021). It remains in the sport however, as the ultimate system goal is to reduce decision error and support referees during decisive moments in a match competition (Zhang et al., 2022). VAR intervention was found to improve decision accuracy from 92.1% to 98.3 across 13 national leagues (Spitz et al., 2021), in addition to an increase in decision making accuracy from 95.6% to 99.35% during the 2018 Men's FIFA World Cup (FIFA, 2018). Whilst these player tracking systems have improved the player-specific spatiotemporal data outputs and officiating decision-making process in-match, it has not provided further limb tracking kinematic insights for in depth analysis in player performance for broader use cases such as training and load monitoring, talent identification, injury and concussion risks, improving technology provider systems, or broadcast and fan engagement outputs. As such, evaluating instances in which 3D markerless motion capture systems perform well or poorly in football specific match situations may provide insight into whether markerless technology can be adapted for different football purposes beyond what was initially intended for these optical systems.

2.2.4 3D limb-tracking

Motion capture systems have evolved into useful tools with the ability to optimise human performance and development, identify injuries and musculoskeletal health risks, and assist in occupational functions such as assisting in clinical rehabilitation, movement tracking, and computer generated imagery for entertainment industries (Ceseracciu et al., 2014; Merriaux et al., 2017). The evolution and technological advancement of motion capture systems led to a demand for marker-based motion capture in clinical settings for as a tool for the treatment, diagnosis, and physical therapy assistance (Colyer et al., 2018). As such, motion capture technology has become a valuable tool within the sporting industry across a wide variety of use-cases.

2.2.4.1 3D marker-based motion capture systems

Marker-based technology historically utilises cameras that track markers attached to human movement landmarks of interest. The ‘gold standard’ for 3D marker-based system is the Vicon (Oxford, UK) 3D motion capture system which is considered the ‘gold standard’ of accuracy (<0.3 millimetre (mm) error) in 3D tracking, and is a valuable tool in clinical and sport performance settings (Ceseracciu et al., 2014; Merriaux et al., 2017). The Vicon system consists of infrared cameras and retro-reflective markers that reflect infrared light back to the camera, allowing 3D position tracking of markers within a capture volume (Colyer et al., 2018). Vicon capture volumes are typically used for their ability to provide accurate results within a closed, indoor space without external variables hindering capture quality, such as sunlight or environmental noise (Robertson et al., 2023). However, the use of 3D marker-based motion capture in sporting environments possesses limitations such as the length of time for setting up captures and markers, cost of data collection, processing, and interpretations, and invasiveness of marker placements on individuals (Mündermann et al., 2006). For instance, professional football players may have a reduced warm up prior to matches due to extra time attaching markers to their body, along with markers affecting athletes’ ability to complete effective sport specific skills. (i.e., kicking while a marker is on the foot) (Song et al., 2023). The availability of 3D markerless motion capture allows athletes to prepare and perform freely without markers, while still capturing valuable technical and performance data for the system end-users.

2.2.4.2 3D markerless motion capture systems

Markerless systems provide the capability to capture 3D data without the requirement of invasive athlete preparation, confinement to a lab, setup and player processing time, and limitations on scalability (i.e., tracking additional athletes during a session). Furthermore, the absence of markers removes the need for perishables such as tape and markers, making the system a more cost-effective and sustainable option for end-users (Mathis et al., 2018). As markerless motion capture systems have increased, various validation studies against ‘gold standard’ Vicon marker-based systems have been conducted using common human movements including walking, squats, jumping, jogging (Rosenhahn et al., 2007; Song et al., 2023). One specific system is the Theia3D markerless motion capture system, which uses artificial intelligence to identify human landmarks and track subsequent movements. Unfortunately, many of these studies were conducted within a clinical or closed laboratory setting and do not provide insight into the system's ability to capture human movements in more complex sporting scenarios such as high intensity movements and congested play areas with multiple humans in a close proximity (Ceseracciu et al., 2014; Ito et al., 2022; Kanko, Laende, Davis, et al., 2021). While markerless motion capture systems like Theia3D show promise, further validation in complex, high-intensity sports settings are needed to fully understand their capabilities outside controlled environments.

Several studies have assessed the accuracy and reliability of markerless systems through kinematic gait analysis in a clinical context, utilising the Theia3D system (Kanko, Laende, Strutzenberger, et al., 2021; McGuirk et al., 2022; Riazati et al., 2022). Specifically, joint kinematics such as joint angle and point position and were found to be important metrics for gait analysis and evaluating the margin of error when compared to marker-based systems (Kanko, Laende, Selbie, et al., 2021; Kanko, Laende, Davis, et al., 2021). Clinical gait studies encourage the use of markerless technology in clinical spaces for the use of rehabilitation and medical diagnosis assistance. Despite their value, these clinical studies lack the diversity of sport-specific movement patterns. To overcome this, in addition to gait analysis, clinical studies have explored the performance of the Theia3D markerless system to track basic anatomical movements such as squatting, hopping, and jogging (Ito et al., 2022). Limited studies involving complex movements such as throwing, kicking, or high speed running have been examined, with a cut and run the closest football-specific movement as it provides changes in direction in multiple planes of movement as well as being a higher speed movement (Song et al., 2023). This movement resulted in the lowest agreement between markerless and marker- based systems with differences as high as 15.9° in hip angle (Song et al., 2023). Whilst these studies provide insight into Theia3D's ability to capture a variety of common human movements, the system's ability to track more complex sport-specific, and football-specific movements is inconclusive. Furthermore, clinical study results may be skewed as rehabilitation patients may possess health factors or anatomical deformities affecting limb identification from the markerless systems (Tang et al., 2022; Wade et al., 2022). As such, it is important to evaluate the Theia3D system in a sport-specific context to ensure the markerless system is capable for capturing sport-specific data, as erroneous as erroneous data can potentially lead poor or risky athlete performance management decisions made by the end- users.

2.3 Applications of markerless motion capture systems in sport

While football is yet to fully embrace the potential that markerless motion capture systems provide in sport, other sports have begun to utilise markerless technology for the purposes of performance analysis, match officiation, injury prevention, load management, and talent identification. Sports with less environmental hinderances (i.e., baseball, athletics) lead the way with assessing markerless technology, providing clear analysis of individual athlete performances in their respective sports, showing the ability for markerless technology to be useful tool that can benefit technical and physical improvements for athletes.

2.3.1 Performance analysis

Markerless motion capture technology has shown increasing potential for performance analysis in sports, allowing for in-depth assessment of movement without the need for physical markers. Importantly, a few sports have already embraced the use of these systems for analysing athlete performance. Specifically, tennis serving performance has been assessed to determine differences in body movements during kick, slice, and flat serves (Abrams et al., 2014). A comparison showed that kick serves produced more demanding posterior shoulder movement, while flat serves had much higher maximum shoulder internal rotation velocity compared to slice serves (Abrams et al., 2014; Sheets et al., 2011). Alternatively, performance analysis in tennis can focus on tracking racquet position rather than solely assessing joint angles and positions. This approach, though requiring further development and integration, could provide valuable insights into swing movements influenced by racquet grip and player technique. Previous studies have demonstrated high precision in racquet tracking, achieving spatial accuracy of 1.96 ± 0.14 mm and less than 0.1% error relative to the image length used for coding (Elliott et al., 2018). Other racquet sports, such as badminton, have used video footage with computer algorithms to track player positions on the court, although this largely focuses on positional data rather than limb kinematics (Weeratunga et al., 2017). While such analyses capture player position tactics and movement trajectories, they are yet to assess metrics such as joint velocity, position or angles during lower body movement patterns.

Athletic sprinting has also been assessed using markerless motion capture systems, with COM and joint velocity errors of 0.197 ± 1.549 metres per second (m/s) for unconventional sprint poses (Needham et al., 2021). Furthermore, track and field sports have also explored markerless technology using footage from the 2017 World Athletics Championship to reconstruct 3D coordinates of athletes' using a basic OpenPose setup hip, knee, and ankle angles in the long jump (Cronin et al., 2024). This analysis showed limited accuracy with a low intraclass correlation coefficient of 0.17, which may be due to a two-camera setup (Cronin et al., 2024). A two-camera setup may yield poorer results as there are insufficient cameras angles to effectively determine a location in a given space, increasing a margin for error during camera calibration. While the agreement was low in this use-case, it demonstrates that a more comprehensive setup can provide joint angles, and aid in analysis as to what athletes must work on in training (i.e., greater knee flexion at take-off to create a greater reaction force). As such, increased number of cameras used in a system setup could enhance the accuracy and reliability of optical-based systems. These studies demonstrate the viability of markerless motion capture systems use for sport performance analysis. However, the lack of application in football requires further research to evaluate its effectiveness in capturing complex, football-specific movements.

2.3.2 Officiating

Officiating technology plays a role in many sports where enforcing rules to uphold fairness and integrity is fundamental, particularly at the elite level. Optical tracking technologies like VAR and VOL systems have already been introduced in football to assist referees in making accurate decisions, particularly when the speed of play or the positioning of referees and players may limit their view. As such the evolution of markerless motion capture technology has the potential to further enhance the accuracy and speed of officiating technology by providing detailed limb kinematic data (Tamir & Bar-eli, 2021). Access to real-time insights on player movements could allow football officials to detect subtle but significant contacts between players, or between player limbs and the ball, allowing more precise calling of handballs and fouls. In rugby, markerless motion capture technology (OpenPose) has been used to detect illegal tackles, achieving a decision accuracy of 62.5% (Martin et al., 2021). This level of agreement is low for an automated tracking system, possibly due to the complexity of tackling movements, with multiple bodies in contact causing difficulty among the tracking system. In professional powerlifting, markerless motion capture achieved an 85% accuracy rate in identifying correct lifts and 95% for incorrect lifts, using joint kinematics to determine whether movements met required standards (Michalopoulos et al., 2019). The integration of officiating systems to aid referees may ensure competition fairness and player safety by accurately identifying dangerous or illegal plays and movements (Martin et al., 2021).

Additionally, technologies that track objects rather than individuals have also reduced subjectivity in sports officiating. In cricket and tennis, ball-tracking systems such as Hawk-Eye and LBW (Leg Before Wicket) technologies are used to verify line calls and assess dismissals, respectively (Collins & Evans, 2012; Mecheri et al., 2016). Initially, these systems supplemented umpire decisions, only activated when a player challenges a call, preserving the authority of human officials (Jayalath, 2021). However, Hawk-Eye's accuracy has led to its full integration, replacing human line judges in major tennis tournaments. Unfortunately, the use case for markerless motion capture technology is yet to be applied in football officiating, despite movement detection automation being explored in other sports.

2.3.3 Injury prevention

In elite sports, injury prevention remains a key challenge, as performance demands continually push athlete capabilities. Proper monitoring is essential to maintain athletes' health and performance. For example, martial arts have incorporated hybrid mixed reality and markerless motion capture systems for rehabilitation. These systems track joint segments in real time while overlaying skeletal data on augmented reality displays to guide recovery exercises, such as karate stances and techniques (Franzò et al., 2023). In basketball, a markerless system was evaluated as a tool to assess ACL injury risk among Norwegian female players, identifying those at high risk for knee instability, allowing for tailored interventions to strengthen knee stability (Moen, 2014). As such, markerless motion capture's integration into medical assessments could enable medical staff to access and analyse kinematic data to monitor injury recovery and rehabilitation progress. This proactive monitoring could allow for early intervention, reducing the impact of regular training on injury progression (Verheul et al., 2020). Furthermore, tracking kinematics throughout training provides insight into athlete progression by quantifying joint positions, angles, velocities, and accelerations. Yet, little research has focused on markerless motion capture for injury prevention in football, highlighting an opportunity to investigate this technology's potential for injury prevention and identification within the sport.

Markerless motion capture research has traditionally focused on clinical applications for assessing limb kinematics. While sport specific validation studies between markerless and marker-based systems exist, many are limited in their focus of full body kinematics in sport-specific contexts transferable to football. Markerless motion capture technology can benefit injury identification and prevention in sport by assessing technical performance, identifying abnormal movement patterns, and potential early diagnosing of injuries early by using movement data acquired (Ortiz-Padilla et al., 2022; Rossi et al., 2018). In baseball, pitching and batting are notable areas of injury risk (Dobos et al., 2023; Fleisig et al., 2022; Fortenbaugh et al., 2009; Sonnenfeld et al., 2021). Previous video analyses identified fatigue-related injury trends in baseball pitching, especially with fastball pitches, with recent developments in markerless motion capture now enabling full-body pitching kinematic analysis (Fleisig et al., 2022; Fortenbaugh et al., 2009; Trasolini et al., 2022). Furthermore, markerless motion capture technology has observed lower pelvic rotation as a potential injury risk among pitchers, which previously could not be observed via traditional movement analyses (Sakata et al., 2023). Additionally, markerless motion capture has been applied to assess injury prevalence among batters, where explosive swings contribute to lower body, spine, and core injuries, which comprise 43% of injuries in the league (Posner et al., 2011). Recent studies of "throwing" athletes show positional discrepancies ranging from 1.1 – 2.4 centimetres (cm) among upper limb joints between markerless and marker- based systems, demonstrating the system’s accuracy (Trasolini et al., 2022). However further validation to ensure reliable implementation for lower body measures is required. Additionally, markerless motion capture has also been applied in tennis to monitor injury risks in serves, assessing both full-body and upper-body kinematics (Abrams et al., 2014; Abrams et al., 2011). Both baseball and tennis feature isolated, repetitive movements that allow effective capture without excessive external interference. However, these movements differ significantly from the complex, variable movements observed in football, limiting the direct applicability of findings across these sports.

2.3.4 Load management

Markerless motion capture technology has had limited application in football for tracking beyond spatiotemporal data but has the potential to enhance player load management. This technology can provide detailed physical and joint-specific data, giving training staff valuable insights to tailor load management and optimize training and match preparation (Drazan et al., 2021; Mündermann et al., 2006; Verheul et al., 2020). Markerless motion capture technology has shown promise for accurately recording high-speed movements and reconstructing athlete techniques across sports like baseball and javelin (El-Sallam et al., 2013). In baseball, shoulder rotation speeds exceeding 10,000°/s have been recorded, with effective momentum transfer traced from foot to shoulder (Gustafson et al., 2022). Validation studies in shoulder and trunk motion have demonstrated markerless systems' potential to serve as viable alternatives to traditional marker-based methods, although challenges like increased variability remain (Dobos et al., 2022; Fleisig et al., 2022). Specific baseball studies using a nine-camera setup for pitcher analysis have shown that while markerless systems provide comparable joint angle measurements, they often have higher variability than marker-based systems (Fleisig et al., 2022). However, differences can be considered minor with shoulder external rotation confidence interval measuring 1.5° (Fleisig et al., 2022). Markerless technology has also been employed to evaluate the effectiveness of baseball training drills by quantifying joint angles under different constraints, allowing for personalised technique adjustments and load management (Dobos et al., 2023). Similarly, javelin throw research has utilised markerless systems to estimate COM approach velocity, with results closely aligning with those of marker-based systems with a maximum difference of 0.09 m/s (Köykkä et al., 2022). Though these examples are not applied in football, they demonstrate the potential of markerless motion capture systems to enhance player load management by providing detailed joint and physical data, confirming the successful integration of this technology for load quantification that are comparable to traditional marker-based methods.

Research remains limited in assessing lower-body-dominant sports, however track and field events, such as high jump and long jump, have applied pose estimation models and deep-learning algorithms embedded in markerless motion capture systems to analyse athlete movements and inform technical improvement (Goldacre, 2023; Gong et al., 2023). While these pose estimation models lack the comprehensive accuracy of markerless systems, they provide valuable data for simple movements. Additionally, sports like boxing have explored markerless capture with Theia3D, achieving full-body overlays to capture upper body joint centres, angles, and velocities (Lahkar et al., 2022). These studies have shown median differences of 2.5 cm at the shoulder and wrist, and an RMSD in joint velocity of 0.17 m/s (Lahkar et al., 2022). Unfortunately, once again these applications focus primarily on upper-body kinematics, leaving opportunities for further exploration of lower-body motion capture in other sports. Martial arts training has also begun integrating low-cost, 3D pose estimation from 2D images, although depth limitations restrict the accuracy compared to full 3D markerless systems (Le, 2020). As such, markerless technology has demonstrated its utility across multiple sports, however its application in football for load management remains unexplored.

2.3.5 Talent identification

Using markerless motion capture to identify youth prospects beyond conventional statistics could improve scouting accuracy for football academies, youth programs, and professional athlete selection. While some sports have integrated sophisticated analysis methods for identifying young talent, markerless technology currently remains underutilised. In football current talent identification data largely utilises vision-based analysis and physical performance algorithms to support decision-making in evaluating talented players (Jauhiainen et al., 2019; Palucci Vieira et al., 2022; Waldron & Worsfold, 2010). In American football, scouting below the college level is similarly vision-based, but the analysis becomes more advanced once players enter college programs, where more resources become available. Statistical data and game footage are critical in predicting NFL success, particularly for certain positions (Gallagher, 2019). For instance, team staff looking to draft explosive players, may initially view draft combine metrics such as vertical jump and 40-yard dash. By adding markerless technology to the 40-yard dash not only shows their current ability, but staff may assess their current running technique and determine their potential for improvement by using metrics such as joint angles, stride lengths, and limb position. Boxing is another sport exploring motion capture technology for talent assessment by wearable tech using the Vicon marker-based system (Lahkar et al., 2022). This study has provided quantitative insights into punch metrics like force, velocity, and acceleration (Menzel & Potthast, 2021). This emerging technology within boxing can help coaches and performance centres assist in boxing technique correction, but it can ultimately identify the potential of emerging athletes in the boxing space regarding performance of boxing strokes including limb acceleration, arm joint angles during strike attempts, and body shape during defense periods, particularly aspects of boxing that can be improved with age, such as strike technique after growth spurts and muscle growth (Menzel & Potthast, 2021). Therefore, integrating existing analytical tools with 3D markerless motion capture systems may provide a more comprehensive analysis of football talent. This in turn may allow an increased confidence in player recruitment for selectors and provide deeper insights into playing styles of athletes (Jauhiainen et al., 2019). Markerless motion tracking systems, though primarily used in sport for injury identification and training load quantification, have the potential to be used for talent identification applications in elite sport, particularly for scouting youth talent or assessing trade options.

2.4 Markerless limb-tracking in football

Validation studies directly comparing marker-based and markerless limb kinematic analysis within a football context are limited. However, in football, EPTS are used to track limb spatiotemporal data using semi-automated offside technology (SAOT) to assist officiating decisions (Mitu et al., 2022). Evaluations of SAOT performance was assessed as an assistance tool for referees in 138 instances across 33 European FIFA tournaments in the 2016 season. This study found decision accuracy of SAOT to be 93.33% when determining offside situations, with the system utilising only positional data (Siratanita et al., 2017). A further study has examined both dominant and non-dominant leg kinematics in football using optical limb tracking motion capture systems in comparison to marker-based systems (Palucci Vieira et al., 2022). Specifically, this study assessed the accuracy of joint positions and joint velocities recorded via a markerless motion capture systems during football shooting drills on a training pitch, noting a mean absolute error of 3.49 cm and range of 2.78 cm to 4.13 cm, determining joint positions among the hip, knee, ankle, and foot COM (Palucci Vieira et al., 2022). While valuable in its capture of shooting movements in its relation to match scenario, this analysis did not capture joint angles or assess upper-body motion, highlighting the need for expanded data collection on limb velocities and accelerations to better capture the complexities of football-specific movement beyond basic positional tracking.

Markerless motion capture systems have shown promising results in other sports, capturing both technical performance and physical outputs such as load management and injury risk. However, previous research has yet to provide comprehensive lower-body kinematics during high-intensity movements. Existing studies have focused on either on lower-body joint kinematics or full-body motion during low-intensity, clinical movements (Kanko, Laende, Davis, et al., 2021; Song et al., 2023; Wade et al., 2022; Wren et al., 2023). Unfortunately, the findings of these studies are not translatable to complex football-specific movements. This study will evaluate the capability of markerless motion capture systems to measure joint positions and angles of key lower body joints during high-speed, football-specific movements such as kicking, and match simulation (i.e., small-sided games). Understanding where these systems excel and where limitations exist is crucial for end-users as inaccurate data can impact coaching decision, hinder athlete development and performance, and reinforce incorrect technique. As such, this study will expand on previous markerless motion capture research through its detailed application in a football-specific context, ensuring valuable insights to end-users and providers of this technology.

Chapter 3: Aims

3.1 Benefits of markerless technology

Motion capture technology within football is typically used for basic limb kinematics for referee officiating, and player tracking metrics such as distance covered and velocity during matches (Ellens et al., 2022). Previous studies have addressed markerless motion capture technology validations by comparing it with marker-based motion capture during basic human movements such as gait analysis, jumps, and squats in a clinical setting (Kanko, Laende, Davis, et al., 2021; Wren et al., 2023). Understanding the football context in which markerless motion capture systems perform well and poorly has yet to be investigated. To address this, the Theia3D markerless motion capture system will be compared against a Vicon 3D motion capture system during football specific movements and game scenarios (i.e., kicking, passing, sprinting, heading, tackling, high vs low player density) for the purpose of classifying movement scenarios into level of tracking performance of lower limb segments. These movements have been selected to provide insight into key football-specific movements that can benefit teams (i.e., load management, performance analysis), markerless tracking system providers (i.e., classification of movements that provide good vs poor tracking quality), automated officiating (i.e., foot contacts for corner kicks, complex set calls), and broadcasters (i.e, live 3D player position reconstruction, fan engagements/interactions/ platforms utilising limb tracking data). As such, this research will investigate a markerless motion capture system for use in a football context by setting the following research aims and questions.

3.2 Aims and research questions

The key aim for this thesis was to investigate the magnitude of difference between the ‘gold standard’ Vicon motion capture system and the Theia3D markerless motion capture system, when capturing lower limb segments during football specific movements.

Specific aims focus on the context in which Theia3D performs best when compared to the Vicon motion capture system.

1. Classify movement patterns into levels of limb tracking accuracy compared to the Vicon system, based on capture quality of the Theia3D markerless motion capture system.

2. Provide guidelines for Theia3D end-users on specific football movements the system can confidently capture.

These aims provided a base for the key research questions to be proposed by this study.

Research Question: What is the magnitude of difference between the Theia3D markerless motion capture system and Vicon ‘gold standard’ marker-based 3D motion capture system during football specific movement patterns.

Specific research questions:

1. Which football-specific movement patterns, lower limb segments, and game situations are contributing to decreased accuracy in the Theia3D markerless motion capture system?
2. Can this research provide specific use-cases whereby markerless motion capture metrics should be used cautiously, or can be used confidently in football specific decision-making by practitioners (i.e., training or officiating)?

Chapter 4: Methods

4.1 Ethics approval

Prior to data capture, this study was approved by the Victoria University Human Research Ethics Committee – HRE24-017. Furthermore, prior to participation, players were provided with details of the study and agreed to participate via signing an informed consent form, a physical risk assessment form, and a biomechanics laboratory safety induction form, ensuring they did not possess any medical conditions that risks their health throughout the study or put other players at risk within the biomechanics laboratory.

4.2 Subjects

Four healthy, recreational players were recruited to participate in the experimental trials. Players consisted of three males and one female, with a mean age of 23 years, mean height of 179.9 cm ± 5.7, and mean weight of 80.1kg ± 3.3. Each player was fitted with a Vicon Velcro suit, which were further adapted to players body shape via Velcro straps. Vicon retro-reflective markers were applied to specific anatomical landmarks of interest according to the Vicon's Plug-in Gait model (Figure 2) (Vicon, 2021). To ensure data capture of joint and limb segments, rigid body clusters were attached to the thigh and shank segments of each player. The addition of rigid body clusters to the Plug-in Gait model allows for targeted limb segment tracking by modelling the thigh and shank segments via Vicon's Optimum Common Shape Technique (OCST). Subsequent joint centres are then modelled between OCST segments to produce Symmetrical Centre of Rotation Estimation (SCoRE) and Symmetrical Axis of Rotation Analysis (SARA) joint values. Medial wrist and hand markers (Figure 4) were omitted from the Plug-in Gait model as they were considered outside the scope of this study.

To simulate realistic conditions optical limb-tracking systems encounter during football matches, players wore numbered football shirts over their Vicon suits. The shirts were included to resemble the type of clothing worn during competitive play and to provide an element of differentiation between multiple players within the Theia3D capture volume. Holes were strategically cut into the football shirts to accommodate the Vicon markers, allowing them to remain visible to the Vicon cameras. This setup was necessary for assessing Theia3D's capability to accurately track movements in scenarios where players are clothed in a manner similar to match play, thereby testing the system's robustness in more applied settings (Figure 3).

4.3 Pilot study and trial space

A pilot study was conducted to ensure the Theia3D system was a plausible optical system for use in this study. The insights from this study provided understanding on the systems optimal installation, including any capture adjustments, ensuring it met the requirements of procedures the main study. The pilot study served as a crucial preparatory step to refine the methodology and initially acclimatise with the Theia3D system and its setup and capturing process.

4.3.1 Theia3D system

The Theia3D system consisted of ten Optitrack Prime Colour FS cameras with 6.8mm F#1.6C mounted lens and four (light emitting diode) LED strobe lights. Cameras were connected with a live feed to the biomechanics computer built with the specifications to effectively run Motive (v2.3.7), a video analysis software developed by Optitrack (Corvallis, USA), to then import footage into Theia3D (v2023.1.0.3161). The Theia3D system auto detected 124 landmarks on the human body, which included limb segments and joint centres during functional movements (i.e., squats, leg swings). All footage was captured through Motive (Corvallis, USA) and exported into relevant folders for skeleton construction and analysis in Theia3D.

4.3.2 Lens calibration

Prior to installing the cameras around the capture volume, a Theia3D lens calibration was completed to determine camera lens parameters and to remove any distortion within the lenses. Lens distortion can cause deformations in a captured image because of light deviations as it passes through a camera lens (Rossi et al., 2015). As such, lens calibration was conducted to minimise any potential systematic or random errors in the capture. All cameras were placed on a desk side by side and in the same orientation as each other. Camera resolutions were set to 1080 pixels (p) and 35 hertz (Hz) as these were suggested as initial camera calibration settings. An increase in sample rate was also investigated during the pilot study to determine a higher sampling rate viability for the main trial. The lens calibration was then undertaken using a custom Theia3D calibration chessboard. The chessboard was held at a distance from the cameras where one quarter of the cameras could capture the board simultaneously. Following this, cameras recorded the board as it moved through the field of view of all cameras. The Theia3D chessboard, designed and built by Theia3D, measured 0.92 m by 0.59 m. Specifically, the chessboard features alternating black and white squares, each measuring 0.10 m x 0.10 m. To define capture volume origin during calibration, the chessboard utilises two dark blue squares in the top left-hand corner of the board (Figure 1). The chessboard was angled in multiple planes (i.e., horizontal, vertical, diagonal) to provide depth perception of the cameras whilst maintaining one quarter coverage of camera views. The recording was stopped after adequate capture of the chessboard and the calibration was completed on the Theia3D system in accordance with Theia3D's calibration instructions (Theia Markerless 2024).

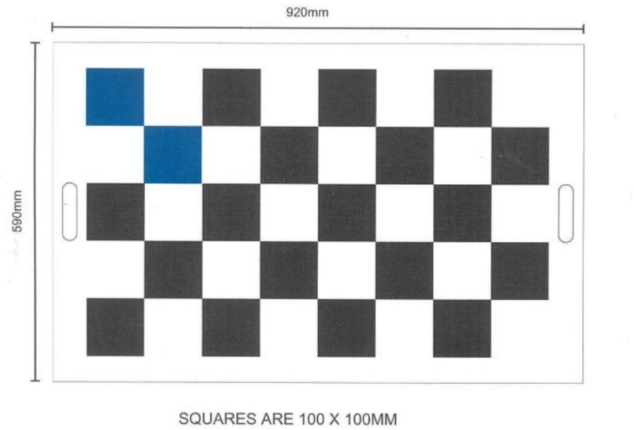
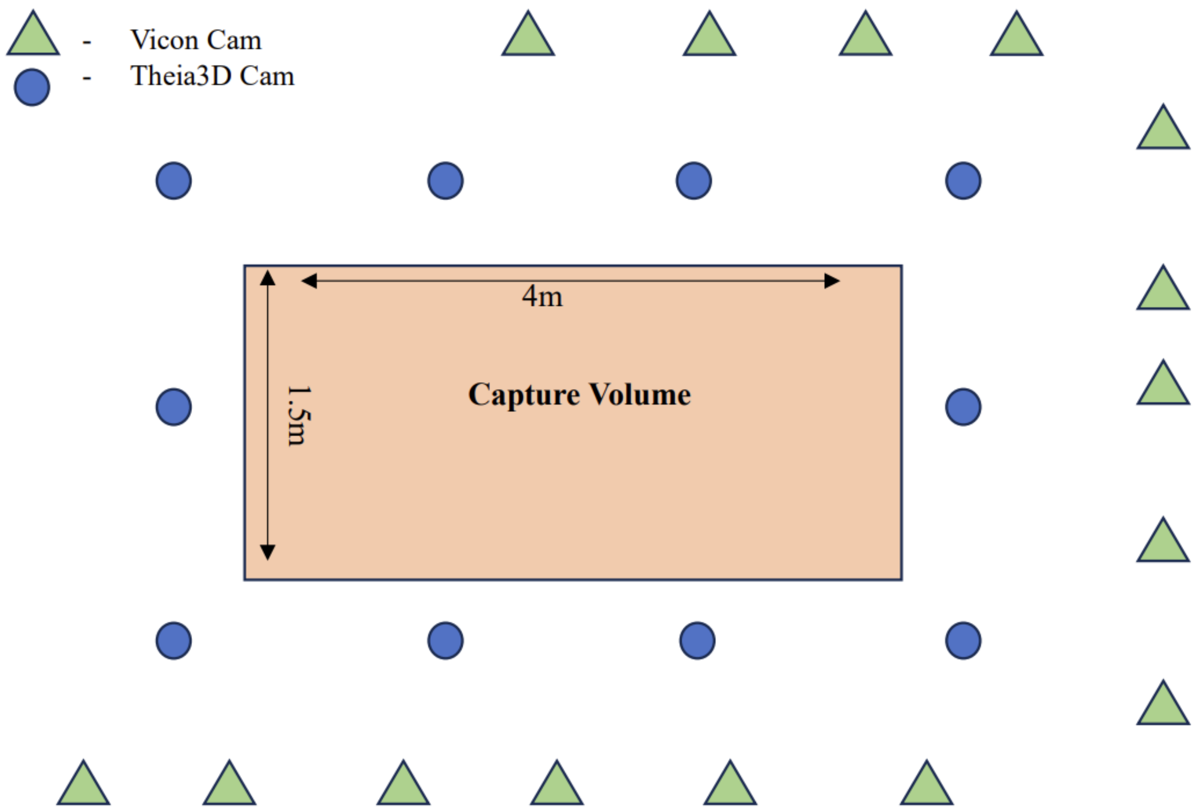


Figure 1. Theia3D calibration chessboard

4.3.3 Pilot capture volume

After completing camera lens calibration, a 4 x 1.5 metre (Figure 2) test space was defined as a suitable test space to complete a functional trial of the system in the biomechanics lab at Victoria University. The Theia3D cameras were positioned to ensure that at least three cameras maintained continuous view of a human subject throughout recording. Four LED light were mounted around the space to provide sufficient lighting for the Theia3D system during trials. Simultaneously, a Vicon setup consisting of 15 Vicon cameras (7 x Vicon Vantage V8 and 8 x Vicon Vantage V16) cameras were installed around the pilot space to ensure no interference occurred between the Vicon system and the Theia3D system during concurrent testing. During pilot testing, adjustments to the Optitrack camera resolution revealed that higher resolution improved footage quality for the Theua3D system, but excessively restricted capture volume, while lower resolution provided a larger capture volume with reduced image resolution. Camera resolution was optimised to 1920 x 1080p to provide a clear picture while maintaining capture volume, thus minimising image quality impacts on XYZ-axis measurements. Both Vicon and Theia3D cameras were adjusted for optimal framerate, aperture, exposure, and focus to ensure high quality recordings while maintaining stable processing power. Once both systems were properly focus and configured, they underwent calibration. For the Theia3D system, the same chessboard used for lens calibration was recorded as it moved around the capture volume. Theia3D calibration required multiple cameras to simultaneously view the chessboard as it moved through the capture volume, with the board placed in the corner of the capture volume to establish the origin. The captured footage was processed and reconstructed in Theia3D to define the capture volume parameters. The Vicon system was calibrated using Vicon's passive wand, which was also placed in the same corner as Theia3D's chessboard to align the origin point with Theia3D's capture volume calibration.

Figure 2. Theia3D and Vicon positions and capture volume dimensions of pilot study.



Initial data capture sample frequencies were selected to meet the specific requirements of the football-specific movement of interest (i.e., obtaining a sample frequency compatible across both systems for high-speed movements). For Vicon, a sample frequency of 200 Hz was selected to ensure capturing of high-speed movements, such as kicking a ball. This would be adjusted for the main testing. The Theia3D system was initially configured to operate at 35Hz based on the previous camera setting adjustments during camera setup. However, this was adjusted to 50Hz for the main trial to complete trials at a comparable frequency to established player tracking systems used withing professional sporting leagues (Aughey et al., 2022). These Vicon and Theia3D sampling frequencies were selected as previous studies investigating sampling frequencies for sporting applications typically noted that sampling frequencies range between 50 Hz and 250 Hz. This allows high enough sampling frequency to capture sporting movements, whilst minimising excessive high frequency noise (van der Kruk & Reijne, 2018). In addition, Theia3D's 50 Hz frequency is replicable with existing player tracking systems in elite sport, as typical analysis of FIFA certified player tracking systems occur at 50 Hz (FIFA, 2022). Furthermore, the increase in Theia3D sample frequency to 50 Hz ensured a high enough sample rate to capture high speed movements effectively, without impacting on capture volume and resolution. The sampling frequencies of Theia3D and Vicon allowed a direct down-sampling of Vicon data to facilitate a direct comparison with the Theia3D data.

4.3.4 Main trial capture volume

The Theia3D system was calibrated prior to the Vicon system calibration to ensure the Theia3D LED lighting system did not interfere with the Vicon capture. Several Theia3D calibrations were completed of ten Optitrack cameras to ensure the lowest calibration error was recorded. All Theia3D cameras sampling frequencies were 50Hz for all trials. Following pilot testing this Theia3D sample frequency was selected as it allowed the highest frame rate and environment settings to capture football-specific movements, without compromising system performance or capture quality. Optimal camera settings for the Theia3D Victoria University biomechanics laboratory setup were noted within Motive software as 8000 exposure, 25 gamma, 7 gain, and additional LED lighting off. Footage captured within the Motive software was exported into relevant folders for processing in the Theia3D software. The following Theia3D footage adjustments were made; white balance was turned on, brightness was set to -6, and frame grab was set at 1. Theia3D's calibration chessboard was used to calibrate the Optitrack cameras and set down in a position to capture the origin. This resultant calibration under these Theia3D system settings yielded the lowest calibration RMSE diagonal value of 1.533mm. The maximum number of human subjects captured within the Theia3D system was set to one or two depending on the trial, with all other settings defaulting to off. The three Degrees of Freedom (DOF) knee joint setting was enabled, and Theia3D's integrated Generalised Cross-Validatory Spline (GCVSPL) lowpass filter cutoff frequency was set between 10-20 Hz, adjusted as needed to address noise in each trial. The key differences in preferences for more complex trials, such as tackles, 2v2, and 3v3 trials, involved enabling "track rotating people", and setting maximum people to two, four, or six, depending on trial requirements.

Vicon setup consisted of 24 x Vicon cameras (5 x Vicon Vantage V16, 14 x Vicon Vantage V8, and 5 x Vicon Vantage V5) cameras mounted and focused on the Theia3D trial space 7 m x 8m capture volume (Figure 3). Vicon calibration occurred at 100Hz using Vicon's passive wand with a capturing capacity of 3000 frames for each camera. Following camera calibration, the Vicon capture volume origin and floor plane was set. A Vicon sampling frequency of 100Hz was selected as the optimal capture frequency for high-speed football movements whilst remaining at a frequency that is directly compatible with Theia3D's 50 Hz capture frequency, to ease the process of down sampling to match data points (Dinu et al., 2012).

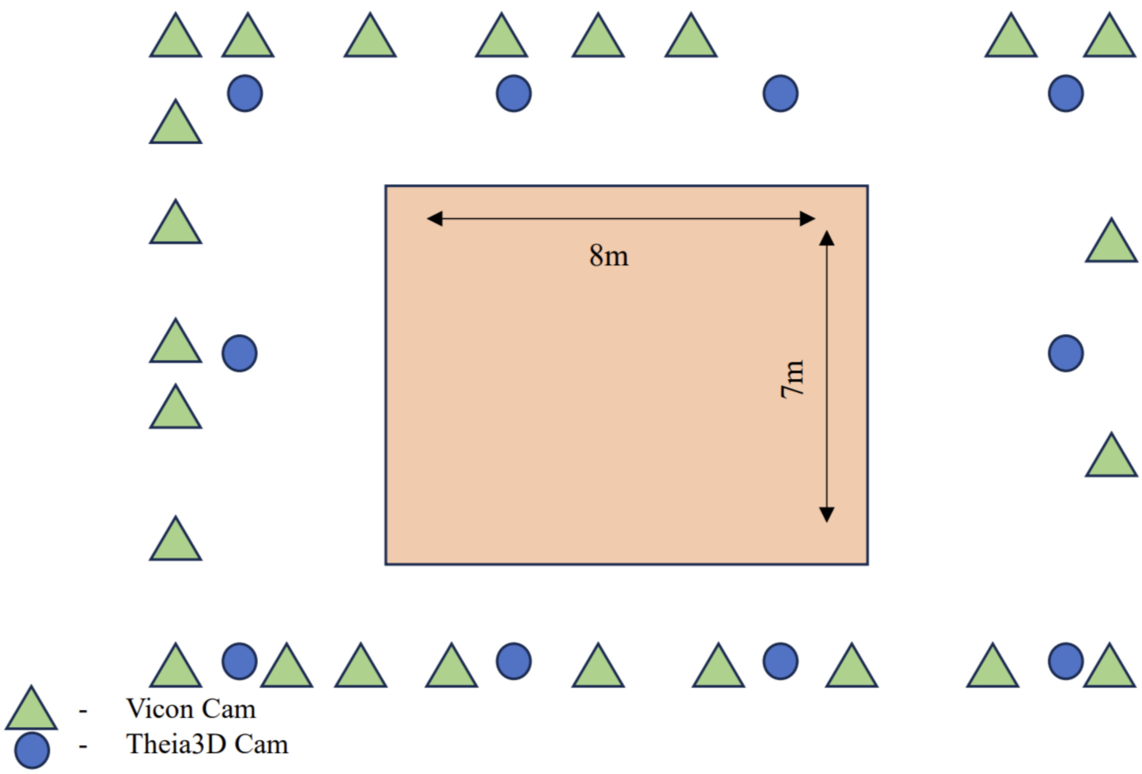


Figure 3. Theia3D and Vicon positions and capture volume dimensions of main testing.

4.3.5 Trial space and camera calibration

Three subsequent pilot trials were conducted on the Theia3D system prior to the main trial using the determined 8 x 7 metre space, to ensure the system was setup to appropriate cameras specifications and capture volume dimensions required for the main testing session. Specifically, these pilot sessions confirmed Theia3D calibration error at the systems maximum capture volume. Calibration of this capture volume over the three pilot trials generated a Root Mean Squared Error (RMSE) diagonal value between 2.07-2.50 mm, with an acceptable RMSE diagonal value being <2.0 mm (Theia Markerless 2024). Adjustment of lighting settings, chessboard placement, and extensions in calibration recording lengths ensured an RMSE diagonal was below 2.0 mm for the main testing. Theia3D system preferences were set to track multiple players within the expanded capture volume. Following these final pilot trials, the Theia3D system demonstrated to be capable of effectively tracking four players simultaneously in the capture volume with the potential to include up to six players in the main trial.

4.3.6 Pilot data collection

The pilot study captured a single player performing movements of interest (i.e., shadow kicks, hip rotation, squats) that were anticipated to be captured during the main test session. A Vicon suit (Oxford, UK) was worn over individuals regular clothing and consisted of pants, long-sleeve top, and headband constructed of a Velcro loop material in which markers were adhered with a Velcro loop base (Figure 4). The Vicon suit was pilot tested with the Theia3D system to ensure the software could identify the individual's joint landmarks whilst wearing the full black Vicon suit within the biomechanics lab space. To ensure optimal marker capture by Vicon, any reflective elements on the individual's shoes were covered with black tape. Subsequently, 43 markers were secured to various anatomical landmarks on the individual's body, following guidelines of Vicon's plug-in gait model (Figure 5).

Figure 4. Example of Vicon suit with retro-reflective marker setup utilised in pilot study and main testing sessions.

Prior to the trial capture, the individual engaged in a brief warm up routine consisting of dynamic stretches, and a short run to increase heart rate. A static and functional calibration was then conducted to allow a human 3D model to be reconstructed for the Vicon system. Calibration movements are designed to target specific joint and limb ranges of movements and include the following: static A-pose, squats, hip rotations, shoulder rotations, bicep curls, leg swings, and side steps (FIFA, 2022). Theia3D human model reconstruction was conducted using Visual3D x64 (v2024.02.2) (HAS-Motion, Ontario, Canada) software. Vicon models were reconstructed using Nexus v2.13. All human model reconstructions were conducted post pilot testing. Following the static and functional calibration trials, the core trials were completed and encompassed the following movements:

- Agility movements (zig zag, side steps)
- Dribbling a football around the perimeter of capture volume
- Shadow kicks – kicks without ball
- Kicks – with ball
- Heading a ball
- 1v1 possession game

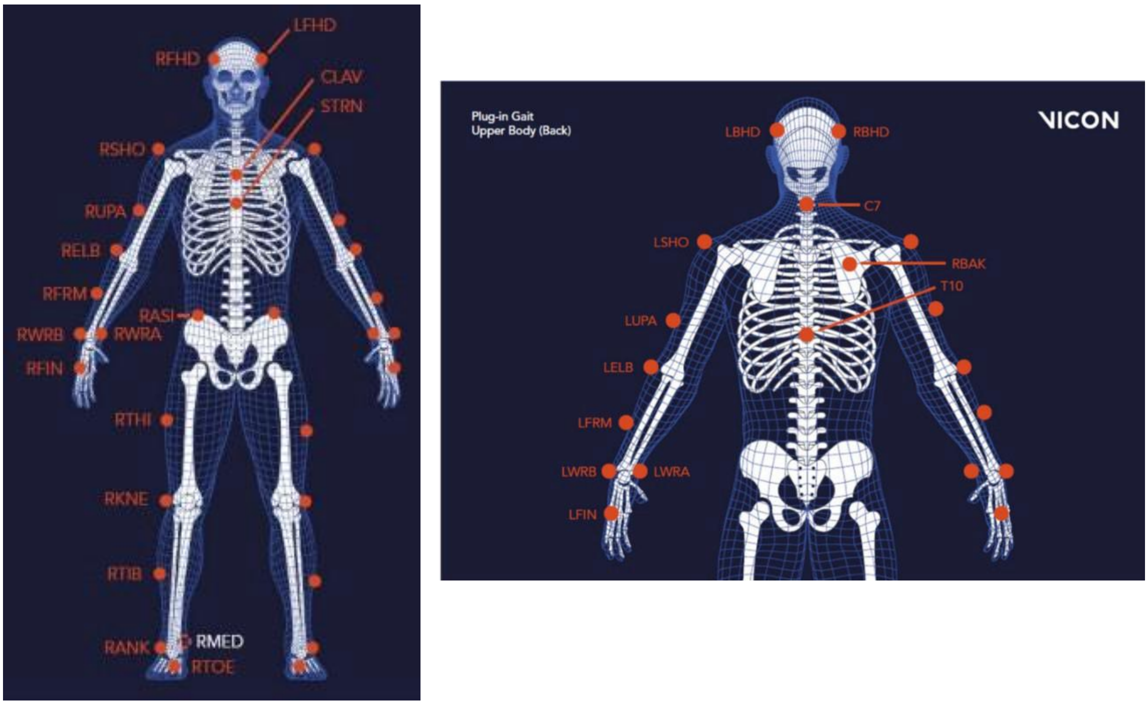


Figure 5. Posterior and anterior placements of the Plug-in Gait Model Full Body Marker set, indicating key marker landmark positions

Source: Vicon Plug-in Gait Reference Guide (Vicon, 2021)

4.4 Main study data collection

All players completed a static and functional calibration battery, that was also utilised as the players' warm up (Vicon, 2015). Functional calibration movements consisted of shoulder swings, bicep curls, squats, leg swings, and side steps and specifically targeted limb segments and joint kinematics of interest in this study. All trials were captured concurrently by the Theia3D and Vicon (2.15, Oxford, UK) systems. Data capture was conducted as players completed a series of trials outlined in Table 1. These movement were adapted from previous movement assessment protocols used in a football validation study by Aughey et al. (2022) as they provided both controlled and complex football movements to be assessed between tracking systems. Specific limb and joint tracking kinematics captured for each player and trial were; joint position (m) defined as the X, Y, Z location within the capture volume, and joint angle (°) defined as the relative ankle between two limb segments.

Table 1. Overview of movements conducted with the length and repetition of each trial.

Drill	Trials
Static and Function Player calibration	4 x A-pose, arm swings, bicep curls, hip rotations, squats, leg swings, side steps
Slow dribble	2 x 3 laps of capture volume
Mid-range passes	2 x 16 passes
Short headers and throw ins	3 x 8 throws and headers
Defensive tackles and intentional fouls	3 x 30 seconds
Power kicks	2 x 6 shots
2v2 possession match	3 x 60 seconds
3v3 possession match	x 60 seconds

4.5 Data processing

4.5.1 Theia3D processing

Following data capture, Theia3D .c3d files were exported and processed in Visual3D to with relevant kinematic metrics exported. To ensure clear player differentiation within each trial dataset, every player was exported as an individual .c3d file. Each Theia3D's .c3d file contained a pre-determined subject model that was processed for joint kinematics using the Visual3D software. The aim of this study was to evaluate the Theia3D system factory standard outputs, as such no additional filtering or data processing was applied to the Theia3D file outputs in Visual3D. To extract joint and limb kinematics, a pipeline was created using the Visual3D "Compute_Model_Based_Data" function. This pipeline extracts the joint position and joint ankle by applying the pipeline functions to the exported Theia3D .c3d file. Each "Compute_Model_Based_Data" pipeline function is set to determine joint metrics for each individual selected joint. Joint angular metrics were selected as named (i.e., joint angle), while joint position was set by selecting either distal or proximal limb segment position ("seg_proximal_joint" or "seg_distal_joint") relative to the Theia3D calibrated capture volume origin (i.e., knee joint position was captured by selecting the distal position of the thigh with the reference segment set to "LAB"). Each function was customised to model joint against relevant limb segments (Table 3). All data was exported as an ASCII .txt file, whereby it was then converted from to a .csv file format for synchronisation and alignment with Vicon system files. A sample of trials from one player was extracted to investigate the impact of data filtering on Theia3D metric outputs to determine if any differences exist between filtered and non-filtered outputs. For this subset of Theia3D data, trials were selected for Player 24, with the following trials selected; calibration, dribble, pass, throws/headers, 2v2, 3v3. An 8.1 Hz low pass Butterworth filter was applied to the processed Visual3D kinematic pipeline by adding the "Lowpass_Filter" function and exported as an ASCII .txt file for .csv conversion and assessment of differences to original data.

4.5.2 Vicon processing

Prior to data analysis, all Vicon trials were reconstructed and processed in Vicon Nexus (v2.13). Individual player vsk models were calibrated and manually labelled for each trial to ensure correct player identification and tracking. Marker gap filling of relevant trials was conducted, with all gaps of 10 or less frames filled using the Woltring Quintic Spline pipeline. A visual inspection of gaps greater than 10 frames was also conducted, with any linear gaps filled with either a spline or cyclic manual gap fill function in Vicon Nexus. Individual player Plug-in Gait model and OCST model were then applied using the inbuilt "Process Static Plug-in Gait Model", "Process OCST", and "Process SCoRE / SARA" Vicon Nexus pipelines, The relevant joint centres outputs obtained from these pipelines are detailed in Table 3.

A residual analysis was conducted on joint data to determine the magnitude of difference between unfiltered Vicon data and the filtered Vicon data, with residuals for each cut-off frequency (5-20 Hz) assessed. Residuals were then plotted and visually inspected to identify the ideal cut-off frequency at the point where residual differences between unfiltered and filtered Vicon data rapidly increased (Challis, 1999; Howenstein, 2020). The residual analysis and residual plot were produced using RStudio (v2024.04.2-764) packages including 'data.table' (Dowle & Srinivasan, 2023), 'caTools'(Tuszynski, 2024), 'dplR' (Bunn, 2008), 'imputeTS' (Moritz & Bartz-Beielstein, 2017), 'ggplot2' (Wickham, 2016), 'signal' (Signal Developers, 2023), 'dplyr' (Wickham, François, et al., 2023), 'sportyR' (Drucker, 2024), and 'purrr' (Wickham & Henry, 2023) packages. A cut-off frequency of 8.1 Hz was determined and applied to all Vicon trials using a fourth order (zero lag) low pass Butterworth filter pipeline in Vicon Nexus. Filtering of Vicon data was conducted to ensure that Theia3D data was being compared to the true Vicon signal of interest, with any high-frequency signal noise removed. Vicon trial data was then exported as .csv files for synchronisation and alignment with the

Theia3D .csv files.

Filtering of Vicon data was conducted to ensure that Theia3D data was being compared to the true Vicon signal of interest, with any high-frequency signal noise removed. The Vicon dataset were exported as .csv files for synchronisation and alignment with the Theia3D .csv files.

Table 2. Joint marker, joint model, and definitions of outputs exported from Vicon Nexus
and Theia3D systems. The table includes comparable joint outputs between systems.

Vicon Markers/models	Marker Definition	Theia3D Points of interest	Marker Definition
PEL	Pelvis Centre of Mass	COM	Pelvis, subject Centre of Mass position
Pelvis_LThigh_score	Left Hip Joint Centre	L-Hip	Left Hip Model Outputs
Pelvis_RThigh_score	Right Hip Joint Centre	R-Hip	Right Hip Model Outputs
LThigh_LTibia_score	Left Knee Joint Centre	L-Knee	Left Knee Model Outputs
RThigh_RTibia_score	Right Knee Joint Centre	R-Knee	Right Knee Model Outputs
LTibia_LFoot_score	Left Ankle Joint Centre	L-Ankle	Left Ankle Model Outputs
RTibia_Rfoot_score	Right Ankle Joint Centre	R-Ankle	Right Ankle Model Outputs

4.6 Data analysis

4.6.1 Data synchronisation and alignment

To enable a direct comparison between the two systems, RStudio was used to standardise the data formats across both datasets. Specifically, this involved applying standardised joint naming conventions, measurement units, and measurement scales between Theia3D and Vicon data. All irrelevant data was removed to ensure only comparable landmarks of interest were retained for analysis (see Table 2). Naming conventions measurement units, and measurement scale standardisation was completed using the ‘tidyverse’ (Wickham et al., 2019), ‘data.table’, ‘tidyr’ (Wickham, vaughan, et al., 2023), ‘plotly’ (Sievert, 2020), ‘spdep’ (Bivand & Wong, 2018), and ‘dplyr’ packages in RStudio. Following formatting for both systems, the datasets were time synchronised based on distinct joint angle movements within each trial. A custom-built R Shiny application was built to facilitate time synchronisation of Theia3D and Vicon data. The application featured interactive plots of selected data, providing a visual trace of the two datasets. The synchronisation process involved shifting the Theia3D system frame by frame against the Vicon system that provided a real-time Root-Mean-Square-Error (RMSE) value between motion capture systems based off the left hip X-axis angle for each trial. This method was selected as RMSE is a robust measure of differences between values produced by multiple systems, making it ideal for synchronising time-series dataset as it ensures the minimisation of potential errors (Robertson et al., 2023). The left hip joint was selected as the sync point as it provided the clearest comparison between the two systems when synchronising. The RMSE was calculated at every frame shift, with the lowest RMSE frame shift being selected as the optimal time synchronisation point between Theia3D and Vicon systems. The interactivity of the R Shiny application enabled a visual inspection element to ensure the lowest RMSE matched with the visual trends of the time-series plot.. The R shiny application was created using the ‘shiny’ (Chang et al., 2023), ‘ggplot2’, ‘plotly’, ‘data.table’, ‘dplyr’, ‘tidyverse’, and ‘tidyr’ packages.

To align the Theia3D data with the Vicon data, a two-step transformation process was used for X, Y, Z rotational alignment and translation shift optimisation between the two systems. Rotational alignment was applied to Theia3D data using a 3x3 rotation matrix. This matrix was computed by sequentially multiplying individual rotation matrices along the X, Y, and Z axes using the following angles: θ_x, θ_y, and θ_z. The optimal rotation parameters were determined by minimising RMSE between Vicon data and transformed Theia3D data. The minimisation procedure was conducted using the Limited-memory Broyden–Fletcher–Goldfarb–Shanno with Box constraints method (L-BFGS-B), which is commonly used in machine learning and data science when dealing with large-scale data optimisation problems (Boggs & Byrd, 2019). To optimise the rotation between Vicon and Theia3D data, initial parameters were set to 0 for each angle (θ_x, θ_y, and θ_z), with the RMSE for each combination of angle parameters between 0-360º. The lowest RMSE angle rotation parameters were returned and applied to each trial for alignment. Following rotational alignment, a translation shift was applied to further minimise any residual displacement between the Vicon and Theia3D systems. The optimal shift values for X, Y, and Z axes (t_x, t_y, t_z) were determined by comparing Vicon and Theia3D data across a range of shifts from -4 to +4 meters, at intervals of 0.1 meters. The best X, Y, Z shift was identified at the lowest RMSE comparison between the two systems data. Prior to applying the rotation and translation to the Theia3d data , the system data was centred by subtracting the mean of each coordinate (X, Y, Z) from the mean coordinated of the Vicon system across all frames. This step ensured that the alignment process was focused on the relative spatial alignment between the two motion capture systems. After rotational and translation optimisations, the Theia3D data was realigned against Vicon by applying the best-fit rotation and shift parameters, with the final aligned and shifted Theia3D positions computed by adding the optimised translation values back to the mean-centred Theia3D data.

To ensure the appropriate rotation and shift parameters were applied, a second custom R Shiny application was developed to create a 3D segment model of positional data. The application simultaneously visualised Theia3D and Vicon joint centre markers connected by segments to visual represent player limbs for comparisons by each frame, with the Mean-Absolute-Error (MAE) for the selected frame provided. This provided a visual inspection on any datasets requiring further manual refinement in the X, Y, or Z axes position. MAE was selected as the optimisation criterion as it provided a robust measure of the average magnitude of error between corresponding data points in both systems. By adjusting the positional parameters to calculate the resulting MAE, the R Shiny application was able to determine the configuration that provided the lowest overall positional error. The custom-built R shiny application presented an interactive user interface, allowing for real-time visualisation of joint position and limb segments of player data from the Theia3D and Vicon systems. Player limb segments were generated by defining the start of a limb segment as the proximal joint XYZ coordinate, and the end of the limb segment as the distal joint XYZ coordinate of a specific limb. The Custom-built R Shiny application presented Theia3D and Vicon player segments and allowed any further rotation and translation adjustments to be made if necessary. The application also allowed for the identification of sections of trials where Theia3D performed better than other sections and provided a visual representation of these specific movements. The R Shiny application used for visualisation of player segments and subsequent frame MAE was developed using the ‘Shiny’, ‘plotly’, ‘tidyverse’, ‘dplyr’, and ‘data.table’ R packages.

4.6.2 Statistical analysis

To assess the magnitude of difference between Theia3D and Vicon, the absolute position difference (m) between each axis (X, Y, Z), and overall XYZ position difference (m) was defined as the Euclidean difference (m) between the X,Y, Z coordinate of Theia3D and Vicon systems. The MAE was calculated using absolute position difference for each axis separately, and the overall XYZ position difference between Theia3D and Vicon systems. Absolute joint angle (°) difference was determined for X, Y, and Z axes, with RMSE calculated to establish the error between Theia3D and Vicon systems. To measure the magnitude of difference between the motion capture systems, position MAE and angle RMSE were calculated for three grouped data levels: i) overall position MAE, and angle RMSE between systems across all trials, ii) position MAE and angle RMSE between systems when grouped by player and joints, iii) position MAE and angle RMSE between systems when grouped by player, joint, and trial. Standard Deviation (SD) and 95% Confidence Intervals (CI) were also calculated for position and joint angle to determine the variation of error between Theia3D and Vicon systems. Data was then plotted for each player, joint, and trial, with error bars representing the 95% CI for each variable grouping. The plots allowed for a visualisation of large error or variances between the two systems, enabling the identification of the specific players, joints or trials that Theia3D may track better than another. Furthermore, timeseries plots were generated for joint X, Y, Z position for select trials. These plots provided context into the sections of trials or specific movement where Theia3D was closely aligned with Vicon, or where Theia3D error increased compared to Vicon. The time series plots provided specific frame point in which an inspection of the movement patterns and football contexts where the system performed well or poorly.

Chapter 5: Results

5.1 Joint position

5.1.1 Overall position difference

Overall joint XYZ position error between Theia3D and Vicon systems across all trials recorded an XYZ MAE ± SD of 0.19 ± 0.06 m, with a 95% CI range of -0.89 to 1.27 m. Position MAE and SD between Theia3D and Vicon systems for individual axes found the following; X-axis: 0.11 ± 0.33 m, (95% CI range: -0.53 to 0.75 m), Y-axis: 0.12 ± 0.45 m, (95% CI: -0.76 to 1.01 m), and Z-axis: 0.03 ± 0.03 m, (95% CI range: -0.02 to 0.08 m).

5.1.2 Trial position difference

The influence of trial type on joint XYZ position MAE, SD, and 95% CI reported between Vicon and Theia3D systems is detailed in Table 3. The smallest difference in XYZ position MAE was noted for throws and headers (MAE: 0.04 ± 0.02 m), followed by shots (MAE: 0.037 ± 0.01 m), and 3v3 (MAE: 0.04 ± 0.02 m) (Figure 6). Shots were found to have the lowest variation between players, with a 95% CI range of 0.01 to 0.06 m (Figure 6). All other trials XYZ position MAE ranged from 0.04 to 0.05 m (95% CI: -0.02 to 0.11 m) (Table 3). Tackles recorded the largest player XYZ variation between Theia3D and Vicon (MAE: 0.56 ± 0.47 m, 95% CI: -0.37 to 1.49 m), followed by 2v2 (MAE: 0.29 ± 0.43 m, 95% CI: -0.54 to 1.13 m) (Figure 6). The higher error observed in the tackle trials may have been attributed to higher error noted in the X and Y axes (0.30 ± 0.25 m and 0.45 ± 0.34 m respectively). Specifically, higher X and Y errors were attributed to Theia3D reassigning Player 07 and Player 13 skeletons during the 2v2 and tackle trials (Figure 6).

Table 3. Joint position error statistics by trial. All measures are reported in metres (m).

Trial	X-axis		Y-axis		Z-axis		Overall	
	MAE ± SD	95% CI	MAE ± SD	95% CI	MAE ± SD	95% CI	MAE ± SD	95% CI
Calibration	0.02 ± 0.01	0.00 – 0.03	0.02 ± 0.01	0.00 – 0.03	0.02 ± 0.02	-0.01 – 0.05	0.04 ± 0.02	0.01 – 0.07
Dribble	0.02 ± 0.01	0.01 – 0.04	0.02 ± 0.01	0.00 – 0.04	0.03 ± 0.02	-0.01 – 0.06	0.05 ± 0.02	0.02 – 0.08
Pass	0.02 ± 0.02	-0.01 – 0.06	0.02 ± 0.02	-0.02 – 0.05	0.03 ± 0.02	-0.02 – 0.07	0.05 ± 0.03	-0.02 – 0.11
Throws/Headers	0.02 ± 0.01	0.00 – 0.04	0.01 ± 0.01	0.00 – 0.02	0.02 ± 0.02	-0.01 – 0.05	0.04 ± 0.02	0.01 – 0.07
Shots	0.02 ± 0.01	0.00 – 0.03	0.01 ± 0.01	0.00 – 0.02	0.02 ± 0.02	-0.01 – 0.05	0.04 ± 0.01	0.01 – 0.06
Tackles	0.28 ± 0.25	-0.21 – 0.77	0.45 ± 0.34	-0.32 – 1.21	0.04 ± 0.02	0.00 – 0.08	0.56 ± 0.47	-0.37 – 1.49
2 v 2	0.18 ± 0.28	-0.37 – 0.73	0.18 ± 0.30	-0.40 – 0.76	0.03 ± 0.02	-0.01 – 0.07	0.29 ± 0.43	-0.54 – 1.13
3 v 3	0.02 ± 0.01	0.00 – 0.04	0.02 ± 0.01	0.00 – 0.03	0.02 ± 0.02	-0.01 – 0.05	0.04 ± 0.02	0.01 – 0.07

CI: 95% Confidence Interval, SD: Standard Deviation, MAE: Mean Absolute Error

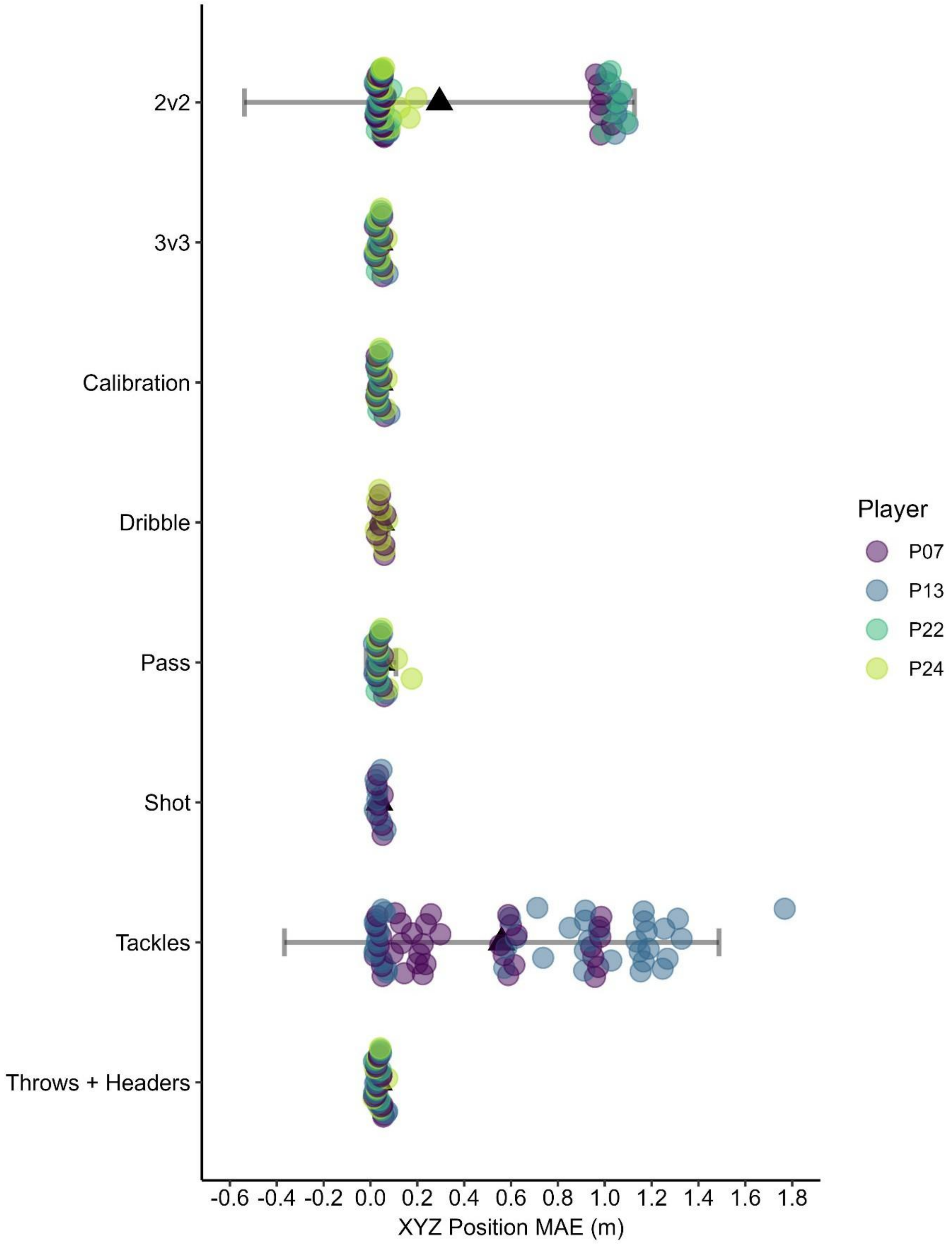


Figure 6. XYZ position MAE grouped by trial with error bars representing the 95% CI range. Points represent individual player joints MAE for each trial.

5.1.3 Player position difference

To evaluate the impact of players body composition on joint centre position accuracy, MAE ± SD, and 95% CI between Vicon and Theia3D systems were grouped by player (see Table 4). It was observed that Player 13 recorded the largest XYZ position error for all trials (MAE: 0.37 ± 0.49 m, 95% CI: -0.59 to 1.33 m), followed by Player 07 (MAE: 0.21 ± 0.32 m, 95% CI: - 0.42 to 0.84 m), and Player 22 (MAE: 0.18 ± 0.35, 95% CI: -0.51 to 0.87 m) (Figure 7). The larger errors found in across these three players is attributed to higher error in noted in the X- and Y-axes (X- axis 95% CI: -0.27 to 0.69 m, Y-axis 95% CI: -0.30 to 0.67 m) (Table 4). The large variation across the X- and Y-axis indicates that the similar body height and composition, particularly of Player 07 and Player 13 influenced the Theia3D system's ability to track joint position throughout the complex, densely populated trials. Specifically, player swapping occurred on several occasions, resulting in larger positional error across complex movement trials. In contrast, Player 24 was found to have the smallest XYZ position error (MAE: 0.06 ± 0.04 m, 95% CI: -0.02 to 0.13 m) (Table 4) as Theia3D was able to continuously track Player 24 through all trials without intermittently swapping with other players (Figure 7).

Table 4. Joint position error statistics by subject. All measures are reported in metres (m).

Subject	X-axis		Y-axis		Z-axis		Overall	
	MAE ± SD	95% CI	MAE ± SD	95% CI	MAE ± SD	95% CI	MAE ± SD	95% CI
Player 07	0.12 ± 0.23	-0.33 – 0.57	0.13 ± 0.22	-0.30 – 0.56	0.03 ± 0.02	0.00 – 0.06	0.21 ± 0.32	-0.42 – 0.84
Player 13	0.19 ± 0.26	-0.31 – 0.69	0.28 ± 0.40	-0.50 – 1.06	0.03 ± 0.02	-0.01 – 0.08	0.37 ± 0.49	-0.59 – 1.33
Player 22	0.09 ± 0.18	-0.27 – 0.45	0.13 ± 0.28	-0.42 – 0.67	0.02 ± 0.02	-0.01 – 0.06	0.18 ± 0.35	-0.51 – 0.87
Player 24	0.03 ± 0.03	-0.02 – 0.08	0.03 ± 0.02	-0.02 – 0.07	0.03 ± 0.02	-0.02 – 0.07	0.06 ± 0.04	-0.02 – 0.13

CI: 95% Confidence Interval, SD: Standard Deviation, MAE: Mean Absolute Error

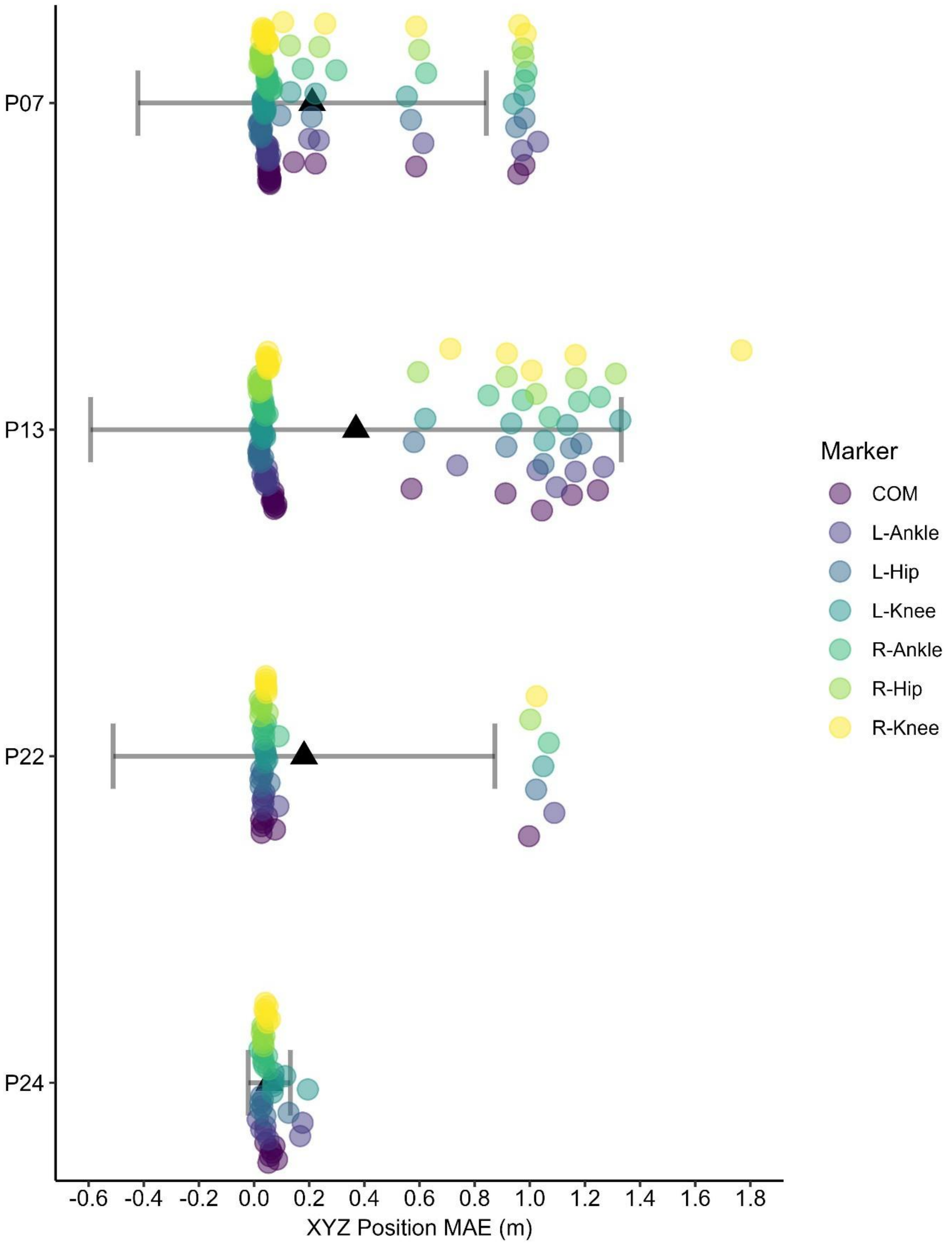


Figure 7. XYZ MAE when grouped by player with error bars representing 95% CI range. Points represent individual player joints MAE for each trial.

5.1.4 Joint position difference

To assess joint position difference between the Theia3D and Vicon systems, instances where Theia3D interchanged player skeletons were removed. Across all tackles and 2v2 trials, player swaps occurred a total of 17 times. The joint centre position MAE ± SD and 95% CI for joint position comparisons between Vicon and Theia3D systems grouped by joint are reported in Table 5. When accounting for interchanging players, the XYZ position MAE ± SD across all joints, players and trials was 0.04 ± 0.03 m (95% CI: -0.01 to 0.10 m). The highest overall joint MAE ± SD axis position difference was exhibited by the Z-axis (MAE: 0.03 ± 0.01 m, 95% CI: -0.00 to 0.05 m), followed by the X-axis (MAE: 0.02 ± 0.01 m, 95% CI: (-0.00 to 0.04 m), and Y-axis observed the lowest position difference (MAE: 0.02 ± 0.01 m, 95% CI: -0.00 to 0.04 m) (Table 5). Specifically, left and right hips displayed the smallest XYZ position difference (MAE: 0.02 ± 0.01 m and 0.02 ± 0.01 m, respectively) compared to other joints (Figure 8). The COM across players and trials was found to have the largest XYZ MAE (0.06 ± 0.02 m, 95% CI: 0.03 to 0.09 m), followed by the left ankle and knee (MAE: 0.05 ± 0.04 m, 95% CI: -0.02 to 0.12 m and MAE: 0.05 ± 0.04 m, 95% CI: -0.02 to 0.12 m, respectively) (Figure 7). Larger variation in left and right ankle MAE values between the Theia3D and Vicon systems was attributed to higher Z-axis MAE error (MAE: 0.04 ± 0.02 m, 95% CI: -0.01 to 0.09 and MAE: 0.03 ± 0.02 m, 95% CI: 0.00 to 0.06, respectively) compared to all other joints with the exception of COM (MAE: 0.05 ± 0.01 m, 95% CI: 0.02 to 0.08 m) (Table 5).

Table 5. Joint position error statistics by target joint. All measures are reported in metres (m).

Joint	X-axis		Y-axis		Z-axis		Overall	
	MAE ± SD	95% CI	MAE ± SD	95% CI	MAE ± SD	95% CI	MAE ± SD	95% CI
COM	0.02 ± 0.01	0.01 – 0.03	0.02 ± 0.01	0.00 – 0.03	0.05 ± 0.01	0.02 – 0.08	0.06 ± 0.02	0.03 – 0.09
L Hip	0.02 ± 0.01	-0.01 – 0.04	0.02 ± 0.01	-0.01 – 0.04	0.01 ± 0.01	0.00 – 0.03	0.03 ± 0.02	-0.01 – 0.07
R Hip	0.02 ± 0.01	0.01 – 0.02	0.01 ± 0.00	0.01 – 0.02	0.01 ± 0.01	0.00 – 0.02	0.03 ± 0.01	0.01 – 0.04
L Knee	0.03 ± 0.03	-0.02 – 0.08	0.03 ± 0.02	-0.01 – 0.06	0.01 ± 0.01	0.00 – 0.03	0.05 ± 0.04	-0.02 – 0.12
R Knee	0.03 ± 0.01	0.01 – 0.04	0.03 ± 0.01	0.01 – 0.04	0.01 ± 0.00	0.00 – 0.02	0.04 ± 0.01	0.03 – 0.06
L Ankle	0.02 ± 0.02	-0.02 – 0.06	0.02 ± 0.02	-0.02 – 0.06	0.04 ± 0.02	-0.01 – 0.09	0.05 ± 0.04	-0.02 – 0.12
R Ankle	0.02 ± 0.01	0.01 – 0.02	0.01 ± 0.01	0.00 – 0.02	0.03 ± 0.02	0.00 – 0.06	0.04 ± 0.01	0.02 – 0.07

CI: 95% Confidence Interval, SD: Standard Deviation, MAE: Mean Absolute Error, L: Left, R: Right

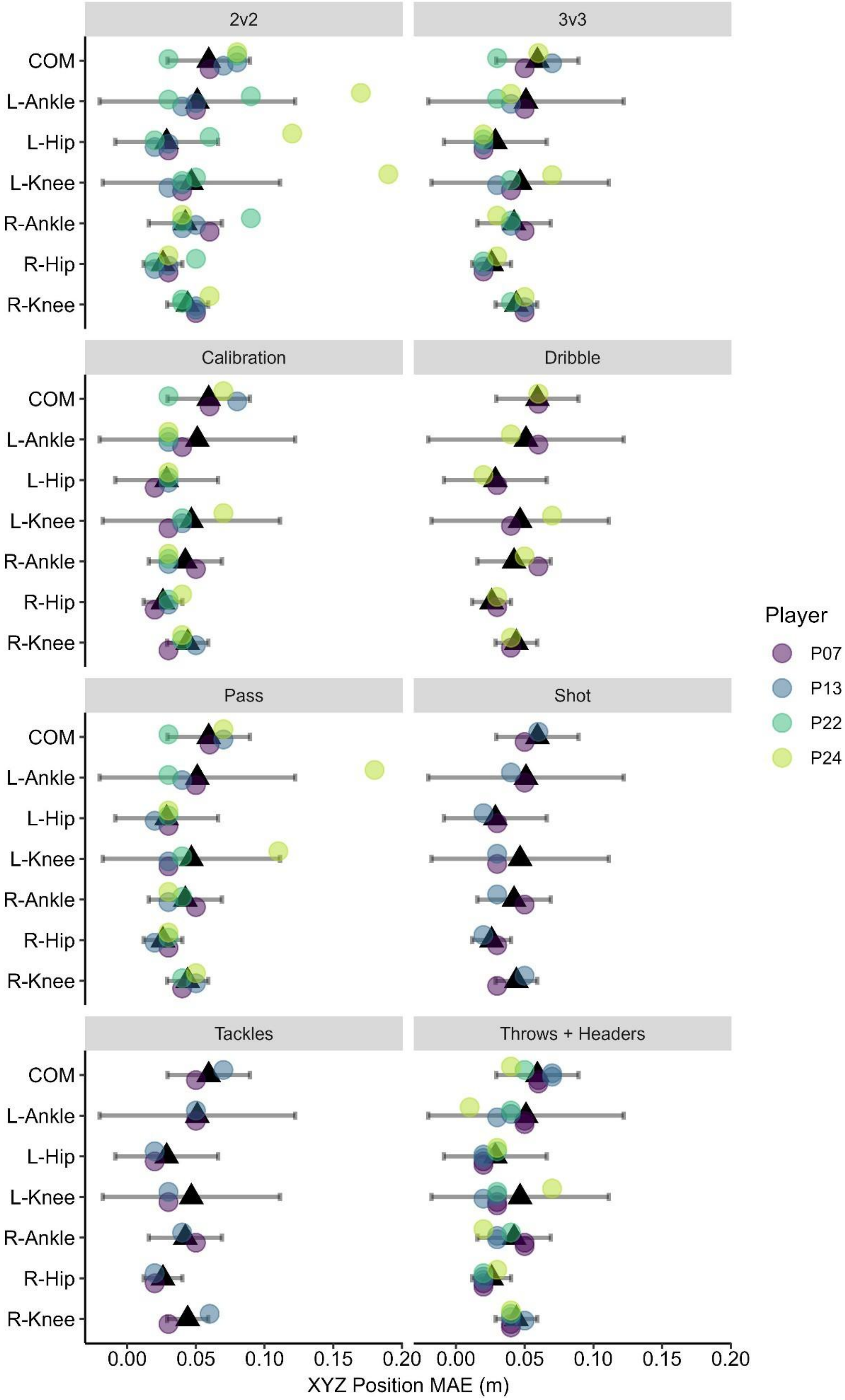


Figure 8. XYZ position MAE when grouped by target joint with error bars representing 95% CI range. Player interchange data has been removed to illustrate position tracking accuracy potential of Theia3D system with multiple players present in capture volume.

5.2 Joint angles

5.2.1 Overall angle difference

Overall angle error between systems across all trials recorded an X-axis RMSE ± SD of 84.8 ± 83.6° and a 95% CI range of -79.0 to 248.6°. The Y-axis measured an RMSE of 18.4 ± 15.6°, while the 95% CI range was -12.1 to 49.0°. The Z-axis angle RMSE and SD measured 42.9 ± 31.6°. The 95% CI range measured -19.1 to 104.8°.

5.2.2 Trial angle difference

The evaluation of joint angle difference between the Theia3D and Vicon systems for each trial and joint are detailed in Appendix A. When comparing Theia3D joint angle to Vicon, it was noted that the system was challenged in tracking player joint angles throughout the trials as a result of player interchanges and signal noise. As such, reported differences are only presented for Player 24 was continuously tracked for all trials. Specifically, joint angle RMSE ± SD and 95% CI with the hips recording the smallest RMSE values compared to other joints (RMSE: X-axis 5.0 ± 0.1°, Y-axis 3.9 ± 0.4°, and Z-axis 23.3 ± 13.2°, respectively). Ankle joints were typically found to have the largest RMSE error and variance, with the highest differences reported in the left ankle in the 2v2 trial (X-axis RMSE: 129.2 ± 388.8°). When considering trial type, the throws/headers trial measured the smallest angle error among for all joints across trials, with all X-axis joint angle error <9.5°, Y-axis error <13°, and Z-axis error <19°. Tackle trials were the worst performing trials, with X-axis values all greater than an RMSE: 11.5°, Y- axis RMSE greater than 12.4° (with the exception of the left hip), and Z-axis errors reporting an RMSE greater than 23.6°. The Theia3D system was challenged in tracking X-axis joint angles during the small-sided game trials (2v2 and 3v3), with both trials producing RMSE values over 90° in the X-axis (2v2 RMSE: 129.2° and 3v3 RMSE: 97.5°) (Appendix A). No Z- axis RMSE values were below 18°, with the lowest occurring Z-axis RMSE found for the left ankle during throws/headers (RMSE: 18.4 ± 8.3°). Due to the challenges in comparing Theia3D joint angle outputs to Vicon, joint angles have been excluded from the system performance evaluation.

5.3 System performance

The following joint, player and trial examples have been selected based on the highest and lowest errors reported in the previous sections (5.1 and 5.2) for the purpose of providing specific movement scenarios in which Theia3D performs well vs poorly compared to Vicon.

5.3.1 Optimal Theia3D tracking

Across trials it was generally noted that the lowest position and angle errors between Theia3D and Vicon were found for the calibration, dribble, passing, shot, and throws/headers trials. As such, the optimal Theia3D tracking conditions involved single players in capture volume, removing all potential occlusions of limb and joints. One such example of accurate Theia3D player joint tracking is Player 22 COM tracking during the calibration trial as it was found to have one of the lowest reported errors across all players and joints in the calibration trial (XYZ MAE: 0.03 ± 0.02 m). A time-series of the X-, Y-, and Z-axis COM instantaneous position difference between Theia3D and Vicon systems for Player 22 during the calibration trial is provided in Figure 9. Instantaneous error for Player 22 COM remained generally low (MAE <0.10 m) throughout the example, with error spike patterns occurring as the player moved through different movement patterns (Figure 9). Specifically, leg swings (frame 2500 to 3000) were the only movement to cause and increase in COM position difference above 0.08 m in the X-axis . The COM error oscillations occurred during the early phases of the calibration trial (between 0.00 - 0.05 m) when Player 22 was completing isolated upper body movements, and lower body was stationary (frames 600 to 1310). Similarly, hip rotations and squats produced error fluctuations in the COM as Player 22 progressed through these movement cycles (frames 1370 to 2400). The Z-axis displayed notable error spikes in the final stages of the trial (frame 3750 to 4050) while Player 22 completed side steps. The movements of hip rotations, squats, and side-steps all force the player to reduce the angle between thigh and pelvis, which may challenge the Theia3D systems ability to track COM in this example. However, Figure 10 depicts the 3D model of lower body joint centres and limb segments of Player 22 during the hip rotation phase of the calibration. The example frame modelled in Figure 10 visualises the spatial differences between the Theia3D and Vicon systems under optimal player tracking conditions (i.e., single player in capture volume, with no occlusion). Similar error profiles were noted in other single player tracking trials with an overall position MAE of 0.03 to 0.05 m.

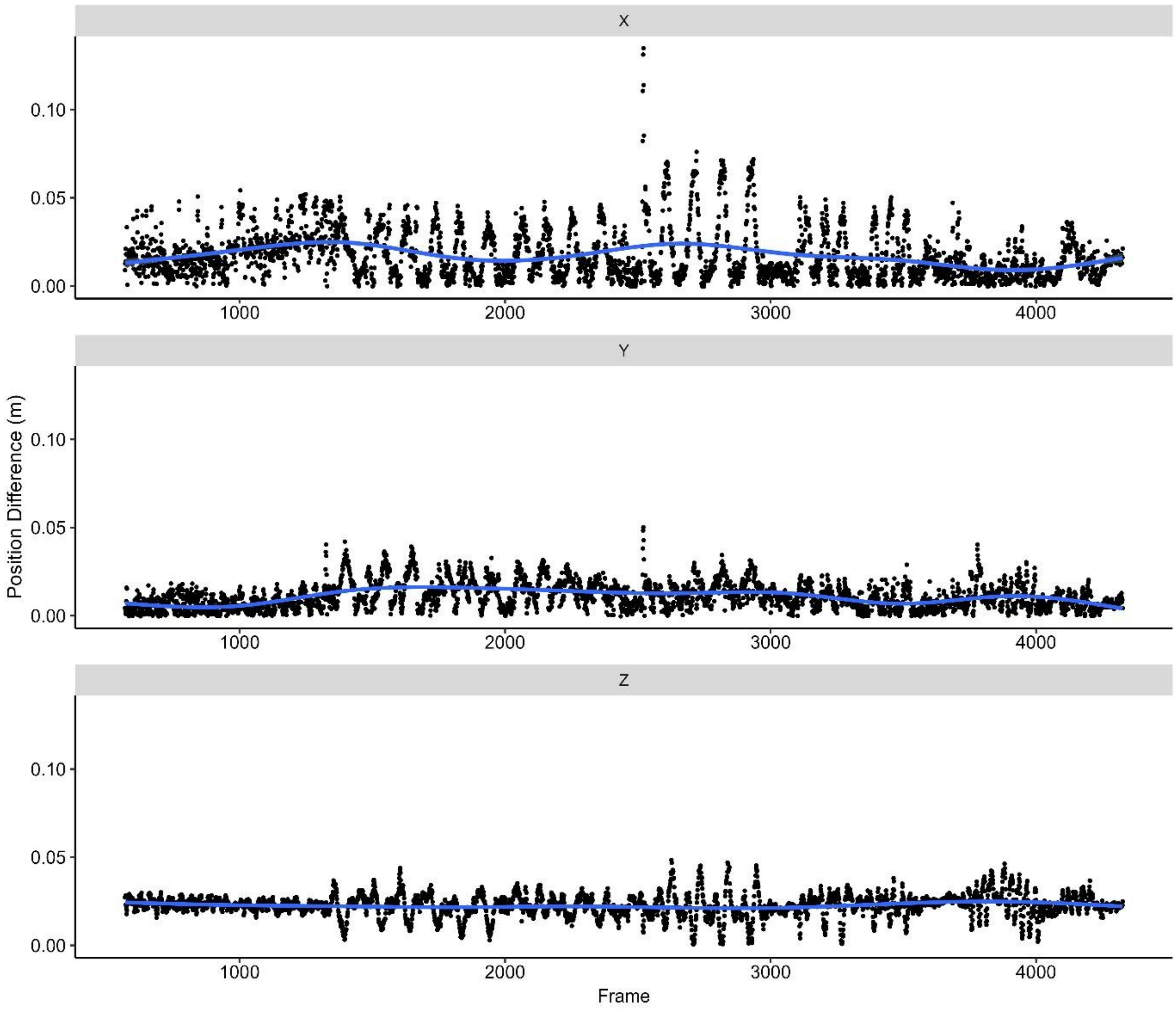


Figure 9. Player 22 Calibration trial, centre of mass position difference in X, Y, Z axes with black points representing the individual position difference per frame, with a blue error trendline throughout the trial.

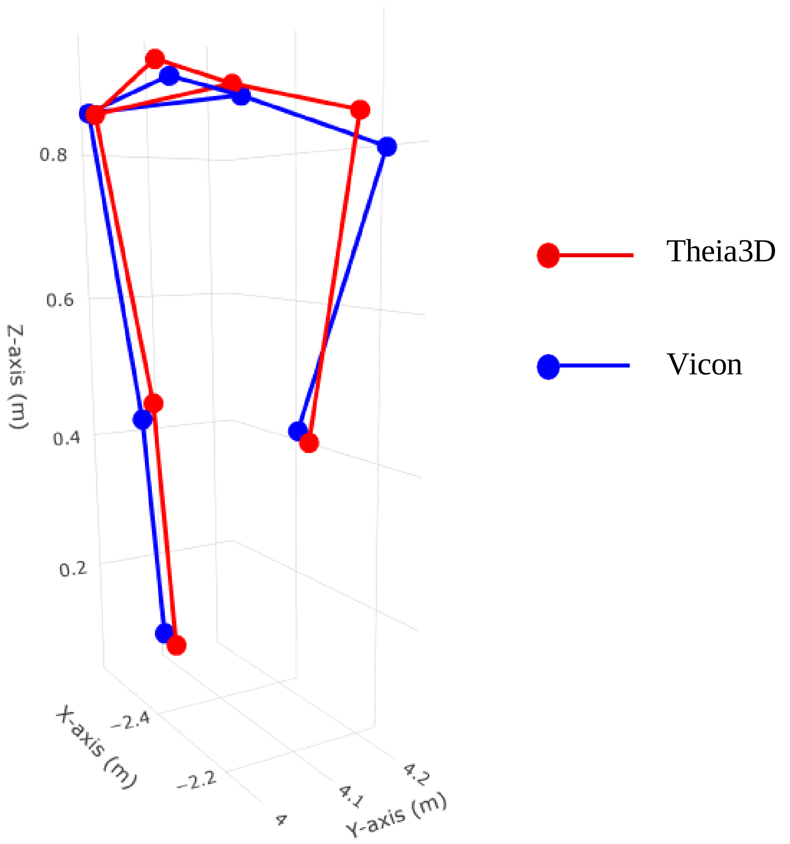


Figure 10. Three-dimensional representation of Player 22 lower limb segments and joint position at frame 1924 of the calibration trial, visualising the spatial differences between the Theia3D (red) and Vicon (blue) systems under optimal tracking conditions.

5.3.2 Sub-optimal Theia3D tracking

Sub-optimal Theia3D trials generally involved more than one player in the capture volume (i.e., 2v2), scenarios where players were required to be in close proximity to each other (i.e., tackles), or during contact with the ball (i.e., dribble, shots). The highest errors across all trials were tackles, with an example position error timeseries of Player 13's COM shown in Figure 11. Compared to the Player 22 COM example above (Figure 9), Theia3D was not able to continually track Player 13 throughout the tackle trial, with notable intermittent system interchanges between the two players involved in the trial (Player 13 and Player 07, see Figure 6 for MAE). Specifically, interchanges generally occurred when players moved close together, or when player moved to the edge of the capture volume. Gaps in Player 13's COM timeseries (Figure 11) occurred when players moved close to the edge of the capture volume. The gaps were typically followed by a spike in the COM position error across the X- and Y-axis as the system attempted to re-initiate player tracking, but was unable to apply the correct player model, thus causing player interchanges. A specific example of players moving close to the capture volume perimeter is demonstrated by the high joint position errors highlighted in Figure 11 (X-axis: 2.08 m, Y-axis: 1.91 m). To provide context to the Player 13 interchange shown in Figure 11, an example player segment 3D model is shown in Figure 12 whereby the Theia3D system is clearly tracks Player 07 as opposed to Player 13 at frame 727.

Similarly, the Theia3D system produced higher errors compared to Vicon as it mis-identified players when they were in close proximity to one another. An example of interchanging occurring between Player 13 and Player 07 during the tackle trial is highlighted in Figure 11 and represents similar position error patterns found in 2v2 trials (see Figure 5 for trial position errors). The clear misidentification of players in Figure 11 is further demonstrated by the difference in stride stages and the right ankle facing different direction for each system exacerbating the error value. As such, there was a noticeable error in overall player position MAE, and joint position MAE across these trials when Theia3D failed to differentiate between multiple players within the capture space.

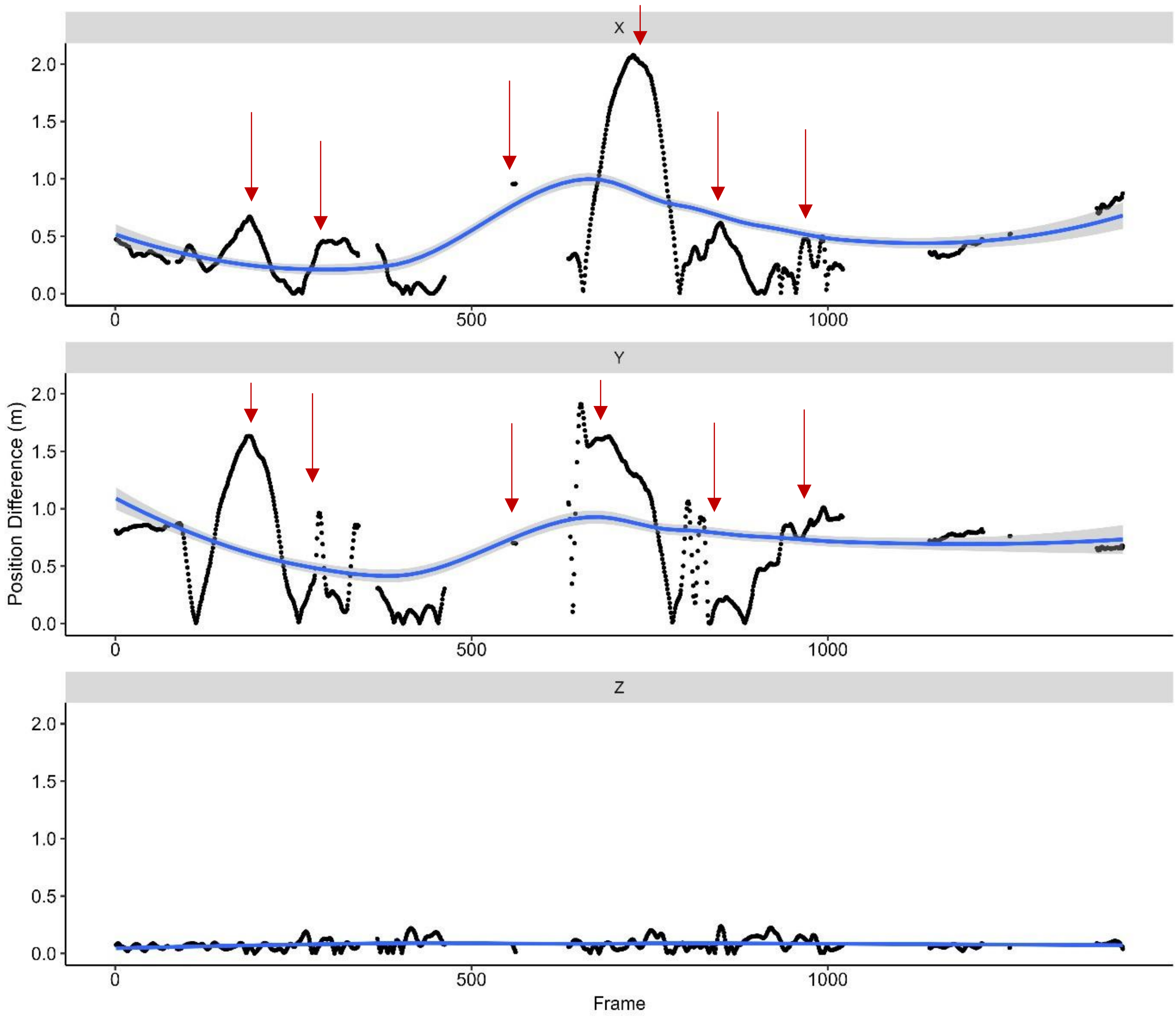


Figure 11. Player 13 Tackle trial, COM position difference in X, Y, Z axes with black points representing instantaneous joint position difference per frame with blue error trendline between Theia3D and Vicon. Red arrows identify position errors occurring where players are misidentified by the system.

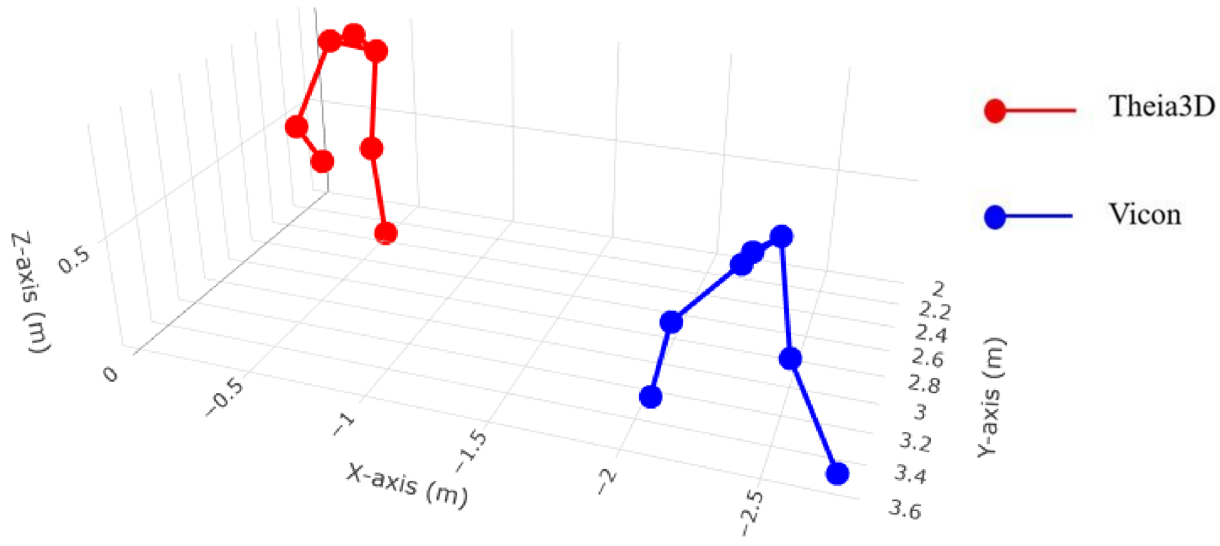


Figure 12. Three-dimensional representation of Player 13 lower limb segments and joint position at frame 727 of the Tackle trial, visualising the spatial differences (player interchange) between the Theia3D (red) and Vicon (blue) systems under sub-optimal tracking conditions.

5.3.3 Influence of ball on foot tracking

One of the aims of this study was the application of the Theia3D system in a football context. As such, the foot tracking accuracy of Theia3D during foot contact with the football was of interest. Specifically, ball occlusion of the ankle joint was observed to influence ankle position error during specific football contact trials (i.e., dribbles, shots, and passes) (Figure 13). In the position error timeseries for Player 07's ankle, it was noted that the inclusion of the ball did not cause the increased error differences between Theia3D and Vicon of 0.12 to 0.19 m across the kicking trials (Figure 13).Whilst the six kicks performed by Player 07 in the shot trial example are clearly six clearly visible across the timeseries (Figure 13), the error speaks in ankle position are a result of the forward swing speed of Player 07's leg during their kicking motion. The minimal ball contact in shot trials did not affect Theia3D's ability to track the ankle. Furthermore, the dribble trials largest error (0.35 m) did not occur through ball occlusion, but through camera coverage of the capture volume perimeter. Additionally, passing trials remained generally found good levels of position accuracy between Theia3D and Vicon ankle tracking, with patterned spikes reaching a maximum of 0.10 m occurring at the point of receiving the pass. As such, football receives seemed to provide the highest involvement of ball occlusion contributing to tracking performance (Figure 13). Therefore, the inclusion of the football did not substantially contribute to the error of ankle tracking, with foot velocity and player position relative to capture volume perimeter being the impacting factors in greater position differences observed between systems during the kicking trials.

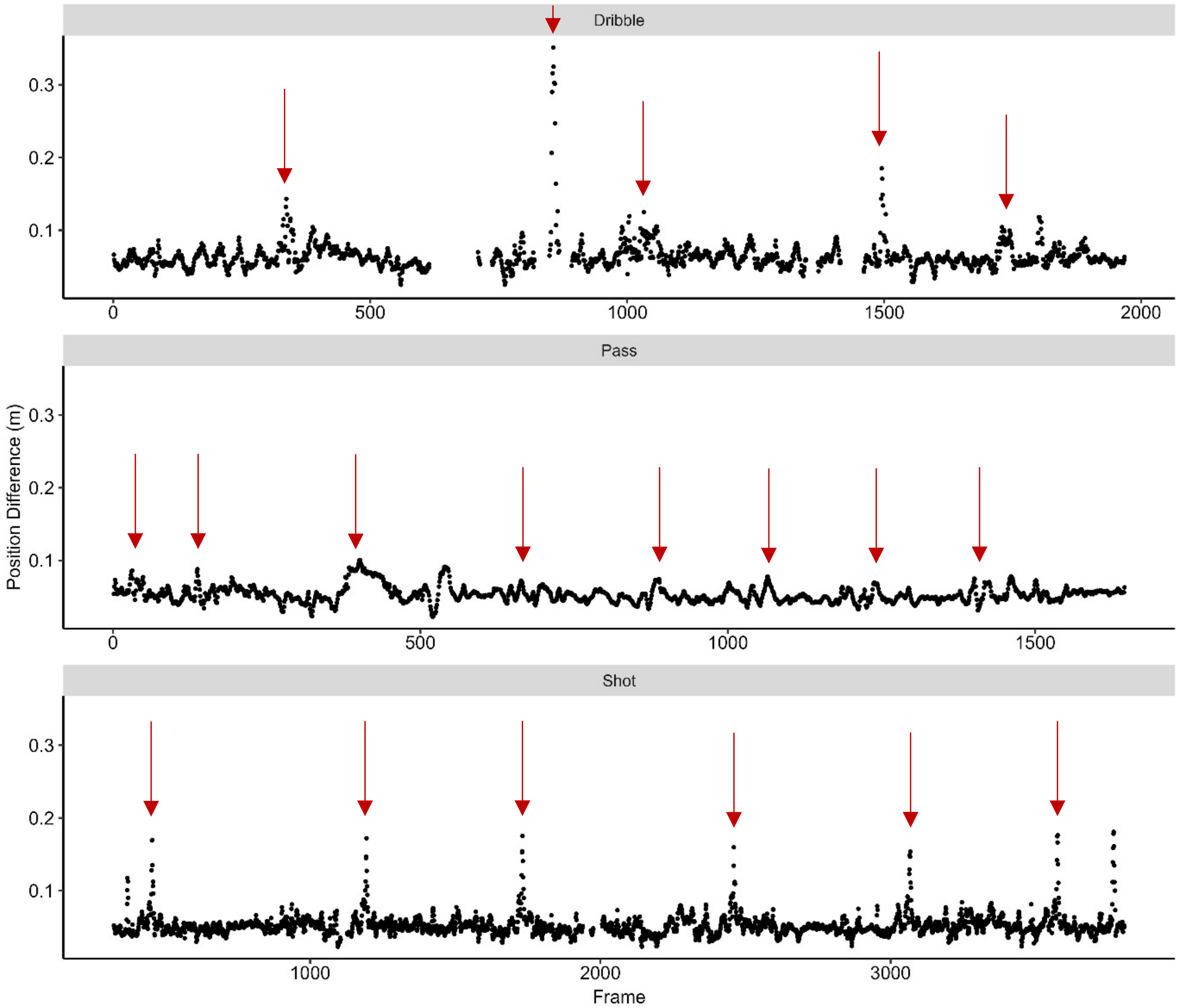


Figure 13. Timeseries of Player 07 right ankle XYZ position difference during kicking trials involving a football. The arrows represent kick points of each task.

5.4 Filtering Theia3D Player 24 data subset

The aim of this study was to compare the Theia3D system outputs exported directly from the system without applying additional data filtering. However, due to system noise observed in the raw Theia3D joint angle and position outputs, a subset of data from Player 24's trials was filtered and an accuracy assessment between Theia3D and Vicon systems was conducted. The aim of this secondary evaluation was to establish whether the application of additional filtering to the Theia3D joint angle and position outputs improves the systems accuracy again Vicon. Trials without any player interchange issues or large errors were selected for comparison. Specifically, overall filtered joint XYZ position error between Theia3D and Vicon systems across Player 24 trials recorded an XYZ MAE ± SD of 0.04 ± 0.02 m (95% CI: 0.00 to 0.07

m), compared to unfiltered Theia3D joint XYZ position error 0.04 ± 0.01 m (95% CI: 0.01 to 0.06 m). Position MAE and SD between filtered Theia3D and Vicon systems for individual axis found the following; filtered X-axis 0.02 ± 0.02 m (95% CI range: -0.01 to 0.05 m) vs. unfiltered X-axis 0.02 ± 0.01 m (95% CI range: 0.00 to 0.04 m), filtered Y-axis 0.02 ± 0.01 m (95% CI: 0.00 to 0.04 m) vs. unfiltered Y-axis 0.01 ± 0.01 m (95% CI: 0.00 to 0.03 m), and filtered Z-axis 0.01 ± 0.01 m (95% CI: -0.01 to 0.03 m) vs. unfiltered Z-axis 0.02 ± 0.01 m (95% CI: 0.00 to 0.04 m). Overall filtered vs unfiltered angle RMSE ± SD between Theia3D and Vicon systems across Player 24 trials found a filtered X-axis joint angle of 11.9 ± 6.4° (95% CI: 0.6 to 24.4°) vs. unfiltered joint angle X-axis 13.1 ± 7.0° (95% CI: -0.6 to 26.8°), filtered Y-axis joint angle of 8.9 ± 5.2° (95% CI: -1.3 to 19.1°) vs. unfiltered joint angle Y-axis 8.8 ± 5.2° (95% CI: -1.4 to 19.0°), and filtered Z-axis joint angle of 37.0 ± 25.0° (95% CI: - 12.0 to 96.0°) vs. unfiltered joint angle Z-axis 38.5 ± 24.0° (95% CI: -8.5 to 85.5°). As such, the influence of filtering on Theia3D outputs prior to comparison against Vicon was found to have a minimal impact on system accuracy.

Chapter 6: Discussion

The Theia3D system demonstrated low magnitude of difference compared to Vicon when tracking joint position during isolated football-specific such as calibration (i.e., joint range of motion tasks), passing, dribble and shooting. Magnitude of difference is defined in this study by the error range of the two systems tracking data, where:

- Low magnitude of difference: ≤ 0.1 m – less than one joint width away from the true joint location OR ≤ 15° - less than one limb width movement from true limb position
- Moderate magnitude of difference: 0.1 < x ≤ 0.15 m – around one joint width away from the true joint location OR 15° < x ≤ 25° - around one limb width movement from true limb position
- High magnitude of difference: > 0.15 m – more than one joint width away from the true joint location OR >25° - more than one limb difference in limb deviation

Joint position tracking during congested or multi-player trials (i.e., tackles and 2v2), and joint angle tracking of distal lower body joints (i.e., ankles) found higher magnitude of difference between the Theia3D and Vicon systems. These results suggest that the Theia3D system is better suited for isolated technique analysis for coaching and technical improvement within football training, while the system may be ineffective for more complex training drills requiring competitive play simulations and tactical evaluations incorporation more than one player and scenarios in which players are required to be in close proximity to each other.

6.1 Positional performance

6.1.1 Single vs multi-player trials

Trials found to have the lowest magnitude of difference between Theia3D and Vicon were calibration, 3v3, throws/headers, shots, dribble, and pass trials. Not surprisingly, these trials, except for the 3v3 SSG and pass trials, involved a single player present within the Theia3D capture volume. These found comparable error values to the calibration trial (0.03 m) to similar movements completed in past optical tracking trials (0.02 to 0.04 m) (Kanko, Laende, Davis, et al., 2021). Football-specific movement trials also displayed a low magnitude of difference; for example, shot trials exhibited high accuracy, despite the higher velocities involved. Specifically, the MAE for shot trials was 0.04 m, aligning closely with alternative optical tracking technology, which has reported errors of 0.035 m while tracking a kicking cycle in football (Palucci Vieira et al., 2022). Trials such as throws/headers, shots, and calibration movements that only required one or two players at once found a lower magnitude of difference between Theia3D and Vicon (4.0 to 50.3°) compared to multi-player trials. Similar findings assessing single player movements have been noted 0.99 to 34.7° (Ceseracciu et al., 2014; Drazan et al., 2021). As such, the improved accuracy in single-player tracking trials can be explained by the small-to-no occlusion observed among these trials.

Conversely, multi-player trials (i.e., tackle and 2v2) were generally found to have a high magnitude of difference between the Theia3D and Vicon systems. The major errors found within the two trials can be attributed to the interchanging and misidentification of players within the capture volume. This is evidenced by the larger errors demonstrated by Player 07 and Player 13 within the multi-player trials (>0.70 m) compared to their individual trials (<0.03 m). Furthermore, small position differences (<0.003 m) have been reported in other studies involving single player Theia3D captures (Strutzenberger et al., 2020). One explanation for Theia3D's reduced limited tracking performance in multi-player trials may be the impact of player occlusion within the capture volume. Specifically, in instances when player occlusion occurred within multi-player trials, it hindered the Theia3D systems ability to differentiate between players effectively. Object occlusion has been previously reported as a limitation to optical tracking systems when tracking racquet sports (Barris & Button, 2008; Tan et al., 2024), therefore occlusion is a consideration for any end-users utilising optical tracking systems. In addition to occlusion, the ambiguity in player height and physical composition across trials is another suggested cause of Theia3D player interchanges occurring in the 2v2 and tackle trials. This is a challenge for optical systems during multi-player tracking scenarios as optical systems rely on image segmentation from video footage to differentiate players (Beetz et al., 2005; Kim, 2019; Liu et al., 2009; Mazzeo et al., 2008). The homogeneity of players physical characteristics, and the incorporation of football jersey and Vicon suits may have led to Theia3D segmenting each player's image as the same skeleton. However, the system did misidentify a male participant with a female participant during the 2v2 trial, suggesting further developments should be made to overcome misidentification caused by video segmentation issues when multiple players are in a capture session (Beetz et al., 2005). These findings demonstrate that the Theia3D system may not yet be suitable for use in football match simulation or tactical training in its current version, but may be suited for individual skill development and technical analysis.

Interestingly, despite having the most players in the capture volume, the 3v3 trial was one of the better performing trials in terms of accuracy between systems. The likely cause for this is the congestion within the capture volume meant players looked for space rather than attacking the ball. Previously, SSGs in football have been shown to significantly influence player movement patterns when changes in field dimensions and player density are applied (Castellano et al., 2015; Hill-Haas et al., 2009). Reducing player numbers within a defined pitch space intensifies physical demands promoting tactical skills (i.e., defending and creating space) (Castellano et al., 2015; Hill-Haas et al., 2009). Similarly in this study, these higher intensity movement patterns and tactical skill changes were noted between players in the 2v2 compared to 3v3 SSG trials in this study. Specifically, players covered less space during the 3v3 compared to 2v2, resulting in less frequent occurrences of close contact between players compared to the 2v2 trials, and thus reducing subsequent accuracy errors.

6.1.2 Joint positional difference

Individual joint tracking is crucial for accurately capturing limb and movement patterns. The individual trials provided insights into the ability of Theia3D system's ability to accurately track joint centres. Generally, hip joints exhibited the lowest error among all joints, which contrasts with previously studies reporting knee joints as the more accurately tracked joint of the lower body (Kanko, Laende, Davis, et al., 2021; Palucci Vieira et al., 2022). As such, the accuracy of Theia3D’s hip joint position in this study may be attributed to a more uniform hip model output relative to the Vicon hip model output used in this study. The hip joint is surrounded by a larger volume of soft tissue artifacts such as skin, muscle, skeletal structures, and adipose tissue compared to more distal lower limb joints (i.e., knee and ankle) (Akbarshahi et al., 2010; Li et al., 2012; Sandau et al., 2014; Tsai et al., 2011). As such, hip joints are susceptible to these artifacts which may explain the knee joints generally reporting better accuracy outcomes in optical tracking compared to hip joint position (Kanko, Laende, Davis, et al., 2021; Palucci Vieira et al., 2022; Sandau et al., 2014). However, the left hip for Player 07 and Player 24 during the dribble trial (0.03 m and 0.02 m, respectively), were also found to be comparable to single player running hip error (0.029 m) reported by Kanko et al. (2023). In this study, Theia3D’s hip model may be more robust to such soft tissue variations, producing a more consistent output for hip position for comparison against the Vicon system.

Player COM largest error across trials which was likely attributed to systematic differences in COM model outputs between the Theia3D and Vicon systems (see Figures 8 & 9). Systematic differences may occur as optical tracking systems like Theia3D track objects via image segmentation and image recognition (Beetz et al., 2005). Furthermore, optical tracking systems used in football tend to identify and track a position near the centre of the pelvis of the player as COM point (Beetz et al., 2005; Manafifard et al., 2017; Robertson et al., 2023). Alternatively, the OCST model utilised to track the player COM in Vicon is reconstructed as the centre point between four markers placed on the left and right, anterior and posterior iliac crest of the pelvis. Previous studies comparing COM between player tracking technologies have reported minor positional differences between systems that may potentially impact tech outputs (Linke & Lames, 2019; Manafifard et al., 2017). Specifically, the magnitude of error found between player COM technologies can be attributed to specific movement characteristics (i.e., low vs high velocity movements) (Linke & Lames, 2019). However, the COM position difference (<0.06 m) between Theia3D and Vicon systems exceeds differences found in inter-system comparisons during sprinting (<0.01 m) (Needham et al., 2021). Therefore, differences observed between Theia3D and Vicon player COM positions may be attributed to differences in system methodologies used to model COM such as aggregated positions of other joints, physical landmarks, or marker placements, making it more vulnerable to compounded errors.

It was found that joints more distal to the players trunk (i.e., knees and ankles) displayed higher positional error compared to trunk joints (i.e., hips). High-speed movements are common challenge in movement tracking systems, and often result in reduced accuracy during high-speed movements (Linke et al., 2018; Ogris et al., 2012). Specifically, shot and pass trials exhibited higher position errors, particularly for the ankle joint. Greater limb velocities expressed at the ankle joint during these kicking trials may explain the higher tracking error from Theia3D when compared to Vicon. Previous studies have reported higher measurement error during high-velocity movements such as kicking, with higher errors resulting from these movements being more susceptible to soft-tissue motion artifacts (Blair et al., 2018; Chiari et al., 2005). While peak limb velocity in kicking motions contributed to increased error, medium-speed movements, like hip rotations and passing, demonstrated lower errors compared to stationary tracking. This indicates that some higher-speed movements may be tracked more accurately than stationary or low velocity movement (van der Kruk & Reijne, 2018). This summation of limb momentum and higher ankle velocity may explain why ankle joints had higher errors (> 0.05 m) than knee or hip joints (< 0.04 m, and < 0.03 m), with similar findings also noted for running (Hip & Knee: -10° to 0°, Ankle: 0 to 10°) speed (Tang et al., 2022). As such a potential solution for end-users to mitigate erroneous Theia3D data is to increase capture frequency if they intend to use the system for assessment of high-velocity movement such as kicking.

6.1.3 Influence of football on position accuracy

As the aim of this study was to validate Theia3D in an applied football context, the impact that the football had on lower-limb tracking was evaluated during the dribble, pass, and shot trials, with minimal effect on joint position accuracy found. The peaks in error observed

in ankle position during shots trials was found to be a result of the high-velocity kicking movement. This was evident as the error peaks occurred during the leg swing phase of the kicks prior to foot contact with the football. Furthermore, ankle position errors in dribble trials were caused by the player positioning against the perimeter of the capture volume, leading to limited Theia3D camera coverage. Passing trials remained generally low in error, with small spike where players receive and kick the ball, indicating there may be small amounts of ball occlusion affecting foot tracking. Past studies have experienced more substantial effect on tracking from footballs inclusion, particularly when ball contact is more forceful and the balls deformation crowds the foot momentarily (Peacock & Ball, 2019). However, the ball did not seem to influence ankle position error in this study. As such, Theia3D is able to account for ball occlusion of the lower limb and therefore the system may be a viable option for kicking analysis.

6.2 Angle performance

In evaluating joint angles, considerable variability in error across individual trials and players was observed between Theia3D and Vicon systems. Generally, joint angle error reflected similar patterns joint position error in that it appeared to be notably higher in multi-player trials compared to single-player trials. This aligns with prior observations suggesting that multi-player scenarios increase occlusion and noise, affecting tracking accuracy (Kim, 2019). Despite some trials reporting reasonable error levels between systems, the magnitude of angular error in this study was significantly higher than values typically reported in previous Theia3D research, with differences across X, Y, and Z axes were often reported below <5° (Kanko, Laende, Selbie, et al., 2021; Wren et al., 2023). In contrast, this study frequently found errors largely exceeding this threshold, particularly along the Z-axis (> 18.4°). Whilst the higher Z- axis angle difference is in agreement with previously reported Theia3D studies, the magnitude of error was significantly higher (Kanko, Laende, Davis, et al., 2021). Interestingly, hip angles in this study displayed lower error levels than expected, contrary to the trend observed in previous studies where soft tissue artifacts, such as muscle and clothing increase hip angle error (Akbarshahi et al., 2010; Li et al., 2012; Sandau et al., 2014; Tsai et al., 2011). Hips may have demonstrated higher tracking accuracy via the Theia3D system's unique algorithm, where it may potentially identify alternative points of interest to other tracking systems. This contradicts previous literature reporting knee joint angles return the lowest error of lower limb joints, which are typically easier to determine joint centres with less soft tissue mass surrounding the joint (Mündermann et al., 2006; Song et al., 2023). Furthermore, knee flexion data in certain football movements (i.e., dribbling, shooting, passing) did yield some angle RMSE values comparable to other sports, such as lead knee flexion during baseball pitching (5.7° in shooting vs. 11.5° in pitching) (Fleisig et al., 2022). This finding suggest that the Theia3D system has potential in providing joint angle outputs in line with other sports. However, issues with the system's ability to report joint angles was challenged.

6.3 Limitations

Theia3D's ability to differentiate players in tackle and 2v2 trials may have been limited by the homogeneity among players during these trials. Specifically, the players were of similar height, wore identical black Vicon suits, and performed in a capture volume with dark walls, which may have contributed to capture data errors. Many optical systems rely on colour differentiation in video pixels to support machine learning algorithms for human skeleton tracking (Barris & Button, 2008). Consequently, the uniformity in player clothing, laboratory capture environment, and similarities in player body composition likely posed challenges for the Theia3D system. It is acknowledged that the methodological inclusion of Vicon suits may have complicated player differentiation. However, Theia3D claims the ability to track multiple human subjects within its capture volume (Theia Markerless, 2019). Other systems have successfully differentiated players by tracking jersey numbers, even among similar-looking individuals (Nady & Hemayed, 2021). As such, attempts to assist Theia3D's player recognition were made by incorporating football shirts over the Vicon suits in this study. However, instances occurred whereby the Theia3D system experienced interchanges between a male and female players of contrasting physical characteristics. Furthermore, the system did not provide the functionality to end-users to allow manual reassignment of player tracking models, meaning tracking errors cause by player identification faults were not easily corrected. Therefore, Theia3D's effectiveness in tracking multiple players for football match scenarios is limited, however may still provide value for individual player tracking.

The decision to analyse the Theia3D data outputs without additional filtering was intentional to simulate a “plug and play” use case reflecting how the system might be employed by a football stakeholder. This approach has been validated in other studies with favourable joint angle accuracy (Tang et al., 2022). Filtering the data may have reduced noticeable noise in some trials, improving agreement between systems by reducing joint tracking noise and oscillations. One study reported higher player differentiation accuracy by applying more extensive post-capture filtering, with a notably reduced variance in the accuracy of data (Needham et al., 2021). As such, an evaluation of Player 24’s raw Theia3D data export was compared with filtered data of the same data subset to determine the effect of filtering on Theia3D data accuracy against Vicon. This evaluation revealed negligible differences Theia3D system accuracy; therefore, the decision was made to evaluate the raw player tracking data in this study. As such, the “plug and play” tracking approach used in this study reflected the with minimal post-processing an end-user of Theia3D may experience as this scenario is for whom the system is designed.

Finally, the constraints of this study being conducted in laboratory setting with a small scale Theia3D capture volume is considered a limitation in to on-pitch football applications. Both Theia3D and Vicon setup limitations resulted in an indoor data capture, inherently affecting the comparison accuracy between Theia3D and Vicon in an on-field football context. An indoor capture is not impacted by environmental factors such as weather exposure and playing surface (Robertson et al., 2023). Both factors may affect natural player movement patterns recorded by the Theia3D system. However, the intention of replicating playing conditions as best as possible in a laboratory environment meant the accuracy outcomes reported in this study may not be replicable in on-pitch applications (Verheul et al., 2020). Furthermore, the indoor constraint led to capture volume size constraints for game play scenarios, particularly during 2v2 and 3v3 trials, therefore the findings in this study may not be transferrable to full-pitch tracking applications (Aughey et al., 2022; Jennings et al., 2010; Robertson et al., 2023). The smaller capture volume meant that player movement velocities may have been limited or inhibited all together during multi-player trials (Robertson et al., 2023). Capturing data on the field would not only provide the option for a larger capture volume, but also allow player tracking in the appropriate football environment.

6.4 Practical applications

The aim of this study was to establish Theia3D as a utility for use in football. As such, this section suggests football-specific applications for football end-users that are supported by findings on the system's optimal and sub-optimal tracking conditions. Specifically, the effectiveness that Theia3D may have the following football use-cases, performance improvement, talent identification and development, and injury prevention and return-to-play.

6.4.1 Performance improvement

Theia3D's accuracy in tracking single-player, isolated movements make it a tool useful for performance enhancement within football. Specifically, trials performed under minimal occlusion, reduced player density, and simplified movement patterns showed a high degree of accuracy in capturing kinematic data. These favourable conditions align with other studies where Theia3D accurately assessed isolated high-intensity actions, such as boxing (Lahkar et al., 2022) and baseball pitching (Fleisig et al., 2022). In football, similar settings allow Theia3D to provide clear, precise tracking for skill refinement, with specific examples provided:

- *Technical Skill Analysis:* Theia3D may be an ideal system for coaches looking to analyse specific technical skills such as dribbling, passing, and shooting. As the system allows 3D movement assessment without markers restricting football movements (Kanko, Laende, Selbie, et al., 2021; Robertson et al., 2023). The data generated can assist coaches in evaluating and improving players' skills by identifying subtle joint and limb adjustments, which may translate to in-match skill performance (i.e., prescribing ankle mobility drills after identifying lower ankle flexion during kicking performance) (Palucci Vieira et al., 2022; Peacock & Ball, 2019).
- *High-Intensity Actions:* For high-speed actions, such as shooting or quick directional changes, Theia3D may benefit from a higher sampling frequency (i.e., 100 Hz) to accurately capture movement without compromising processing time (Lutz et al., 2020; van der Kruk & Reijne, 2018). To further optimise performance tracking of high- intensity movements, coupling Theia3D with supplemental technologies such as ankle-mounted accelerometers, may enhance accuracy in capturing high speed movements (i.e., penalty shot kicks and passes) (Dinu et al., 2012; Ward et al., 2005).

While the Theia3D system performance is robust in controlled, isolated settings, its limitations in multi-player and high-velocity scenarios must be considered by football end-users. As such, its practical application for measuring tactical skills of players during match simulation should be avoided.

6.4.2 Talent identification and development

Theia3D's ability to accurately track isolated movements is also advantageous for talent identification and player development. Its accuracy in low-occlusion scenarios offers a reliable method for assessing technical skills as key indicators of football talent. The following are specific areas where Theia3D can specifically be used to improve technical skill benchmarking and skill development in football:

- *Technical Skill Benchmarking:* Isolated movement analysis allows scouts and coaches to benchmark players' technical skills against set criteria. Movements such as foot positioning, dribbling techniques, and shooting accuracy can be captured reliably to identify players with advanced technical capabilities (Jauhiainen et al., 2019).
- *Skill Development:* Theia3D may be used as a tool for objective assessment in football training by coaches through tracking isolated football skills under various conditions (i.e., dribble constraints, long vs short pass) (Waldron & Worsfold, 2010). The 3D tracking data obtained through Theia3D may assist coaches in quantifying developing player movement, providing a benchmark from which they can monitor player progress over time (Vaughan et al., 2021). In turn, this may allow targeted skill training and performance improvement in younger or less experienced players.

However, the Theia3D's system effectiveness is reduced in crowded settings or multi-player drills, where player proximity can cause misidentification. In these situations, larger spaces or additional tracking systems may be required to maintain accuracy, as evidenced by other optical tracking research (Kim, 2019; Liu et al., 2009).

6.4.3 Injury prevention and return-to-play

Theia3D's historically being developed for clinical applications suggest that the system may be a useful tool for football injury prevention and return-to-play use-cases (Ito et al., 2022; Kanko, Laende, Davis, et al., 2021; Wren et al., 2023). Furthermore, the system's accuracy in capturing isolated joint movements and slow-to-moderate football movements in this study supports its use in monitoring players during return-to-play programs, with specific practical applications suggested below:

- *Injury Assessment and Monitoring:* Theia3D is particularly suited for clinical assessments. Where isolated, slower movements are required to assess joint integrity and recovery progress. Accurate tracking of joint angles and muscle movements provides clinicians with reliable data for identifying and monitoring of players identified as potentially high-risk for injury occurrence (Abrams et al., 2011; Fortenbaugh et al., 2009; Martin et al., 2021). Specifically, accurate tracking mayidentify joint movements beyond optimal ranges, stretching soft tissue and risking injury. Identifying this prior to injury allows relevant technique or training load changes to be made (Ortega & Jimenez-Olmedo, 2017).

- *Return-to-Play Decision Support:* Utilising Theia3D for capturing movement mechanics during rehabilitation drills may assist medical practitioners in determining when a player is physically ready to return to competition. The system's accuracy in 3D joint position may enables medical practitioners to benchmark players' movement against pre-injury baselines or healthy norms, reducing the risk of re-injury by ensuring that they meet recovery criteria (Franzò et al., 2023; Mündermann et al., 2006).

In high-velocity actions, Theia3D may require additional adjustments and is not recommended for return-to-play or injury prevention use cases. However future system developments, such as a higher sampling rate to maintain accuracy may allow this application. Alternatively, elite players performing high-speed movements may be better served by supplemental devices, such as ankle accelerometers, high-speed cameras, or marker-based 3D motion capture systems capable of capturing rapid limb actions with greater precision (Lutz et al., 2020; van der Kruk & Reijne, 2018).

As such, Theia3D's practical applications in football are most beneficial for single-player, isolated skills, and movement analysis, making it a valuable tool in assessing performance improvement, talent identification, and injury prevention. While the system may perform well under these conditions, it is limited in congested or high-velocity football contexts, and supplemental technology may be required to ensure optimal performance outcomes in those settings. The system's clinical precision also provides a strong foundation for injury prevention and rehabilitation, enabling targeted interventions that promote player health and performance.

6.5 Future directions

Future directions for this research should include expanding methods to incorporate upper body joint kinematics, enabling a more comprehensive validation of Theia3D for full-body player tracking. Specifically, overcoming the challenges such as ball and player occlusion, particularly in uncontrolled or high-velocity settings, would be crucial for adapting markerless tracking in real-world football scenarios. Further validation of Theia3D metrics such as joint angular velocity may expand football applications by providing greater contextual insights into high-velocity football movements, where movement timing, speed, and control are crucial (Aughey et al., 2022; Palucci Vieira et al., 2022; Waldron & Worsfold, 2010). This inclusion would also enhance understanding of how players coordinate weight distribution and segment interactions during skills such as tackling, dribbling, and sprinting (Modric et al., 2020; Waldron & Worsfold, 2010). Furthermore, examining ball dynamics during kicks, with a particular focus on high-power shots and curved kicks, would yield valuable information on foot-to-ball interaction, ball trajectory, and impact forces, which are essential for optimising player skill execution (Palucci Vieira et al., 2022; Peacock & Ball, 2019). Additionally, future research may seek to conduct research utilising football turf (i.e., grass or synthetic turf), with players in full uniform to further enhance ecological validity of Theia3D's application in football (Robertson et al., 2023; Verheul et al., 2020). Furthering the Theia3D research in these areas could provide a foundation for 3D limb tracking data-drive training strategies, injury prevention programs, and performance optimisation that fit the unique demands of football stakeholders.

Long-term potential of the Theia3D markerless motion capture could be evaluating the system's integration at the club level for injury prevention, player load management, and technical development. Football clubs, motivated by high injury rates despite advances in strength and conditioning, could find markerless technology a valuable tool. For example, in Australia's A-League, 917 injuries affected 421 players between the 2012/13 and 2017/18 seasons (Lu et al., 2020). Similarly, injury prevalence in England's top-flight league costs teams an average of £45 million in performance-related losses annually (Eyal et al., 2020). These statistics highlight the need for innovative injury prevention and performance tracking solutions. Beyond injury prevention, the implementation of Theia3D markerless technology could enhance player analysis and development. The English Premier League, for instance, invested £1.6 billion into youth academies between the 2012/13 and 2020/21 seasons to boost the number of professional English players (EY, 2022). Using Theia3D markerless capture technology in youth development could allow for more precise assessment of physical and technical attributes, fostering targeted training and better long-term outcomes (Jauhiainen et al., 2019). Markerless motion capture technology offers promising potential for football clubs, addressing injury prevention, player load management, and technical development, while enabling more precise player analysis and youth development through targeted training.

Chapter 7: Conclusions

This study evaluated the tracking performance of Theia3D markerless motion capture system against the 'gold standard' Vicon 3D marker-based motion capture system within a football-specific context. A main objective of this study was to provide practical guidance to end-users on use-cases where the Theia3D system may or may not be suitably applied. Specifically, this study analysed the magnitude of difference between the Theia3D and Vicon when measuring lower body joint angles and joint positions by concurrently tracking football-specific movements (i.e., calibration, dribble, shot, pass, throws, 2v2, 3v3). Joint position tracking performance showed a generally low magnitude of difference between the systems, with low error observed in most trials. In single-player trials (i.e., calibration, pass, shot, dribble, throws) all joints demonstrated an acceptable level of accuracy. However, overall joint position error was found to increase in more congested, multi-player trials. The reduced agreement in 2v2 and tackle trials was largely due to Theia3D interchanging players during trials, with this usually occurring when players were in close proximity to one another, or near the capture volume perimeter. Evaluation of specific joint found the hips exhibited the smallest position differences between Theia3D and Vicon, while the centre of mass (COM) and ankles showed the largest differences. The higher error reported in COM tracking likely stems from modelling reconstruction differences between the two systems. Ankle position errors were also higher, likely attributed to higher velocities observed at these joints when compared to the knees and hips. Joint angle magnitude of difference was moderate, though showed greater variance between systems. Angle differences were relatively consistent across trials; however, significant error was noted for joint angles, particularly in ankle joints. It was suggested that angle error was likely influenced by system noise or ambiguity in Theia3D's definition of joint angle, meaning there is uncertainty in the comparability of this metric against Vicon's joint angle definition. The results of this study indicate that the Theia3D system is effective in tracking player joint positions during isolated movements, though it is limited in capturing multiple players within a congested space. For football applications, this system could be highly beneficial for end-users seeking to track isolated football-specific movements (i.e., shooting, long passes) to support technique analysis, injury identification and prevention, and talent identification. However, the system is less suitable for tracking in match play and match simulation training or tactical drills where team positioning, tactical analysis, or officiating that requires multiple players.

A key limitation affecting tracking accuracy was Theia3D's difficulty capturing multiple players with similar physical characteristics. Challenges were particularly evident in multi-player trials involving black Vicon suits in the laboratory space, which may have impeded tracking accuracy due to image homogeneity in the video capture. These limitations suggest that while Theia3D shows promise for football applications, end-users should exercise caution when analysing joint angles or multiple players in low-speed contexts to avoid misinterpretation that could impact training or recovery. As such, future research should assess Theia3D in settings that more closely represent football environments (i.e., grass pitches, standard playing uniforms and footwear). Additionally, examining alternative metrics such as linear and angular velocity could provide further insights into Theia3D's accuracy with high-speed movements. Overall, this study offers insight into the viability of Theia3D as a system for improving football performance outcomes by providing practical guidance for optimal use-cases in football-specific contexts.

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Appendices

Appendix A: Results table of joint angle per trial. All measures are reported in degrees (°).

Trial / Joint	X-axis		Y-axis		Z-axis	
	RMSE ± SD	95% CI	RMSE ± SD	95% CI	RMSE ± SD	95% CI
Calibration						
L Hip	9.0 ± 2.7	3.7 – 14.3	5.5 ± 2.5	0.7 – 10.4	29.1 ± 13.7	2.3 – 55.9
R Hip	8.4 ± 2.8	3.0 – 13.9	6.2 ± 3.7	-1.0 – 13.4	24.7 ± 8.1	8.8 – 40.7
L Knee	8.3 ± 4.0	0.4 – 16.1	13.9 ± 5.7	2.7 – 25.1	27.7 ± 19.2	-10.0 – 65.3
R Knee	7.7 ± 4.4	-0.9 – 16.2	12.0 ± 4.4	3.4 – 20.5	36.7 ± 25.0	-12.2 – 85.7
L Ankle	7.1 ± 2.0	3.2 – 10.9	8.8 ± 2.8	3.4 – 14.3	20.3 ± 8.1	4.5 – 36.1
R Ankle	9.8 ± 2.8	4.4 – 15.3	12.2 ± 1.2	9.9 – 14.5	33.4 ± 26.4	-18.3 – 85.1
Dribble						
L Hip	11.0 ± 8.5	-5.7 – 27.8	3.9 ± 0.4	3.0 – 4.7	32.7 ± 4.3	24.3 – 41.1
R Hip	11.3 ± 8.9	-6.2 – 28.8	6.0 ± 0.7	4.7 – 7.3	23.1 ± 18.7	-13.5 – 59.6
L Knee	11.5 ± 0.4	10.7 – 12.3	16.6 ± 1.5	13.6 – 19.6	30.5 ± 14.5	2.0 – 59.0
R Knee	12.0 ± 10.5	-8.6 – 32.7	15.9 ± 12.6	-8.8 – 40.5	55.2 ± 27.6	1.1 – 109.3
L Ankle	8.1 ± 4.2	-0.1 – 16.4	11.3 ± 4.1	3.2 – 19.4	23.3 ± 12.2	-0.6 – 47.2
R Ankle	13.5 ± 6.0	1.8 – 25.2	12.1 ± 1.6	8.9 – 15.3	42.5 ± 36.2	-28.4 – 113.3
Pass						
L Hip	8.2 ± 5.3	-2.3 – 18.7	4.0 ± 0.7	2.5 – 5.3	28.5 ± 12.7	3.6 – 53.5
R Hip	8.4 ± 5.4	-2.3 – 19.0	5.5 ± 2.1	1.4 – 9.7	27.1 ± 10.0	7.5 – 46.8
L Knee	9.7 ± 6.5	-3.0 – 22.4	9.3 ± 5.3	-1.0 – 19.7	49.0 ± 48.0	-45.0 – 143.0
R Knee	9.9 ± 9.3	-8.4 – 28.1	12.5 ± 7.8	-2.8 – 27.9	41.7 ± 22.7	-2.9 – 86.3
L Ankle	66.9 ± 121.0	-170.3 – 304.0	10.1 ± 2.1	6.0 – 14.2	30.2 ± 21.9	-12.7 – 73.1

R Ankle	10.8 ± 7.0	-3.0 – 24.5	11.6 ± 2.3	7.2 – 16.0	33.7 ± 23.3	-11.9 – 79.4
Shot						
L Hip	5.0 ± 0.1	4.7 – 5.3	6.7 ± 2.4	1.9 – 11.4	25.2 ± 5.4	14.6 – 35.9
R Hip	6.4 ± NA	NA	11.1 ± NA	NA	21.7 ± NA	NA
L Knee	9.9 ± 6.3	-2.4 – 22.1	10.8 ± 4.1	2.7 – 18.8	29.3 ± 23.2	-16.2 – 74.8
R Knee	5.7 ± NA	NA	7.4 ± NA	NA	50.3 ± NA	NA
L Ankle	7.6 ± 0.5	6.6 – 8.6	9.1 ± 0.4	8.3 – 9.9	28.4 ± 18.8	-8.5 – 65.4
R Ankle	9.5 ± NA	NA	16.2 ± NA	NA	30.2 ± NA	NA
Throws/headers						
L Hip	6.7 ± 7.0	-7.0 – 20.4	4.0 ± 0.8	2.5 – 5.5	23.3 ± 13.2	-2.7 – 49.2
R Hip	7.3 ± 8.2	-8.8 – 23.5	6.2 ± 2.9	0.5 – 11.8	25.8 ± 10.2	5.7 – 45.8
L Knee	7.2 ± 4.9	-2.4 – 16.9	8.5 ± 3.9	1.0 – 16.1	23.4 ± 16.1	-8.1 – 55.0
R Knee	9.5 ± 5.4	-1.1 – 20.0	9.9 ± 6.3	-2.4 – 22.2	35.5 ± 18.0	0.1 – 70.8
L Ankle	5.9 ± 1.1	3.7 – 8.0	12.9 ± 3.2	6.6 – 19.2	18.4 ± 8.3	2.2 – 34.7
R Ankle	8.6 ± 5.1	-1.5 – 18.6	10.9 ± 4.7	1.7 – 20.1	23.1 ± 23.3	-22.6 – 68.9
Tackles						
L Hip	12.4 ± 6.7	-7.0 – 20.4	7.9 ± 2.3	3.4 – 12.3	27.7 ± 6.8	14.4 – 41.0
R Hip	13.0 ± 7.5	-8.8 – 23.5	12.4 ± 2.4	7.8 – 17.0	26.5 ± 6.4	14.1 – 39.0
L Knee	17.5 ± 8.2	-2.4 – 16.9	14.8 ± 5.5	3.9 – 25.6	23.6 ± 12.3	-0.5 – 47.8
R Knee	17.3 ± 8.8	-1.1 – 20.0	13.1 ± 7.2	-1.0 – 27.2	49.9 ± 12.2	26.0 – 73.8
L Ankle	11.5 ± 3.5	3.7 – 8.0	13.3 ± 4.5	4.5 – 22.2	23.9 ± 10.1	4.1 – 43.7

R Ankle	14.6 ± 7.3	-1.5 – 18.6	17.3 ± 2.7	12.0 – 22.7	29.1 ± 9.3	10.9 – 47.3
2v2						
L Hip	9.2 ± 4.9	-0.5 – 19.0	6.1 ± 2.1	1.9 – 10.3	30.0 ± 10.9	8.6 – 51.4
R Hip	9.9 ± 5.4	-0.7 – 20.5	8.0 ± 3.4	1.4 – 14.6	28.1 ± 10.5	7.6 – 48.6
L Knee	11.8 ± 5.1	1.7 – 21.9	14.0 ± 5.0	4.3 – 23.8	31.0 ± 29.6	-26.9 – 88.9
R Knee	32.5 ± 70.0	-104.7 – 169.7	15.8 ± 7.7	0.9 – 30.8	60.5 ± 68.1	-72.9 – 194.0
L Ankle	129.2 ± 388.8	-641.8 – 882.3	17.5 ± 15.1	-12.1 – 47.0	22.8 ± 17.1	-10.7 – 56.4
R Ankle	25.1 ± 48.9	-70.8 – 12-.9	28.2 ± 45.8	-61.5 – 117.9	45.2 ± 54.0	-60.6 – 151.1
3v3						
L Hip	7.8 ± 5.7	-3.4 – 19.1	4.8 ± 1.3	2.2 – 7.3	30.7 ± 9.4	12.3 – 49.0
R Hip	8.3 ± 5.5	-2.5 – 19.1	7.2 ± 3.0	1.3 – 13.2	26.5 ± 12.4	2.2 – 50.7
L Knee	8.8 ± 5.0	-0.9 – 18.5	15.3 ± 3.9	7.6 – 23.0	24.6 ± 12.4	0.4 – 48.9
R Knee	7.8 ± 6.6	-5.0 – 20.7	13.6 ± 7.5	-1.1 – 28.3	40.5 ± 23.6	-5.8 – 86.9
L Ankle	6.3 ± 1.7	2.9 – 9.7	11.6 ± 1.5	8.6 – 14.6	20.8 ± 6.2	8.7 – 32.8
R Ankle	97.5 ± 180.7	-256.7 – 451.7	15.9 ± 7.6	0.9 – 30.8	34.5 ± 29.0	-22.4 – 91.4

CI: 95% Confidence Interval, SD: Standard Deviation, RMSE: Root Mean Square Error, L: Left, R: Right