Invisible Monitoring Using Athlete Worn Sensors in Elite Women's Soccer

By

Patrick Cormier

BSc.Kin., University of New Brunswick, 2017

MSc.HPS, Catholic University San Antonio Murcia, 2018

A Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

DOCTOR OF PHILOSOPHY

in the School of Exercise Science, Physical and Health Education

We acknowledge and respect the Lək̓ʷəŋən (Songhees and Xʷsepsəm/Esquimalt) Peoples on whose territory the university stands, and the Lək̓ʷəŋən and W̱SÁNEĆ Peoples whose historical relationships with the land continue to this day.

Supervisory Committee

Invisible Monitoring Using Athlete Worn Sensors in Elite Women's Soccer

By

Patrick Cormier

BSc.Kin., University of New Brunswick, 2017

MSc.HPS, Catholic University San Antonio Murcia, 2018

Supervisory Committee

Dr. Marc Klimstra (School of Exercise Science, Physical and Health Education; Canadian Sport Institute Pacific)

Supervisor

Dr. Ming-Chang Tsai (Canadian Sport Institute Pacific)

Outside Member

Dr. Dave Clarke (Department of Biomedical Physiology and Kinesiology, SFU)

Outside Member

Dr. Cesar Meylan (Toronto FC, Health and Physical Performance Department)

Outside Member

Abstract

Supervisory Committee

Dr. Marc Klimstra (School of Exercise Science, Physical and Health Education; Canadian Sport Institute Pacific)

Supervisor

Dr. Ming-Chang Tsai (Canadian Sport Institute Pacific)

Outside Member

Dr. Dave Clarke (Department of Biomedical Physiology and Kinesiology, SFU)

Outside Member

Dr. Cesar Meylan (Toronto FC, Health and Physical Performance Department)

Outside Member

The primary objective of this dissertation was to develop valid and reliable monitoring of soccer players' maximal acceleration and speed sprinting ability in an inobtrusive manner. To accomplish this goal, we studied methods that used observational data collected with sensors that are typically worn in every training and match in international level women's soccer (i.e., invisible monitoring).

First, to achieve this objective, it was necessary to evaluate the validity and reliability of different athlete athlete-worn sensors (global navigation satellite systems [GNSS]) against gold-standard devices for measurement of instantaneous velocity (radar) and standard time-distance sensors (timing gates). These sensors can be used to model and calculate various force-velocity (FV) metrics related to horizontal acceleration, velocity, force, power, and efficiency of the oriented force throughout linear sprinting protocols. It was demonstrated that GNSS sensors could be used to model linear sprints with adequate reliability and validity depending on the GNSS sensor used.

Second, to provide a more comprehensive assessment of the state of GNSS for FV linear sprint profiling, a systematic review with quantitative (meta-analysis) and narrative analysis was carried out on the literature comparing GNSS to radar and laser. It was found through this process that GNSS can be valid and reliable, however, there are several methodological challenges that

need to be considered which informed our research designs going forward and allowed for improvement of modeling recommendations for future research and application.

Third, although having the ability to model linear FV sprint capacity in the field using GNSS sensors is impactful, it still requires a degree of protocol standardization and requires anthropometric and environmental metrics to be collected for effective modelling. Therefore, we evaluated a novel athlete monitoring approach that requires no dedicated sprint testing or additional metrics to be collected. Acceleration-speed (AS) profiles using regular training and game data were compared to FV profiles in an elite women's soccer cohort to determine whether AS profiles could provide practitioners with similar information to FV profiling without the need for any isolated sprint testing. It was found that within a 4-week national team camp, it was possible to construct valid AS profiles that can inform practitioners on the acceleration and speed of the athletes in aggregated data sets of training and games. Since this data can contain outliers, multiple outlier techniques to construct AS profiles were also evaluated and shown to be an important aspect to consider.

Fourth, since AS profiling was determined to be valid with 4-weeks of data which may not be ecologically valid due to variations in national team camp lengths (typically a week or longer), it was then necessary to determine the minimal number of events necessary to construct valid AS profiles. Therefore, an optimization approach whereby all possible combinations of 19 training or game events were performed, and it was determined that nine events were necessary for a valid profile to be constructed, and that the inclusion of maximal sprint efforts can improve the reliability and (reduce) the number of events necessary.

In the fifth and final study, we conducted a larger scale analysis on 3-years of women's national team training camp and international match data. Since the AS profiles represent the athletes AS ability during and surrounding the camp, we could use the AS regression as a reference to normalize the maximal speed and acceleration points across velocity bands typically used in soccer (i.e., low, moderate, high, and very-high speed running). This resulted in the introduction of novel invisible monitoring metrics such as normalized acceleration and power, which allowed for the quantification of athlete's relative effort in matches compared to their physiological and biomechanical maximal capacity. These data were then used to demonstrate the differences and possible benefits of normalization or non-normalization of acceleration and power and how it varies based upon position, goal differential, and match half.

Altogether, the findings from this thesis suggests that it is possible to reliably generate "invisibly" monitored acceleration-speed profiles in international women's soccer contexts using GNSS technology. Further, AS profiling provides a benchmark for physical and tactical staff which can be compared to absolute athlete data and may inform rehabilitation, strength & conditioning programs, training sessions and match tactics. Further research is necessary to determine effective application in other team sports.

Table of Contents

Contents

List of Tables

List of Figures

Acknowledgments

Marc, you've been an incredible mentor and supervisor. I'll never forget the countless hours spent editing and discussing the contents of this thesis. Always taking the time to chat and check in to see how you can support me in life, sport, and academia, enabling me to learn and grow, and your ability to help me see the greater picture. I am grateful for that and the opportunities you created for me. I look forward to what we can create together!

Ming, you are the definition of tough love, yet I wouldn't have wanted anyone else as a co-supervisor and I thank you for trusting me with this project. I consider you a friend and someone who has taught me many skills and life lessons. I'm forever grateful for the way you have supported me and so many of us at CSIP.

Ces, I can't thank you enough for the doors you've opened and the incredible mentorship and friendship throughout the years. You took me under your wing and stuck your neck out for me on many occasions. I'll never forget the early morning national team camp runs and lifts in Vancouver, travels to Honduras and football chats. I think it's hard for many to understand how a game can impact your life and bring so much joy and heartache, yet passion and human connections always pull us back. You understand this perfectly and thank you for your encouragement to keep going and pushing my limits.

Dave, thank you for your support and guidance. Our chats were always enlightening, and you always took the time to patiently discuss the concepts and models in this thesis. Your insights have greatly contributed.

This whole process has felt like a steep hill to climb, and I don't know to this day what having or achieving a doctorate degree means to me, but I know that I've become a little more patient, graceful, knowledgeable, and my skin is a little bit tougher, and that makes it worth it in my books. There are many mentors, lab mates, and athletes that have fueled my passion for human performance and continuing my journey in sport. Thank you. You know who you are.

To my parents, Hubert, and France. I sincerely couldn't have done any of this without your support. You always lovingly supported my ambitions, no matter how far-fetched they seemed and the values you taught me from an early age have kept me humble through this process. To my partner and all my extended family and friends, I couldn't have done this without your support and understanding as I spent long periods away from home on the other side of the country working towards my goals. Thinking of you all has kept what really matters in life in perspective over the years.

Dedication

This work is dedicated to my family and those who believe in me

Chapter 1 – General Introduction

1.1 Invisible monitoring

The concept of "invisible" in-situ monitoring comes from the potential to ambiently collect data from athletes during their regular training and competition to develop a rich data-set from an accumulation of each bout of activity (Morin et al., 2021). This rich data set can be subject to different analytical approaches to determine biomechanical and physiological profiles. These profiles can be used as benchmarks to test training interventions as well as to understand an athlete's current physical capacity and readiness. Beyond the valuable insights gained from this approach, invisible monitoring requires no specialized testing sessions and therefore can remove the time and resource requirements of group testing in elite sport environments. While there is exciting potential for invisible monitoring, each sport possesses unique characteristics resulting in the need for the development of a unique analysis with diverse technologies.

1.2 Wearable sensors for invisible monitoring

As a starting point to appreciate the potential of invisible monitoring it is important to highlight that the use of wearable microtechnology has become an essential part of elite sports for monitoring and quantifying movement and effort (Aughey, 2011). For example, it is common practice in team sport settings to use motion sensing technologies such as global navigation satellite system (GNSS) sensors during training and competition. GNSS sensors are capable of providing location and speed information with location accuracy of ~ 1m at 10-20Hz (Dennison et al., 2025), making these sensors suitable to track athlete movements. However, these sensors are limited to an outdoor environment due to the requirement to sufficiently connect to GNSS constellations. GNSS sensors form the basis for athlete monitoring devices, however these devices may also include inertial measurement units (IMU) which can provide high resolution acceleration and angular velocity. Therefore, in team sports whose primary training and competition environment is outdoors, GNSS sensors can provide fundamental kinematic information for athlete movement at their extremes of effort during training and competition as well as during specialized testing. Ultimately, the use of wearable micro technologies during training, competition and dedicated testing has enabled sport scientists to continuously monitor external workload (Cummins et al., 2013), rehabilitation status (Greig et al., 2019), high speed running efforts (Meylan et al., 2017), and other physiological markers. This use of wearable sensors paves the way for invisible monitoring as the amount of data that can be accumulated from each athlete, in many states and conditions, can help to build a complete profile of capacity, as well as other workload measures and potentially remove the requirement of standalone standardized testing.

1.3 Standalone athlete performance testing

The purpose of standalone testing in sport is to quantify the athlete's capacity in controlled settings. A valuable standalone test is sprint testing, where athletes start from a stationary position and then accelerate maximally to obtain a top speed within a predetermined distance. Often, times to complete the entire distance as well segments (splits) during the sprint are used to compare between athletes and within the same athlete over time (T. Haugen et al., 2020). For example, the times at the beginning of the sprint (0-10m) are used to define the ability of an athlete to accelerate and the times at the end of the sprint (30-40m) are used to determine the top speed of the athlete (Agar-Newman et al., 2017; Poehling et al., 2021). While simple approaches of sprint assessment are valuable there has been growing interest in modelling data from the entire sprint to produce systematic variables associated with theoretical force, velocity and power of the athlete based on sprinting data (Samozino et al., 2016; Volkov & Lapin, 1979). This approach is called horizontal force-velocity (FV) profiling and has received substantial research interest for its ability to provide reproducible variables defining an athlete's maximal force and speed expression (Samozino et al., 2016).

1.4 Horizontal force-velocity profiling

As sprinting is crucial in team sports like soccer and rugby (T. A. Haugen et al., 2020; Watkins et al., 2021), horizontal FV profiles developed from standalone sprint testing are being used to analyze and understand an athlete's capacity related to workload, training, and rehabilitation (Morin & Samozino, 2016). Horizontal FV profiles are created by modelling velocity or split time data collected from an all-out sprint performed by an athlete from a stationary start. The technique uses radar and GNSS velocity data which is fitted using a mono-exponential model to estimate the acceleration constant and maximal sprint speed (Figure 1-1. left panel). These values are then used to estimate theoretical maximum force (F_0), force at zero velocity, and theoretical maximum velocity (V_0), velocity at zero force; as well as maximal mechanical power. There has also been investigation into other metrics to quantify the sprint efficiency such as the slope of the FV relationship, the maximum value for the ratio of force, and the decrease in force ratio (Bezodis et al., 2021; Morin & Samozino, 2016). Given the detailed metrics that FV profiles can provide, their usage enables a more thorough assessment of sprinting data than traditional methods. Further, metrics derived from this approach have been valuable to support investigations of positional demand and competition level. For example, in a study by Watkins et al. (2021), analyzing FV profiles, it was determined that international and professional players possessed superior peak horizontal force production ability at the start of the sprint and across a variety of sprint FV attributes than club level players. The technique of developing a FV profile, however, requires dedicated sprint testing where athletes are required to perform multiple isolated sprints, which can take valuable time away from normal practice sessions.

1.5 Acceleration-speed profiling

Similar to FV profiling, acceleration-speed (AS) profiling is another method of biomechanically profiling using athlete worn wearable microtechnology (Morin et al., 2021). While FV profiles use speed or time/distance data collected during testing an individual sprint, AS profiles use data from body worn GNSS sensors to collect speed and acceleration data from every sampled time point during sport specific or in-situ training or competition situations. This results in a data cloud of all the accelerations mapped to their associated speed, from multiple events, as seen in Figure 1-1, right panel. This includes both many maximal efforts, after selecting the maximal acceleration values at each speed and the cleaning and removal of any outlier data, the profile is generated via a linear regression of the highest positive acceleration at each speed achieved by the athlete (Cormier, Tsai, Meylan, & Klimstra, 2023; Morin et al., 2021). Morin et al. (2021) defined the important metrics in the AS Profile as: the theoretical maximal acceleration at zero velocity-intercept (A_0), the theoretical maximal speed at zero acceleration-intercept (S_0), and the AS slope or overall orientation of the AS profile. There are few investigations into this type of profiling. Although there is promise in the ability to determine player maximum AS biomechanical capacity without the need for dedicated tests, there are various factors that must be investigated.

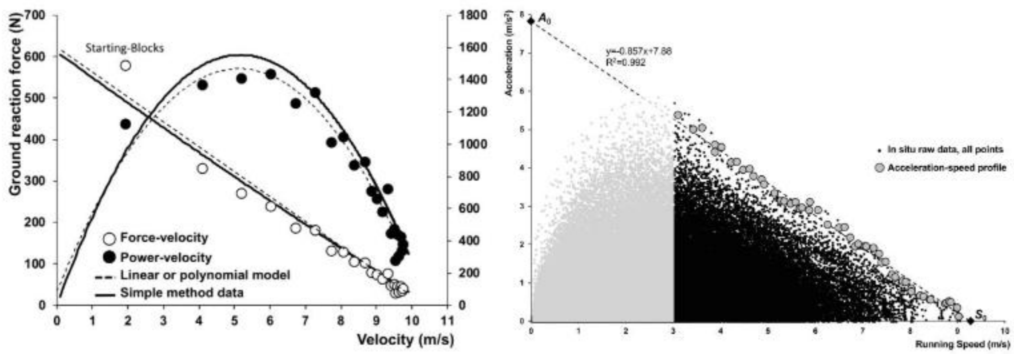


Figure 1-1. Comparison of FV profile (left) using sprint data and AS profile (right) from training session data. Figures reproduced from Morin et al. (2019, 2021).

1.6 Thesis objectives

The primary objective of the thesis was to determine the feasibility of constructing valid and reliable FV and invisibly monitored AS profiles using typically worn athlete worn sensors. To achieve this, it is necessary to:

i. Determine the validity and reliability of GNSS sensors to generate FV profiles from standalone sprints experimentally (Chapter 2).
ii. Aggregate all studies using GNSS to generate FV profiles in a meta-analysis to determine the overall validity and reliability while also examining moderator variables in the analysis to inform GNSS sprint modelling in subsequent studies (Chapter 3).
iii. Determine optimal outlier removal of maximal effort running data points while also investigating whether AS profiles are comparable to FV profile metrics (Chapter 4).
iv. Determine the optimal number of random training session and game data necessary to construct a valid AS profile (Chapter 5).
v. Introduce novel invisible monitoring metrics such as normalized acceleration and power to quantify relative effort in matches (Chapter 6).
    a. Demonstrate the differences and possible benefits of normalization or non-normalization of acceleration and power data to contextualize players' physical performance based upon position, goal differential, and match half.

Together, this information will help establish this ambient approach to determine athlete acceleration-speed ability in soccer as there is the potential ability to use the AS metrics to support athlete specific training recommendations as well as a more athlete-centered approach to tactical and technical decision making.

Chapter 2 – Validity and reliability of GNSS sensors for force-velocity sprint profiling[1]

2.1 Abstract

This study evaluated the validity and reliability of common systems to assess sprint-derived horizontal force-velocity (FV) profile metrics. Two double constellation athlete monitoring systems (STATSports Apex and Catapult Vector S7) and one timing gate system (Brower) were compared to a radar gun for the computation of FV metrics. Inter-system validity was assessed using Intraclass, Pearson Correlation Coefficients (ICC, and R^2), and Bland-Altman plots with absolute and percent agreement. Intra-system reliability was assessed with agreement bias and ICC. STATSports demonstrated moderate agreement for F_0, P_{max}, τ, and D_{rf} (8.62, 6.46, -9.81, and 9.96%, respectively), and good agreement for V_0 and MSS (-2.18 and -1.62%). Catapult displayed good agreement across all metrics (F_0, V_0, P_{max}, MSS, τ, and D_{rf}: -0.96, -0.89, -1.85, -0.84, 0.38, and -0.27% respectively). Timing gates demonstrated good agreement with V_0 and MSS (-2.62 and -1.71%) and poor agreement with F_0, P_{max}, τ, and D_{rf} (19.17, 16.64, -20.49, and 20.18%). Intra-system reliability demonstrated good agreement (<2% bias) with very large to near perfect ICC (0.84-0.99) for Catapult and STATSports systems. Overall, GNSS 10Hz technology is reliable across devices and can provide moderate-to-good accuracy of FV metrics in single maximal effort sprints. However, Catapult provided better agreement for more FV metrics than STATSports which may be related to differences in proprietary algorithms. Also, modeling timing gate data using current FV profiling techniques results in poor bias that requires greater investigation. GNSS data can be used for FV profiling which could inform performance and rehabilitation processes.

[1] Cormier, P., Tsai, M.-C., Meylan, C., Agar-Newman, D., Epp-Stobbe, A., Kalthoff, Z., & Klimstra, M. (2023). Concurrent validity and reliability of different technologies for sprint-derived horizontal force-velocity-power profiling. Journal of Strength and Conditioning Research. https://doi.org/10.1519/JSC.0000000000004429

2.2 Introduction

Microtechnology has supported the evolution of team-sport athlete monitoring and the development of precise and individualized approaches to physical preparation. A prime example is the ability to derive important athlete specific physical metrics from sprinting (Harper et al., 2021; Peeters et al., 2019) through modelling maximal stand-alone sprint efforts (Furusawa et al., 1927; Morin et al., 2019; Nagahara, Mizutani, et al., 2017; Samozino et al., 2016; Volkov & Lapin, 1979). The horizontal force-velocity (FV) profile (Morin et al., 2019; Morin & Samozino, 2016; Samozino et al., 2016), is based upon a model applying the laws of motion to the athlete's center of mass (CoM) during maximal sprinting from which various mechanical sprinting outputs can be quantified and applied to inform training, match-play and rehabilitation (Mendiguchia et al., 2016a; Morin & Samozino, 2016). This technique has received extensive support and investigation and is becoming a common approach for athlete assessment (Jiménez-Reyes et al., 2020; Lahti et al., 2020).

While this sprint modeling technique is in frequent use by sport science practitioners in research and field application, there are methodological considerations that need to be carefully adhered to in order to support its reliable use (T. Haugen et al., 2020; Malone et al., 2017; Vescovi & Jovanović, 2021). Some challenges concerning the use of this methodology are related to protocol and analysis considerations of various devices used to collect and compare athlete data (Lacome et al., 2019; Malone et al., 2017). For example, a FV profiling session often requires individual athletes to perform maximal sprints using timing gates or radar as a collection modality. A limitation is, only one athlete can sprint at a time often requiring a separate testing session which is not always practical for professionals in the field. With improvements in field-based wearable athlete tracking systems (global navigation satellite systems [GNSS]) to reliably measure athlete movement (Lacome et al., 2019, 2020), these tools have shown great promise in their ability to be used to derive FV profile metrics in a time-efficient manner with large groups of players using automated processing of data. For example, Clavel et al. (2022) assessed FV profiling from 50m sprints with national level rugby union players from GNSS augmented systems (double constellation) and showed nearly perfect correlations with radar derived profiles, with minimal intra-system variability suggesting that GNSS could be a valid alternative to other field-methods. Also, Nagahara et al. (2017) reported concurrent validity of GNSS systems (both 5 and 20Hz units) with well-trained rugby and soccer players in 30-50m sprints, with 20Hz units resulting in more accurate estimation of FV profile metrics.

While different systems have been assessed separately for their ability to provide valid and reliable FV profile metrics, no studies have compared the concurrent validity of multiple systems. Further, few investigations have assessed the validity of different GNSS systems concurrently (Lacome et al., 2019, 2020; Nagahara, Botter, et al., 2017) and to the authors knowledge, no studies have directly compared FV profile metrics from two of the biggest system manufactures in the industry (ie, Catapult and STATSports). Additionally, while considerations for developing FV profile using timing gates and radar have been examined separately, few studies have compared FV profile outputs between timing gates and radar directly (T. Haugen et al., 2020; van den Tillaar et al., 2022). Since many systems are used to develop and compare FV profile metrics within and between athlete populations it is important to determine the level of agreement as well as methodological considerations and challenges to support applied research with this approach. Thus, the aims of this study were to: (a) assess the validity of FV profiles derived from two different widely used GNSS systems, and timing gates against the criterion measurement device, radar; and (b) determine the intra-system reliability of GNSS systems for the computation of FV profiles.

2.3 Methods

2.3.1 Approach to the problem

A concurrent protocol was conducted to assess the validity and reliability of FV profiles derived from double constellation GNSS, timing gates, and radar data whilst maximally sprinting. Specifically, the systems STATSports (10Hz, Apex v3.00, STATSports, Newry, UK) and Catapult (10Hz, Vector S7 v3.4.0, OpenField Cloud Analytics, Catapult Innovations, Melbourne, Australia) were compared due to their use in elite sport. Furthermore, the traditional field method, single-beam timing gates (Brower Timing Systems, Draper, USA) was also analyzed. The criterion measurement device was a radar gun (46.875 Hz, Stalker ATS System, Radar Sales, Minneapolis MN, USA).

2.3.2 Subjects

Subjects were recruited from university level teams and ranged from recreationally trained to trained/national performance caliber (n = 5, were national developmental rugby players) (McKay et al., 2022). The teams that participated were women's rugby (age = 20.41 ± 2.37 yrs, mass = 74.84 ± 12.03 kg, height = 1.68 ± 0.06 m, n= 30) and men's ice hockey (age = 22.27 ± 1.57 yrs, mass = 87.15 ± 9.58 kg, height = 1.83 ± 0.07 m, n= 25). Ethical approval was obtained from the University of Victoria's Human Research Ethics Board. This study complied with the principles outlined in the Declaration of Helsinki.

2.3.4 Procedures

Inter-system validity

The procedure took place on two separate days on an outdoor rubberized track surface in an open field stadium. Subjects wore standard running shoes. On day 1, participants performed a warm up consisting of a 20 min general and dynamic movement followed by three progressive sprints at increasing intensities as similarly described in previous studies (Samozino et al., 2022). Two all-out 40 m sprints were performed with 5 minutes of passive rest in between each trial. Subjects were required to position their feet in a staggered stance for all trials with 5s of no movement before beginning the sprint. This helped avoid any backwards movement prior to the sprint, as well as allowing for automated detection of sprint onsets when processing the data (Clavel et al., 2022). If sprint efforts were not maximal (e.g., slip on track surface or other factors), the trials were omitted. 63 concurrent trials were kept for analysis on Day 1. Subject height (m) and body mass (kg) were collected according to The International Society for the Advancement of Kinanthropometry (ISAK) procedures. Also, barometric pressure, wind velocity, and ambient air temperature were collected on every testing day from the University of Victoria weather station (latitude 48.46, longitude -123.6, elevation 60m) with barometer, anemometer, and thermometers readings (Vantage Pro2, Davis Instruments Corporation, California, USA) for the FV profile computation (1,013 hPa, 7°C, measured wind velocity of 2km/h (blowing south to north) on Day 1, 1,025 hPa, 9°C, wind velocity of 2km/h (south to north) on Day 2). The sprint was ran from north to south. Horizontal dilution of precision (HDOP) was 0.68 ± 0.07 for Catapult and 0.40 ± 0.05 for STATSports. The number of satellites acquired was 16 ± 2 for Catapult and 19 ± 1 for STATSports.

During each trial, instantaneous velocity data (46.875 Hz) was recorded with the radar gun placed on a tripod 5m behind the athlete at a height of 1m adjusted to be pointed directly at the middle of the low back (standardized at 0.40m with a measuring tape from the GNSS placement), approximately the CoM (di Prampero et al., 2005; Nagahara et al., 2016). Data was then analyzed using Stalker Stats II software (Version 5.0.3.0, Applied Concepts, Dallas, TX, USA) provided by the manufacturer. The radar velocity data was filtered before export by the software (Dig Medium, fourth order, zero lag, Butterworth filter) similar to previous research (di Prampero et al., 2005).

The GNSS units were turned on 10-15mins before trials began and placed in a modified Catapult vest with two pouches stitched on either side of the original pouch placement, 5 cm apart (Figure 2-1). This enabled the athletes to sprint with both the STATSports unit and the Catapult unit simultaneously.

Timing gates were placed at 0.75, 5.75, 10.75, 20.75, 30.75, and 40.75m distances (Figure 2-1). Studies traditionally use set distance increments (e.g., 0, 5, 10, 20, 30, 40) (T. Haugen et al., 2020), however in our study, the subjects' front foot was placed in line (midfoot) with tape 0.75m from the first set of timing gates to minimize the risk of the gate being prematurely triggered with the arms since a single-beam system was used (T. Haugen et al., 2020). The first gate was set at 0.5m height while the others were set at 1m height.

Intra-system reliability

On day 2 (day 1 + 48hrs), subjects returned to perform the same procedure. However, rather than placing two units from different manufacturers in the modified vest, two system units were placed in the same vest assigned to each subject (e.g., athlete 1 – Catapult & Catapult system on the same sprint trial). On this day, 41 concurrent trials were analyzed for STATSports and 36 concurrent trials for the Catapult system. HDOP was 0.68 ± 0.06 for Catapult and 0.40 ± 0.06 for STATSports. The number of satellites acquired was 16 ± 1 for Catapult and 19 ± 1 for STATSports.

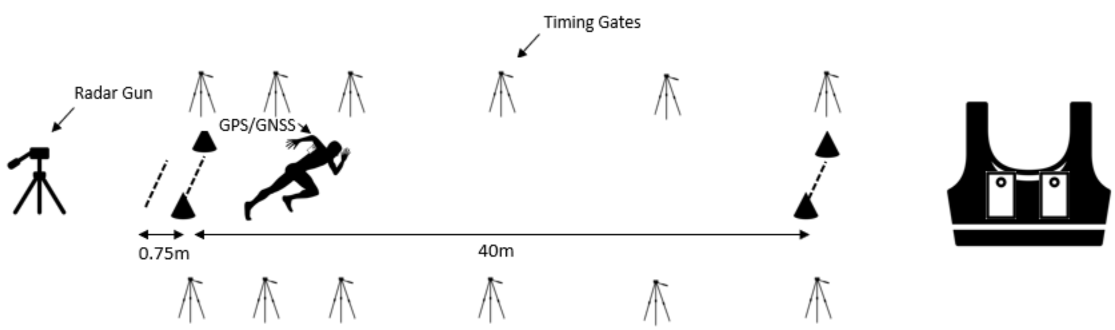


Figure 2-1. Concurrent data collection day set up with example of GNSS placement in vest.

2.3.5 Data processing

Horizontal force-velocity profiling procedure

Radar & GNSS

Data were exported from the respective GNSS and radar software. The GNSS data were obtained through the doppler-shift method which provide the most accurate reading (Malone et al., 2017). For all devices, the mono-exponential equations proposed by Samozino et al. (2016) were used to compute the FV profile variables with custom-made R script (R Core Team, 2021, Vienna, Austria). To synchronize the sprint trials, the onset of movement was set as the moment at which the acceleration increased above 0.1 $m \cdot s^2$ at the beginning of the maximal sprint acceleration (Lacome et al., 2019). Furthermore, to enable equated comparison to be made between all devices, the end of the sprint was identified at distance ≤ 40.75 m. A non-linear least-squares regression was used to estimate the maximal sprint speed (MSS) and the acceleration time constant τ with Equ. [1], applied to the horizontal velocity-time data that was continuously tracked with radar and GNSS.

$$\text{Equ. [1]} \quad v_H(t) = MSS \cdot \left(1 - e^{-\frac{t}{\tau}}\right)$$

Where t is time. Then, the horizontal acceleration was computed as:

$$\text{Equ. [2]} \quad a_H(t) = (MSS/\tau) \cdot \ e^{-\frac{t}{\tau}}$$

Position of the athlete as a function of time throughout the sprint:

$$\text{Equ. [3]} \quad x(t) = MSS \cdot \left(t + \tau \cdot e^{-\frac{t}{\tau}}\right) - MSS \cdot \tau$$

The net horizontal antero-posterior ground reaction force F_H applied to the CoM over time:

$$\text{Equ. [4]} \quad F_H(t) = m \cdot a_H(t) \ + F_{aero}(t)$$

Where F_{aero} is the aerodynamic air resistance (Arsac & Locatelli, 2002) and m is the athlete's body mass (kg). To determine the mechanical effectiveness of force application of the athlete, the ratio of force (RF) percentage, was computed as the step-averaged horizontal component of the ground reaction force to the corresponding resultant force (Morin & Samozino, 2016; Samozino et al., 2016).

$$\text{Equ. [5]} \quad RF = \frac{F_H}{\sqrt{{F_H}^2 + {F_V}^2}} \cdot 100$$

And D_{rf} is the rate of decrease in RF with increasing velocity throughout the sprint acceleration and is computed as the slope of the linear RF ~ v_H relationship when t > 0.3 s. Finally, computing the main components of the FV profile, F_0 is the horizontal force at zero velocity, y-intercept of the linear F-V relationship, and V_0 is velocity at zero force production, x-intercept of the F-V relationship. P_{max} is the maximal mechanical power expressed in the horizontal direction and is computed as: $F_0 \cdot V_0 / 4$ (Morin & Samozino, 2016).

Timing gates

Equ. [6] was used to determine the parameters τ and MSS (*shorts* package) with an estimated time correction (Vescovi & Jovanović, 2021) to provide a more accurate modeling of the sprint using split times.

$$\text{Equ. [6]} \qquad t(d) = \tau \cdot W\left(-e^{-\frac{-d}{MSS \cdot \tau}} - 1\right) - \frac{d}{MSS} + \tau - \text{time correction}$$

Where W is Lambert's W function (Goerg, 2022) and d is the timing gate distance. The mean of estimated time corrections applied was 0.46s (± 0.12). This is similar to the fixed 0.5s time correction employed at a similar fly in start distance of 0.60 m as reported in previous research (T. A. Haugen et al., 2019, 2020; Vescovi & Jovanović, 2021). Once the parameters τ and MSS were estimated, the same procedure was applied with equations [1-5] to determine the FV profile.

2.3.6 Statistical analysis

Normality (Shapiro-Wilk test) was checked for all data ($p<.05$). To assess the validity of the devices to the criterion measurement, the level of agreement of measurement was assessed using a Bland-Altman plot analysis including limits of agreement (LOA) defined as the mean difference ± 1.96*SD of the difference reported in mean absolute values and percent difference (Bland & Altman, 1986). The mean percent bias was interpreted as poor (>10%), moderate (5–10%), or good (<5%) as priori based on percent bias thresholds reported in previous research (Beato, Coratella, et al., 2018; Beato, Devereux, et al., 2018). Intraclass correlation coefficient (ICC, A, 1, two-way random, absolute agreement) are also reported. Furthermore, for systematic bias, the slope of the data's linear regression (Figure 2-2) was tested against the line of identity (slope = 1), using a one-sample t-test. Also, proportional bias was assessed by linear regression of the difference and the mean difference for each metric, where a significant parameter estimate coefficient (i.e., different from zero) indicates bias was present. The intra-system reliability was assessed using Bland-Altman analysis and the ICC. ICC`s were interpreted using the following thresholds: small 0-0.30, moderate (0.31-0.49), large 0.50-0.69, very large 0.70-0.89, and near perfect 0.90-1.00 (Hopkins et al., 2009).

2.5 Results

For F_0, P_{max}, and τ, STATSports and timing Gates showed poor to moderate agreement with a significant systematic deviation from the identity line (Table 2-1, Figures 2-3). With respect to mechanical efficiency (D_{rf}), STATSports and timing Gates presented moderate to poor agreement regarding the difference to the criterion with a significant systematic deviation from the identity line (Table 2-1, Figures 2-3). Catapult demonstrated good agreement for all metrics, however there was a significant systematic deviation for: F_0, P_{max}, τ, and D_{rf} (Table 2-1, Figures

2-2 and 2-3). Estimated V_0 and MSS displayed good biases for all devices (Table 2-1, Figures 2-2 and 2-3). However, it is important to note that the inter-system metrics LOA's were poor (LOA > 10%) for F_0, P_{max}, τ, and D_{rf} (Table 2-1 and Figure 2-3) with all systems. Furthermore, proportional bias was present with F_0 and P_{max} for STATSports, τ for Catapult, and D_{rf} for timing Gates (Figure 2-3). Both GNSS devices reported very large to near perfect agreement (ICC) and good bias results regarding intra-system reliability (Table 2-2).

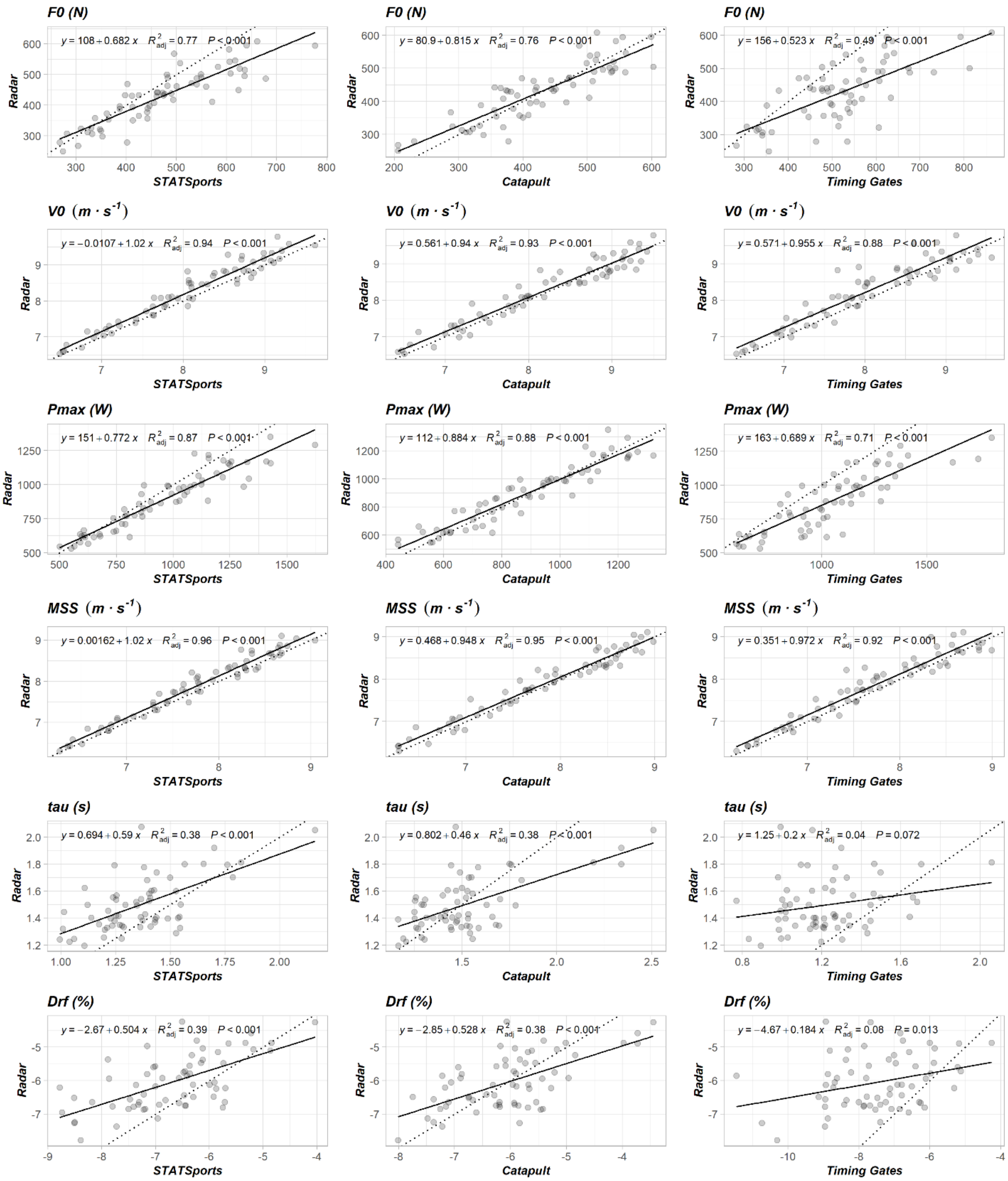


Figure 2-2. Linear regression for each metric with the relationship to the radar gun (full line) and identity line (dotted line, y=x) for systematic bias.

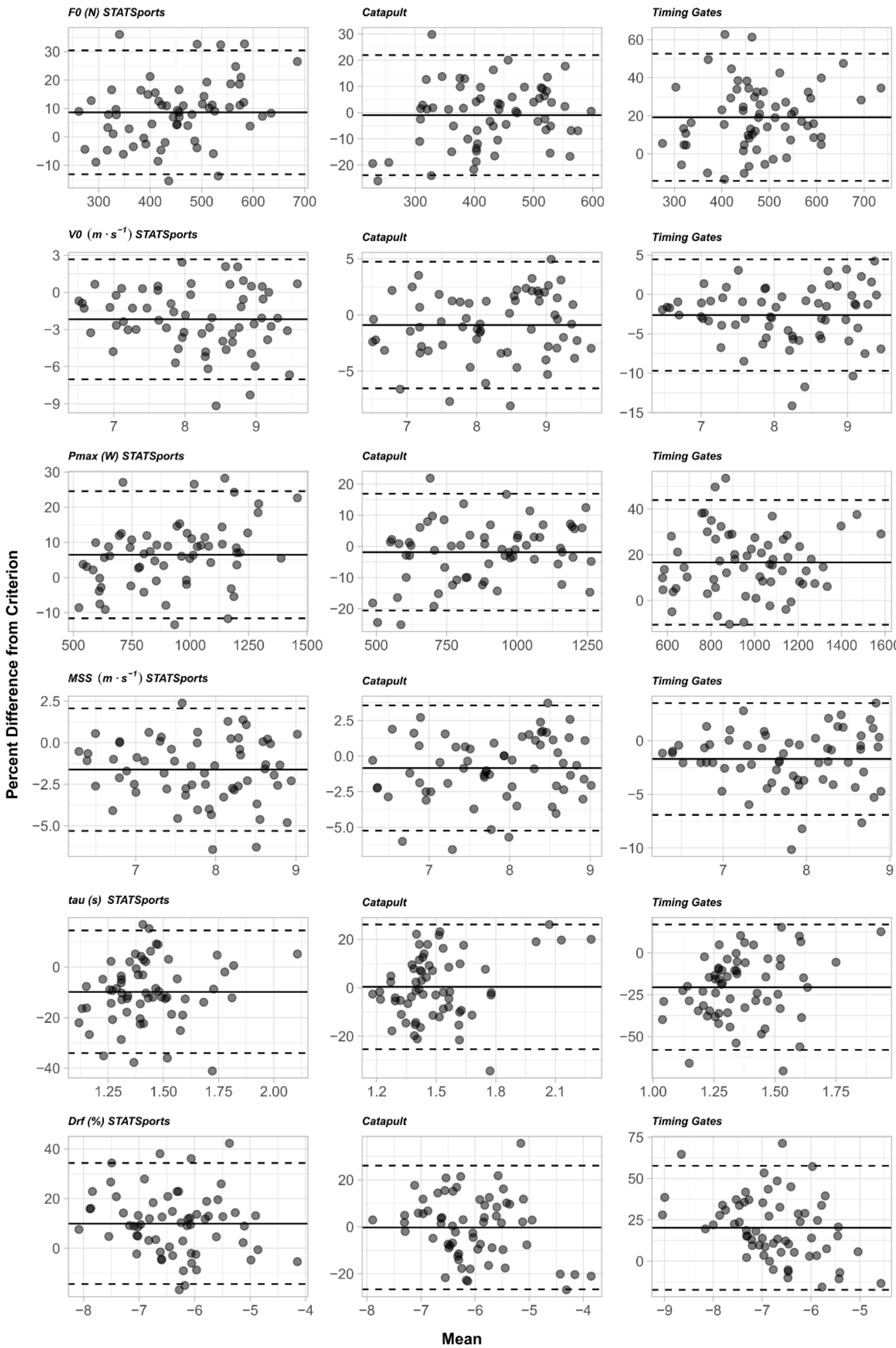


Figure 2-3. Percent bias for each metric with LOA comparing GNSS and timing gates to the criterion measure (radar gun).

Table 2-1. Day 1 inter-system validity between radar gun and field measure.

	Measurement Device	Absolute Bias (lower-upper LOA)	SEM	%Bias (lower-upper LOA)	Bias Interpretation	Mean (SD)	ICC	ICC interpretation
F_0 (N)	Radar	-	-	-	-	429.25 (88.55)	-	-
	STATSports	42.23 (-67.19, 151.64)	7.03	8.62 (-13.18, 30.42)	moderate	471.47 (113.89)	0.78	very large
	Catapult	-2.00 (-93.49, 89.50)	5.88	-0.96 (-23.87, 21.95)	good	427.25 (94.74)	0.87	very large
	Timing Gates	94.09 (-72.07, 260.25)	10.68	19.17 (-14.27, 52.61)	poor	523.34 (119.60)	0.48	moderate
V_0 (m·s^{-1})	Radar	-	-	-	-	8.24 (0.87)	-	-
	STATSports	-0.18 (-0.60, 0.23)	0.03	-2.18 (-7.02, 2.67)	good	8.06 (0.82)	0.95	near perfect
	Catapult	-0.07 (-0.53, 0.39)	0.03	-0.89 (-6.52, 4.74)	good	8.17 (0.89)	0.96	near perfect
	Timing Gates	-0.21 (-0.81, 0.39)	0.04	-2.62 (-9.70, 4.46)	good	8.02 (0.85)	0.91	near perfect
P_{max} (W)	Radar	-	-	-	-	886.51 (216.72)	-	-
	STATSports	66.82 (-125.63, 259.28)	12.37	6.46 (-11.64, 24.56)	moderate	953.33 (262.17)	0.88	very large
	Catapult	-11.06 (-163.66, 141.54)	9.81	-1.85 (-20.60, 16.89)	good	875.45 (230.71)	0.94	near perfect
	Timing Gates	163.33 (-115.32, 441.98)	17.91	16.64 (-10.64, 43.91)	poor	1049.84 (265.93)	0.68	large
MSS (m·s^{-1})	Radar	-	-	-	-	7.84 (0.76)	-	-
	STATSports	-0.13 (-0.42, 0.17)	0.02	-1.62 (-5.30, 2.07)	good	7.72 (0.74)	0.97	near perfect
	Catapult	-0.06 (-0.40, 0.28)	0.02	-0.84 (-5.23, 3.55)	good	7.78 (0.79)	0.97	near perfect
	Timing Gates	-0.13 (-0.55, 0.29)	0.03	-1.71 (-6.91, 3.50)	good	7.71 (0.75)	0.95	near perfect
τ (s)	Radar	-	-	-	-	1.50 (0.2)	-	-
	STATSports	-0.14 (-0.49, 0.21)	0.02	-9.81 (-34.06, 14.45)	moderate	1.36 (0.21)	0.51	large
	Catapult	0.01 (-0.41, 0.43)	0.03	0.38 (-25.40, 26.16)	good	1.51 (0.27)	0.60	large
	Timing Gates	-0.27 (-0.80, 0.25)	0.03	-20.49 (-57.99, 17.02)	poor	1.23 (0.23)	0.13	small
D_{rf} (%)	Radar	-	-	-	-	-6.05 (0.81)	-	-
	STATSports	-0.65 (-2.22, 0.92)	0.10	9.96 (-14.38, 34.30)	moderate	-6.70 (1.01)	0.49	moderate
	Catapult	-0.01 (-1.53, 1.51)	0.10	-0.27 (-26.64, 26.11)	good	-6.06 (0.95)	0.62	large
	Timing Gates	-1.43 (-4.09, 1.23)	0.17	20.18 (-17.35, 57.70)	poor	-7.48 (1.37)	0.13	small

SEM Standard Error of Measurement, LOA Limits of Agreement, ICC Intraclass Correlation Coefficient, % percent, SD Standard Deviation

Table 2-2. Day 2 intra-system reliability between the units from same manufacturer (eg, Catapult vs Catapult on same sprint).

	Measurment Device	Absolute Bias (lower-upper LOA)	SEM	% Bias (lower-upper LOA)	Bias Interpretation	ICC	Interpretation
F_0 (N)	STATSports	-4.31 (-56.09, 47.46)	4.13	-1.01 (-11.33, 9.31)	good	0.98	near perfect
	Catapult	-1.48 (-49.49, 46.54)	4.08	-0.65 (-11.93, 10.64)	good	0.96	near perfect
V_0 (m·s^{-1})	STATSports	-0.03 (-0.34, 0.29)	0.02	-0.37 (-4.39, 3.65)	good	0.98	near perfect
	Catapult	0.03 (-0.31, 0.36)	0.03	0.31 (-3.52, 4.15)	good	0.97	near perfect
P_{max} (W)	STATSports	-14.02 (-84.93, 56.90)	5.65	-1.37 (-8.85, 6.10)	good	0.99	near perfect
	Catapult	-2.09 (-82.25, 78.06)	6.82	-0.34 (-8.95, 8.27)	good	0.98	near perfect
MSS (m·s^{-1})	STATSports	-0.03 (-0.28, 0.23)	0.02	-0.39 (-3.87, 3.09)	good	0.98	near perfect
	Catapult	0.02 (-0.23, 0.27)	0.02	0.23 (-2.80, 3.26)	good	0.98	near perfect
τ (s)	STATSports	0.01 (-0.15, 0.17)	0.01	0.62 (-12.39, 13.62)	good	0.84	very large
	Catapult	0.02 (-0.20, 0.24)	0.02	0.86 (-12.59, 14.31)	good	0.92	near perfect
D_{rf} (%)	STATSports	0.02 (-0.99, 1.03)	0.08	-0.57 (-13.77, 12.64)	good	0.85	very large
	Catapult	0.04 (-0.77, 0.85)	0.07	-0.93 (-14.81, 12.94)	good	0.90	near perfect

SEM Standard Error of Measurement, LOA Limits of Agreement, ICC Intraclass Correlation Coefficient, % percent, SD Standard Deviation

2.6 Discussion

This study demonstrated that GNSS 10Hz technology may provide a valid and reliable alternative to the criterion measure for calculation of FV profiles in single maximal effort sprinting. However, while ICC's support good to moderate agreement between these devices and the criterion, poor LOA ranges (Table 2-1 and Figure 2-3) for specific FV profile metrics justify more inquiry into the differences in proprietary technology and modeling that may affect their accuracy and precision. Additionally, while timing gates are often used to calculate FV profiles, modeling timing gate data using current FV profiling techniques results in poor bias and LOA, especially for F_0 (Table 2-1). Therefore, important considerations are warranted when comparing FV profile outputs between devices and more investigation carried out to ensure appropriate evaluation and comparison of FV profile metrics between cohorts, as well as improvement of the accuracy and precision based on the measurement error found in this study.

There are very few studies investigating the use of GNSS systems for the computation of FV profiles. Nagahara et al. (2017) reported the concurrent validity of GNSS devices (both 5 and 20Hz units) with radar derived FV profiles. In their study, 20Hz GNSS units overestimated V_0, MSS, τ, and 20 m sprint time (0.5, 0.1, 9.7, 2.1%, respectively), and underestimated F_0 and P_{max} (-7.9 and 6.9%). 5Hz units overestimated F_0 and 20 m sprint time (4.1 and 2.9%), and underestimated V_0, MSS, P_{max}, and τ (-5.1, -4.8, -2.1, -3.2%, respectively). Our results for 10Hz Catapult slightly underestimated F_0, P_{max}, V_0, MSS, and D_{rf} and slightly overestimated τ. Clavel et al. (2022) recently reported nearly identical findings using the same Catapult system (F_0 -0.19, P_{max} -0.56, V_0 -0.27, MSS -0.28, and τ 0.28%), confirming that validity of such system for FV profiling. Regarding STATSports, the MSS and τ values are underestimated which explains the overestimations in F_0, P_{max}, and D_{rf} metrics. Accordingly, lower τ values represent the ability to achieve greater percentages of MSS earlier in the sprint (Clark et al., 2019; Healy et al., 2022), hence large variations in this parameter can affect the FV profile significantly. As such, Catapult showed the lowest underestimation of MSS and τ. When considering the two GNSS systems assessed in this study, Catapult had better agreement across all FV profile metrics to the criterion, however it is important to consider that regardless of the manufacturer, there were still considerably poor LOA ranges which demonstrate a variability of accuracy of FV profile metrics outputs from these systems using current analysis and modeling practices. This may suggest a necessary improvement in the system measurement output or a modification to the current FV profile modelling practices or both. It is important to note that both GNSS systems tested demonstrated good intra-system reliability from the same manufacturer (e.g., unit 1 STATSports vs unit 2 STATSports paired on the same sprint) with less than 2% bias, and very large to near perfect ICC values. Overall, these results show the variability of findings in this and previous studies that may be due to differences between the systems hardware, sampling rate and proprietary analysis techniques.

When comparing different GNSS manufactures it is important to consider the proprietary differences between the technologies, including on-board sensors and filtering techniques to understand the capabilities and limitations of each system (Delves et al., 2021). First, both systems tested in this study included GPS and GNSS supporting consistent sensors usage. Conversely, Beato et al. (2018) compared two STATSports models (one with GPS/GNSS [10Hz] and one with GPS alone [18Hz]) and found good agreement, supporting the potential interchangeable use of these sensor combinations. However, they did not compare FV profile outputs from these sensors. Recent advances in sensor technology have improved the accuracy and precision of player movement tracking through sensor fusion techniques which involves combining GPS/GNSS with inertial sensors (Apte et al., 2020; Aughey, 2011). These new innovations may help mitigate issues of accuracy and precision observed in this study. In terms of filtering, neither manufacture has disclosed their proprietary techniques, similar to other GNSS technology manufacturers where the details of such techniques are not specified making it difficult to make comparisons between devices and studies (Malone et al., 2017). Other systems have implemented filtering techniques to smooth the data or attempt to improve the signal-to-noise ratio. Namely, moving averages (0.2s-0.5s moving average) (Lacome et al., 2019; Reports, 2022), local polynomial regression fitting (loess) (Lacome et al., 2020), and filtering similar to those traditionally used with radar technology (i.e., radar, Butterworth) (di Prampero et al., 2005). Lacome et al. (2019) reported a bias percentage underestimation of -3% for MSS with raw 16Hz GPS data, and better MSS -1.61% with smoothed data (0.5s moving average). Similarly, in this study, STATSports data resulted in an MSS underestimation of -1.62% whereas the filtering applied by Catapult was -0.84% which was more analogous to the criterion, radar. We did not apply any filtering of the GPS/GNSS systems data in our comparison which may modify the results. Standardization and comparison of different filtering techniques may assist in improving accuracy and precision of athlete tracking systems for FV profile metric outputs.

Timing gates have been used as a cost-effective solution to speed profiling, however there are methodological shortcomings of this technique for determining FV profile metrics. Firstly, the timing and start procedure (e.g., staggered, 3-point, fly-in, etc.) has a great impact on the sprint models. To avoid the premature triggering of the first timing gate (onset of sprint) with the upper limbs, a fly-in distance is often incorporated (e.g., 0.3, 0.6, or 0.75 m), however the lag time between the actual first instance of force application and the triggering of the first gate results in overestimation of several FV profile metrics (Vescovi & Jovanović, 2021). Thus, in this study an 'estimated time correction' was applied to the timing gates data to provide more accurate sprint acceleration modeling (Vescovi & Jovanović, 2021). A time correction was favored since fixed and estimated time corrections provide a better FV profile than with no correction (Jovanović & Vescovi, 2021; Vescovi & Jovanović, 2021). Furthermore, our study employed a 0.75 m fly-in which is different from the 0.60 m employed in previous research, thus we could not apply the same recommended +0.5s correction. Although, it is interesting to note that the mean of estimated time corrections was similarly 0.46s (± 0.12) in this report despite our 0.15 m larger fly-in distance. This may be due to the caliber, better acceleration ability, and age of the athlete (T. A. Haugen et al., 2019, 2020; Vescovi & Jovanović, 2021). Accordingly, the timing gates percentage bias was overestimated for relative F_0 and P_{max}. It is important to note that timing gates are good for measuring split times and MSS in linear sprinting, however, probably due to the low sampling rate and start initiation limitations, the FV profile may not be valid using the data processing techniques based on current practices. Since the short acceleration at the beginning of a sprint will have a large impact on the estimation of τ, a greater amount of timing gates placed towards the beginning of the sprint could offer another solution by increasing the sampling rate, thus improving the modeling of FV profiles. Furthermore, using dual-beam systems would minimize the possibility of the beam being triggered with the arm rather than the CoM whilst also requiring a shorter fly-in distance, likely resulting in better sprint modeling.

There are some limitations to this study that should be addressed in future research. Firstly, to make comparisons between all devices, a set distance was used to indicate the end of a sprint, which may have affected the FV model fit as an athlete's speed may fluctuate during the later portion of the sprint, after the MSS is achieved and a plateau may not be sustained. Secondly, as mentioned, the distance from the start-line to the first set of timing gate for the sprint was longer than in previous research which may have negatively impacted the timing gate metrics (T. A. Haugen et al., 2020; Vescovi & Jovanović, 2021). Another limitation is that GPS/GNSS manufacturers do not disclose data filtering techniques or onboard sensor fusion techniques employed which makes it difficult to compare findings across studies. Accordingly, the major limitation in our study and others on this topic, is the "black box" nature of available GPS/GNSS technologies (Malone et al., 2017). More research is needed in the area with less ambiguous reporting of data processing techniques to compare results between studies.

There are challenges to consider in the use of the different devices, specific FV profile modeling parameters in this study. First, the equations used to determine the FV profile metrics for radar and GPS/GNSS imply modeling with a velocity over time equation whereas the timing gate data is modeled with a time over distance equation which isn't a direct model comparison in this study. Further, timing gate data in other research has been modeled with different variations of velocity/time and time/distance equations (Samozino et al., 2016; Stenroth et al., 2020). These modeling differences could be the reason why timing gate data results in a large bias in F_0, thus further research is required to improve the accuracy and precision of the timing gates for FV profile outputs potentially through investigating alternative modelling techniques. We have provided regression-based corrections for all field measurement systems against radar which may improve the agreement with the criterion. The equations displayed in Figure 2-2 can be used to predict (correct) the criterion values for each metric with the values from the practical field measure (ie, criterion measure = intercept + slope * (practical field measure) or eg., radar V_0 = intercept + slope * (timing gate V_0 value). Although helpful, it is important to keep in mind that they will not remove the random errors present when using this technology.

Despite these limitations, this study provides practitioners with information relevant for the use of GNSS systems for FV profiling. While there are limitations in timing gates for the FV profile modeling, they are still recommended for top speed metrics from split times and may be cost effective. Given the promise of GPS/GNSS technology for FV sprint profiling, there is diverse potential for application. Sport scientists could potentially assess changes in FV qualities of each individual player throughout a yearly training plan (Jiménez-Reyes et al., 2020) or assess adaptations to training stimuli (Buchheit et al., 2014; Cross et al., 2018; Lahti et al., 2020) with minimal time demands. Furthermore, accumulated FV profile data could be used to inform decisions on player selection, injury-prevention, and return to performance protocols (Lahti et al., 2021). Practitioners could test players' maximal acceleration speed qualities without separate testing sessions which can be challenging. For example, in short international windows where training camps and matches take place. Accordingly, for the FV profiling assessment, integration of only a few maximal 40m sprints at the end of a training session warm-up could provide FV profiling metrics (Lacome et al., 2020).

2.7 Practical applications

This study provides practical insights regarding the use of GNSS and timing gate systems. Specifically, practitioners should be aware that the inter-system validity of both Catapult and STATSports devices appear to be good to moderate for specific FV profile metrics, and the intra-system reliability appear to be good for both GNSS systems assessed, thus practitioners can attain “consistent” profiles across a large team of players. However, caution should be taken since poor LOA ranges were still present for all devices concerning some of the metrics assessed. Notably, the Catapult system demonstrated the best validity. It is possible that with more robust data processing procedures practitioners could provide more analogous and valid FV profiles across systems. Regression-based metric corrections are also presented as part of the results of this paper. Finally, despite these results, practitioners should still consider the radar gun or gold standard track embedded force plates as the criterion measure for FV research and testing purposes due to the measurement error still present using this technology.

Chapter 3 – A systematic review and meta-analysis on GNSS for linear sprint profiling[2]

3.1 Abstract

An emerging and promising practice is the use of global navigation satellite system (GNSS) technology to profile team-sports athletes in training and competition. Therefore, the purpose of this narrative systematic review with meta-analysis was to evaluate the literature regarding satellite system sensor usage for sprint modelling and to consolidate the findings to evaluate its validity and reliability. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, an electronic search of the databases, Pubmed and SPORTDiscus (EBSCO) was conducted. Concurrent validity and reliability studies were considered, and sixteen studies were retained for review from the initial 1485 studies identified. The effects on outcomes were expressed as standardized mean differences (SMDs, Cohens d) for each outcome (i.e., maximal sprint speed [MSS], the acceleration constant [τ], maximal theoretical velocity [V_0], relative force [F_0] and relative power [P_{max}]). Effect magnitudes represented the SMD between GNSS-derived and criterion-derived (i.e., radar and laser) and resulted in the following estimates: small for MSS (d = 0.22, 95% CI 0.01 to 0.42), τ (d = -0.18, 95% CI -0.60 to 0.23), V_0 (d = 0.14, 95% CI -0.08 to 0.36), relative F_0 (d = 0.15, 95% CI -0.25 to 0.55), and relative P_{max} (d = 0.21, 95% CI -0.16 to 0.58). No publication bias was identified in meta-analyzed studies and moderator analysis revealed that several factors (sampling rate and sensor manufacturer) influenced the results. Heterogeneity between studies were considered moderate to high. This highlighted the differences between studies in sensor technology differences (i.e., sampling rate, sensor fusion, satellite network acquisition), processing techniques, criterion technology used, sprint protocols,

---

[2]Cormier, P., Meylan, C., Agar-Newman, D., Geneau, D., Epp-Stobbe, A., Lenetsky, S., & Klimstra, M. (2022). A Systematic Review and Meta-Analysis of Wearable Satellite System Technology for Linear Sprint Profiling: Technological Innovations and Practical Applications. The Journal of Strength & Conditioning Research, 10-1519.

outcome reporting, and athlete characteristics. These findings may be useful in guiding improvements in sprint modelling using GNSS technology and enable more direct comparisons in future research. Implementation of all-out linear sprint efforts with GNSS technology can be integrated into sport-specific sessions for sprint modelling when robust and consistent data processing protocols are performed, which has important implications for fatigue monitoring, program design, systematic testing, and rehabilitation in individual and team-sports.

3.2 Introduction

The integration of wearable microsensor technology has become commonplace within elite sports teams to monitor and quantify athlete movement and inform sport science and medicine disciplines (Aughey, 2011; Cummins et al., 2013; Greig et al., 2019; Mendiguchia et al., 2016a; Morin & Samozino, 2016; Torres-Ronda et al., 2022). Global Navigation Satellite Systems (GNSS) and Global Positioning Systems (GPS), collectively referred to as GNSS for the purposes of this paper, are some of the most commonly used tracking sensors in sport. These sensors provide measurements of athlete acceleration, velocity and displacement which are often the basis for training and competition load monitoring metrics (Aughey, 2011; Halson, 2014). Alongside training and match metrics, GNSS sensors can be used to assess sprint acceleration capabilities. Accordingly, all-out sprint protocols are commonly performed, from which measures of distance, time, peak velocity, and acceleration are quantified (T. Haugen et al., 2020; Morin & Samozino, 2016). An example of which, is horizontal force-velocity (FV) profiling, an approach which models athlete speed or distance over time from an all-out sprint allowing for the estimation of an athlete's theoretical horizontal maximal force and velocity capability (Samozino et al., 2016). While FV profiling is becoming a well-established technique, various field and lab technology (e.g., radar, timing gates, treadmill, and force plates) have been preferred to collect force, speed, or timing data to model with the FV approach (T. Haugen et al., 2020; Samozino et al., 2016). Since GNSS technology is commonplace in daily training environments and is a technology capable of measuring athlete acceleration and velocity (Goodale et al., 2016; McLaren et al., 2018), there is great potential for the use of this tool to measure sprints and model GNSS velocity data using the FV approach. However, there is uncertainty as to the validity and reliability of GNSS technology with respect to sprint modeling due to the lack of consistency in its application with no reviews consolidating the findings from available studies thus far.

While practitioners have been applying sprint modeling techniques using GNSS data in the field, and wearable sensor manufacturers have begun to incorporate sprint profiling into their user outputs, there is a need to determine the current state of GNSS technology for FV profiling (Barr et al., 2019; Clavel et al., 2022; Cormier, Tsai, Meylan, Agar-Newman, et al., 2023; Lacome et al., 2019). To confidently use GNSS technology for sprint modeling, an assessment of the validity and reliability of this technology must be carried out, since the metrics outputted may be affected by the technical specifications of the devices, sprint protocols, and data processing approaches (Malone et al., 2017). As there are many GNSS sensors available from manufacturers, studies continually validate sensors using different methodologies and protocols with various cohorts of individual and team-sport athletes (Crang et al., 2021a, 2021b). Additionally, while there has been a focus on the validation and potential application of GNSS technology for FV profiling, there are inconsistent findings. For example, early attempts to construct sprint profiles with GNSS have been subject to measurement error impacting the validity and reliability of systems due to low sampling rates (e.g. ≤ 5Hz) and limited satellite network capacity (Malone et al., 2017). As GNSS technology evolves, with increased sampling rates (≥10Hz) and multiple sensor usage (e.g., fusion of inertial measurement units [IMU] with GNSS) to improve accuracy and precision, the potential for its effective use for the purposes of sprint modeling is improving (Clavel et al., 2022; Fornasier-Santos et al., 2022).

Given the discrepancies in study methodology, changes in this technology over recent years, and lack of recommendations on sprint modeling protocols using GNSS. The purpose of this review was to systematically assess the current literature available, exploring satellite positioning system sensor usage for sprint modeling, consolidate and summarize the findings as well as identify gaps in the literature to guide future research. Therefore, a systematic review and meta-analysis with narrative review was performed to provide a comprehensive and contextualized understanding of this subject for researchers and practitioners in the field.

3.3 Methods

3.3.1 Experimental approach to the problem

A systematic-narrative hybrid review with meta-analysis approach was taken where a comprehensive systematic search linked to the research question was carried out. Articles were selected based on uniform criteria, each selected critically and evaluated with elements of qualitative and quantitative synthesis with evidence-based inferences (Turnbull et al., 2023). Further, moderating analyses were performed to determine if methodological factors impacted the effect estimates.

3.3.2 Data sources and search strategy

This review was guided by a systematic search of the literature following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021). An electronic search of the databases Pubmed and SPORTDiscus (EBSCO) was carried out including papers published up until July 1st, 2023, using the following Boolean search phrase: *("GPS" OR "GNSS" OR "global positioning system" OR "global navigation satellite system" OR "accelerometer" OR "inertial measurement unit" OR "sensor fusion") AND ("sprinting" OR "team-sports" OR "athletes")*. A search of reference lists from relevant literature was also performed to identify papers that fit the criteria.

3.3.3 Inclusion and exclusion criteria

Inclusion criteria included: (a) usage of GNSS/GPS system for maximal linear sprint acceleration assessment; (b) validity and reliability estimates reported; (b) studies published in English; (c) over ground sprint mechanical characteristics (eg, horizontal acceleration, force, velocity, or power) derived from continuous velocity-time GNSS data reported as an outcome measure; and (d) peer-reviewed literature. Exclusion criteria were the following: (a) participants had any musculoskeletal disorders; (b) caliber of participants fell below the classification of "recreationally active" as defined by recently proposed frameworks (McKay et al., 2022); (c) other positioning systems such as local positioning systems or optical tracking systems were used and (d) surveys/reviews. This protocol was registered with the Open Science Framework (osf.io/tsg6r).

3.3.4 Study selection

Databases were searched by one author (PC). After removal of duplicates, abstracts and titles were screened independently by two authors (PC, DG) based on the inclusion and exclusion criteria. A third party settled any disagreements on study inclusions (MK). After this initial screening, all article pdfs were sourced and evaluated by two authors (PC and DG) and data extracted by one author (PC).

3.3.5 Study quality assessment

The quality of the included studies was assessed with a modified Downs & Black (1998) checklist, similar to previous validity study quality assessment reviews (Crang et al., 2021b; Johnston et al., 2018). The items 1, 2, 3, 6, 7, 10, 16, 18, and 20 were selected. Items were scored as 1 yes, 0 no, and 0 unable to determine. Item 20 was only applied if the study assessed validity. The study bias and quality were assessed by two authors (PC and DG) with any disagreements resolved by a third author (MK). Description of items can be found online in the supplemental digital content (see Table 1, http://links.lww.com/JSCR/A453).

3.3.6 Data extraction

The FV metrics extracted were the maximal sprint speed (MSS), acceleration constant (τ), theoretical maximal horizontal force at zero velocity (F_0), theoretical maximum velocity at zero force (V_0), theoretical maximal power (P_{max}), and decrease in ratio of force (Drf %). These were reported in absolute and/or normalized to body mass. See Morin and Samozino (Morin & Samozino, 2016) for more details as well as further explanations and interpretations of FV metrics. Studies that included peak velocity estimates from all-out linear sprint validity and reliability studies outside of the FV profiling approach were also included and reported as MSS, so long as the data was derived from continuously collected instantaneous GNSS data (ie, not obtained from speed “zones”).

The data extracted regarding the agreement of measurement were mean bias from Bland Altman plots with confidence intervals (CI) with limits of agreement (LOA) and correlation coefficients. Bias was computed from mean differences between averages from the field measure being assessed against a criterion measure. Intraclass correlation coefficient (ICC), typical error of measurement (TEM), and typical error (TE) (sometimes expressed as the coefficient of variation CV) were also extracted from studies. For the sake of clarity, the reliability (precision) was termed “inter-system” when comparing between manufacture units, “intra-system” when assessing reliability between units from the same manufacturer, “inter-trial” when determining between-trial reliability, “inter-model” when assessing different models from the same manufacturer. Attempts were made to contact study authors in cases where information was missing relevant to the review.

3.3.7 Statistical analyses

Meta-analysis

Analyses were carried out in R statistical software (Version 4.2.2; R Core Team, 2020). Only studies using valid FV profiling criterions capable of accurately measuring speed (i.e., radar and laser) (T. Haugen & Buchheit, 2016) were eligible for the analysis. Outcomes were only included if more than one study reported the metrics, therefore Drf, absolute F_0 and P_{max} were left out of the analysis. Retained data were analyzed using a mixed-effects meta-analysis (*metafor* package (Viechtbauer, 2010)) to determine the overall difference of effect on outcomes (i.e., MSS, τ, V_0, relative F_0, and relative P_{max}) between the criterion and the GNSS-derived FV metrics. The effect sizes were quantified and expressed as standardized mean differences (SMD, Cohens d) with 95% confidence intervals (CI). The weighted average effect size estimate was calculated, and a significant z-statistic test (p <0.05) determined whether the summary estimate was significantly different from zero, where a significant difference indicated overall poor agreement between the outcomes (GNSS) compared to the criterion. Threshold values for effect sizes (SMD) were 0.2 – 0.49 (small), 0.5 – 0.79 (medium), and ≥ 0.8 (large) (Cohen, 1988). A moderator analysis was then performed to determine whether sampling rate (≥10 Hz vs < 10Hz) or sensor manufacturer affected the outcomes of the model (*Computing Adjusted Effects Based on Meta-Regression Models [The Metafor Package]*, n.d.).

Heterogeneity (I^2) between studies and between study variance (τ^2) was evaluated. Heterogeneity was interpreted on a scale of magnitude of low < 25 %, medium 25-75 %, and high > 75% (Higgins, 2008; Higgins et al., 2003). A p-value of < 0.1 for the chi^2 indicated the presence of heterogeneity and a $\tau^2 > 1$ suggests substantial heterogeneity (Higgins et al., 2003). Publication bias was evaluated through an asymmetry test as estimated from a funnel plot and egger test (Egger et al., 1997) and $p < 0.05$ was considered statistically significant.

Narrative analysis

Using the entire dataset, a narrative and quantitative summary was used to identify trends in the agreement (validity), and reliability studies. This approach was chosen due to the heterogeneity in types of reported outcomes for validity and reliability. As a priori, we interpreted the extracted percent agreements as good < 5%, moderate 5-10%, and poor > 10% based on thresholds from prior GNSS validation research (Beato, Coratella, et al., 2018; Beato & de Keijzer, 2019; Cormier, Tsai, Meylan, Agar-Newman, et al., 2023). Extracted FV profile metrics means and standard deviations for the criterion and the GNSS measurement are displayed if reported in the included studies (Table 3-2, Figures 3-2 to 3-6).

To determine whether changes in performance were meaningful, some studies in this review have reported TE/CV (i.e., noise) as well as group mean and standard deviation results to calculate the smallest worthwhile change (SWC), calculated as the between-subject SD·0.2 and have further assessed the signal-to-noise ratio of the collected metric data (e.g., SWC/TE) (Roe et al., 2016) (Table 3-3). This was extracted from the studies if reported with signal-to-noise calculated or if TE and SWC were both reported. Signal-to-noise ratio was classified as < 0.80 = poor, 0.80 – 1.00 = okay, and > 1.00 = good and CVs < 5 % considered good (Portney & Watkins, 2009; Roe et al., 2016). ICCs were classified as < 0.50 = poor, 0.50 to 0.75 = moderate, 0.75 to 0.90 = good, and > 0.90 = excellent (Koo & Li, 2016).

3.4 Results

3.4.1 Study inclusion

The search strategy yielded 1458 results after removal of duplicates. After initial removal of articles by title and abstract inspection, based on the exclusion criteria, only studies assessing linear sprinting with GNSS were retained (n=42). After this initial screen, all article pdfs were sourced and evaluated. Following this final screen, 16 studies were retained for the review (Figure 3-1).

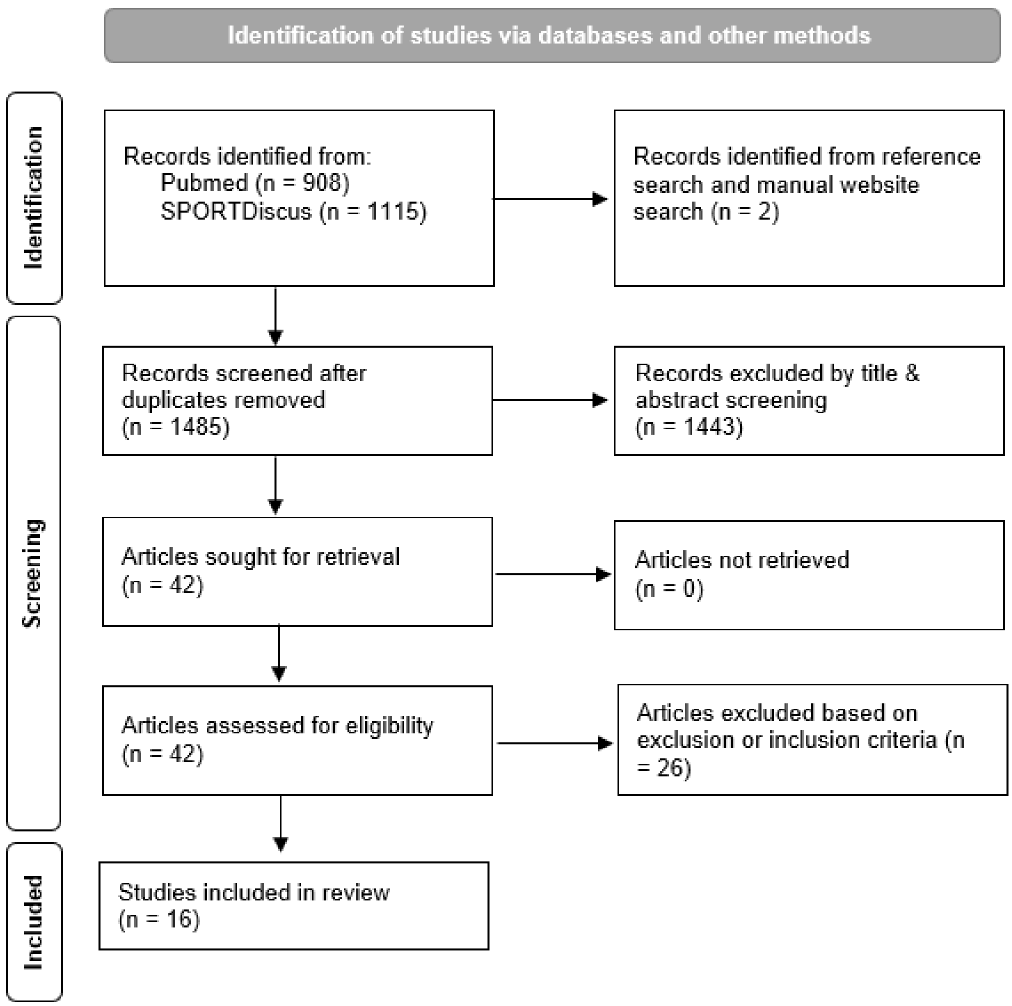


Figure 3-1. Study selection flow chart (PRISMA 2020).

3.4.2 Participant & study characteristics

Out of the 16 studies included, all studies were concurrent validity and/or reliability studies assessing the accuracy of a GNSS field system to a criterion measurement device or assessing various types of reliability. Namely, the criterions were a radar gun (Apte et al., 2020; Clavel et al., 2022; Cormier, Tsai, Meylan, Agar-Newman, et al., 2023; Lacome et al., 2019; Nagahara, Botter, et al., 2017), laser (Huggins et al., 2020; Nagahara, Botter, et al., 2017; Varley et al., 2012), video kinematic analysis (Beato et al., 2016), sliding platform (Akenhead et al., 2014), and timing gates (Alphin et al., 2020; Apte et al., 2020; Barr et al., 2019; Hoppe et al., 2018; Reinhardt et al., 2019; Waldron et al., 2011). Two studies utilized inertial measurement units (IMU) to correct or improve their GNSS velocity and acceleration estimates (Apte et al., 2020; Reinhardt et al., 2019). Trial numbers ranged from 2-3, with subjects performing 20-100 m sprints depending on the aims of the study. Trials were performed on different surfaces such as rubberized tracks (Cormier, Tsai, Meylan, Agar-Newman, et al., 2023), artificial grass (Akenhead et al., 2014; Hoppe et al., 2018; Lacome et al., 2019), grass (Clavel et al., 2022; Lacome et al., 2020; Nagahara, Botter, et al., 2017), or unspecified track surfaces (Apte et al., 2020; Barr et al., 2019; Beato et al., 2016; Beato & de Keijzer, 2019). All protocols were performed outdoors.

Table 3-1. Summary of participant characteristics and study quality

Reference	Subjects (n)	f (%)	Caliber	Sport	Age (yr)	Height (m)	Body mass (kg)	Study Quality (%)
(Fornasier-Santos et al., 2022)	18	28	Trained to Elite	Sprinters	27 ± 6.7	1.79 ± 0.1	72.0 ± 12.6	89
(Cormier, Tsai, Meylan, Agar-Newman, et al., 2023)	55	55	Trained to Highly Trained/National (University)	Rugby, Ice Hockey	20.4 ± 2.4 & 22.3 ± 1.6	1.68 ± 0.06 & 1.83 ± 0.07	74.8 ± 12.0 & 87.2 ± 9.6	100
(Cormier, Tsai, Meylan, & Klimstra, 2023)	15	100	Elite/International	Soccer	26.23 ± 5.19	1.68 ± 0.07	63.1 ± 4.8	100
(Clavel et al., 2022)	16	0	Elite/International	Rugby	NI	1.78 ± 0.08	78.3 ± 13.2	100
(Apte et al., 2020)	9	22	Trained to Elite	Sprinters	NI	NI	NI	100
(Alphin et al., 2020)	24	100	Highly Trained (University)	Lacrosse	19.7 ± 1.2	1.66 ± 0.06	64.8 ± 6.5	100
(Huggins et al., 2020)	15	0	Highly Trained (University)	Soccer	20.0 ± 1.0	1.77 ± 0.08	71.6 ± 7.2	100
(Beato & de Keijzer, 2019)	10	0	Recreationally Trained	Team-sport	22.0 ± 1.0	1.75 ± 0.06	71.8 ± 5.0	89
(Barr et al., 2019)	28	0	Highly Trained (University)	Football	19.0 – 24.0	NI	81.0 - 141.0	100
(Lacome et al., 2019)	15	NI	Elite/International	Rugby 7s	26.0 ± 5.0	1.81 ± 0.08	90.0 ± 12.0	100
(Reinhardt et al., 2019)	34	0	Highly Trained	Soccer	20.0 ± 4.0	1.80 ± 0.06	74.0 ± 7.0	89
(Hoppe et al., 2018)	6	0	Trained	Team-sport	27.0 ± 2.0	1.77 ± 0.04	80.0 ± 2.8	89
(Nagahara, Botter, et al., 2017)	32	0	Trained to Highly Trained	Rugby, Soccer	20.0 ± 2.2	1.76 ± 0.07	73.7 ± 9.7	89
(Beato et al., 2016)	10	0	Trained	Soccer	24.0 ± 1.5	1.84 ± 0.06	80.0 ± 8.6	88
(Akenhead et al., 2014)	1	0	Highly Trained	Soccer	21.0	1.79	85.0	89
(Waldron et al., 2011)	19	0	Highly Trained	Rugby League	14.7 ± 0.5	1.88 ± 0.07	72.8 ± 10.7	100

NI *No information available, f (%) percentage of sample that was female.*

3.4.3 Quality assessment

Overall, all identified studies were deemed of good quality (89-100%), therefore no studies were omitted after the inclusion and exclusion criteria omissions (Table 1). Criteria from items 18 (appropriate statistical test reporting) and 20 (appropriate criterion) were most often violated. See supplementary materials for scoring details (http://links.lww.com/JSCR/A453).

3.5.4 Meta-Analysis and moderator analysis

For pooled effect estimates, representing differences between GNSS-derived values compared to criterion-derived, effect magnitudes were small for MSS (d = 0.22, 95% CI 0.01 to

0.42, I^2 = 55%), τ (d = -0.18, 95% CI -0.60 to 0.23, I^2 = 87%), V_0 (d = 0.14, 95% CI -0.08 to 0.36, I^2 = 56%), F_0 (d = 0.15, 95% CI -0.25 to 0.55, I^2 = 87%), and P_{max} (d = 0.21, 95% CI -0.16 to 0.58, I^2 = 80%) (Figures 3-6). It must be noted that heterogeneity was considered high for τ, F_0, and P_{max} and moderate for V_0 and MSS. Visual inspection of the funnel plots and egger tests did not suggest publication bias.

Moderator analysis (Table 3-5) revealed a moderate overestimation of MSS for SensorEverywhere (d = 0.59, 95% CI 0.18 to 0.99) and SPI (d = 0.75, 95% CI 0.38 to 1.11) with a moderate overestimation in systems with sampling rates < 10 (d = 0.75, 95% CI 0.38 to 1.11). τ was overestimated moderately with StatSports (d = 0.68, 95% CI 0.32 to 1.04) and largely underestimated using GPEXE (d = -0.86, 95% CI -1.18 to -0.53). V_0 was overestimated with SPI (d = 0.73, 95% CI 0.37 to 1.10) with a moderate overestimation in systems with sampling rates < 10 (d = 0.73, 95% CI 0.37 to 1.10). F_0 was largely overestimated with GPEXE (d = 0.95, 95% CI 0.62 to 1.27), and moderately underestimated by StatSports (d = -0.64, 95% CI -0.99 to -0.28). P_{max} was moderately overestimated with GPEXE (d = 0.69, 95% CI 0.38 to 1.01).

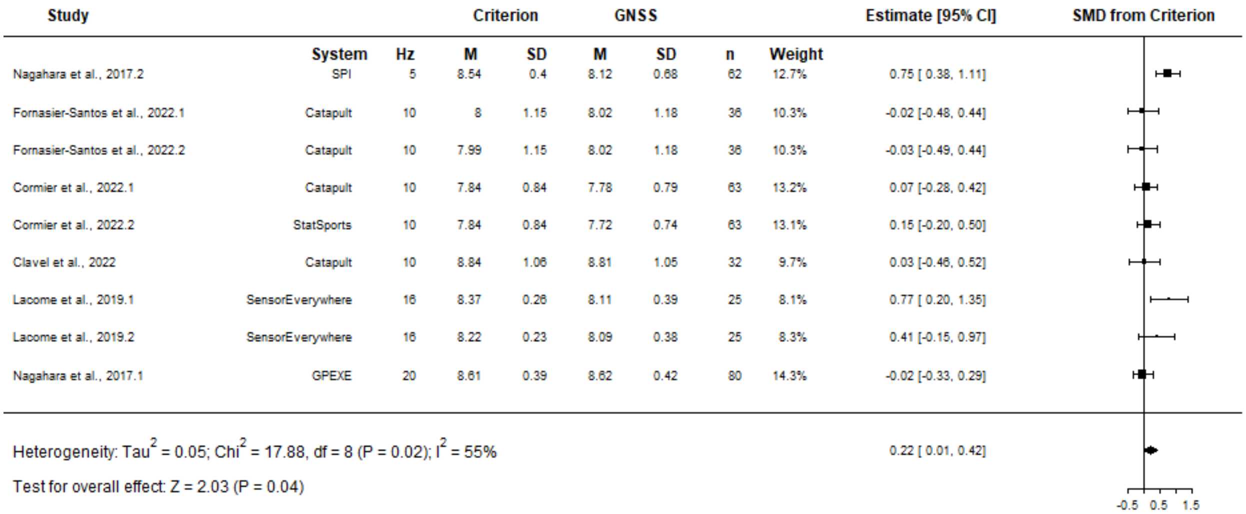


Figure 3-2. Forest plot with summary effect for MSS.

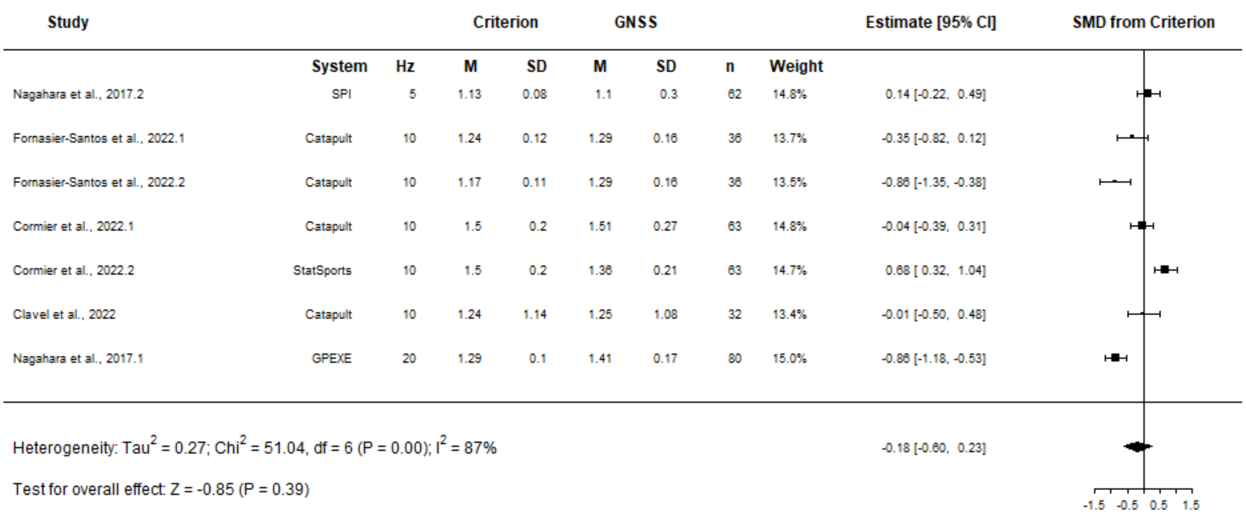


Figure 3-3. Forest plot with summary effect for τ.

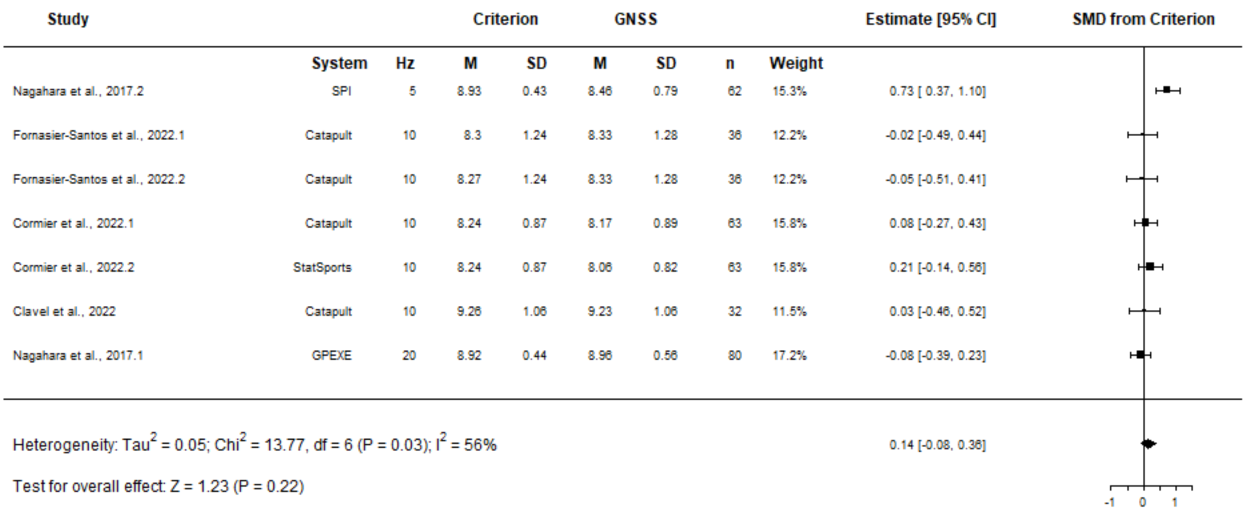


Figure 3-4. Forest plot with summary effect for V0.

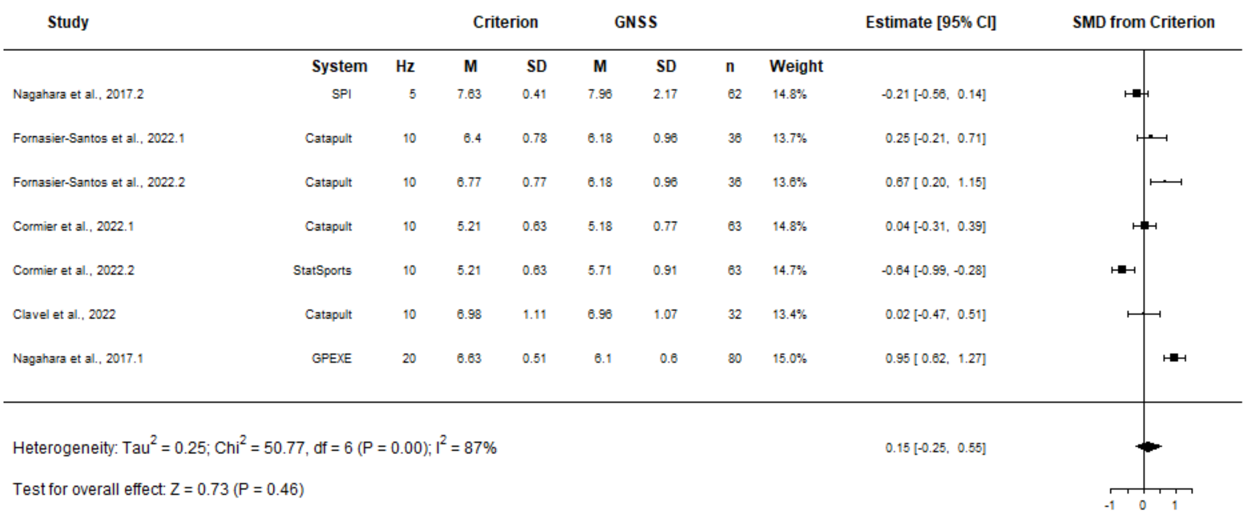


Figure 3-5. Forest plot with summary effect for relative F0.

Study			Criterion		GNSS				Estimate [95% CI]
	System	Hz	M	SD	M	SD	n	Weight	
Nagahara et al., 2017.2	SPI	5	17.02	1.23	16.69	4.13	62	20.5%	0.11 [-0.24, 0.46]
Cormier et al., 2022.1	Catapult	10	10.77	1.96	10.62	2.2	63	20.6%	0.07 [-0.28, 0.42]
Cormier et al., 2022.2	StatSports	10	10.77	1.96	11.55	2.48	63	20.5%	-0.35 [-0.70, 0.00]
Clavel et al., 2022	Catapult	10	16.7	1.12	16.08	1.1	32	17.2%	0.55 [0.05, 1.05]
Nagahara et al., 2017.1	GPEXE	20	14.68	1.41	13.66	1.51	80	21.2%	0.69 [0.38, 1.01]
Heterogeneity: $Tau^2 = 0.14$; $Chi^2 = 21.21$, df = 4 (P = 0.00); $I^2 = 80\%$									0.21 [-0.16, 0.58]
Test for overall effect: Z = 1.11 (P = 0.27)									

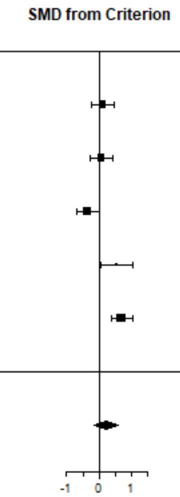


Figure 3-6. Forest plot with summary effect for relative Pmax.

Table 3-2. FV profiling metric comparison between field measure and criterion for each validity study.

	τ (s)		V_0 (m·s^{-1})		F_0 (N)		F_0 (N·kg^{-1})		P_{max} (W)		P_{max} (W·kg^{-1})		Drf (%)	
Reference (Hz)	**Criterion**	**Field**	**Criterion**	**Field**	**Criterion**	**Field**	**Criterion**	**Field**	**Criterion**	**Field**	**Criterion**	**Field**	**Criterion**	**Field**
(Fornasier-Santos et al., 2022) (10Hz)	1.24 (0.12)	1.29 (0.16)	8.30 (1.24)	8.33 (1.28)	-	-	6.40 (0.78)	6.18 (0.96)	-	-	-	-	-	-
(Cormier, Tsai, Meylan, Agar-Newman, et al., 2023) (10Hz)	1.50 (0.2)	1.51 (0.27)	8.24 (0.87)	8.17 (0.89)	429.3 (88.6)	427.3 (94.7)	5.21 (0.63)*	5.18 (0.77)*	886.5 (216.7)	875.5 (230.7)	10.77 (1.96)*	10.62 (2.20)*	-6.05 (0.81	-6.06 (0.95)
(Clavel et al., 2022) (10Hz)	1.24 (1.14)	1.25 (1.08)	9.26 (1.06)	9.23 (1.06)	-	-	6.98 (1.11)	6.96 (1.07)	-	-	16.7 (1.12)	16.08 (1.10)	-	-
(Hoppe et al., 2018) (10Hz)	1.1 (0.0)	1.38	8.2 (0.1)	8.2	-	-	7.7 (0.1)	6.42	-	-	16.1 (0.4)	13.48	-	-
(Hoppe et al., 2018) (18Hz)	1.1 (0.0)	1.38	8.2 (0.1)	8.04	-	-	7.7 (0.1)	6.39	-	-	16.1 (0.4)	13.38	-	-
(Nagahara, Botter, et al., 2017) (20Hz)	1.29 (0.10)	1.41 (0.17)	8.92 (0.44)	8.96 (0.56)	-	-	6.63 (0.51)	6.10 (0.60)	-	-	14.68 (1.41)	13.66 (1.51)	-	-
(Nagahara, Botter, et al., 2017) (5Hz)	1.13 (0.08)	1.10 (0.30)	8.93 (0.43)	8.46 (0.79)	-	-	7.63 (0.41)	7.96 (2.17)	-	-	17.02 (1.23)	16.69 (4.13)	-	-
(Cormier, Tsai, Meylan, Agar-Newman, et al., 2023) (10Hz)	1.50 (0.2)	1.36 (0.21)	8.24 (0.87)	8.06 (0.82)	429.3 (88.6)	471.5 (113.9)	5.21 (0.63)*	5.71 (0.91)*	886.5 (216.7)	953.3 (262.2)	10.77 (1.96)*	11.55 (2.48)*	-6.05 (0.81	-6.70 (1.01)

Data in Mean (SD) or solely Mean due to SD not reported or only % difference reported, *unpublished results.

3.4.5 Narrative assessment

All outcomes (including all possible criterions) were extracted and reported in Table 3-3 and percent agreement displayed in Figure 3-7. It was found that the highest bias for acceleration-based outcomes was demonstrated when timing gates were used as a criterion. System sensors sampling at 5Hz showed larger bias than sensors sampling at 10Hz and above when compared to radar/laser. Two studies used sensor fusion which resulted in a minimal mean bias of -0.01 $m{\cdot}s^{-1}$ for MSS, -0.17 $m{\cdot}s^{-1}$ for V_0, -0.02 $N{\cdot}kg^{-1}$ for relative F_0, and -0.31 $W{\cdot}kg^{-1}$ for relative P_{max} compared to radar or timing gates (Apte et al., 2020; Reinhardt et al., 2019). Filtering or smoothing the GNSS velocity signal resulted in better estimates than the use of raw data (Akenhead et al., 2014; Lacome et al., 2019). Modelling metrics such as measures of peak velocity/speed were considered in good agreement, and measures of acceleration, force were considered in moderate agreement compared to a criterion measure (e.g., radar/laser). Poor percent agreement was observed for acceleration, force and power metrics when timing gates or a laser were used as the criterion (Figure 3-6).

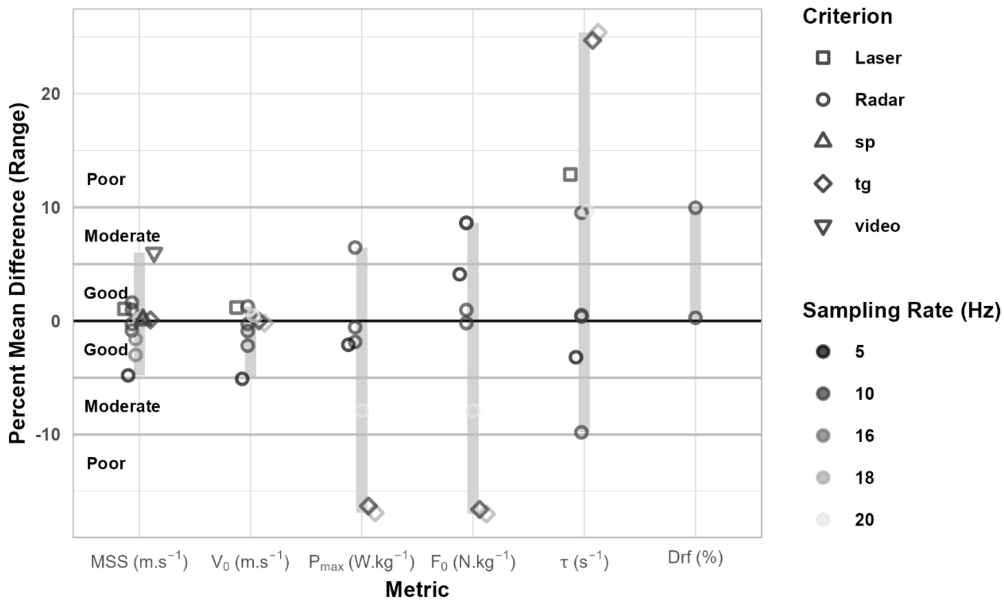


Figure 3-7. Range [min to max] percent mean difference values for GNSS-radar/laser agreement reported with priori percent agreement thresholds with interpretations.

Regarding intertrial reliability outcomes, altogether, studies reported CVs < 5% for MSS, V_0, and relative P_{max}, while F_0 and τ were > 5% (Table 3-3). Intra-system CV comparing raw versus smoothed velocity 10 Hz signal was 15.6 and 3.1%, respectively. Sixteen Hz raw and smoothed velocity resulted in a CV of 0.5% for both raw and smooth (filtered) velocity (ICC = 0.99 for both). ICCs demonstrated *good* to *excellent* reliability, however acceleration-based metrics (ie, τ, F_0, Drf) displayed good reliability. One study assessed inter-model reliability for MSS which resulted in a CV of 0.15 %, and an ICC of 0.98 (Beato & de Keijzer, 2019). The signal-to-noise ratio was considered "good" for MSS, V_0, and P_{max}, but "poor" for F_0 and τ (Barr et al., 2019; Lacome et al., 2019) (Table 3-4, Figures 3-7 to 3-8).

Table 3-3. Concurrent validity of each metric using absolute (A) and/or mean differences (%) between field measurements with criterion by system.

				MSS ($m{\cdot}s^{-1}$)		τ (s)		V_0 ($m{\cdot}s^{-1}$)		F_0 (N)		F_0 ($N{\cdot}kg^{-1}$)		P_{max} (W)		P_{max} ($W{\cdot}kg^{-1}$)		Drf (%)	
Reference	**System (filter)**	**Hz**	**Criterion (filter)**	**A**	**%**	**A**	**%**	**A**	**%**	**A**	**%**	**A**	**%**	**A**	**%**	**A**	**%**	**A**	**%**
Fornasier-Santos (2022)	Catapult (S)	10	Radar/Laser (NI/S)	-0.01/0.03[e]	0.97/1.06*	0.05/0.13	9.51/12.89*	0.03/0.06	1.27/1.18*			-0.21/-0.59	8.63/11.54*						
Cormier (2023)	Catapult (S)	10	Radar (4o0B)	-0.06[e]	-0.84[e]	0.01	0.38	-0.07	-0.89	-2	-0.96	-0.03**	-0.96**	-11.1	-1.85	-0.14**	-1.85**	-0.01	-0.27
Clavel (2022)	Catapult (S)	10	Radar (4o0B)	-0.05[e]	-0.28[e]	0.04	0.51	-0.04	-0.27			-0.02	-0.19			-0.05	-0.56		
Hoppe (2018)	Catapult (1HzcoB)	10	TG (NA)				24.7		0				-16.6				-16.3		
Akenhead (2014)	Catapult (R, S)	10	SP (NA)		0.2_{raw}, 0.03_{smooth}														
Apte (2020)	Fieldwiz[f] (KM)	10	Radar, TG (KM, NA)					-0.17				-0.02				-0.31			
Hoppe (2018)	GPEXE (1HzcoB)	18	TG (NA)				25.4		-0.2				-17				-16.9		
Nagahara (2017)	GPEXE (NI)	20	Radar, Laser (NI)	0.01[c]	0.2[e]	0.12[c]	9.7	0.04[c]	0.5			-0.53	-7.9			-1.02	-7.9		
Huggins (2020)	Polar Team Pro (R)	10	TG & Laser (NA, NI)	0.1															
Reinhardt (2019)	Polar Team Pro[f] (K)	10	TG	-0.01															
Lacome (2019)	Sensoreverywhere (R, MA)	16	Radar (MA)		-3.0_{raw}, -1.6_{smooth}														
Barr (2019)	SPI (NI)	5	TG (NA)	0.09															
Waldron (2011)	SPI (NI)	5	TG (NA)	0.56															
Nagahara (2017)	SPI Pro (NI)	5	Radar, Laser (NI)	-0.42	-4.8[e]	-0.03	-3.2	-0.47	-5.1			0.33	4.1			-0.33	-2.1		
Cormier (2023)	STATSports (R)	10	Radar (4o0B)	-0.13[e]	1.62[e]	-0.14	-9.81	-0.18	-2.18	42.23	8.62	0.5**	8.62**	66.82	6.46	0.79**	6.46**	-0.65	9.96
Beato (2016)	STATSports (R)	10	Video (NA)		3 to 9														
Alphin (2020)	VX Sport (MS)	10	TG (NA)		0.09														

Sorted by GPS/GNSS systems and sampling rate. *difference with laser, raw raw velocity export, smooth specific filtering or s moothing technique used, [e] estimated, [f] reported sensor fusion approach with IMU **unpublished results [c] calculated after the fact, S smooth manufacturer filter, R raw data , SP sliding platform, TG timing gates, NI no information, 4o0B digital fourth-order zero lag Butterworth, 1HzcoB digital low-pass two-passes 1Hz cut-off Butterworth, NA not applicable, K Kalman, M Madgwick, MA 0.5s moving average, MS software from manufacturer

Table 3-4. Reported reliability estimates from each study.

Refs	**System, Hz**	**Reliability type**	**MSS ($m \cdot s^{-1}$)**	**τ (s)**	**V_0 ($m \cdot s^{-1}$)**	**F_0 (N)**	**F_0 ($N \cdot kg^{-1}$)**	**P_{max} (W)**	**P_{max} ($W \cdot kg^{-1}$)**	**Drf (%)**
(Fornasier-Santos et al., 2022)	Catapult, 10	inter-trial	CV 1.47, % Δ 0.9, TEM -0.18	CV 5.74, % Δ 2.0, TEM 0.09	CV 1.63, % Δ 1.0, TEM 0.20		CV 5.64, % Δ -1.1, TEM -0.40			
(Cormier, Tsai, Meylan, & Klimstra, 2023)	Catapult	inter-trial			CV % 1.29, % Δ 0.15, TE 0.33, ICC 0.92		CV % 3.74, % Δ -0.77, TE 0.51, ICC 0.76		CV % 3.68, % Δ -0.66, TE 0.52, ICC 0.83	
(Cormier, Tsai, Meylan, Agar-Newman, et al., 2023)	Catapult, 10	intra-system	% Bias 0.23, TEM 0.02, ICC 0.98	% Bias 0.62, TEM 0.02 ICC 0.92	% Bias 0.31, TEM 0.03, ICC 0.97	%Bias -0.65, TEM 4.08, ICC 0.96		% Bias -0.31, TEM 6.82, ICC 0.98		% Bias -0.93, TEM 0.07, ICC 0.9
	STATSports, 10	intra-system	% Bias -0.39, TEM 0.02, ICC 0.98	% Bias 0.86, TEM 0.01, ICC 0.84	% Bias -0.37, TEM 0.02, ICC 0.97	% Bias -1.01, TEM 4.13, ICC 0.98		% Bias -1.37, TEM 5.65, ICC 0.99		% Bias -0.57, TEM 0.08, ICC 0.85
(Clavel et al., 2022)	Catapult, 10	intra-system	CV % 0.5, TE 0.1, ICC 0.99, SWC 1.0 %	CV % 2.0, TE 0.28, ICC 0.93, SWC 1.5 %	CV % 0.6, TE 0.12, ICC 0.99, SWC 1.1 %		CV % 1.8, TE 0.28, ICC 0.93, SWC 1.4 %		CV % 1.4, TE 0.15, ICC 0.98, SWC 2.0 %	
(Huggins et al., 2020)	Polar Team Pro, 10	inter-trial	CV % 2.43, TE 0.18, SWC 0.06 $m \cdot s^{-1}$							
(Beato & de Keijzer, 2019)	STATSports, 10 (Apex vs Apex)	intra-system	CV % 0.12, ICC 0.99							
	STATSports, 10 (Viper vs Viper)	inter-system	CV % 0.20, ICC 0.97							
	STATSports, 10 (Apex vs Viper)	inter-model	CV % 0.15, ICC 0.98							
(Barr et al., 2019)	SPI, 5	inter-system	CV % 0.11, Δ 0.1, TEM 0.11, SWC 1.21 %, r = 0.55							

(Lacome et al., 2019)	V2 SensorEverywhere, 16	intra-system - raw	CV % 0.5, TE 0.09, ICC 0.99, SWC 0.9 %				
		intra-system - smooth	CV % 0.5, TE 0.09, ICC 0.99, SWC 0.9%				
(Hoppe et al., 2018)	GPEXE, 18	intra-system			CV % 3.1	CV % 7.5	CV % 7.4
	Catapult, 10	intra-system			CV % 3.3	CV % 20.9	CV % 18.8
(Nagahara, Botter, et al., 2017)	GPEXE, 20	inter-trial	CV % 2.3	CV % 8.3	CV % 2.5	CV % 5.6	CV % 2.5
	SPI, 5	inter-trial	CV % 5.1	CV % 17.5,	CV % 6.0,	CV % 19.2	CV % 15.8
(Akenhead et al., 2014)	Catapult, 10	intra-system - raw	CV % 15.6, TE 0.21, r=0.98				
		intra-system - smooth	CV % 3.1, TE 0.08, r=0.99				
(Waldron et al., 2011)	SPI, 5	inter-trial	CV % 0.78				

Sorted by year, CV coefficient of variation, ICC intraclass correlation coefficient, TE typical error, TEM typical error of measurement, SWC smallest worthwhile change (reported from study), % Δ percent change between units (from same manufacturer), r = Pearson’s correlation coefficient.

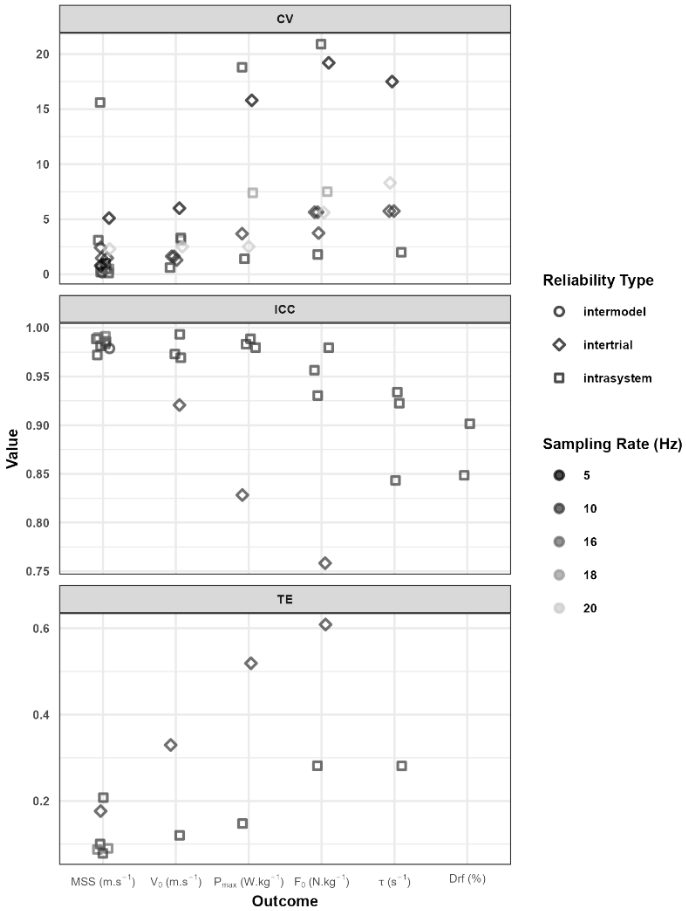


Figure 3-8. Intermodel, intertrial, and intrasystem reliability for each metric/study categorized by sampling rate (Hz).

3.5 Discussion

This review evaluated the state of wearable satellite technology for athlete sprint modeling applications. There are currently sixteen studies assessing aspects of validity and reliability of different GNSS sensors for sprint modeling. Quantitative analysis revealed that pooled effects showed good agreement between GNSS-derived outcomes with criterion measurements. Moderator analysis further revealed influences of sampling rates

(≥ 10 Hz vs < 10 Hz) and sensor manufacturers. Common evaluated outcomes point to agreement of modelling metrics such that measures of peak velocity/speed are considered in good agreement, and measures of acceleration, force are considered in moderate agreement compared to a criterion measure (e.g., radar). Most studies shared good inter-trial, inter-model, and intra-system reliability. However, the CVs reported show potential inconsistency either within athlete variation or random error rooted within the technology itself. While the consolidated studies in this review provide normative values and ranges for sprint modeling using GNSS there are major identified differences that highlight gaps and opportunities for improvement of this technology. Important differences between studies relate to sensor technology differences (e.g., sampling rate, sensor fusion, satellite network acquisition), processing techniques, criterion technology used, sprint protocols, outcome reporting, and athlete characteristics (Malone et al., 2017; Varley et al., 2017). These identified considerations may be useful to guide the improvement of the state of this technology and enable more direct comparison of results.

Table 3-5. Moderator analysis results.

Outcome		**Subgroup random-effects model**								
		k	SMD	95%-CI		tau^2	I^2	pvalue	Effect Size	p-diff
MSS ($m \cdot s^{-1}$)	**Sampling rate**									
	≥ 10	8	0.11	-0.04	0.26	<0.0001	9.40%	0.14	Small	0.001
	< 10	1	0.75	0.38	1.11	--	--	<.0001	Moderate	
	System									
	Catapult	4	0.02	-0.19	0.24	0	0.00%	0.83	Small	
	StatSports	1	0.15	-0.20	0.50	--	--	0.40	Small	
	SensorEverywhere	2	0.59	0.18	0.99	0	0.00%	0.00	Moderate	0.002
	GPEXE	1	-0.02	-0.33	0.29	--	--	0.88	Small	
	SPI	1	0.75	0.38	1.11	--	--	<.0001	Large	
τ (s)	**Sampling rate**									
	≥ 10	6	-0.24	-0.71	0.24	0.311	89.50%	0.33	Small	0.219

	< 10	1	0.14	-0.22	0.49	--	--	0.82	Small	
	System									
	Catapult	4	-0.30	-0.68	0.08	0.098	65.40%	0.12	Small	
	StatSports	1	0.68	0.32	1.04	--	--	0.06	Moderate	< 0.001
	GPEXE	1	-0.86	-1.18	-0.53	--	--	0.02	Large	
	SPI	1	0.14	-0.22	0.49	--	--	0.71	Small	
V_0 ($m \cdot s^{-1}$)	**Sampling rate**									
	≥ 10	6	0.03	-0.12	0.19	0	0.00%	<.0001	Small	0.001
	< 10	1	0.73	0.37	1.10	--	--	0.68	Moderate	
	System									
	Catapult	4	0.02	-0.19	0.23	0	0.00%	0.86	Small	
	StatSports	1	0.21	-0.14	0.56	--	--	0.24	Small	0.004
	GPEXE	1	-0.08	-0.39	0.23	--	--	0.62	Small	
	SPI	1	0.73	0.37	1.10	--	--	<.0001	Moderate	
F_0 ($N \cdot kg^{-1}$)	**Sampling rate**									
	≥ 10	6	0.21	-0.24	0.67	0.281	89.10%	0.36	Small	0.150
	< 10	1	-0.21	-0.56	0.14	--	--	0.71	Small	
	System									
	Catapult	4	0.23	-0.06	0.51	0.035	41.40%	0.12	Small	
	StatSports	1	-0.64	-0.99	-0.28	--	--	0.01	Moderate	<.0001
	GPEXE	1	0.95	0.62	1.27	--	--	0.00	Large	
	SPI	1	-0.21	-0.56	0.14	--	--	0.42	Small	
P_{max} ($W \cdot kg^{-1}$)	**Sampling rate**									
	≥ 10	4	0.24	-0.24	0.71	0.195	85.60%	0.33	Small	0.670
	< 10	1	0.11	-0.24	0.46	--	--	0.82	Small	
	System									
	Catapult	2	0.28	-0.19	0.74	0.067	58.10%	0.24	Small	
	StatSports	1	-0.35	-0.70	0.01	--	--	0.27	Small	<.001
	GPEXE	1	0.69	0.38	1.01	--	--	0.02	Moderate	
	SPI	1	0.11	-0.24	0.46	--	--	0.73	Small	

p-diff = test for Subgroup differences. SMD = standardized mean differences (d). k = number of studies. CI = confidence interval.

3.5.1 Technological innovations

Based on the consolidated outcomes in this review, it has been shown that small SMDs were found for all meta-analyzed outcomes. When considering the entire dataset, there are favorable results with regards to GNSS-criterion agreement for maximum velocity (MSS and V_0) whereas acceleration-derived metrics such as τ, F_0, P_{max}, and Drf, achieve good to moderate agreement for percentage differences. These results may be closely tied to the current limitations of sensor technology. For example, sampling rates are an important factor in sprint profiling with GNSS sensors. Nagahara et al. (2017) identified that lower sampling rates (<10Hz) resulted in poor agreement with some profiling metrics with sampling rates ≥10Hz providing superior agreement and reliability. More recent studies have since shown improvements in agreement outcomes (CVs <5%) across metrics with improved intra-system and inter-system reliability using 10Hz GNSS (Clavel et al., 2022; Cormier, Tsai, Meylan, Agar-Newman, et al., 2023; Fornasier-Santos et al., 2022). While measures of speed are achieving good agreement with higher sampling rates, present results suggest that GNSS is still suboptimal for quantifying acceleration metrics (Ellens et al., 2022; Varley et al., 2017). It has been suggested that low sampling rates limit the ability to determine changes in velocity during the initial portions of the sprint where acceleration is likely the highest. As acceleration is the rate of change in velocity, limitations in adequate sample rate will have implications for calculation of accurate acceleration. This can be observed in technology such as timing gates where low temporal resolution during the initial portion of the sprint will tend to overestimate F_0 in sprint modeling studies (Cormier, Tsai, Meylan, Agar-Newman, et al., 2023). As shown in Figure 3-3, both inter-trial and intra-system values for all metrics improve with increased sampling rates. These results suggest that optimal sampling rates for GNSS (and other sensors) derived sprint modelling still need to be determined. As current systems range between 10-20Hz, systems with greater sampling rates may need to be developed or enhanced.

Most GNSS systems include IMUs which consist of an accelerometer, gyroscope and magnetometer. IMUs can provide accurate and useful measurement of sensor orientation and motion within a short distance and time range and are considered assistive to GNSS technology. However, IMUs, as opposed to GNSS technology, are not yet suitable to determine absolute changes in distance and speed over large ranges and each sensor technology can play useful and complementary roles in athlete monitoring (Cummins et al., 2013). Recently, the outputs of GNSS and IMU sensors systems have been combined ("sensor fusion") and used to correct the GNSS signal output, increase the sampling rate, and provide additional kinematic information for output variables. For example, Apte et al. (2020) and Reinhardt et al. (2019) both used a sensor fusion approach for signal correction in their study with a 200Hz IMU and 10Hz GNSS unit using Madgwick and Kalman filtering which resulted in very high agreement between the metrics derived from the GNSS system and the criterion selected. Although more research is warranted to implement sensor fusion for sprint modeling, its application could resolve many sprint modeling limitations of GNSS technology.

3.5.2 Data processing considerations

There are many considerations with respect to the GNSS data used and how it is processed before sprint modeling outputs are derived. First it is important to consider what kinematic variables are used as sprint modeling input parameters. Current sprint modelling practices require continuous acceleration/velocity or distance/time data. Acceleration values exported from GNSS manufacturer software may be derived either from embedded accelerometers or velocity and time samples (Wu & Swartz, 2022). Velocity is estimated via two methods, positional differentiation (distance/time) or Doppler-shift, with the latter preferred due to superior accuracy (Townshend et al., 2008). It is important to differentiate between these two methods since some studies report them interchangeably or concurrently which should influence the methodology, interpretation of findings and study comparisons. Furthermore, acceleration and velocity outputs from manufacturer software are subject to proprietary filtering and algorithms as well as post processing techniques used by researchers, as such the specific processing and cleaning methods may be unknown and may change with different software updates (Malone et al., 2017).

Another aspect that could impact sprint modeling outcomes is data filtering (Malone et al., 2017). Most GNSS system manufacturers employ undisclosed or proprietary filtering techniques, resulting in differently processed signals from sensors. Therefore, some sensors may output raw GNSS calculations while others have onboard pre-processing before the user is given the data. These preprocessing steps are often undisclosed, potentially hindering post export applications conducted by sport scientists. While the level of pre-processing is usually unknown, it is still common practice for sport scientists to use signal post-processing to further condition the data for sprint modelling. There were a variety of approaches identified in this review with unclear methodology being reported. Of note, Butterworth filters (Hoppe et al., 2018), rolling averages (e.g., 0.5 s) (Lacome et al., 2019), and locally weighted regression smoothing (loess) (Clavel et al., 2022) were used in the signal processing protocols. Otherwise, manufacturers' "smooth" export, or raw data were used (Table 3-2). Studies in this review demonstrate that filtered data improves agreement with criterion measurement. For example, Lacome et al. (2019) and Akenhead et al. (2014) observed that maximal sprint speed and maximum acceleration biases were larger with raw data versus smoothed (moving average) data during linear sprinting tasks.

In accordance with previous literature (Ellens et al., 2022), a low-pass Butterworth filter was the most frequently reported filtering technique with both radar and GNSS data in this review. However, as mentioned, and important to note, only two GNSS studies reported all specific filtering specifications (e.g., digital, low-pass, dual-pass, 1Hz cut-off Butterworth) (Table 3-3). Other studies exported the raw data or “smoothed” data from the manufacturers. Additionally, regarding the criterion systems (e.g., radar), important information such as cut-off frequency, filter order, and number of passes were also frequently left out, which makes comparison of study findings difficult. Similar to sampling rate considerations, the choice of filter and filter frequency is of utmost importance in ensuring that the true signal is not attenuated, and accurate sprint modeling metrics can be developed (Robertson & Dowling, 2003). However, based on this review it is not yet evident which filtering techniques are optimal for GNSS processing, and more research needs to be performed to ensure consistency between comparisons.

Once appropriate data filtering is performed, other methodological decisions are required to prepare the data for sprint modeling such as determining the onset and end of sprint identification. When examining the reported onset of sprint detection and end of sprint detection, there were various methodologies employed. These thresholds are often selected to avoid “noise” of the signal before the onset or inflection point of the sprint. In this review, onsets reported where: when derived acceleration > 0.1 $m{\cdot}s^{-2}$, accelerometer acceleration > 0 $m{\cdot}s^{-2}$, synchronization with timing gates (Apte et al., 2020; Huggins et al., 2020), velocity rising above a threshold deviation (e.g., +2 *SD*s) (Lacome et al., 2019), velocity > 0.3 $m{\cdot}s^{-1}$ (Clavel et al., 2022), and velocity > 0.5 $m{\cdot}s^{-1}$ with video correction (Fornasier-Santos et al., 2022). Concerning the onset, with current modeling practices, it is recommended that the lowest velocity or acceleration threshold be used based on the sampling rate of the system, although more robust techniques must be developed (to avoid signal noise and over or under-estimations of profile metrics) and used consistently between studies to allow for result comparisons and to apply in the field. When detecting the end of the sprint: set distance or integrated distance (Cormier, Tsai, Meylan, Agar-Newman, et al., 2023), velocity drop thresholds after peak velocity was achieved (e.g., -0.4 $m \cdot s^{-1}$) (Clavel et al., 2022; Fornasier-Santos et al., 2022), visually trimmed data, and synchronization with other technology (e.g., timing gates or software) (Apte et al., 2020; Huggins et al., 2020) were used to identify the onset and end of the sprint. The velocity modelling techniques of the studies included in this review were mostly mono-exponential models (with or without time delay) (Morin et al., 2019; Samozino et al., 2016). Considering that sprints are performed over short distances (up to 50m), and knowing this model implies a maximum asymptotic value where the highest point of the model should be near or at peak velocity of the athlete, using a cut off shortly after peak velocity is achieved is the rationale choice when using this model with shorter distances (40-50 m). Accordingly, future research should assess how the different data processing procedures affect sprint modeling metric outcomes with GNSS technology.

3.5.3 Criterion

Various criterion devices were used in these studies (Table 3-3). However, not all studies used appropriate criterion devices for sprint profiling. For example, the use of timing gates for horizontal FV sprint profiling overestimates certain FV metrics associated with the acceleration phase of the sprint (i.e., τ, F_0, and P_{max}) (Cormier, Tsai, Meylan, Agar-Newman, et al., 2023; Fornasier-Santos et al., 2022). This is due to methodological considerations related to low sampling rates, sprint start limitations (e.g., fly-in distance to avoid the arm breaking the beam), beam system type (single vs dual), as well as velocity modelling technique limitations (T. Haugen et al., 2020). Therefore, using current sprint modeling practices, timing gates may not be suitable for use as a criterion measurement in validity studies, although highly practical as a tool in the field. These limitations may have caused the high percentage differences observed in some of the studies included in this review (Table 3-3). Recent evidence shows that using video to mitigate some sprint onset limitations can improve the agreement with radar (Fornasier-Santos et al., 2022), however this still resulted in an overestimation in F_0 and as well this may not be an accessible approach to many sport science practitioners due to logistical considerations. Concerning other criterion technologies reported in this review, Fornasier-Santos et al. (2022) showed that lasers and linear encoders have good agreement with radar for maximum velocity metrics, whereas force/acceleration metrics tend to display moderate to poor agreement. Radar provides practitioners with criterion reference that has been validated in previous research and may be superior due to the higher sampling rates and the ability to directly measure instantaneous velocity.

3.5.4 Reporting in GNSS research

Distinction must be made between GPS and GNSS networks when reporting in sprint modeling studies due to differences in the sensors' (i.e., receiver) ability to acquire satellites. To accurately track position a minimum of four satellites is required, thus GNSS compatible systems allow for higher satellite network acquisition with some having the ability to acquire > 10 satellites (Castellano et al., 2011; Clavel et al., 2022; Cormier, Tsai, Meylan, Agar-Newman, et al., 2023; Varley et al., 2012). Horizontal dilution of precision (hdop) shows the relationship between the organization of the satellites in relation to the receiver and positional measurement precision, where values can fall between 0 and 50, with values below 1 deemed beneficial (Malone et al., 2017). In this study, values from 5 Hz devices (older models) tended to exhibit hdop values > 1 and newer (≥ 10Hz) models tend to report values < 1 (Beato & de Keijzer, 2019; Clavel et al., 2022; Cormier, Tsai, Meylan, Agar-Newman, et al., 2023; Varley et al., 2012; Waldron et al., 2011). It is important to report the sensor networks, satellite acquisition and positional precision values in GNSS/GPS sprint modeling research as sprint profiles may be sensitive to nuances in the quality of the signal due to environmental or location limitations (i.e., stadium structures, cloud cover, etc.).

3.5.5 Recommendations and future research

There are existing recommendations that sports scientists should evaluate when planning studies and disseminating findings from GNSS-derived outcomes (see Malone et al. (2017) and Ellen et al. (2022)). This review adds to these recommendations by highlighting the need for standardization and transparent reporting of data processing to support best practice of sprint modelling. The first consideration is from the post-manufacturer processed data. Practitioners should evaluate whether the data is filtered or raw, and whether the acceleration data is derived or obtained from IMUs. It is recommended that the raw data is filtered or that sport scientists compare their own signal processing to that of the manufacturers to allow for replication of findings. As stated in previous research, the Doppler method is preferred over positional differentiation and information on signal acquisition and quality must be considered since this could impact the accuracy of the GNSS or GPS signal and consequently the sprint profiling. Secondly, when applying a sprint model to the data, it is important to consider that lower sampling rates or poor data processing procedures will lead to poor estimation of acceleration-based metrics; thus, it is recommended that GNSS with higher sampling rates are used and that the lowest possible thresholds for sprint onset be implemented. Data processing techniques such as sensor fusion may provide a solution to improve sampling and data fidelity, having already been proven in some studies (Reinhardt et al., 2019). In addition, when modelling the sprint, the determination of sprint end needs to be considered in relation to the mathematical equation used for modeling. For example, data inputted into the mono-exponential model should be trimmed at or shortly after the peak velocity is achieved. Other models (e.g., biexponential (Morin et al., 2012) or including fly-in velocities (Volkov & Lapin, 1979)) may necessitate different protocols concerning the onset and end of sprint detection. Therefore, studies to determine optimal sprint trimming parameters for differing collection protocols and techniques are required. Finally, it is important to report enough information for researchers and practitioners to replicate the methodology and compare findings across studies. Validity estimates (ie, Bland-Altman, regression, etc.) with variability estimates (eg, LOA, *SD*, TE) as well as reliability statistics (eg, CV, ICC, etc.) should be reported. Further, information on athlete characteristics, sprint protocols, and specifications of the technology used (i.e., GNSS model, firmware and software) and signal quality should be reported. Researchers are encouraged to share data processing procedures through journal supplementary materials, online repositories, or have extremely detailed methodology outlined in their research. For example, two studies included in this review shared their coding protocols through supplementary materials or detailed protocols in their methodology (Clavel et al., 2022; Cormier, Tsai, Meylan, Agar-Newman, et al., 2023). The application of the recommendations made in this review in future research will allow for accelerated improvement of current sprint modeling practices.

3.5.6 Practical applications

As it has been shown that it is possible to derive valid and reliable FV profiles from GNSS data given that appropriate methodology is carried out by sport science practitioners, potential for application in the field is promising. Studies have suggested the possibility to integrate multiple standardized maximal sprint efforts (e.g., 2 x 40-50 m sprints) to provide systematic information on athlete sprint acceleration capabilities (Clavel et al., 2022; Lacome et al., 2019). These studies have included coding scripts to efficiently process the data included in supplementary materials. Hicks et al. (2020) have provided practical recommendations to improve mechanical effectiveness of force application and has recently introduced a framework to profile and individualize programs to address force and velocity components. For example, an approach that could be taken is plotting athletes' V_0 on the x-axis and F_0 on the y-axis with a scatterplot divided into four quadrants by the medians of each variable, then identifying deficits to target with different training modalities (e.g., resisted sprinting or resistance training) (Hicks et al., 2022) or identify strengths to maximize. In team-sports with large rosters, it may be beneficial to group athletes based on their FV characteristics to inform training programs. These methods could especially be beneficial for sports in which long linear or semi-linear sprints are frequently performed in training and competition such as soccer, rugby codes (e.g., Sevens rugby), football (American and Australian rules), and so on. The actual integration of sprints into normal training has now been demonstrated in two cases, both displaying valid and reliable results (Clavel et al., 2023; Cormier, Tsai, Meylan, & Klimstra, 2023).

3.6 Conclusions

This review outlines the currently available literature on linear sprint modeling with GPS/GNSS systems, identifying gaps and opportunities for improvement. Primarily, sport science practitioners are encouraged to open dialogue with sport technology companies to better understand GNSS units' proprietary signal processing algorithms. If this information cannot be shared, sports scientists should consider the post-manufacturer processing, sprint model processing and reporting of sprint protocol and specification of the GNSS technology used (Ellens et al., 2022; Malone et al., 2017). This will allow for better comparisons of the findings across studies and improvements in future research.

3.7 Practical applications

While there are some methodological challenges to sprint modeling using GNSS technology, validity and reliability studies suggest that sprint modelling can be carried out and show promise for sprint monitoring in the field. The key consideration is that the most up-to-date modeling practices should be used consistently with similar sprint protocols, since the methodology will affect sprint profiling outcomes. As suggested in previous research (Clavel et al., 2022; Cormier, Tsai, Meylan, Agar-Newman, et al., 2023; Lacome et al., 2019, 2020), the integration of maximal standardized linear sprint efforts can be integrated into training sessions with team-sport and individual sport athletes. Systematic sprint modeling could allow performance teams to monitor fatigue and readiness, better-informing periodization and training stimulus prescription. This has important implications for concepts like "invisible monitoring" (i.e., testing without testing) (Cormier, Tsai, Meylan, & Klimstra, 2023; Morin et al., 2021), systematic testing, fatigue monitoring, rehabilitation, performance, and training design.

Chapter 4 – Comparison of force-velocity and acceleration-speed profiles in elite women's soccer[3]

4.1 Abstract

This study aimed to (1) compare "in-situ" monitored acceleration-speed ($AS_{in\text{-}situ}$) profile metrics from training/competition data in elite female soccer players to similar metrics from profiles developed from isolated maximal sprint efforts (AS_{sprint}) and; (2) compare the confidence interval (CI) and a Tukey boxplot (BP) outlier removal technique on the training/competition data to derive $AS_{in\text{-}situ}$ profiles. Fifteen national team soccer players participated in a 4-week camp while wearing 10 Hz GNSS units. Towards the middle of the camp, 2 x 40 m isolated maximal sprints were performed. $AS_{in\text{-}situ}$ profiles (theoretical maximum acceleration A_0 in m•s^{-2} and speed S_0 in m•s^{-1}) were computed using the CI and BP techniques with training/competition data. The sprint data were modelled separately to construct horizontal force-velocity (FV) profiles, from which AS_{sprint} profiles were derived. Bland-Altman analysis was used to assess agreement between the CI- and BP-derived $AS_{in\text{-}situ}$ profiles to the AS_{sprint} profiles, as well as regression analysis for systematic and proportional bias. Additionally, 1-way ANOVAs with Tukey posthoc compared the metrics between each method of analysis. Using the BP method, good agreement of the $AS_{in\text{-}situ}$ with AS_{sprint} profile metrics A_0/S_0 was displayed, whereas good to moderate agreement was shown for the CI. The CI technique showed a proportional bias for A_0/S_0. Good to excellent intertrial reliability was demonstrated for isolated sprint metrics. Both BP and CI techniques provided comparable $AS_{in\text{-}situ}$ profiles to AS_{sprint}

[3]Cormier, P., Tsai, M. C., Meylan, C., & Klimstra, M. (2023). Comparison of acceleration-speed profiles from training and competition to individual maximal sprint efforts. Journal of Biomechanics, 157, 111724.

profiles. This current research demonstrates that $AS_{in\text{-}situ}$ profiling is applicable in elite women's soccer and will have further application in many team sports.

4.2 Introduction

The quantification of external training and competition load metrics through the use of athlete tracking devices with global navigation satellite system (GNSS) technology is now commonplace in many team sports (Torres-Ronda et al., 2022). As the conditions in training and competition often require the athlete to reach maximum levels of speed and acceleration, and this data can be captured with GNSS athlete tracking devices, there may be a diminished need to perform isolated tests to assess these physical characteristics. For example, an ambient assessment technique called “invisible” and “in-situ” monitoring, or specifically, acceleration-speed ($AS_{in\text{-}situ}$) profiling can be constructed by determining the highest acceleration efforts across a range of speeds from GNSS-derived competition or training data (Morin et al., 2021). Plotting the accelerations and speeds on the y and x axes results in a cloud of points, which allows for a linear regression through the maximal points (Figure 4-1). The main components of $AS_{in\text{-}situ}$ profiling are: y-intercept (vertical axis), maximum acceleration at zero speed (A_0 in $m{\cdot}s^{-2}$); x-intercept (horizontal axis), speed at zero acceleration (S_0 in $m{\cdot}s^{-1}$); and the slope of the relationship (Morin et al., 2021).

The evaluation of these player performance metrics is conceptually comparable to horizontal force-velocity (FV) assessments (Morin et al., 2019; Samozino et al., 2016). FV profiling traditionally requires dedicated speed testing sessions where sprint velocity-time data is modeled using a mono-exponential function, from which the model parameters peak speed and the acceleration constant are calculated. Then using these parameters, the metrics of speed, acceleration, force, and power are derived (Samozino et al., 2016). While this has become a valuable standard testing and analysis method, it involves substantial time and effort to collect consistently over time. With the large amount of data collected in training and competition, across a great range of athlete efforts, the potential to extract players' physical characteristics using invisible monitoring is advancing. For $AS_{in\text{-}situ}$ monitoring to be used in a comparable manner to isolated sprint testing methods, there is a need to compare the outcomes from these two similar yet unique techniques. If comparable profiling outcomes can be derived using only training and competition data without the need for dedicated sprint testing, it could be possible to use these profiles to longitudinally track players' physical condition which can inform rehabilitation protocols, injury-prevention strategies, training design, and optimization of the maximal acceleration and velocity for each player (Lahti et al., 2021; Mendiguchia et al., 2016b). This has implications for invisible monitoring across many team sports where frequent maximal sprint efforts are performed such as rugby sevens.

With the potential to efficiently collect and process $AS_{in\text{-}situ}$ profiles from games and training (Morin et al., 2021), great caution is required as there are few studies on $AS_{in\text{-}situ}$ profiling (Alonso-Callejo et al., 2022; Clavel et al., 2023; Imbach et al., 2022; López-Sagarra et al., 2022; Morin et al., 2021) without a confirmed method for analysis (eg, data cleaning, outlier removal, and signal processing). It is common for GNSS velocity and acceleration data to contain outliers (Malone et al., 2017); therefore, it is the best practice to eliminate (or remove) such data to derive accurate profiles from isolated sprints or training/competition data (Delves et al., 2021). For example, a proposed method of data cleaning and processing is the confidence interval (CI) outlier technique to produce an AS profile from soccer training data (Morin et al., 2021). However, there are common outlier removal techniques, such as the Tukey box plot (BP) technique (Tukey, 1977) that may also be viable and present some unique benefits. The BP method is a standard technique where interquartile ranges (IQR) and upper and lower fences are used to detect outliers. The BP technique may have benefits in robustness (ie, ability to detect the AS profile data points in noisier data) and greater weighting of acceleration points (occurring at a higher frequency in soccer) (Trewin, Meylan, Varley, & Cronin, 2018). More robust analysis may allow for more repeatable methodology between AS profiling studies using technologies from different companies with different levels of quality. While the CI outlier removal technique proposed by Morin et al. (2021) for AS profiling sets an important standard, it is not known how this technique compares to the Tukey BP technique.

Therefore, the aims of this study were two-fold: 1) to compare AS profile metrics developed using GNSS data collected during training and competition ($AS_{in\text{-}situ}$) in elite soccer players to similar metrics outputs from AS profiles developed from isolated maximal sprint efforts (AS_{sprint}), and 2) compare the CI technique and a common Tukey BP technique for AS profiling, as the analysis methods for the development of an AS profile has not been standardized. The suitability of each outlier removal technique will be based on the level of agreement between the isolated sprint effort AS profile and the training/competition data derived AS profile. The results of this research may permit the elimination of isolated sprinting trials and confirm the efficacy of GNSS data to create AS profiles.

4.3 Methodology

4.3.1 Participants

Data were analyzed from fifteen soccer players on the Canadian Senior Womens National Team (age = 26.23 ± 5.19 years, height = 1.68 ± 0.07 m, body mass = 63.05 ± 4.80 kg) ranked 6th in the world (FIFA, 2023). Ethical approval was obtained from the

University of Victoria Human Research Ethics Board and complied with the Declaration of Helsinki.

4.3.2 Design

Concerning the AS monitoring using GNSS technology, the data acquired from 19 aggregated training and competition events ($AS_{in\text{-}situ}$) throughout a 29-day camp and were compared to maximal sprint efforts performed in a separate sprint testing session (ie, AS_{sprint}). It must be noted that the AS_{sprint} data were analyzed separately from the $AS_{in\text{-}situ}$ data. Throughout the camp the players participated in a minimum of 15 and a maximum of 19 events (5 international matches and 14 training sessions).

4.3.3 Data collection

Throughout the camp, Catapult GNSS units (Vector S7, firmware 8.1.0, Catapult Innovations, Melbourne, Australia) sampling at 10 Hz were worn by the participants in tightly fit vests between the scapulae. The filtered velocity data (Doppler method, calculated via the change in frequency of the satellite signal) (Malone et al., 2017; Varley et al., 2017) were exported and the derivative of the velocity data with respect to time was used to calculate acceleration (Figure 4-1). Horizontal dilution of precision (HDOP) and number of satellites throughout the training camp were 0.85 ± 0.14 and 13.8 ± 3.5, respectively (atmospheric pressure = 758-766 torr, wind = 0-3 $m{\cdot}s^{-1}$, temperature = 29-33 °C).

On the morning of the AS_{sprint} protocol which took place on day 11 of the 29-day camp, height, and body mass were collected. The warm-up consisted of a 20 min general and dynamic movement followed by three progressive sprints at increasing intensities over 30 m with 3 min rest. Players stood in two lines 5 m apart and performed 2 x 40 m maximal all-out sprints with their feet positioned in a staggered stance with 3-5 min of rest between trials, and players were encouraged to sprint as fast as possible. The protocol was carried out on an open grass field (atmospheric pressure = 765 torr, wind = 0 $m{\cdot}s^{-1}$, temperature = 30 °C, HDOP = 0.61 ± 0.04, and number of satellites = 18.02 ± 1.30).

4.3.4 Data analysis

The CI analysis (Figure 4-1B) consisted of grouping positive acceleration velocity data into 0.1 $m{\cdot}s^{-1}$ subintervals and taking the maximum two values in each group. Subintervals were adapted due to the low sampling rate in this study (from 0.2 in the original concept) (Morin et al., 2021). Then, a linear regression of the speed-acceleration points was performed. Residual points, from the regression, outside of the 95 % CI upper and lower limits were removed. The Tukey BP technique (Figure 4-1A) consisted of taking the top two percent of positive acceleration and velocity data points. This data were then divided into 0.1 $m{\cdot}s^{-1}$ subintervals. The BP requires a minimum sample of 5 data points (Krzywinski & Altman, 2014), hence why these initial parameters were chosen to allow for retention of enough maximal points. Then, within the subintervals, points outside the upper and lower limits of accelerations were removed (ie, IQR [Q3-Q1]; upper fence = Q3 + 1.5 · IQR, lower fence = Q1 – 1.5 · IQR) (Tukey, 1977). The maximum values in the subintervals were kept. Data above a velocity of 3 $m{\cdot}s^{-1}$ were retained for the $AS_{in\text{-}situ}$ analysis (Morin et al., 2021). After the outlier removal methods were applied to the aggregated training and match data, a linear regression between retained acceleration and velocity points were performed to construct the $AS_{in\text{-}situ}$ profiles. Examples of the AS profiles using each approach are shown in Figure 4-1.

The isolated sprint velocity data (Figure 4-1C) were modelled through a nonlinear least-squares regression (including a time delay) (Morin et al., 2019), whereby the estimated parameters maximal sprint speed (MSS $m{\cdot}s^{-1}$) and the acceleration constant (τ s) were used to calculate the horizontal FV sprint variables as well as the AS_{sprint} metrics: maximum acceleration at zero velocity (A_0 $m{\cdot}s^{-2}$); horizontal force at zero velocity (F_0 $N{\cdot}kg^{-1}$); velocity/speed at zero force [or acceleration] (V_0 $m{\cdot}s^{-1}$, S_0 $m{\cdot}s^{-1}$); and horizontal maximal power (P_{max} $W{\cdot}kg^{-1}$). The average of both isolated sprint trials were retained to reduce measurement variability in profiled metrics (Simperingham et al., 2019) and results reported normalized relative to body mass.

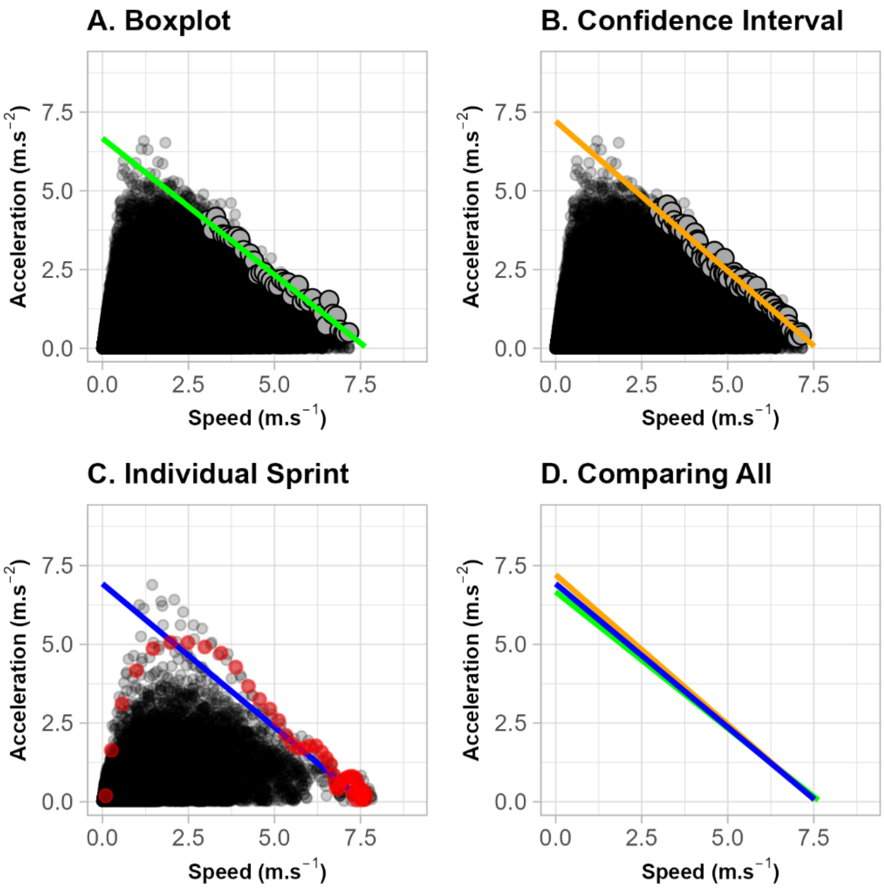


Figure 4-1. Example of AS profiles from one midfield player over the camp period: ***A.*** *$AS_{in\text{-}situ}$ using the BP method;* ***B.*** *$AS_{in\text{-}situ}$ using the CI method;* ***C.*** *AS_{sprint} and full sprint from the player (red points); and* ***D.*** *comparing all AS profiles together. Grey points are retained points after outlier removal (R^2 for CI = 0.97, ~ 80 points; and BP = 0.97, ~50 points in this example). A subset of the Catapult smoothed velocity data was compared to the data before smoothing (raw) using a low-pass, 4th order, 1Hz cut-off, dual-pass Butterworth filter (ICC, 2,1 of 0.99) showing the level of filtering to allow for reproducibility. All data processing procedures were conducted using customized R scripts (Version 4.2.2, R Core Team, Vienna, Austria, 2022). Scripts for both outlier removal techniques are in the Supplementary materials (https://doi.org/10.1016/j.jbiomech.2023.111724).*

4.3.5 Statistical analysis

To evaluate the agreement between the CI- and BP-derived $AS_{in\text{-}situ}$ with the AS_{sprint}, Bland-Altman plot analysis was performed (ie, mean differences with limits of agreement, 90% confidence LOA) (Bland & Altman, 1986). Percent bias was interpreted as *good*, *moderate*, and *poor* (<5, 5-10, and >10%, respectively). Systematic bias was calculated through a 1-sample t-test whereby the linear regression slope was tested against a slope of 1. Proportional bias was also assessed for each metric in the linear regression model where a significant parameter estimate coefficient (ie, different from zero) indicated bias was present. A 1-way ANOVA was performed for each AS variable between profiling methods (CI-, BP-derived $AS_{in\text{-}situ}$, and AS_{sprint}) and a Tukey posthoc procedure was used to control for type I error in making multiple comparisons, to determine the significant difference between the parameter estimates. The level of statistical significance was taken to be [alpha] = 0.05 for all tests. The inter-trial reliability of the AS_{sprint} profile metrics were evaluated with the typical error (TE), TE (expressed as the coefficient of variation [CV]), and ICCs (3, 1) (Hopkins et al., 2009). CVs <5% were interpreted as *good*. ICCs were classified as <0.5 *poor*, 0.5-0.75 *moderate*, 0.75-0.9 *good*, and >0.9 *excellent* (Koo & Li, 2016).

4.4 Results

Using the BP method, *good* agreement between $AS_{in\text{-}situ}$ and AS_{sprint} was found for A_0/V_0, and using the CI method, *good* to *moderate* agreement was found (Table 4-1 and Figure 4-2).

One-sample t-tests demonstrated no systematic bias for all metrics when comparing the CI and BP derived $AS_{in\text{-}situ}$ to the isolated AS_{sprint} profiles (Table 4-1). However, according to the linear regression models, the CI technique displayed proportional bias for A_0 ($p = .021$) and S_0 ($p = .009$) (Table 4-1 and Figure 4-2).

The 1-way ANOVA demonstrated a main effect for profiling method for A_0 only ($p = .034$), with the posthoc identifying that the CI techniques derived significantly higher values than BP ($p = .048$). No statistically significant differences were found between the CI and BP method-derived $AS_{in\text{-}situ}$ with the isolated AS_{sprint} profiles (Table 4-1).

Intertrial reliability results showed *good* to *excellent* ICCs, and *good* CVs across all isolated sprint metrics (Table 4-2).

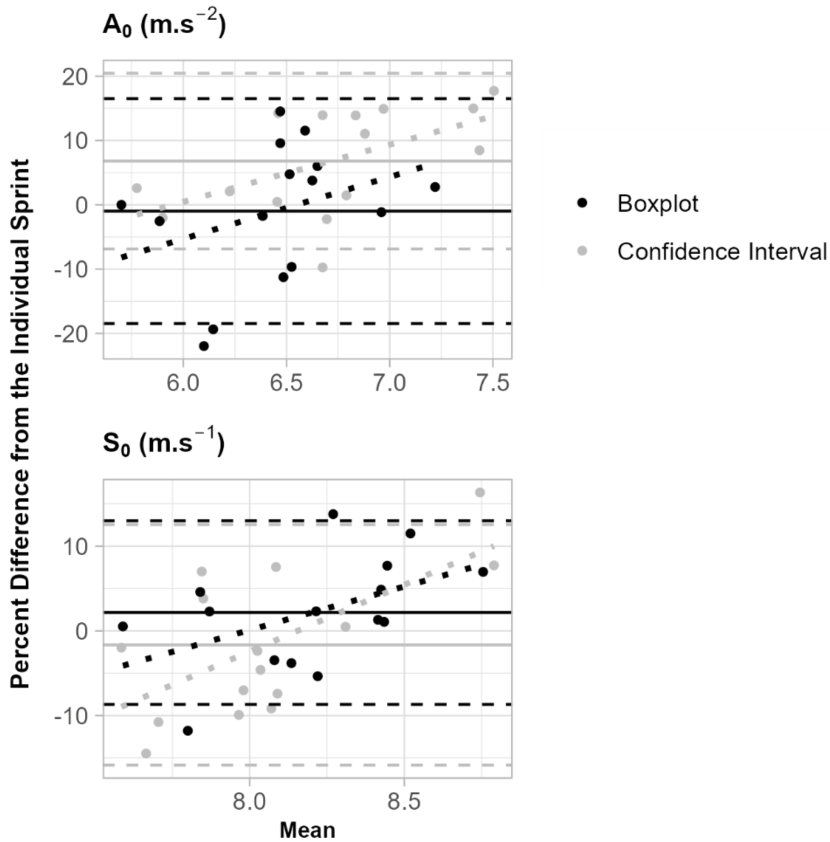


Figure 4-2. Bland-Altman plots of each metric displaying mean and percent differences for each athlete (averaged trials, n =15), dashed lines = ± 90% Confidence LOA. Dotted lines to visually illustrate the line of best fit and proportional bias.

4.5 Discussion

This study demonstrated that GNSS-derived $AS_{in\text{-}situ}$ profiles generated from training/matches are comparable to isolated AS_{sprint} profiles. Additionally, in this investigation, the standard Tukey BP outlier removal technique provided a slightly more robust analysis to the CI technique, although no significant differences were found between each outlier removal method with the isolated AS_{sprint} method (Table 4-1). Therefore, it is possible to derive $AS_{in\text{-}situ}$ profiles, permitting the elimination of the need for isolated standardized sprint testing.

Table 4-1. Bland-Altman analysis and regression results show the differences between each outlier removal technique and the isolated AS_{sprint} reference.

	A_0 Sprint $m \cdot s^{-2}$	A_0 CI $m \cdot s^{-2}$	A_0 BP $m \cdot s^{-2}$	S_0 Sprint $m \cdot s^{-1}$	S_0 CI $m \cdot s^{-1}$	S_0 BP $m \cdot s^{-1}$
Mean (SD)	6.47 (0.41)	6.95 (0.72) *‡	6.42 (0.59) ‡	8.11 (0.30)	7.99 (0.64) *	8.29 (0.51)
Mean Δ (90 CI LOA)	-	0.48 (-0.48, 1.44)	-0.05 (-1.15, 1.05)	-	-0.12 (-1.28, 1.04)	0.19 (-0.7, 1.08)
TE (90 CI)	-	0.15 (0.06, 0.24)	0.17 (0.06, 0.28)	-	0.18 (0.06, 0.30)	0.14 (0.11, 0.17)
Percent mean Δ (90 CI LOA)	-	6.79 (-6.88, 20.46)	-0.98 (-18.46, 16.5)	-	-1.65 (-15.86, 12.56)	2.17 (-8.68, 13.02)
Interpretation	-	Moderate	Good	-	Good	Good

SD standard deviation, LOA limits of agreement, TE typical error, Δ difference, CI confidence interval. Proportional bias from the linear regression model *p less than .05. Tukey posthoc significance ‡ p less than .05 between BP and CI techniques.

There were some commonalities and differences for AS profiling outcomes between outlier removal techniques. Where CI profiles overestimated A_0 and underestimated S_0; the BP profiles contrarily underestimated A_0 and overestimated S_0 (Table 4-1 and Figure 4-2). However, the magnitude of the differences was less for the BP method. Additionally, the CI technique displayed a proportional bias for both A_0 and S_0 (Table 4-1). This finding may be explained by the following: the CI technique is dependent on the initial two maximal acceleration points retained for the linear regression function, thus resulting in an overestimated profile if outliers exist, impacting the initial regression and consequently diminishing the effectiveness of the technique. Alternatively, the BP method uses an outlier removal technique where extreme outliers in the subinterval points will not influence $AS_{in\text{-}situ}$ profiling because the IQR includes the majority of clustered data. To mitigate the limitation of extreme outliers with the CI technique, the velocity data must be carefully filtered and screened for outliers, based on GNSS recommendations (Delves et al., 2021; Malone et al., 2017), prior to applying the $AS_{in\text{-}situ}$ profiling method. In summary, if the aim is to replicate or derive similar metrics outputs to the isolated sprint

AS_{sprint} method through $AS_{in\text{-}situ}$ monitoring, the BP outlier removal technique provides a slightly superior alternative for a more precise profile.

With respect to the maximal isolated sprint modeling using GNSS, the inter-trial reliability showed *excellent* ICCs for velocity and *good* for acceleration metrics (Table 4-2), and previous studies have demonstrated its validity (bias <1 %) when compared to standard field criterion measurements (ie, radar gun) (Clavel et al., 2022; Cormier, Tsai, Meylan, Agar-Newman, et al., 2023; Fornasier-Santos et al., 2022), thus supporting the use of this modeling method as a reference for comparison.

Table 4-2. Intertrial reliability statistics concerning sprint data with normative AS_{sprint} and FV relationship metric values.

	AS_{sprint}		**FV**		
	A_0 m·s^{-2}	**S_0 m·s^{-1}**	**F_0 N·kg^{-1}**	**V_0 m·s^{-1}**	**P_{max} W·kg^{-1}**
Mean (SD)	6.47 (0.41)	8.11 (0.30)	6.41 (0.41)	8.41 (0.33)	13.49 (0.97)
Mean trial 1 (SD)	6.48 (0.39)	8.10 (0.32)	6.42 (0.39)	8.41 (0.34)	13.50 (0.95)
Mean trial 2 (SD)	6.43 (0.51)	8.11 (0.32)	6.37 (0.51)	8.42 (0.34)	13.41 (1.21)
% Δ in mean (90 CI)	-0.78 (-3.04, 1.58)	0.11 (-0.66, 0.89)	-0.77 (-3.09, 1.61)	0.15 (-0.67, 0.98)	-0.66 (-2.94, 1.68)
ICC (90 CI)	0.76 (0.48, 0.90)	0.91 (0.80, 0.96)	0.76 (0.49, 0.89)	0.92 (0.81, 0.97)	0.83 (0.61, 0.93)
TE as CV % (90 CI)	3.73 (2.85, 5.48)	1.2 (0.90, 1.80)	3.74 (2.87, 5.51)	1.29 (0.99, 1.89)	3.68 (2.82, 5.42)
TE (90 CI)	0.61 (0.47, 0.90)	0.34 (0.26, 0.49)	0.61 (0.47, 0.89)	0.33 (0.25, 0.48)	0.52 (0.40, 0.76)

SD standard deviation, ICC Intraclass correlation coefficient, TE typical error, Δ difference, CI confidence interval, CV coefficient of variation

4.5.1 Limitations

While the results of this study are promising, some limitations can be improved in future research. First, it is not yet known how much data is necessary to construct reliable profiles. Clavel et al. (2023) have shown effective week-to-week reliability of $AS_{in\text{-}situ}$ profiling using the CI technique; however only training sessions were used limiting ecological validity. The present study employed a conservative method, using 15-19 events including both training and matches, however, it is likely and more practical to necessitate a smaller number of events utilizing a moving window of monitoring and accounting for session intensity. For example, it was shown that the reliability of week-to-week $AS_{in\text{-}situ}$ profiling was improved when a dedicated maximal sprint effort was included weekly (Clavel et al., 2023). Secondly, there are some important characteristics of the data output from the players during AS monitoring that need to be considered such as the greater frequency of acceleration data and fewer data points nearing maximal velocity in soccer (Trewin, Meylan, Varley, & Cronin, 2018). Therefore, it may be necessary to add more weighting to these points using modified $AS_{in\text{-}situ}$ profiling models.

4.6 Conclusions

This study confirmed that GNSS data from isolated prescribed sprints can be reliably used to create AS profiles. Though, to limit the need for standardized sprinting protocols and equipment set-up, the current study demonstrated the promise of $AS_{in\text{-}situ}$ profiling with training and match data, using two different outlier removal techniques. Practitioners now can establish baseline and continuous tracking of player AS capabilities, monitor training interventions, and return to performance without formal testing. Although this study provides important information concerning normative AS data for world-class female soccer players, this monitoring tool will have applications across many team sports.

Chapter 5 – Minimal number of events necessary for acceleration-speed profiling in elite women's soccer[4]

5.1 Abstract

Purpose: Determine the minimum number of events (training or matches) for producing valid acceleration-speed (AS) profiles from GNSS data. Methods: Nine elite female soccer players participated in a 4-week training camp consisting of 19 events. AS profile metrics calculated from different combinations of athlete events were compared to force velocity (FV) profile metrics from 2 × 40-m stand-alone sprint effort trials, using the same GNSS 10 Hz technology. FV profiles were calculated, from which AS profiles were obtained. AS profiles from training and matches were generated by plotting acceleration and speed points and performing a regression through the maximal points to obtain the AS metrics (theoretical maximal speed, x-intercept (S_0 m·s^{-1}), theoretical maximal acceleration, y-intercept (A_0 m·s^{-2}), and slope s^{-1}). A linear mixed model was performed with the AS metrics as the outcome variables, and the number of events as a fixed effect, and the participant identifier as a mixed effect. Dunnett's post hoc multiple comparisons were used to compare the means of each number of event grouping (1-19 events) to those estimated from the dedicated sprint test. Results: S_0 and A_0 means were no longer significantly different from the isolated sprint reference with 9-19 (small to trivial differences =-0.31 to -0.04 m·s^{-1}, p=.12 to .99) and 6-19 (small differences =-0.4 to -0.28 m·s^{-2}, p=.06 to .79) events, respectively, and the slopes were no longer different with 1-19 events (trivial differences=0.06 to 0.03 s^{-1}, p=.35 to .99). Conclusions: AS profiles can be

[4]Cormier, P., Tsai, M. C., Meylan, C., Soares, V. H., Clarke, D. C., & Klimstra, M. (2023). Minimal Number of Events Required for Acceleration–Speed Profiling in Elite Women's Soccer. International Journal of Sports Physiology and Performance, 18(12), 1457-1460.

estimated from a minimum of nine days of tracking data. Future research should investigate methodology resulting in AS profiles estimated from fewer events.

5.2 Introduction

Acceleration-speed (AS) profiling is an emerging approach to player monitoring using global navigation satellite system (GNSS) technology, in which the highest acceleration values observed across a range of speeds are used to assess player maximal effort (Morin et al., 2021). Presently, a popular method of player assessment is force-velocity (FV) profiling, achieved by modeling isolated sprints (Samozino et al., 2016). These techniques estimate horizontal force, velocity, acceleration, and power production by fitting velocity- or time-displacement data (Morin et al., 2019; Samozino et al., 2016). However, this approach requires standardized protocols and separate testing sessions.

Wearable technologies like GNSS enable ambient athlete monitoring, known as invisible or in-situ monitoring (Morin et al., 2021). AS profiles derived from GNSS data provide insights similar to FV profiles obtained through isolated sprint testing as supported by recent findings (Cormier, Tsai, Meylan, & Klimstra, 2023), suggesting agreement between single sprint FV and AS profiles with four weeks of training/competition data. Several gaps in knowledge still exist with regard to AS profiling in soccer players. As such, uncertainty persists regarding the minimum number and content of events needed for accurate AS profiles. Clavel et al. (2023) demonstrated the development of AS profiles from weekly soccer training sessions and found that session content influenced AS metrics, particularly S_0. They recommended the purposeful inclusion of maximal standardized linear sprint efforts within the weekly training sessions for optimal reliability. However, prescribing and testing isolated sprinting protocols (ie, all-out 40-50m linear sprint accelerations) may lack ecological validity during short international match/training windows where time outside of technical and tactical preparation is limited. These short camp windows also have other logistical challenges such as players arriving in different physical states (eg, fitness or injury) and traveling through multiple time zones (eg, jet lag and poor sleep) impacting readiness and ability to perform testing protocols on the first days of the camp.

The minimum number of events needed for AS profiling remains unknown. Additionally, few AS profiling studies have been assessed in world-class female soccer cohorts (Cormier, Tsai, Meylan, & Klimstra, 2023). Previous studies have applied AS profiling throughout long seasons (Imbach et al., 2022; López-Sagarra et al., 2022) and evaluated positional differences (Alonso-Callejo et al., 2022) with elite male soccer cohorts, however, inconsistent AS data processing methodologies were applied without prior validation. As such, further investigations are necessary to establish the validity and reliability of AS profiling across different athlete cohorts, ensuring robust and reproducible analysis.

The purpose of this study was to determine the minimal number of sessions needed to generate valid AS profiles. Specifically, we compared AS profiles generated from different numbers of events from a training camp with AS profiles generated through dedicated sprint testing. The findings from this approach may allow for the application of AS profiling when it is not possible to perform standardized sprint FV protocols and will have the ability to inform training design (Hicks et al., 2022), rehabilitation programs (Mendiguchia et al., 2016b), and facilitate longitudinal physical monitoring (López-Sagarra et al., 2022) of players throughout their careers.

5.3 Methodology

5.3.1 Subjects

Nine female soccer players selected for the Senior Canadian Women's National Team (age = 26.2 ± 5.2 years, height = 1.68 ± 0.1 m, body mass = 63.1 ± 4.8 kg) ranked 6th in the world participated in a 4-week camp (14 training events and 5 match events). The players included were categorized as center backs (n = 2), fullbacks (n = 3), midfielders (n = 2), and forwards (n = 2). Ethical approval was obtained from the University of Victoria and Simon Fraser University Research Ethics Boards and complied with the recommendations of the Declaration of Helsinki.

5.3.2 Design

Throughout the 4-week camp, data were collected with Catapult GNSS units (10 Hz, Vector S7, firmware 8.1.0, Catapult Innovations, Melbourne, Australia) worn by the players between the scapulae. To derive the players' FV profiles, on day 11 of the camp, 2 × 40-m linear maximal sprints were performed (Clavel et al., 2022). The players were positioned in two lines and were instructed to perform an “all-out” effort throughout the 40-m distance from a stationary start. The data from this FV event were analyzed separately from the continuously monitored AS data.

5.3.3 Data processing

The velocity data from the Catapult GNSS software were exported and filtered using a 1-Hz dual-pass second-order Butterworth filter (Clavel et al., 2023). The derivatives of the filtered velocity with respect to time were used to calculate acceleration (Wu & Swartz, 2022). The GNSS signal quality is reflected with the horizontal dilution of precision (HDOP) of 0.85 ± 0.14 and 13.8 ± 3.5 satellites acquired. The isolated sprints were performed on an outdoor grass field in clear weather conditions (765 Torr, wind = 0 m.s^{-1}, no clouds, temperature = 30°C, HDOP = 0.61 ± 0.04, number of satellites = 18.02 ± 1.30).

5.3.4 Isolated sprint data FV profiling

Data from the isolated sprint trials were modeled using the FV mono-exponential function (Morin et al., 2019). The parameters of maximal sprint speed (MSS m·s^{-1}) and the acceleration time constant (τ) were estimated from the velocity data using nonlinear least-squares regression. From these parameters, theoretical maximal speed/velocity (S_0 m·s^{-1}), theoretical maximal acceleration (A_0 m·s^{-2}), and the slope s^{-1} of the AS relationship were calculated. The average of the two trials was used (Simperingham et al., 2019). Trials were retained if the players' MSS was ≥ 95% of previously recorded best MSS observed through GNSS monitoring throughout the players Senior career (Clavel et al., 2023).

5.3.5 Training and competition data AS optimization approach

An optimization approach was employed by generating AS profiles from all possible combinations of 1 to 19 events for each player (corresponds to 524,287 combinations per player and ~ 4.7 million total combinations). Player acceleration and speed data sets were aggregated from the selected events to form a cloud of points. Maximum positive acceleration points within a speed range of 3 m·s^{-1} to the player's peak speed were retained for each player. After removing outliers using the Tukey boxplot method (Cormier, Tsai, Meylan, & Klimstra, 2023), a linear regression was performed on the maximum remaining points, from which AS metrics were calculated (theoretical maximal speed, x-intercept (S_0 m·s^{-1}), theoretical maximal acceleration, y-intercept (A_0 m·s^{-2}), and the slope s^{-1} of the AS relationship) (Morin et al., 2021).

5.3.6 Statistical analysis

Statistical procedures were performed using R software (Version 4.2.2; R Core Team, 2022). Linear mixed models were specified for each outcome variable (A_0, S_0, and slope) with the number of event groupings as the fixed effect and subject as the mixed effect, and the isolated sprint reference set to the intercept. Dunnett's posthoc multiple comparisons procedure was used to compare the metric means from each group to the dedicated FV sprint (significance set at $p < .05$). Effect sizes with Hedge's *g* correction were also calculated for each comparison and the differences were interpreted as: <0.2 trivial, 0.2-0.6 small, 0.6-1.2 moderate, 1.2-2.0 large, 2.0-4.0 very large, and >4.0 and extremely large (Hopkins et al., 2009).

5.4 Results

The mean (SD) isolated sprint reference values for S_0, A_0, and slope were: 8.31 $m \cdot s^{-1}$ (0.24), 6.07 $m \cdot s^{-2}$ (0.50), and -0.73 s^{-1} (0.05), respectively. The between-trial coefficient of variations ranged from 1.2 to 3.73% and the intraclass correlation coefficients ranged from 0.76 to 0.91. The statistical tests (Figure 5-1) revealed that AS-profile means were not statistically different from the dedicated sprint reference when S_0 was computed from 9-19 events (differences = -0.31 to -0.04, SE = 0.12 to 0.17, p = 0.12 to .99, effect size (*g*) = small to trivial, respectively), and A_0 from 6 to 19 events (differences = -0.4 to -0.28, SE = 0.14 to 0.2, p = 0.06 to .79, *g* = small, respectively), and the slopes for 1-19 events (differences = 0.06 to 0.03, SE = 0.04, p = 0.35 to .99, *g* = trivial, respectively). The fixed effect estimates and detailed posthoc test results are reported in the supplementary materials (available online).

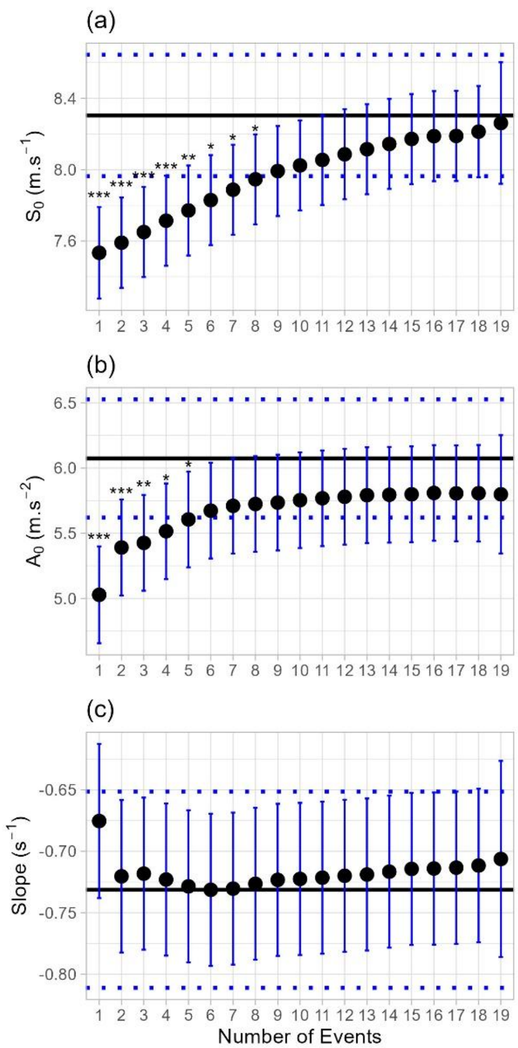


*Figure 5-1. AS metrics (a)-(c) as a function of the number of sessions compared to the isolated sprint FV. The values were obtained from the mixed-model effect estimates: the data points are the means of the invisible monitoring combination data; the black solid lines are the mean values from the isolated sprint testing; dotted lines and error bars represent the ± 95% confidence intervals for their corresponding means. Statistically significant differences from the reference: *** <.0001, **<.01,* <.05.*

5.5 Discussion

This study demonstrated that data from a minimum of nine training/competition events are required to establish valid AS profiles at the group level in elite female soccer players. Accuracy improved with more events from small to trivial differences, requiring a minimum of nine for S_0 and six for A_0. The slope required fewer events for consistent estimates. A reduced number of events resulted in underestimated AS profile metrics compared to FV profiles.

Morin et al. (2021) introduced the "in-situ" AS profile, utilizing a minimum of five training sessions in male professional soccer with 18 Hz GNSS units, and suggested the possibility of only needed one event. Our study supports the notion that an AS profile could be derived from one event data; however, this approach may introduce high variance depending on the selected event data. It has been suggested (Clavel et al., 2023) that the inclusion of isolated sprint efforts in the analysis; however, ecological validity may be limited if standardized 40-50 m sprints are used in international soccer contexts. Conversely, caution should be taken when comparing findings from different studies as there are some technical differences between them (data processing, sampling rates, GNSS units, etc.) (Malone et al., 2017).

Including more events resulted in improved estimates (Figure 5-1), reflecting the movement demands. Players typically do not reach maximum acceleration and velocities in every session or match, requiring more events to observe multiple instances of maximal sprinting to estimate S_0. Conversely, A_0 can be determined with fewer sessions due to frequent short accelerations. This observation aligns with previous findings that S_0 reliability depends on session content while A_0 is less affected (Clavel et al., 2023). Soccer training events vary in characteristics, including short accelerations (e.g., small-sided games) and longer accelerations leading to peak-velocity running (e.g., moderate- and large-sided games), with intensity and duration variations. This observation may highlight the value of developing training criteria to support an optimal range of velocities and maximum accelerations to develop reliable AS profiles with fewer sessions. Additionally, match exposure to maximum efforts is influenced by factors like opposition difficulty, seasonal variations, and positional differences (Alonso-Callejo et al., 2022; López-Sagarra et al., 2022). Therefore, it may be challenging to develop AS profiles from single match data alone.

The slopes of the AS relationship did not differ significantly from the FV reference across all event groupings, while S_0 and A_0 did exhibit differences. Minor changes in the slope can lead to substantial variations in S_0 and A_0, explaining the observed differences. Therefore, considering the entire profile components is advisable rather than focusing solely on the slope.

There are limitations that can be improved in future research. Firstly, it was not possible to control the conditions throughout the camp and changes in venues (eg, weather and matches in stadiums), however acceptable GNSS signal quality was reported in this study (Malone et al., 2017). Secondly, players' positions were not accounted for in our model, therefore it is possible that the minimum number of events necessary will vary across positions (López-Sagarra et al., 2022). Thirdly, a separate analysis was not carried out on the minimal number of games or training sessions separately. Finally, only nine players could be included in the analysis since it was a requisite for each player to have had the opportunity to participate in each event for an appropriate mixed model. Further research is necessary to ensure the practical application of this promising athlete monitoring tool which may be useful across many team sports (eg, rugby codes).

5.6 Practical applications

- The possibility of generating valid AS profiles through invisible monitoring with GNSS technology was demonstrated in the present study which can inform future research and practice.

- Nine sessions achieved a comparable AS profile to FV. However, the required events can vary based on content.

- Practitioners should consider all metrics for informed decisions on training and competition.

5.7 Conclusions

The present study demonstrated that AS profiles with elite women's soccer players could be generated with a minimum of nine training sessions/game events. Future research should quantify session acceleration and speed, optimize data processing, and explore training interventions. These findings suggest monitoring athletes' physical state during training camps or international windows can be done without standardized testing.

Chapter 6 – Normalizing acceleration and power in elite soccer using acceleration-speed profiles: A case study of game segment, position, and goal differential[5]

6.1 Abstract

Purpose: Acceleration-speed (AS) profiling provides a novel and effective way to quantify team sport players' maximum running ability without requiring dedicated sprint tests. This study explored how normalizing player effort with AS profiles could enable an estimation of effort compared to non-normalized values during goal differential conditions throughout matches and across positions. Methods: AS profiles were developed from GNSS sensor data from 3 years of match play from a women's national soccer team. Acceleration and power data were then grouped into low, moderate, high and very high-speed domains using either non-normalized maximum values or using normalized values based on individualized AS profiles (i.e., ratio between the observed acceleration and the maximum interpolated AS profile value). Normalized and non-normalized acceleration and power data were compared across speed domains, positions and goal differential between first to second match halves. Separate linear mixed model analyses were carried out for normalized and non-normalized data. Results: The analysis revealed that while there were common trends between normalized and non-normalized acceleration efforts, normalization may impact the alignment of data which could result in unique differences. When examining changes in acceleration effort based on goal differential, both normalized and non-normalized values showed a general increase in effort when either in a draw or winning in the first half. In addition, they displayed a trend of sustained effort when losing in the first half or losing/drawn throughout the match. The differences were mostly

[5]Submitted and Under Review in the International Journal of Physiology and Performance (IJSPP) in January of 2025.

displayed at high to very high running speed domains for normalized and moderate to low-speed zones for non-normalized metrics. For normalized power, there were similar patterns to normalized acceleration, however changes in effort in low-speed zones may be related to the resolution of observation of AS metrics in addition to the calculation of power as a comprehensive secondary metric. Conclusions: Overall, these findings highlight the value of using individual AS profiles to normalize effort to facilitate investigation of relative players and position specific differences. Further this study demonstrated important tactical and positional behaviors displayed when in draw, losing, or winning states from first to second half.

6.2 Introduction

Acceleration-speed (AS) profiling is an approach that uses an athletes aggregated velocity data from multiple distinct running efforts collected during training and/or competition, to determine their maximum acceleration ability across different speeds (Morin et al., 2021). This approach results in outputs similar to those of standalone sprint-based horizontal force-velocity (FV) profiles, yet it does not require dedicated testing, as the data can be collected through the use of athlete-worn sensors (Cormier, Tsai, Meylan, & Klimstra, 2023; Cormier, Tsai, Meylan, Soares, et al., 2023). Due to the unobtrusive nature of this measurement, use of this approach has grown considerably with respect to performance tracking in team sports such as rugby and soccer (Maviel et al., 2024; Miguens et al., 2024). As this technique is gaining interest as an athlete performance analysis tool, there are now many investigations attempting to refine its methodology and extend its use within different contexts (Alonso-Callejo et al., 2022, 2024; Cardoso et al., 2023; Clavel et al., 2023; Cormier, Tsai, Meylan, & Klimstra, 2023; Cormier, Tsai, Meylan, Soares, et al., 2023, 2023; López-Sagarra et al., 2022; Maviel et al., 2024; Miguens et al., 2024; Morin et al., 2021).

A unique application of the AS profile, that has yet to be explicitly examined, is the potential to use its output for the normalization of athlete acceleration speed data. In this context, normalization refers to the representation of data as a percentage of some maximum value and is common in many research and sport settings. For example, normalizing training load to individual-specific training zones can reveal greater context for understanding an athlete's training state and is also critical for prescribing training intensity and duration (K. S. Seiler & Kjerland, 2006; S. Seiler, 2010). Normalization of athlete-worn global navigation satellite system (GNSS) sensor data to the corresponding maximal acceleration within the same speed zones would enable relative performances of different players to be directly compared (Phatak et al., 2022). Sonderegger et al. (2016) demonstrated that initial running speeds must be accounted for the quantification of acceleration alongside the promise of using maximal accelerations in relation to initial running speeds. They further introduced the classification of high-intensity accelerations as a percentage of maximal accelerations across speed zones. However, theoretical AS profiles were not used but represent a similar concept and methodology.

In soccer, it is critical to understand how physical and tactical factors of the game modulate an individual’s or position-specific effort (Abbott et al., 2018; T. A. Haugen et al., 2020). For example, in elite male soccer, AS profiles differ across positions during training and games (Alonso-Callejo et al., 2022). Specifically, players in wide positions such as fullbacks and wide midfielders exhibit the highest theoretical speeds, and central defenders exhibit the highest theoretical acceleration values. In elite women’s soccer, Trewin et al. (2018) has shown that whole-game goal differential (GD) is associated with running demands, as a draw was associated with increased high-speed running and acceleration counts, whereas a loss or a win were associated with decreased total distance. Redwood-Brown et al. (2018) demonstrated that in the English Premier League, , more high-speed running is done by midfielders and defenders when losing and more by attackers when winning when the GD is high in the second half against more challenging opposition. Each of the results were expressed in absolute non-normalized terms. While insightful, it would be valuable to also consider the impact of these changes relative to each athletes' individual AS profiles (Morgans et al., 2024; Redwood-Brown et al., 2018).

As opposed to submaximal efforts, near maximal efforts will have a greater physiological consequence and may also represent a potentially important area of focus related to the relationship between the demands of the game and athlete capacity. Therefore, athlete specific normalization of acceleration may have a substantial impact on the interpretation of data and action outcomes related to current and future performance. While previous research provides an invaluable insight into the impact of GD on running demands on whole team, as well as positions specific cohort absolute values, without the appropriate context of each athlete's maximal capacity those findings alone make it difficult to identify the changes in relative effort. This critical context could assist coach led planning and real-time decision making on match strategy, substitutions, player lineups, team selection as well as important considerations for athlete specific and positional strength and conditioning programming.

Therefore, in this study we investigated AS normalization of athlete acceleration speed data across several match contextual factors known to impact running demands in soccer. Differences between non-normalized and normalized AS data analysis were compared between player position, goal differential (GD) and game segment (i.e., first and second half). Each individual athletes' maximal AS profile, across predefined individualized speed domains (ie, low-speed, moderate-speed, high-speed, and very-high speed) (Park et al., 2019) were used to normalize accelerations from matches and compared in relative speed zones. While statistical models already account for within and between individual and group differences, normalization by AS profiles may assist in determining changes in effort that highlight important performance trends not observed in non-normalized data. Therefore, we hypothesized that normalized acceleration values will reveal greater effort from midfielders and defenders when GD is negative or neutral (eg, draw or losing) from the first to second half, and greater effort from attackers when the GD is positive (eg, winning) (Redwood-Brown et al., 2018). We further hypothesized that the greatest differences in acceleration effort will be observed in higher speed domains (eg, high-speed or very-high-speed) which would be the most strenuous efforts contributing to player load (Trewin, Meylan, Varley, Cronin, et al., 2018). Overall, the use of AS profile metrics to normalize athlete acceleration speed data may present a unique application of AS profiles as well as an important approach to the evaluation of relative effort.

6.3 Methods

6.3.1 Design

We employed an observational research design in which training and match data from a women's national soccer team were retrospectively analyzed. Specifically, 3 years of GNSS data collected from elite women's soccer players in every training and game played within international team camps were used for analysis. The data were collected through Catapult GNSS sampling at 10 Hz (Vector S7, Catapult Innovations, Melbourne, Australia) worn in tightly fitted vests between the scapulae. AS profiles were generated for each player for each training camp by fitting a regression line to their acceleration-speed relationship. Power was computed as the product of the AS components and the athlete mass. The maximum accelerations and power values from each match were normalized to the players individual AS regression lines to obtain normalized AS profile metrics within predefined speed domains.

6.3.2 Subjects

Thirty-six female soccer players from the Senior Canadian Women's National Team (age = 27.73 ± 3.15, height= 1.69 ± 0.05 m, body mass = 68.60 ± 3.87 kg) participated in the study. Ethical approval was obtained from the University of Victoria's Human Research Ethics Board.

6.3.3 Data analysis

All statistical analyses and data processing procedures were carried out using R Statistical Package (v4.2.3, "Shortstop Beagle", Vienna, Austria). Data were extracted via the Catapult API system (CatapultR package, version 0.0.0.52). The threshold for the horizontal dilution of precision (hdop) was <1 and the number of satellites acquired > 10 for a training session or game to be retained for analysis (Varley et al., 2017). For all analyses, the velocity data were filtered (2nd order, dual-pass, 1 Hz cut-off Butterworth) and acceleration was calculated as the first time- derivative of velocity, as done previously (Cormier, Tsai, Meylan, & Klimstra, 2023; Cormier, Tsai, Meylan, Soares, et al., 2023).

6.3.3.1 Camp AS profiles

Since it was established that valid AS profiles can be obtained from individual training camps (Cormier, Tsai, Meylan, Soares, et al., 2023), the following procedure was performed (Clavel et al., 2023; Cormier, Tsai, Meylan, Soares, et al., 2023). Within each unique international team camp during the period of 3-years (2020 - 2023), the top 1% of each player's acceleration and speed data points within 0.1 $m \cdot s^{-1}$ speed intervals were aggregated from training and game events to form a cloud of points for each player. Maximum positive acceleration points for speeds above 3 $m \cdot s^{-1}$ were retained for each player (Morin et al., 2021). After removing outliers using the Tukey boxplot method

(Cormier, Tsai, Meylan, & Klimstra, 2023), a linear regression was performed on the remaining data points of highest magnitude. This represented the AS profile for each player where theoretical maximal speed is the x-intercept (S_0 m·s^{-1}) and theoretical maximal acceleration is the y-intercept (A_0 m·s^{-2}) (Morin et al., 2021), and the slope of the AS relationship regression was also calculated (Table 6-1). From the values of the AS line of best fit, power (W) was calculated by multiplying the acceleration by player mass (force), then multiplying by the corresponding velocity (Table 6-1). The peak power value represented the theoretical maximal power (P_0 W). Note that these power values do not fully represent power because the aerodynamic forces are not considered, in contrast to the FV profiling method in which these forces are modelled (Cormier, Tsai, Meylan, & Klimstra, 2023; Morin et al., 2019; Samozino et al., 2016). The player mass was measured every morning as part daily wellness testing. The AS profile represents each player's theoretical maximum capacity during each camp. Typically, in the days leading up to matches, "speed exposure" sessions with a target of maximum speed > 90% were often carried out within this cohort which contributes to the reliability of the AS profiles (Clavel et al., 2022, 2023; Cormier et al., 2024). Normative data for each position can be found in Table 6-1.

Table 6-1. AS profile metric by position for this player cohort generated from camp-to-camp.

Position	**A_0 (m·s^{-2})**	**Slope (s^{-1})**	**S_0 (m·s^{-1})**	**P_0 (W·kg^{-1})**	**P_0 (W)**
CB	7.71 ± 0.91	-0.93 ± 0.13	8.30 ± 0.45	14.35 ± 2.51	971.8 ± 184.9
FB	8.17 ± 1.29	-0.97 ± 0.18	8.49 ± 0.54	15.68 ± 3.1	936.0 ± 177.3
FWD	7.84 ± 0.79	-0.92 ± 0.12	8.56 ± 0.54	15.54 ± 2.26	991.9 ± 142.9
MF	7.83 ± 1.26	-0.96 ± 0.17	8.21 ± 0.52	14.68 ± 3.17	899.0 ± 184.9

CB = Center Backs, FB = Full Backs, FWD = Forwards, MF = Midfielders.

6.3.3.2 Speed intervals

The speed interval thresholds cut-offs were individualized to each unique athlete in our cohort whereby speed intervals were defined by each player's speed distribution > 3 $m \cdot s^{-1}$. As such, individual velocity quartiles (Q1 = 25th percentile, Q2 = 50th percentile, Q3 = 75th percentile, and Q4 = 95th percentile) were calculated for each player to account for individual variability. The four levels of speed were categorized as <Q2 as low-speed (LSR), Q2-3 as moderate-speed (MSR), Q3-4 as high-speed running (HSR), and >Q4 as very high-speed running (VHSR) (Table 6-2) (Vigne et al., 2013). These relative individual speed thresholds were applied to categorize speeds for both normalized and non-normalized profiles.

Table 6-2. The percentile means and standard deviations for 25, 50, 75, and 95% (Q1-4) used as speed cut-offs in this study.

Quartile	**Percentile**	**Mean $m \cdot s^{-1}$ (SD)**
Q1	25	3.33 (0.03)
Q2	50	3.78 (0.09)
Q3	75	4.46 (0.16)
Q4	95	5.77 (0.31)

6.3.4 Normalization of acceleration and power

With the AS profiles for each player and camp in hand (Section 6.3.3.1), we then analyzed the players' game data. A total of 58 games over the 3-year period (22 camps total) were included in the analysis. Games were matched to the closest respective AS profile generated from the camp. Within each game, positive acceleration points were aggregated and grouped into speed intervals (same as Section 6.3.3.2). Power values were also calculated from product of player mass and acceleration with speed. Then, the unique maximal acceleration (Amax) and power (Pmax) point within each speed interval was identified and retained. The camp-to-camp derived AS profiles regression values were then used to normalize acceleration (NA = Amax ÷ $Amax_{regression}$ × 100) and power (NP = Pmax ÷ $Pmax_{regression}$ × 100), respectively for each speed interval threshold, whereby a percentage to the maximal theoretical regression line was calculated for each speed interval, where a higher value represents an expression closer to their AS or power capacity.

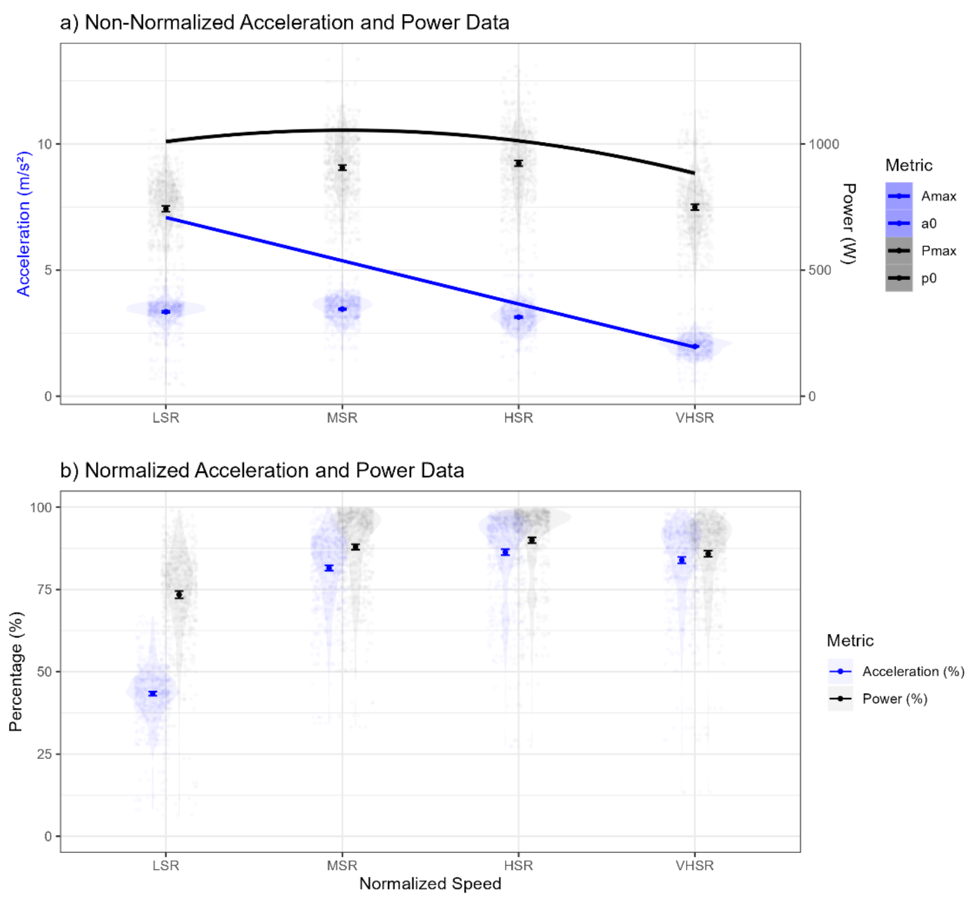


Figure 6-1. All data from our dataset plotted: a) non-normalized player efforts expressed as maximum acceleration (Amax) and power (Pmax) from games across individual speed zones with regression lines representing the maximal AS profile [theoretical maximal acceleration (A_0) and power (P_0)]; and b) Normalized to maximal AS profiles generated from camp-to-camp aggregated data. Data presented as Mean and 95% confidence intervals with raw points

wrapped in violin to show distribution. LSR = low-speed running; MSR = moderate-speed running; HSR = high-speed running; VHSR = very-high speed running.

6.3.5 Position and tactical data

The players' tactical position data were continuously collected and stored in a database throughout the years by a dedicated data scientist. The positions were categorized in a standard way into forwards, midfielders, center backs, and fullbacks (ie, FWD, MF, CB, and FB) based on the categories established by the Canadian Soccer Federation. The halves were determined as first (45min + extra time), second (45-90min + extra time), and third (overtime and shoot-outs). The goal data were extracted from an online video analysis database (Wyscout, Hudl, 2024) and the GD calculated as Canada Score – Opponent Score within each half. The GD was coded as Losing if GD $\leq$ -1, Draw if GD = 0, and Winning is GD $\geq$ 1. Goalkeepers were omitted from the analysis due to little GNSS data availability and the overtime was removed as well since there were very few cases occurred.

6.4 Statistical analysis

Linear mixed models were generated for both normalized and non-normalized acceleration and power values as outcome variables and the positions, halves, GD, and speed interval as fixed effects, and the subjects as random effects. Pairwise post hoc comparisons of factor levels were conducted, and p-values were adjusted using the Tukey method. Significance was set to an alpha of 0.05.

6.5. Results

Main interaction effects and the post-hoc results are presented herein. The estimated marginal means and standard error intervals are shown in Figures 6-2 to 6-3 and results are summarized in Table 6-3. Tables with normalized and non-normalized normative data can be found in the Appendix section.

6.5.1 Acceleration

Significant interactions between half, position, and GD within speed intervals were observed for both normalized ($F=3.12$, $p=0.004$) and non-normalized data ($F=4.63$, $p=0.0001$).

Normalized - Between Halves, Within Position

In the Draw - Winning condition, MFs in MSR ($p = .018$), CBs in HSR ($p = .011$), FWDs in HSR ($p < .001$), and FWDs in VHSR ($p = .007$) demonstrated significant increases. In the Winning - Winning condition, MFs in MSR ($p = .003$), CBs in VHSR ($p = .008$), FWDs in HSR ($p < .001$), and FWDs in VHSR ($p = .020$) all showed significant increases. MFs in HSR ($p = .019$) also showed a significant increase. Lastly, under the Draw - Losing condition, FWDs in HSR experienced a significant increase ($p = .003$).

Non-Normalized - Between Halves, Within Position

In the Winning - Winning condition, CBs in LSR ($p = .002$), FWDs in LSR ($p = .002$), and MFs in MSR ($p < .001$) demonstrated significant increases. FWDs in HSR ($p < .001$) also showed a significant increase. In the Draw - Winning condition, FBs in LSR ($p = .043$), CBs in MSR ($p = .032$), CBs in HSR ($p = .009$), and FWDs in HSR ($p = .011$) exhibited significant increases. Lastly, under the Draw - Draw condition, FWDs in VHSR experienced a significant increase ($p = .042$).

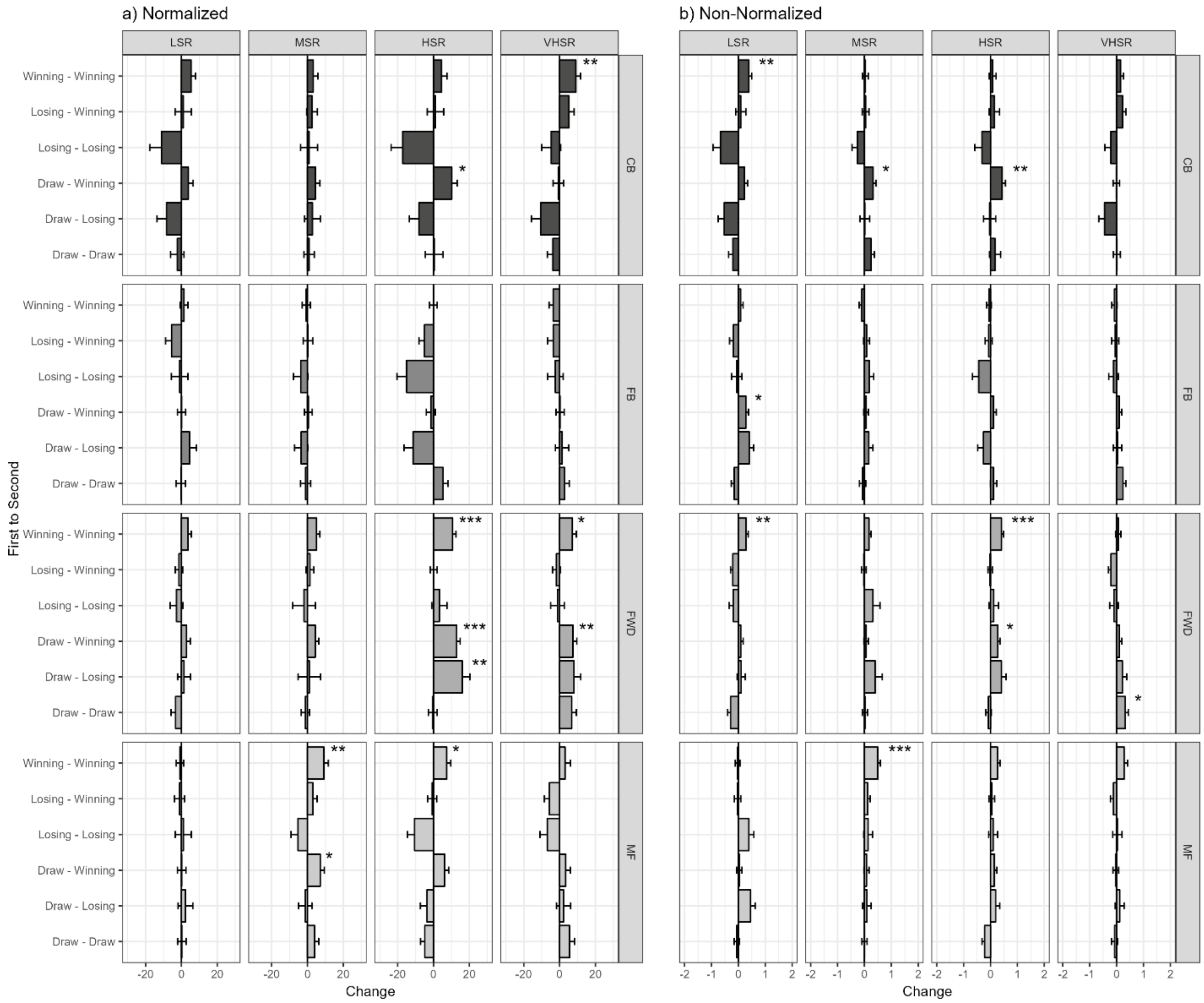


*Figure 6-2. a) Normalized acceleration contrasts by position across GD, speed intervals, and halves, and b) Max non-normalized acceleration contrasts by half, across GD, speed intervals, within position. *<.05, **<.001, and ***<0.001. Data presented as mean differences with standard error bars.*

6.5.2 Power

Significant interactions between half, position, and GD within speed intervals were observed for both normalized (F=3.61, p=0.001) and non-normalized data (F=4.63, p=0.0001).

Normalized - Between Halves, Within Position

In the Draw - Winning condition, CBs in LSR ($p = .016$), MFs in MSR ($p = .028$), and FWDs in HSR ($p < .001$) demonstrated significant increases. In the Winning - Winning condition, CBs in LSR ($p = .003$), MFs in MSR ($p < .001$), and FWDs in HSR ($p < .001$) also showed significant increases. Under the Losing - Winning conditions, FBs in LSR experienced a significant decline ($p = .006$). Lastly, in the Draw - Losing condition, FWDs in HSR exhibited a significant increase ($p = .006$).

Non-Normalized - Between Halves, Within Position

In the Draw - Winning condition, MFs in MSR ($p = .031$) and FWDs in HSR ($p = .005$) demonstrated significant declines. In the Losing - Losing condition, MFs in HSR showed a significant increase ($p = .027$). Under the Draw - Draw condition, FWDs in VHSR exhibited a significant increase ($p = .028$), while MFs in VHSR experienced a significant decline ($p = .004$).

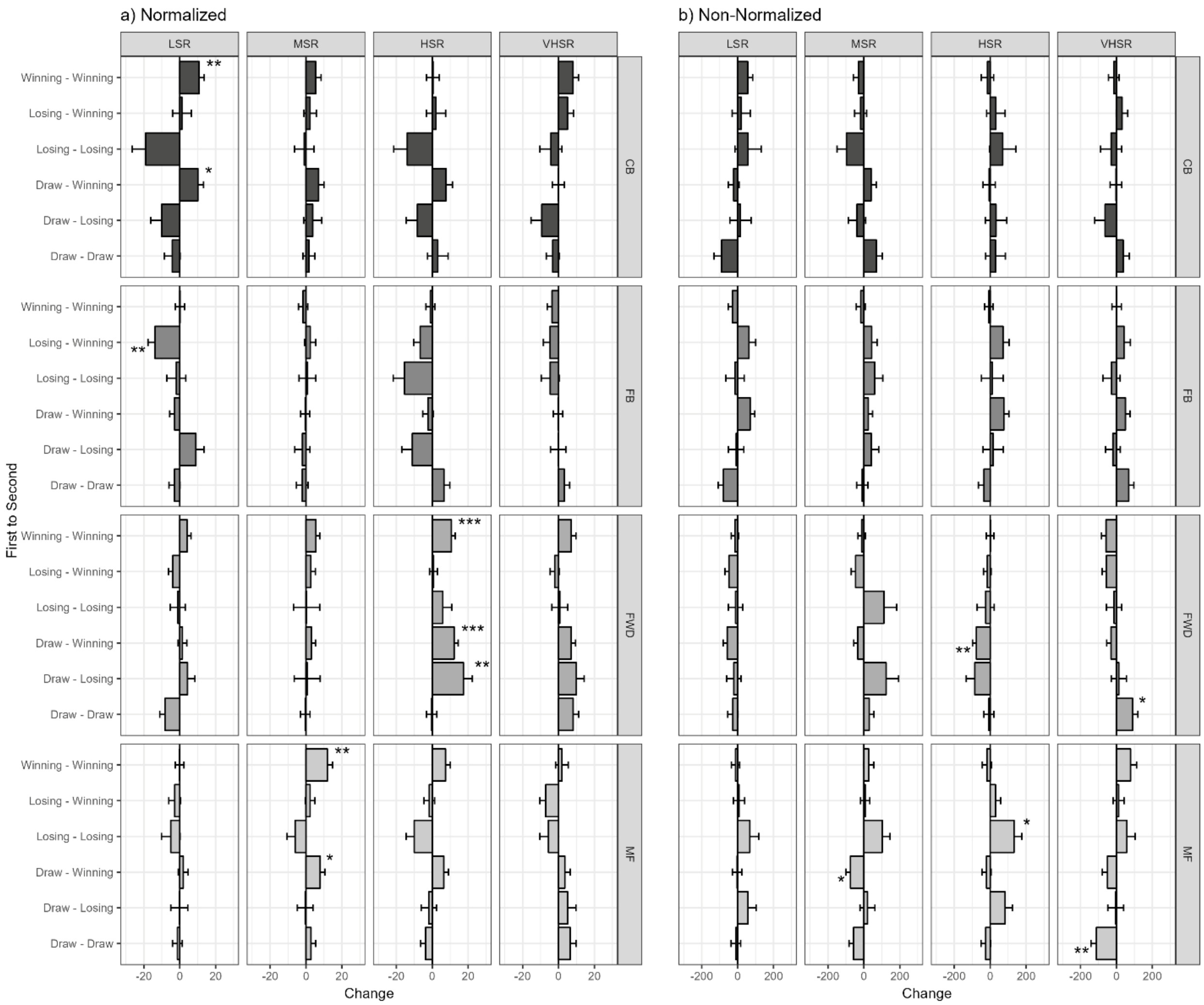
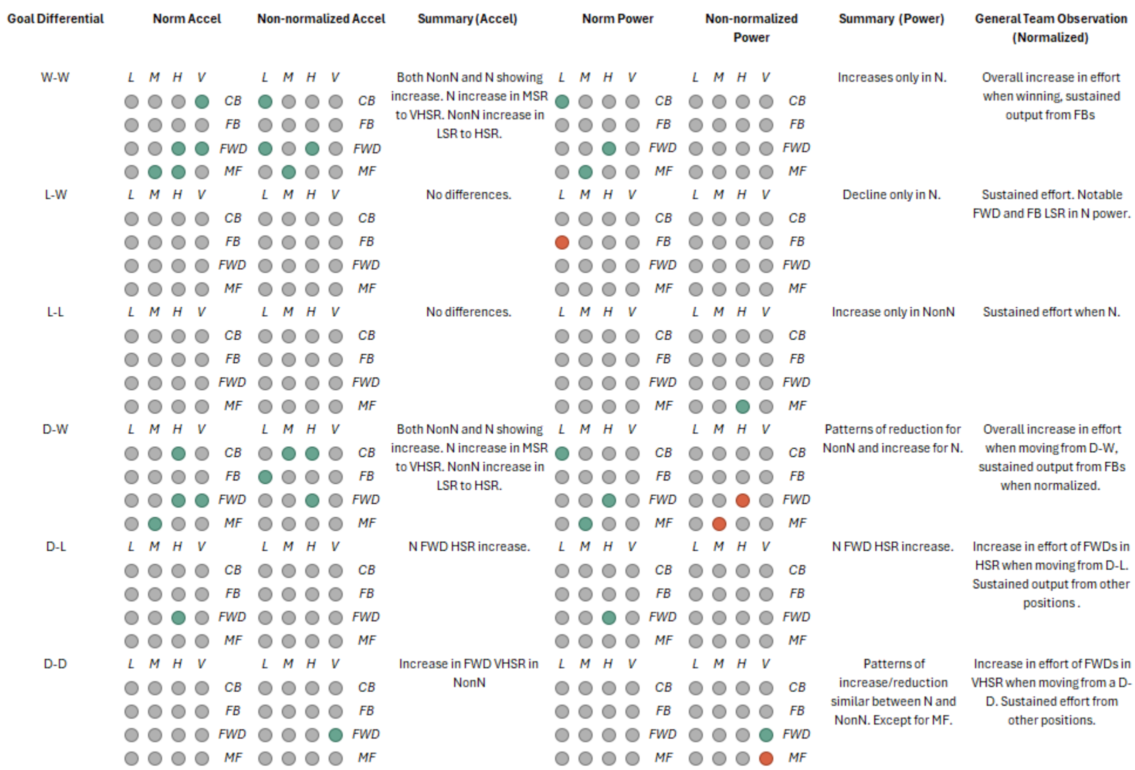


*Figure 6-3. a) Normalized power contrasts by position across GD, speed intervals, and halves, and b) Max non-normalized power contrasts by half, across GD, speed intervals, within position. *<.05, **<.001, and ***<0.001. Data presented as mean differences with standard error bars.*

*Table 6-3. Interpretation table of the results and summary of differences from non-normalized to normalized data. **



*Only significantly different results reported. W = Winning GD, L = Losing GD, D = Draw GD. L = LSR, M = MSR, H = HSR, V = VHSR. N = Normalized. NonN = non-normalized. Red is a decrease from the first to second half, and green is an increase from first to second half.

6.6. Discussion

In this study, the use of theoretical AS profiles to normalize match-specific data demonstrated unique findings compared to non-normalized data with respect to GD, player position, and match half. While normalized and non-normalized data displayed common trends, normalization better represented individualized athlete effort and may improve player and position specific comparisons (Phatak et al., 2022). Further, when examining power, changes in normalized values mimicked trends observed for normalized acceleration. However, non-normalized power and acceleration values were dissimilar which may suggest that greater variability in player relative effort, not accounted for in non-normalized data (Carling et al., 2016; Oliva-Lozano et al., 2021) may also result in greater variability in calculated values. When examining changes in acceleration effort based on GD, both normalized and non-normalized values showed a general increase in effort when either in a draw or winning in the first half and a general trend in sustained effort when losing in the first half or losing/drawn throughout the match. Further, it was found that normalized data differences were mostly displayed at high to very high running speed domains for normalized and moderate to low-speed zones for non-normalized.

The first finding of this study was that AS normalization of athlete effort displayed similar yet unique and more homogeneous trends when compared to non-normalized data. When AS data is normalized, there appears to be more consistent trends across acceleration and power, which results in common interpretation across metrics and potentially negates the influence of the player and positional variance (Phatak et al., 2022). This approach resembles common normalization techniques in sport science like the use of mass normalization (eg, momentum) or using scaling factors for tactical analysis (Phatak et al., 2022). Additionally, our normalization approach reflects common practices in physical preparation and physiology where absolute values are often expressed as a percentage of a reference obtained from a maximal test or physiological capacity/ability (eg, percentage of maximum heart rate to prescribe running intensity). The inconsistencies between absolute acceleration and power metrics observed in the present study may also be because power is a secondary metric which is the product of speed, acceleration and mass. It may be that variability in both primary measures of speed and acceleration could contribute to greater variability in power. Some of the differences between non-normalized and normalized acceleration and power may also be due to the relative speed bands used. In the present analysis, the intervals may be dissimilar between players. Additionally, only four speed zones were compared to align with standard practices. As different speeds influence the ability to express acceleration, without sufficient speed resolution this may result in comparisons without proper speed context. As both speed and acceleration are included in the calculation of power, power values assist in contextualizing the effort in both the speed and power domains. For example, FWDs in the Winning – Winning condition displayed differences at low and high speed non-normalized acceleration shifted to high and very-high speed when normalized and only HSR differences were found in normalized power (Table 6-3, Figure 6-4). This also suggests that a greater number of speed domains may help to reveal a more detailed assessment of relative effort with respect to acceleration. Although this may produce too many metrics which could be deleterious in a practical setting where decisions must be made based on a concise number of metrics.

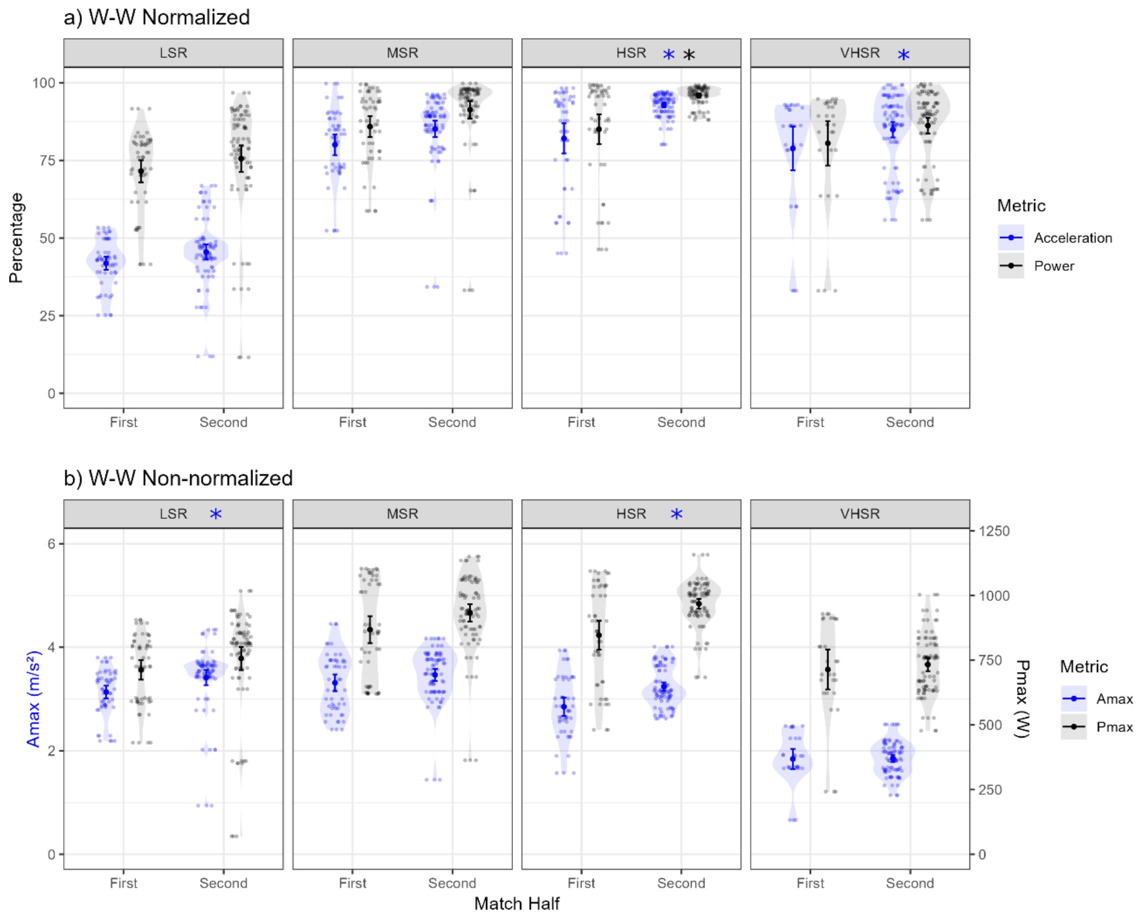


*Figure 6-4. Data from FWDs only in Winning – Winning conditions a) Normalized acceleration and power across first and second halves, and b) non-normalized acceleration and power across first and second halves. Data presented as violin plots as well as mean and 95% confidence intervals. Black * = sig. difference between halves for power metrics. Blue * = sig. differences between halves for acceleration metrics.*

In our study, it was found that both non-normalized and normalized acceleration uncovered differences in player effort between halves of soccer matches. Morgans et al. (2024) reported significant alterations in physical outputs from first to second halves depending on the GD condition. However, the authors analyzed more common GNSS running metrics (eg, meterage per min, high metabolic load distance, and so on) and found reductions in output from the first to second half in winning to draw, draw to win, losing to win, and losing/winning/drawing the whole game. This contrasts with our findings showing that most GD conditions resulted in increased or sustained effort. The present finding can be rationalized given that losing would imply tough opposition which would require greater effort. It may be that our additional position and normalization analysis could have uncovered nuanced differences in athlete effort. However, this study (Morgans et al., 2024) was conducted with subjects of different sex and level to this current cohort (male premier league vs female international). Redwood-Brown et al. (2018) found that narrow GDs resulted in elevated running outputs, and large GDs resulted in lower outputs which was further emphasized when losing. This coincides with our findings, where sustained effort was produced when losing in the first half, however contrasts our findings when in a draw conditions, as we saw sustained effort when in a draw throughout matches and an increase in effort from FWDs when going from a Draw – Losing conditions. This highlights the importance and influence of the first half difficulty and score on the behaviors and tactics exhibited in the second half. Additionally, our hypothesis that greater effort would be expressed by midfielders and defenders when GD is negative or neutral (eg, draw or losing) from the first to second half, and greater normalized effort from attackers when the GD is positive (eg, winning) is partially supported by our findings. In fact, significant increases in effort were found for attacking players like FWDs and MFs, and CBs when in Winning or Draw – Winning conditions, but not when losing in the first half. This could be due to tactical and behavioral shifts where less effort is given by the players since they or the team are already losing. Alternately the opposing team may be allowing territorial advantage resulting in reduced running as most of the game is being played in the opposition's half.

Another important finding of this study, which justified a hypothesis, was that alterations in player normalized efforts were mostly distributed at high to very high-speed domains. As low speed efforts may be more variable, due to frequency and dispersion of data, less significant differences to normalized efforts were observed. Further, at high speeds, where there is less dispersion of data around the mean in normalized values, more prominent differences were found. Interestingly, when considering the speed domains used in the present study, the individual speed percentile cut-offs for HSR (> 75%, ~ 4.46 $m \cdot s^{-1}$ or ~ 16 kph) and VHSR (> 95%, 5.77 $m \cdot s^{-1}$ or ~ 20.8 kph), resemble that of the relative thresholds used previously for HSR and sprinting (VHSR) in female cohorts (Bradley & Vescovi, 2015). The HSR zone threshold in this study is also consistent with maximal aerobic speeds exhibited in similar female cohorts (~ mean of 4.58 $m \cdot s^{-1}$) reported in prior studies with Canadian National Team players (Bradley & Vescovi, 2015; Meylan et al., 2017; Trewin, Meylan, Varley, & Cronin, 2018). Given most of the significant differences in normalized match performance and effort in this study, are at speeds above HSR, it would be reasonable to speculate that anaerobic energy contributing to explosive high velocity actions are important and contribute to a great deal of the variance in matches when opposition is challenging (Redwood-Brown et al., 2018; Trewin, Meylan, Varley, & Cronin, 2018). Since these efforts are undertaken in high-speed scenarios, it could be an important quality to train in elite women's soccer to best prepare for games.

6.7. Limitations

There are some limitations to this study. First, although the AS approach is a proxy to FV qualities in this cohort, it cannot be known for certain whether the AS profile is the true maximum of the player. However it provides a better alternative to current methodologies using only one timepoint to assess maximal capacity (Cormier, Tsai, Meylan, & Klimstra, 2023). Second, we did not analyze situational factors (eg, home or away) on the outcomes, nor could we quantify changes in tactics within and throughout the game (eg, position or formation changes from the opposition), although we did try to control for this by accounting for halves and position. Finaly, we did not include deceleration efforts in our analysis, which is a notable component that would impact the total work performed (Harper et al., 2019). However, deceleration-speed profiles have yet to be validated, therefore we could not do this analysis in this study (deceleration normalization). Another observation is that not all first to second half conditions were available in the player cohort. For example, there were no situations where this team was winning and then transitioned to a losing or draw condition, nor losing to draw condition. Therefore, a further analysis on multiple cohorts or a longer collection period may allow for the inclusion of more match contexts.

6.8. Perspectives and practical applications

This study found that AS profiles can be used to normalize athlete specific speed and acceleration data during training and competition which supports comparisons of athlete relative effort across speeds. While this study has presented a valuable approach to athlete data normalization, it is also important to highlight the complimentary use and interpretation of both normalized and non-normalized data since both offer different, yet relevant information into physical performance in soccer. For example, the normalized data offers a measure of relative effort to each player’s maximal capacity, whereas in some cases it would be beneficial to compare players from the same team or to opposition using absolute measures as the absolute expression will be most relevant for important game moments (eg, two opposing team players sprinting to the ball at a same distance or one on one duels). Ultimately each has benefits and limitations which need to be considered thoroughly before being implemented and interpreted.

6.9. Conclusions

This study highlights the efficacy of using AS profiles to normalize match data. These profiles have proven valuable for assessing normalized acceleration and power across various speed domains that represent the individual player effort. It has been demonstrated that normalization to athlete capacity has an influence on differences observed and the interpretation of soccer tracking data. This could have an impact on how practitioners use data to inform training and match decisions.

Chapter 7 – Thesis conclusions

7.1 Summary of main findings

Altogether, the findings arising from this thesis demonstrated the promise of sprint force-velocity (FV) and acceleration-speed (AS) profiling as an invisible monitoring approach using athlete worn sensors that are valid and reliable whether computed using dedicated sprint testing data or solely invisibly monitored training and game data (Chapters 2-5). Since the AS profile provides insights into the upper level of performance for each player across speeds, any player's performance can be normalized to this profile. This was demonstrated in this thesis (Chapter 6), whereby normalization of acceleration and power data uncovered interpretable differences when contextualized to tactical factors such as position, goal differential, and game segment in elite women's soccer matches.

7.2 Practical applications

Arising from the investigations are several practical applications which are summarized below:

i. GNSS athlete worn sensors can be used to model athlete velocity to produce FV profiles in a valid and reliable manner. However, appropriate methodology must be carried out.

ii. FV profiling was carried out in a national team setting from across several camps which demonstrates that FV profiling can be carried out with GNSS sensors in an integrated way without taking away from technical and tactical time in sessions.

iii. The development of parameters surrounding the construction of valid AS profiles allows us to monitor FV qualities without the need for any sprinting protocols and allows for true "invisible monitoring" of athlete AS capacity.

iv. Although there is great potential of application of AS profiling across many domains of external load monitoring research, AS profiles can be used as a benchmark to normalize effort in elite soccer cohorts.

The methods developed through this thesis have led to innovative applications in the elite women's sport. We have developed a Shiny application (Web Application Framework for R, version 1.10.0.9000) which has allowed us to extract 10 Hz GNSS data directly from Catapult API storage using their open-source package (catapultR, version 0.0.0.52). From there, we were able to generate AS profiles across several camps which has led to the invisible monitoring of this cohort without the need for any standardized testing as demonstrated in Chapter 6.

From an applied perspective, there is a great potential of AS profiling to inform the training process. Given the ability to conveniently extract high resolution data rapidly by sport science practitioners from open-source packages, there is an ability to generate both FV and AS profiles efficiently. This data can be used to inform tactical and physical analyses as well as training interventions. Using weekly or camp monitored AS profiles, deficiencies in either maximal theoretical acceleration or speed abilities could aid in identifying injury mitigation strategies or strength interventions in the gym (Hicks et al., 2022). For example, deficits in A_0 could expose an athlete to heightened injury risk (Edouard et al., 2021, 2024; Lahti et al., 2021; Mendiguchia et al., 2016b) and this variable could be targeted in training through individualized interventions emphasizing running mechanics in the initial acceleration of sprinting (e.g., drills or resisted sprinting) (Wild et al., 2023b, 2023a), and resistance training in the gym (Hicks et al., 2022). Now that the ability to monitor AS profiles have been validated, future research should investigate the influence of training interventions on AS abilities.

The findings from Chapter 6 also uncovered that normalized match data in soccer was most influenced at high to very high speed across positions from the first to the second half in different game states. Since accelerations (changes in velocity) at already high velocities appear to contribute to a great deal of variance throughout matches. It would be wise to emphasise this quality in training to best prepare for games. This could be achieved by performing moderate to high “fly-in” runs into quick bursts of accelerations in an isolated way or integrated in soccer training sessions by designing drills where the players must run at high speeds and quickly accelerate to finish an action or score a goal.

7.3 Statistical considerations

This thesis adopts frequentist statistics as the primary analytical framework due to its well-established theoretical foundation and widespread acceptance in scientific research. Frequentist methods, including hypothesis testing, confidence intervals, and linear modeling, provide a consistent approach to evaluating the likelihood of observed outcomes under a null hypothesis. On the other hand, in applied sport science, magnitude-based inference (MBI) has been proposed as an alternative, aiming to address the limitations of traditional null hypothesis testing, particularly its perceived disregard for practical or clinical significance. MBI emphasizes effect sizes and the magnitude of effect. While MBI can aid interpretation in small-sample or applied contexts, it lacks the statistical rigor of frequentist or Bayesian methods. In this thesis, MBI is acknowledged for its role in communicating practical relevance but is not used for inferential conclusions. Instead, effect sizes and confidence intervals are reported alongside traditional analyses to provide context in some studies.

7.4 Limitations and future directions

These findings present several potential practical applications in athlete monitoring and performance analysis in team sports. The feasibility and implementation of athlete worn sensors for FV and AS profiling, and the potential benefits of data normalization opens the door to several future directions. First, a common theme in Chapters 2-3 was the accuracy and precision of GNSS sensors to develop FV profiles, yet throughout the investigations, the resolution and random errors present in these technologies are still a limitation that should be investigated. Continued queries into data collection and processing are necessary to allow for accurate modeling of maximal effort running in soccer and other team sports. Second, while the minimum number of random training and game events necessary to construct a valid AS profile is now known, it is not known how many training sessions alone or games alone are necessary, and there is uncertainty to how the AS profile is influenced by the specific content or theme of the training session. Recently, Maviel et al. (2024) found that while using a similar optimization approach to us, only 160mins from game data were necessary to obtain a reliable AS profile in men’s rugby union and in some preliminary findings from this research group, it was found that only three matches could be necessary in elite women’s sevens rugby. Therefore, since the characteristics of the sport and session content will influence reliability of the AS profile, investigation into optimal data parameters necessary to construct reliable AS profiles by level, sport, and sex could be an interesting direction for future research. Third, although we have shown the promise of FV and AS profiling using GNSS technology, there is growing scrutiny of these methods that must be acknowledged. Most recently, there have been critique of the FV profiling concept (Bobbert et al., 2023; Ettema, 2024). The models applied and introduced in this thesis are based on simple modeling of sprint running that have been validated on track embedded force plates (Morin et al., 2019) and provide practitioners with relevant information that can aid in profiling, monitoring, and training prescription (Morin & Samozino, 2016). It is, however, acknowledged that sprinting involves complex neuromuscular and technical factors that may not be captured in a simple model. Accordingly, practitioners should not fixate on one metric (e.g., power), but should take this information as a piece of a greater puzzle. Finaly, while we displayed potential of AS profiling normalization, an interesting avenue of investigation would be in the periodization of training sessions leading into games whereby all events (training or games) could be normalized to a theoretical maximal capacity. While this thesis focused on quantification of maximal capacities of acceleration, speed and power in running, it cannot be ignored that duration is a crucial component that must be studied and quantified in relation to maximal metrics (eg, acceleration-speed-power-duration profiles) to provide greater contexts into the physiology and biomechanics of running in soccer (similar to velocity-duration profiles) (Clarke et al., 2014; Mizelman et al., 2024). We believe that adding this last component in addition to AS normalization could provide sport scientists with a comprehensive assessment of athlete physical running effort in soccer and many other team-sports.

Bibliography

Abbott, W., Brickley, G., & Smeeton, N. J. (2018). Positional differences in GPS outputs and perceived exertion during soccer training games and competition. *Journal of Strength and Conditioning Research*, *32*(11), 3222–3231. https://doi.org/10.1519/JSC.0000000000002387

Agar-Newman, D. J., Goodale, T. L., & Klimstra, M. D. (2017). Anthropometric and physical qualities of international level female rugby sevens athletes based on playing position. *Journal of Strength and Conditioning Research*, *31*(5), 1346–1352. https://doi.org/10.1519/JSC.0000000000001167

Akenhead, R., French, D., Thompson, K. G., & Hayes, P. R. (2014). The acceleration dependent validity and reliability of 10 Hz GPS. *Journal of Science and Medicine in Sport*, *17*(5), 562–566. https://doi.org/10.1016/j.jsams.2013.08.005

Alonso-Callejo, A., García-Unanue, J., Guitart-Trench, M., Majano, C., Gallardo, L., & Felipe, J. L. (2024). Validity and reliability of the acceleration-speed profile for assessing running kinematics' variables derived from the force-velocity profile in professional soccer players. *The Journal of Strength & Conditioning Research*, *38*(3), 563. https://doi.org/10.1519/JSC.0000000000004637

Alonso-Callejo, A., García-Unanue, J., Perez-Guerra, A., Gomez, D., Sánchez-Sánchez, J., Gallardo, L., Oliva-Lozano, J. M., & Felipe, J. L. (2022). Effect of playing position and microcycle days on the acceleration speed profile of elite football players. *Scientific Reports*, *12*(1), Article 1. https://doi.org/10.1038/s41598-022-23790-w

Alphin, K. L., Sisson, O. M., Hudgins, B. L., Noonan, C. D., & Bunn, J. A. (2020). Accuracy assessment of a GPS device for maximum sprint speed. *International Journal of Exercise Science*, *13*(4), 273–280.

Apte, S., Meyer, F., Gremeaux, V., Dadashi, F., & Aminian, K. (2020). A sensor fusion approach to the estimation of instantaneous velocity using single wearable sensor during sprint. *Frontiers in Bioengineering and Biotechnology*, *8*, 838. https://doi.org/10.3389/fbioe.2020.00838

Arsac, L. M., & Locatelli, E. (2002). Modeling the energetics of 100-m running by using speed curves of world champions. *Journal of Applied Physiology (Bethesda, Md.: 1985)*, *92*(5), 1781–1788. https://doi.org/10.1152/japplphysiol.00754.2001

Aughey, R. J. (2011). Applications of GPS technologies to field sports. *International Journal of Sports Physiology and Performance*, *6*(3), 295–310. https://doi.org/10.1123/ijspp.6.3.295

Barr, M., Beaver, T., Turczyn, D., & Cornish, S. (2019). Validity and reliability of 15 Hz global positioning system units for assessing the activity profiles of university football players. *Journal of Strength and Conditioning Research*, *33*(5), 1371–1379. https://doi.org/10.1519/JSC.0000000000002076

Beato, M., Bartolini, D., Ghia, G., & Zamparo, P. (2016). Accuracy of a 10 Hz GPS unit in measuring shuttle velocity performed at different speeds and distances (5 – 20 M). *Journal of Human Kinetics*, *54*, 15–22. https://doi.org/10.1515/hukin-2016-0031

Beato, M., Coratella, G., Stiff, A., & Iacono, A. D. (2018). The validity and between-unit variability of GNSS Units (STATSports Apex 10 and 18 Hz) for measuring distance and peak speed in team sports. *Frontiers in Physiology*, *9*, 1288. https://doi.org/10.3389/fphys.2018.01288

Beato, M., & de Keijzer, K. L. (2019). The inter-unit and inter-model reliability of GNSS STATSports Apex and Viper units in measuring peak speed over 5, 10, 15, 20 and 30 meters. *Biology of Sport*, *36*(4), 317–321. https://doi.org/10.5114/biolsport.2019.88754

Beato, M., Devereux, G., & Stiff, A. (2018). Validity and reliability of global positioning system units (STATSports Viper) for measuring distance and peak speed in sports. *Journal of Strength and Conditioning Research*, *32*(10), 2831–2837. https://doi.org/10.1519/JSC.0000000000002778

Bezodis, N., Colyer, S., Nagahara, R., Bayne, H., Bezodis, I., Morin, J.-B., Murata, M., & Samozino, P. (2021). Ratio of forces during sprint acceleration: A comparison of different calculation methods. *Journal of Biomechanics*, *127*, 110685. https://doi.org/10.1016/j.jbiomech.2021.110685

Bland, J. M., & Altman, D. G. (1986). Statistical methods for assessing agreement between two methods of clinical measurement. *Lancet (London, England)*, *1*(8476), 307–310.

Bobbert, M. F., Lindberg, K., Bjørnsen, T., Solberg, P., & Paulsen, G. (2023). The force-velocity profile for jumping: What it is and what it is not. *Medicine and Science in Sports and Exercise*, *55*(7), 1241–1249. https://doi.org/10.1249/MSS.0000000000003147

Bradley, P. S., & Vescovi, J. D. (2015). Velocity thresholds for women's soccer matches: Sex specificity dictates high-speed running and sprinting thresholds - Female

Athletes in Motion (FAiM). *International Journal of Sports Physiology and Performance*, *10*(1), 112–116. https://doi.org/10.1123/ijspp.2014-0212

Buchheit, M., Samozino, P., Glynn, J. A., Michael, B. S., Al Haddad, H., Mendez-Villanueva, A., & Morin, J. B. (2014). Mechanical determinants of acceleration and maximal sprinting speed in highly trained young soccer players. *Journal of Sports Sciences*, *32*(20), 1906–1913.

Cardoso, P., Tavares, F., Loureiro, N., Ferreira, R., Araújo, J. P., Reis, J., & Vaz, J. R. (2023). In-situ acceleration-speed profile of an elite soccer academy: A cross-sectional study. *Journal of Sports Sciences*, *41*(20), 1868–1874. https://doi.org/10.1080/02640414.2024.2305005

Carling, C., Bradley, P., McCall, A., & Dupont, G. (2016). Match-to-match variability in high-speed running activity in a professional soccer team. *Journal of Sports Sciences*, *34*(24), 2215–2223. https://doi.org/10.1080/02640414.2016.1176228

Castellano, J., Casamichana, D., Calleja-González, J., Román, J. S., & Ostojic, S. M. (2011). Reliability and accuracy of 10 Hz GPS devices for short-distance exercise. *Journal of Sports Science & Medicine*, *10*(1), 233–234.

Clark, K. P., Rieger, R. H., Bruno, R. F., & Stearne, D. J. (2019). The national football league combine 40-yd dash: How important is maximum velocity? *The Journal of Strength & Conditioning Research*, *33*(6), 1542–1550. https://doi.org/10.1519/JSC.0000000000002081

Clarke, A. C., Presland, J., Rattray, B., & Pyne, D. B. (2014). Critical velocity as a measure of aerobic fitness in women's rugby sevens. *Journal of Science and Medicine in Sport*, *17*(1), 144–148. https://doi.org/10.1016/j.jsams.2013.03.008

Clavel, P., Leduc, C., Morin, J.-B., Buchheit, M., & Lacome, M. (2023). Reliability of individual acceleration-speed profile in-situ in elite youth soccer players. *Journal of Biomechanics*, *153*, 111602. https://doi.org/10.1016/j.jbiomech.2023.111602

Clavel, P., Leduc, C., Morin, J.-B., Owen, C., Samozino, P., Peeters, A., Buchheit, M., & Lacome, M. (2022). Concurrent validity and reliability of sprinting force-velocity profile assessed with GPS devices in Elite athletes. *International Journal of Sports Physiology and Performance*, *12*(10), 1527–1531. https://doi.org/10.1123/ijspp.2021-0339

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Routledge. https://doi.org/10.4324/9780203771587

Computing Adjusted Effects Based on Meta-Regression Models [The metafor Package]. (n.d.). Retrieved July 16, 2023, from https://www.metafor-project.org/doku.php/tips:computing_adjusted_effects

Cormier, P., Meylan, C., Agar-Newman, D., Geneau, D., Epp-Stobbe, A., Lenetsky, S., & Klimstra, M. (2024). A systematic review and meta-analysis of wearable satellite system technology for linear sprint profiling: Technological innovations and practical applications. *Journal of Strength and Conditioning Research*, *38*(2), 405–418. https://doi.org/10.1519/JSC.0000000000004689

Cormier, P., Tsai, M.-C., Meylan, C., Agar-Newman, D., Epp-Stobbe, A., Kalthoff, Z., & Klimstra, M. (2023). Concurrent validity and reliability of different technologies for sprint-derived horizontal force-velocity-power profiling. *Journal of Strength and Conditioning Research*. https://doi.org/10.1519/JSC.0000000000004429

Cormier, P., Tsai, M.-C., Meylan, C., & Klimstra, M. (2023). Comparison of acceleration-speed profiles from training and competition to individual maximal sprint efforts. *Journal of Biomechanics*, *157*, 111724. https://doi.org/10.1016/j.jbiomech.2023.111724

Cormier, P., Tsai, M.-C., Meylan, C., Soares, V. H. T., Clarke, D. C., & Klimstra, M. (2023). Minimal number of events required for acceleration-speed profiling in elite women's soccer. *International Journal of Sports Physiology and Performance*, *18*(12), 1457–1460. https://doi.org/10.1123/ijspp.2023-0223

Crang, Z. L., Duthie, G., Cole, M. H., Weakley, J., Hewitt, A., & Johnston, R. D. (2021a). The inter-device reliability of global navigation satellite systems during team sport movement across multiple days. *Journal of Science and Medicine in Sport*. https://doi.org/10.1016/j.jsams.2021.11.044

Crang, Z. L., Duthie, G., Cole, M. H., Weakley, J., Hewitt, A., & Johnston, R. D. (2021b). The validity and reliability of wearable microtechnology for intermittent team sports: A systematic review. *Sports Medicine*, *51*(3), 549–565. https://doi.org/10.1007/s40279-020-01399-1

Cross, M. R., Lahti, J., Brown, S. R., Chedati, M., Jimenez-Reyes, P., Samozino, P., Eriksrud, O., & Morin, J.-B. (2018). Training at maximal power in resisted sprinting: Optimal load determination methodology and pilot results in team sport athletes. *PloS One*, *13*(4), e0195477. https://doi.org/10.1371/journal.pone.0195477

Cummins, C., Orr, R., O'Connor, H., & West, C. (2013). Global positioning systems (GPS) and microtechnology sensors in team sports: A systematic review. *Sports

Medicine (Auckland, N.Z.), *43*(10), 1025–1042. https://doi.org/10.1007/s40279-013-0069-2

Delves, R. I. M., Aughey, R. J., Ball, K., & Duthie, G. M. (2021). The quantification of acceleration events in elite team sport: A systematic review. *Sports Medicine - Open*, *7*(1), 45. https://doi.org/10.1186/s40798-021-00332-8

Dennison, L., Duthie, G. M., Ehrmann, F., & Psarakis, M. A. (2025). Concurrent validity and interunit reliability of 25-Hz GNSS units for profiling sprinting performance. *Journal of Strength and Conditioning Research*, *39*(1), 107–114. https://doi.org/10.1519/JSC.0000000000004961

di Prampero, P. E., Fusi, S., Sepulcri, L., Morin, J. B., Belli, A., & Antonutto, G. (2005). Sprint running: A new energetic approach. *Journal of Experimental Biology*, *208*(14), 2809–2816. https://doi.org/10.1242/jeb.01700

Downs, S. H., & Black, N. (1998). The feasibility of creating a checklist for the assessment of the methodological quality both of randomised and non-randomised studies of health care interventions. *Journal of Epidemiology and Community Health*, *52*(6), 377–384. https://doi.org/10.1136/jech.52.6.377

Edouard, P., Chapon, J., Université Savoie Mont-Blanc, Inter-university Laboratory of Human Movement Biology (EA 7424), Saint-Etienne, France, Navarro, L., Plais, A., Morin, J.-B., Tondut, J., & Hollander, K. (2024). Sprint acceleration mechanical outputs and lower limb injuries: A follow-up of sprint, jumps and combined events athletes during an athletics season. *Deutsche Zeitschrift Für Sportmedizin*, *75*(4), 149–156. https://doi.org/10.5960/dzsm.2024.603

Edouard, P., Lahti, J., Nagahara, R., Samozino, P., Navarro, L., Guex, K., Rossi, J., Brughelli, M., Mendiguchia, J., & Morin, J.-B. (2021). Low horizontal force production capacity during sprinting as a potential risk factor of hamstring injury in football. *International Journal of Environmental Research and Public Health*, *18*(15), Article 15. https://doi.org/10.3390/ijerph18157827

Egger, M., Smith, G. D., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *BMJ*, *315*(7109), 629–634. https://doi.org/10.1136/bmj.315.7109.629

Ellens, S., Middleton, K., Gastin, P. B., & Varley, M. C. (2022). Techniques to derive and clean acceleration and deceleration data of athlete tracking technologies in team sports: A scoping review. *Journal of Sports Sciences*, 1–16. https://doi.org/10.1080/02640414.2022.2054535

Ettema, G. (2024). The force-velocity profiling concept for sprint running is a dead end. *International Journal of Sports Physiology and Performance*, *19*(1), 88–91. https://doi.org/10.1123/ijspp.2023-0110

FIFA. (2023). *Women's Ranking*. https://www.fifa.com/fifa-world-ranking/origin1904-p.cxm.fifa.com/fifa-world-ranking/women

Fornasier-Santos, C., Arnould, A., Jusseaume, J., Millot, B., Guilhem, G., Couturier, A., Samozino, P., Slawinski, J., & Morin, J.-B. (2022). Sprint acceleration mechanical outputs derived from position– or velocity–time data: A multi-system comparison study. *Sensors*, *22*(22), Article 22. https://doi.org/10.3390/s22228610

Furusawa, K., Hill, A. V., & Parkinson, J. L. (1927). The dynamics of “sprint” running. *Proceedings of the Royal Society of London. Series B, Containing Papers of a Biological Character*, *102*(713), 29–42. https://doi.org/10.1098/rspb.1927.0035

Goerg, G. M. (2022). *LambertW: Probabilistic models to analyze and gaussianize heavy-tailed, skewed data* (Version 0.6.7) [Computer software]. https://CRAN.R-project.org/package=LambertW

Goodale, T. L., Gabbett, T. J., Stellingwerff, T., Ming-Chang Tsai, & Sheppard, J. M. (2016). Relationship between physical qualities and minutes played in international women’s rugby sevens. *International Journal of Sports Physiology & Performance*, *11*(4), 489–494.

Greig, M., Emmerson, H., & McCreadie, J. (2019). Quantifying functional ankle rehabilitation progression criteria using GPS: A preliminary study. *Journal of Sport Rehabilitation*, *28*(7), 729–734. https://doi.org/10.1123/jsr.2018-0045

Halson, S. L. (2014). Monitoring training load to understand fatigue in athletes. *Sports Medicine*, *44*(2), 139–147. https://doi.org/10.1007/s40279-014-0253-z

Harper, D. J., Carling, C., & Kiely, J. (2019). High-intensity acceleration and deceleration demands in elite team sports competitive match play: A systematic review and meta-analysis of observational studies. *Sports Medicine*, *49*(12), 1923–1947. https://doi.org/10.1007/s40279-019-01170-1

Harper, D. J., Sandford, G. N., Clubb, J., Young, M., Taberner, M., Rhodes, D., Carling, C., & Kiely, J. (2021). Elite football of 2030 will not be the same as that of 2020: What has evolved and what needs to evolve? *Scandinavian Journal of Medicine & Science in Sports*, *31*(2), 493–494. https://doi.org/10.1111/sms.13876

Haugen, T. A., Breitschädel, F., & Seiler, S. (2019). Sprint mechanical variables in elite athletes: Are force-velocity profiles sport specific or individual? *PLOS ONE*, *14*(7), e0215551. https://doi.org/10.1371/journal.pone.0215551

Haugen, T. A., Breitschädel, F., & Seiler, S. (2020). Sprint mechanical properties in soccer players according to playing standard, position, age and sex. *Journal of Sports Sciences*, *38*(9), 1070–1076. https://doi.org/10.1080/02640414.2020.1741955

Haugen, T., Breitschädel, F., & Samozino, P. (2020). Power-force-velocity profiling of sprinting athletes: Methodological and practical considerations when using timing gates. *Journal of Strength & Conditioning Research*, *34*(6), 1769–1773.

Haugen, T., & Buchheit, M. (2016). Sprint Running Performance Monitoring: Methodological and Practical Considerations. *Sports Medicine*, *46*(5), 641–656. https://doi.org/10.1007/s40279-015-0446-0

Healy, R., Kenny, I. C., & Harrison, A. J. (2022). Profiling elite male 100-m sprint performance: The role of maximum velocity and relative acceleration. *Journal of Sport and Health Science*, *11*(1), 75–84. https://doi.org/10.1016/j.jshs.2019.10.002

Hicks, D. S., Drummond, C., Williams, K. J., Pickering, C., & van den Tillaar, R. (2022). Individualization of training based on sprint force-velocity profiles: A conceptual framework for biomechanical and technical training recommendations. *Strength & Conditioning Journal*, 10.1519/SSC.0000000000000790. https://doi.org/10.1519/SSC.0000000000000790

Hicks, D. S., Schuster, J. G., Samozino, P., & Morin, J.-B. (2020). Improving mechanical effectiveness during sprint acceleration: Practical recommendations and guidelines. *Strength & Conditioning Journal*, *42*(2), 45. https://doi.org/10.1519/SSC.0000000000000519

Higgins, J. P. T. (2008). Commentary: Heterogeneity in meta-analysis should be expected and appropriately quantified. *International Journal of Epidemiology*, *37*(5), 1158–1160. https://doi.org/10.1093/ije/dyn204

Higgins, J. P. T., Thompson, S. G., Deeks, J. J., & Altman, D. G. (2003). Measuring inconsistency in meta-analyses. *BMJ (Clinical Research Ed.)*, *327*(7414), 557–560. https://doi.org/10.1136/bmj.327.7414.557

Hopkins, W. G., Marshall, S. W., Batterham, A. M., & Hanin, J. (2009). Progressive statistics for studies in sports medicine and exercise science. *Medicine and Science in Sports and Exercise*, *41*(1), 3–13. https://doi.org/10.1249/MSS.0b013e31818cb278

Hoppe, M. W., Baumgart, C., Polglaze, T., & Freiwald, J. (2018). Validity and reliability of GPS and LPS for measuring distances covered and sprint mechanical properties in team sports. *PloS One*, *13*(2), e0192708. https://doi.org/10.1371/journal.pone.0192708

Huggins, R. A., Giersch, G. E. W., Belval, L. N., Benjamin, C. L., Curtis, R. M., Sekiguchi, Y., Peltonen, J., & Casa, D. J. (2020). The validity and reliability of global positioning system Units for measuring distance and velocity during linear and team sport simulated movements. *Journal of Strength and Conditioning Research*, *34*(11), 3070–3077. https://doi.org/10.1519/JSC.0000000000003787

Imbach, F., Ragheb, W., Leveau, V., Chailan, R., Candau, R., & Perrey, S. (2022). Using global navigation satellite systems for modeling athletic performances in elite football players. *Scientific Reports*, *12*(1), Article 1. https://doi.org/10.1038/s41598-022-19484-y

Jiménez-Reyes, P., Garcia-Ramos, A., Párraga-Montilla, J. A., Morcillo-Losa, J. A., Cuadrado-Peñafiel, V., Castaño-Zambudio, A., Samozino, P., & Morin, J.-B. (2020). Seasonal changes in the sprint acceleration force-velocity profile of elite male soccer players. *Journal of Strength and Conditioning Research*. https://doi.org/10.1519/JSC.0000000000003513

Johnston, R. D., Black, G. M., Harrison, P. W., Murray, N. B., & Austin, D. J. (2018). Applied sport science of Australian Football: A systematic review. *Sports Medicine (Auckland, N.Z.)*, *48*(7), 1673–1694. https://doi.org/10.1007/s40279-018-0919-z

Jovanović, M., & Vescovi, J. D. (2021). *shorts: Short Sprints* (Version 1.1.6) [Computer software]. https://CRAN.R-project.org/package=shorts

Koo, T. K., & Li, M. Y. (2016). A guideline of selecting and reporting intraclass correlation coefficients for reliability research. *Journal of Chiropractic Medicine*, *15*(2), 155–163. https://doi.org/10.1016/j.jcm.2016.02.012

Krzywinski, M., & Altman, N. (2014). Visualizing samples with box plots. *Nature Methods*, *11*(2), Article 2. https://doi.org/10.1038/nmeth.2813

Lacome, M., Owen, C., Peeters, A., Piscione, J., LeMeur, Y., & Leduc, C. (2020). *Force-velocity profiling with GPS: Is it reliable?* https://sportperfsci.com/force-velocity-profiling-with-gps-is-it-reliable/

Lacome, M., Peeters, A., Mathieu, B., Marrier, B., Carling, C., & Piscione, J. (2019). Can we use GPS for assessing sprinting performance in rugby sevens? A concurrent validity and between-device reliability study. *Biology of Sport*, *36*(1), 25–29. https://doi.org/10.5114/biolsport.2018.78903

Lahti, J., Jiménez-Reyes, P., Cross, M. R., Samozino, P., Chassaing, P., Simond-Cote, B., Ahtiainen, J., & Morin, J.-B. (2020). Individual sprint force-velocity profile adaptations to in-season assisted and resisted velocity-based training in professional rugby. *Sports (Basel, Switzerland)*, *8*(5), E74. https://doi.org/10.3390/sports8050074

Lahti, J., Mendiguchia, J., Edouard, P., & Morin, J.-B. (2021). A novel multifactorial hamstring screening protocol: Association with hamstring muscle injuries in professional football (soccer) – a prospective cohort study. *Biology of Sport*, *39*(4), 1021–1031. https://doi.org/10.5114/biolsport.2022.112084

López-Sagarra, A., Baena-Raya, A., Casimiro-Artés, M. Á., Granero-Gil, P., & Rodríguez-Pérez, M. A. (2022). Seasonal changes in the acceleration–speed profile of elite soccer players: A longitudinal study. *Applied Sciences*, *12*(24), Article 24. https://doi.org/10.3390/app122412987

Malone, J. J., Lovell, R., Varley, M. C., & Coutts, A. J. (2017). Unpacking the black box: Applications and considerations for using GPS devices in sport. *International Journal of Sports Physiology and Performance*, *12*(Suppl 2), S218–S226. https://doi.org/10.1123/ijspp.2016-0236

Maviel, C., Couderc, A., Duché, P., Morin, J.-B., & Vercruyssen, F. (2024). Establishing reliable acceleration-speed profiles: Minimum data requirements in rugby union matches. *Journal of Sports Sciences*, 1–6. https://doi.org/10.1080/02640414.2024.2436814

McKay, A. K. A., Stellingwerff, T., Smith, E. S., Martin, D. T., Mujika, I., Goosey-Tolfrey, V. L., Sheppard, J., & Burke, L. M. (2022). Defining training and performance caliber: A participant classification framework. *International Journal of Sports Physiology and Performance*, *1*(aop), 1–15. https://doi.org/10.1123/ijspp.2021-0451

McLaren, S. J., Macpherson, T. W., Coutts, A. J., Hurst, C., Spears, I. R., & Weston, M. (2018). The relationships between internal and external measures of training load and intensity in team sports: A meta-analysis. *Sports Medicine (Auckland, N.Z.)*, *48*(3), 641–658. https://doi.org/10.1007/s40279-017-0830-z

Mendiguchia, J., Edouard, P., Samozino, P., Brughelli, M., Cross, M., Ross, A., Gill, N., & Morin, J. B. (2016a). Field monitoring of sprinting power–force–velocity profile before, during and after hamstring injury: Two case reports. *Journal of Sports Sciences*, *34*(6), 535–541.

Mendiguchia, J., Edouard, P., Samozino, P., Brughelli, M., Cross, M., Ross, A., Gill, N., & Morin, J. B. (2016b). Field monitoring of sprinting power-force-velocity profile before, during and after hamstring injury: Two case reports. *Journal of Sports Sciences*, *34*(6), 535–541. https://doi.org/10.1080/02640414.2015.1122207

Meylan, C., Trewin, J., & McKean, K. (2017). Quantifying explosive actions in international women's soccer. *International Journal of Sports Physiology and Performance*, *12*(3), 310–315. https://doi.org/10.1123/ijspp.2015-0520

Miguens, N., Brocherie, F., Moulié, L., Milhet, P., Bon, M., Lassus, P., Toussaint, J.-F., & Sedeaud, A. (2024). Individual in-situ GPS-derived acceleration-speed profiling: Toward automatization and refinement in male professional rugby union players. *Sports Medicine - Open*, *10*(1), 6. https://doi.org/10.1186/s40798-023-00672-7

Mizelman, E., Pearson, A., Chu, D., & Clarke, D. C. (2024). Critical speed models of high-resolution speed-duration profiles describe peak running demands in soccer. *International Journal of Sports Science & Coaching*, *19*(5), 2056–2066. https://doi.org/10.1177/17479541241246951

Morgans, R., Radnor, J., Oliver, J., Scholten, J., Zmijewski, P., Kavanagh, R., Ryan, B., Haslam, C., King, M., & Oliveira, R. (2024). Can different scores in first and second halves influence running and explosive-based measures? *Biology of Sport*, *42*(2), 169–175. https://doi.org/10.5114/biolsport.2025.144296

Morin, J.-B., Bourdin, M., Edouard, P., Peyrot, N., Samozino, P., & Lacour, J.-R. (2012). Mechanical determinants of 100-m sprint running performance. *European Journal of Applied Physiology*, *112*(11), 3921–3930.

Morin, J.-B., Le Mat, Y., Osgnach, C., Barnabò, A., Pilati, A., Samozino, P., & di Prampero, P. E. (2021). Individual acceleration-speed profile in-situ: A proof of concept in professional football players. *Journal of Biomechanics*, *123*, 110524. https://doi.org/10.1016/j.jbiomech.2021.110524

Morin, J.-B., & Samozino, P. (2016). Interpreting power-force-velocity profiles for individualized and specific training. *International Journal of Sports Physiology & Performance*, *11*(2), 267–272.

Morin, J.-B., Samozino, P., Murata, M., Cross, M. R., & Nagahara, R. (2019). A simple method for computing sprint acceleration kinetics from running velocity data: Replication study with improved design. *Journal of Biomechanics*, *94*, 82–87. https://doi.org/10.1016/j.jbiomech.2019.07.020

Nagahara, R., Botter, A., Rejc, E., Koido, M., Shimizu, T., Samozino, P., & Morin, J.-B. (2017). Concurrent validity of GPS for deriving mechanical properties of sprint acceleration. *International Journal of Sports Physiology and Performance*, *12*(1), 129–132. https://doi.org/10.1123/ijspp.2015-0566

Nagahara, R., Mizutani, M., Matsuo, A., Kanehisa, H., & Fukunaga, T. (2017). Association of step width with accelerated sprinting performance and ground reaction force. *International Journal of Sports Medicine*, *38*(7), 534–540. https://doi.org/10.1055/s-0043-106191

Nagahara, R., Morin, J.-B., & Koido, M. (2016). Impairment of sprint mechanical properties in an actual soccer match: A pilot study. *International Journal of Sports Physiology and Performance*, *11*(7), 893–898. https://doi.org/10.1123/ijspp.2015-0567

Oliva-Lozano, J. M., Muyor, J. M., Fortes, V., & McLaren, S. J. (2021). Decomposing the variability of match physical performance in professional soccer: Implications for monitoring individuals. *European Journal of Sport Science*, *21*(11), 1588–1596. https://doi.org/10.1080/17461391.2020.1842513

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-

Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372,* n71. https://doi.org/10.1136/bmj.n71

Park, L. A. F., Scott, D., & Lovell, R. (2019). Velocity zone classification in elite women's football: Where do we draw the lines? *Science and Medicine in Football*. https://www.tandfonline.com/doi/abs/10.1080/24733938.2018.1517947

Peeters, A., Carling, C., Piscione, J., & Lacome, M. (2019). In-match physical performance fluctuations in international rugby sevens competition. *Journal of Sports Science & Medicine*, *18*(3), 419–426.

Phatak, A. A., Mehta, S., Wieland, F.-G., Jamil, M., Connor, M., Bassek, M., & Memmert, D. (2022). Context is key: Normalization as a novel approach to sport specific preprocessing of KPI's for match analysis in soccer. *Scientific Reports, 12,* 1117. https://doi.org/10.1038/s41598-022-05089-y

Poehling, R. A., Tsai, M.-C., Manson, S. A., Koehle, M. S., & Meylan, C. M. P. (2021). Physical performance development in a female national team soccer program. *Journal of Science and Medicine in Sport*, *24*(6), 597–602. https://doi.org/10.1016/j.jsams.2020.12.009

Portney, L. G., & Watkins, M. P. (2009). *Foundations of Clinical Research: Applications to Practice*. Pearson/Prentice Hall.

Redwood-Brown, A. J., O'Donoghue, P. G., Nevill, A. M., Saward, C., Dyer, N., & Sunderland, C. (2018). Effects of situational variables on the physical activity profiles of elite soccer players in different score line states. *Scandinavian Journal* *of Medicine & Science in Sports*, *28*(12), 2515–2526. https://doi.org/10.1111/sms.13271

Reinhardt, L., Schwesig, R., Lauenroth, A., Schulze, S., & Kurz, E. (2019). Enhanced sprint performance analysis in soccer: New insights from a GPS-based tracking system. *PloS One*, *14*(5), e0217782. https://doi.org/10.1371/journal.pone.0217782

Reports, S. (2022, April 13). *Sprint acceleration mechanical outputs: Direct comparison between GPEXE Pro2 and 1080 Sprint devices*. Sport Performance & Science Reports. https://sportperfsci.com/sprint-acceleration-mechanical-outputs-direct-comparison-between-gpexe-pro2-and-1080-sprint-devices/

Robertson, D. G. E., & Dowling, J. J. (2003). Design and responses of Butterworth and critically damped digital filters. *Journal of Electromyography and Kinesiology*, *13*(6), 569–573. https://doi.org/10.1016/S1050-6411(03)00080-4

Roe, G., Darrall-Jones, J., Till, K., Phibbs, P., Read, D., Weakley, J., & Jones, B. (2016). Between-days reliability and sensitivity of common fatigue measures in rugby players. *International Journal of Sports Physiology and Performance*, *11*(5), 581–586. https://doi.org/10.1123/ijspp.2015-0413

Samozino, P., Peyrot, N., Edouard, P., Nagahara, R., Jimenez-Reyes, P., Vanwanseele, B., & Morin, J.-B. (2022). Optimal mechanical force-velocity profile for sprint acceleration performance. *Scandinavian Journal of Medicine & Science in Sports*, *32*(3), 559–575. https://doi.org/10.1111/sms.14097

Samozino, P., Rabita, G., Dorel, S., Slawinski, J., Peyrot, N., Saez de Villarreal, E., & Morin, J. - B. (2016). A simple method for measuring power, force, velocity properties, and mechanical effectiveness in sprint running. *Scandinavian Journal of Medicine & Science in Sports*, *26*(6), 648–658.

Seiler, K. S., & Kjerland, G. Ø. (2006). Quantifying training intensity distribution in elite endurance athletes: Is there evidence for an "optimal" distribution? *Scandinavian Journal of Medicine & Science in Sports*, *16*(1), 49–56. https://doi.org/10.1111/j.1600-0838.2004.00418.x

Seiler, S. (2010). What is best practice for training intensity and duration distribution in endurance athletes? *International Journal of Sports Physiology and Performance*, *5*(3), 276–291. https://doi.org/10.1123/ijspp.5.3.276

Simperingham, K. D., Cronin, J. B., Pearson, S. N., & Ross, A. (2019). Reliability of horizontal force–velocity–power profiling during short sprint-running accelerations using radar technology. *Sports Biomechanics*, *18*(1), 88–99. https://doi.org/10.1080/14763141.2017.1386707

Sonderegger, K., Tschopp, M., & Taube, W. (2016). The challenge of evaluating the intensity of short actions in soccer: A new methodological approach using percentage acceleration. *PLOS ONE*, *11*(11), e0166534. https://doi.org/10.1371/journal.pone.0166534

Stenroth, L., Vartiainen, P., & Karjalainen, P. A. (2020). Force-velocity profiling in ice hockey skating: Reliability and validity of a simple, low-cost field method. *Sports Biomechanics*, 1–16. https://doi.org/10.1080/14763141.2020.1770321

Torres-Ronda, L., Beanland, E., Whitehead, S., Sweeting, A., & Clubb, J. (2022). Tracking systems in team sports: A narrative review of applications of the data and sport specific analysis. *Sports Medicine - Open*, *8*(1), 15. https://doi.org/10.1186/s40798-022-00408-z

Townshend, A. D., Worringham, C. J., & Stewart, I. B. (2008). Assessment of speed and position during human locomotion using nondifferential GPS. *Medicine and Science in Sports and Exercise*, *40*(1), 124–132. https://doi.org/10.1249/mss.0b013e3181590bc2

Trewin, J., Meylan, C., Varley, M. C., & Cronin, J. (2018). The match-to-match variation of match-running in elite female soccer. *Journal of Science and Medicine in Sport*, *21*(2), 196–201. https://doi.org/10.1016/j.jsams.2017.05.009

Trewin, J., Meylan, C., Varley, M. C., Cronin, J., & Ling, D. (2018). Effect of match factors on the running performance of elite female soccer players. *Journal of Strength and Conditioning Research*, *32*(7), 2002–2009. https://doi.org/10.1519/JSC.0000000000002584

Tukey, J. W. (with Internet Archive). (1977). *Exploratory data analysis*. Reading, Mass. : Addison-Wesley Pub. Co. http://archive.org/details/exploratorydataa00tuke_0

Turnbull, D., Chugh, R., & Luck, J. (2023). Systematic-narrative hybrid literature review: A strategy for integrating a concise methodology into a manuscript. *Social Sciences & Humanities Open*, *7*(1), 100381. https://doi.org/10.1016/j.ssaho.2022.100381

van den Tillaar, R., Haugen, M. E., & Falch, H. N. (2022). A comparison of sprint mechanical parameters measured with timing gates and a laser gun. *Frontiers in Sports and Active Living*, *4*. https://www.frontiersin.org/article/10.3389/fspor.2022.877482

Varley, M. C., Fairweather, I. H., & Aughey, R. J. (2012). Validity and reliability of GPS for measuring instantaneous velocity during acceleration, deceleration, and constant motion. *Journal of Sports Sciences*, *30*(2), 121–127. https://doi.org/10.1080/02640414.2011.627941

Varley, M. C., Jaspers, A., Helsen, W. F., & Malone, J. J. (2017). Methodological considerations when quantifying high-intensity efforts in team sport using global positioning system technology. *International Journal of Sports Physiology and Performance*, *12*(8), 1059–1068. https://doi.org/10.1123/ijspp.2016-0534

Vescovi, J. D., & Jovanović, M. (2021). Sprint mechanical characteristics of female soccer players: A retrospective pilot study to examine a novel approach for correction of timing gate starts. *Frontiers in Sports and Active Living*, *3*, 629694. https://doi.org/10.3389/fspor.2021.629694

Viechtbauer, W. (2010). Conducting Meta-Analyses in R with the metafor Package. *Journal of Statistical Software*, *36*, 1–48. https://doi.org/10.18637/jss.v036.i03

Vigne, G., Dellal, A., Gaudino, C., Chamari, K., Rogowski, I., Alloatti, G., Wong, P. D., Owen, A., & Hautier, C. (2013). Physical outcome in a successful Italian Serie A soccer team over three consecutive seasons. *Journal of Strength and Conditioning Research*, *27*(5), 1400–1406. https://doi.org/10.1519/JSC.0b013e3182679382

Volkov, N. I., & Lapin, V. I. (1979). Analysis of the velocity curve in sprint running. *Medicine and Science in Sports*, *11*(4), 332–337.

Waldron, M., Worsfold, P., Twist, C., & Lamb, K. (2011). Concurrent validity and test-retest reliability of a global positioning system (GPS) and timing gates to assess sprint performance variables. *Journal of Sports Sciences*, *29*(15), 1613–1619. https://doi.org/10.1080/02640414.2011.608703

Watkins, C. M., Storey, A., McGuigan, M. R., Downes, P., & Gill, N. D. (2021). Horizontal Force-Velocity-Power Profiling of Rugby Players: A Cross-Sectional Analysis of Competition-Level and Position-Specific Movement Demands. *The Journal of Strength & Conditioning Research*, *35*(6), 1576–1585. https://doi.org/10.1519/JSC.0000000000004027

Wild, J. J., Bezodis, I. N., North, J. S., & Bezodis, N. E. (2023a). Enhancing the initial acceleration performance of elite rugby backs. Part I: Determining individual technical needs. *International Journal of Sports Physiology and Performance*, *18*(9), 1012–1018. https://doi.org/10.1123/ijspp.2023-0090

Wild, J. J., Bezodis, I. N., North, J. S., & Bezodis, N. E. (2023b). Enhancing the initial acceleration performance of elite rugby backs. Part II: Insights from multiple longitudinal individual-specific case-study interventions. *International Journal of Sports Physiology and Performance*, *18*(9), 1019–1029. https://doi.org/10.1123/ijspp.2023-0091

Wu, L. Y., & Swartz, T. B. (2022). The calculation of player speed from tracking data. *International Journal of Sports Science & Coaching*, 17479541221124036. https://doi.org/10.1177/17479541221124036

Appendix

Table 0-1. Descriptive statistics denoting the means (SE) for normalized acceleration (%) across match and position contexts.

Half	GD	Speed	CB	FB	FWD	MF
First	Draw	LSR	39.24 (2.88)	45.85 (2.23)	44.18 (2.12)	37.74 (2.15)
First	Draw	MSR	76.34 (2.87)	84.56 (2.13)	82.12 (1.96)	71.33 (2.03)
First	Draw	HSR	79.81 (3.02)	88.81 (2.46)	81.57 (2.00)	78.86 (2.04)
First	Draw	VHSR	86.07 (3.15)	84.87 (2.16)	78.14 (2.15)	74.48 (2.32)
First	Losing	LSR	42.04 (4.78)	51.41 (3.29)	48.40 (2.06)	38.91 (2.73)
First	Losing	MSR	78.21 (3.31)	84.79 (2.64)	85.09 (2.22)	75.42 (2.16)
First	Losing	HSR	88.86 (4.78)	92.36 (3.00)	94.34 (1.94)	85.81 (2.42)
First	Losing	VHSR	80.17 (3.16)	88.64 (3.09)	87.36 (2.21)	83.59 (2.57)
First	Winning	LSR	37.70 (2.85)	44.48 (2.06)	43.33 (1.82)	38.69 (1.88)
First	Winning	MSR	77.48 (2.94)	85.74 (2.20)	81.39 (1.85)	69.29 (2.35)
First	Winning	HSR	85.55 (3.26)	87.40 (1.98)	83.85 (1.90)	77.71 (2.17)
First	Winning	VHSR	76.30 (2.94)	88.67 (2.20)	78.46 (2.27)	74.84 (2.90)
Second	Draw	LSR	36.97 (3.70)	45.55 (2.35)	40.94 (2.17)	37.98 (1.91)
Second	Draw	MSR	77.28 (3.05)	83.54 (2.64)	81.00 (2.01)	75.38 (2.03)
Second	Draw	HSR	80.20 (4.78)	94.13 (2.33)	81.14 (2.25)	73.98 (2.00)
Second	Draw	VHSR	82.35 (3.04)	87.71 (2.32)	84.89 (2.24)	80.04 (2.22)
Second	Losing	LSR	30.92 (4.85)	50.43 (3.72)	45.67 (3.37)	40.01 (3.89)
Second	Losing	MSR	79.13 (4.51)	81.05 (3.57)	83.18 (6.17)	70.14 (3.56)
Second	Losing	HSR	71.69 (4.85)	77.41 (4.90)	97.61 (4.15)	75.21 (3.39)
Second	Losing	VHSR	75.51 (5.21)	86.30 (3.57)	86.15 (3.52)	76.72 (3.56)
Second	Winning	LSR	43.10 (2.67)	45.94 (2.00)	47.05 (1.63)	37.90 (1.94)
Second	Winning	MSR	80.74 (2.68)	85.07 (1.90)	86.48 (1.62)	78.47 (1.93)
Second	Winning	HSR	89.99 (2.81)	87.35 (2.01)	94.49 (1.61)	85.05 (1.94)
Second	Winning	VHSR	85.38 (2.75)	85.12 (2.04)	85.58 (1.61)	77.89 (2.02)

Table 0-2. Descriptive statistics denoting the means (SE) for acceleration ($m \cdot s^{-2}$) across match and position contexts.

Half	GD	Speed	CB	FB	FWD	MF
First	Draw	LSR	3.30 (0.12)	3.26 (0.09)	3.28 (0.09)	3.20 (0.09)
First	Draw	MSR	3.29 (0.12)	3.51 (0.09)	3.37 (0.08)	3.28 (0.09)
First	Draw	HSR	3.02 (0.13)	3.11 (0.10)	2.92 (0.09)	2.98 (0.09)
First	Draw	VHSR	2.17 (0.14)	1.79 (0.09)	1.70 (0.09)	1.93 (0.10)
First	Losing	LSR	3.44 (0.20)	3.73 (0.14)	3.58 (0.09)	3.26 (0.12)
First	Losing	MSR	3.57 (0.14)	3.49 (0.11)	3.45 (0.09)	3.23 (0.09)
First	Losing	HSR	3.31 (0.20)	3.29 (0.13)	3.20 (0.08)	3.08 (0.10)
First	Losing	VHSR	1.94 (0.14)	1.94 (0.13)	2.01 (0.09)	2.01 (0.11)
First	Winning	LSR	3.14 (0.12)	3.46 (0.09)	3.08 (0.08)	3.26 (0.08)
First	Winning	MSR	3.58 (0.13)	3.67 (0.09)	3.26 (0.08)	2.86 (0.10)
First	Winning	HSR	3.37 (0.14)	3.28 (0.08)	2.78 (0.08)	2.86 (0.09)
First	Winning	VHSR	2.01 (0.13)	1.97 (0.09)	1.74 (0.10)	1.62 (0.12)
Second	Draw	LSR	3.09 (0.16)	3.11 (0.10)	2.99 (0.09)	3.14 (0.08)
Second	Draw	MSR	3.54 (0.13)	3.44 (0.11)	3.38 (0.09)	3.28 (0.09)
Second	Draw	HSR	3.19 (0.20)	3.22 (0.10)	2.84 (0.10)	2.76 (0.09)
Second	Draw	VHSR	2.18 (0.13)	2.03 (0.10)	2.02 (0.10)	1.85 (0.09)
Second	Losing	LSR	2.77 (0.20)	3.67 (0.16)	3.39 (0.14)	3.65 (0.16)
Second	Losing	MSR	3.30 (0.19)	3.67 (0.15)	3.77 (0.26)	3.37 (0.15)
Second	Losing	HSR	2.99 (0.20)	2.85 (0.21)	3.32 (0.17)	3.17 (0.14)
Second	Losing	VHSR	1.72 (0.22)	1.83 (0.15)	1.91 (0.15)	2.04 (0.15)
Second	Winning	LSR	3.53 (0.12)	3.54 (0.09)	3.37 (0.07)	3.23 (0.08)
Second	Winning	MSR	3.61 (0.12)	3.57 (0.08)	3.43 (0.07)	3.35 (0.08)
Second	Winning	HSR	3.45 (0.12)	3.22 (0.09)	3.19 (0.07)	3.12 (0.08)
Second	Winning	VHSR	2.16 (0.12)	1.89 (0.09)	1.80 (0.07)	1.90 (0.09)

Table 0-3. Descriptive statistics denoting the means (SE) for normalized power (%) across match and position contexts.

Half	GD	Speed	CB	FB	FWD	MF
First	Draw	LSR	64.49 (3.35)	76.51 (2.59)	75.48 (2.46)	68.01 (2.50)
First	Draw	MSR	79.48 (3.34)	92.84 (2.47)	89.46 (2.28)	77.22 (2.35)
First	Draw	HSR	82.60 (3.51)	93.80 (2.85)	85.32 (2.32)	81.67 (2.37)
First	Draw	VHSR	84.58 (3.67)	87.75 (2.51)	79.46 (2.49)	76.16 (2.69)
First	Losing	LSR	73.37 (5.54)	87.39 (3.81)	80.88 (2.39)	72.76 (3.16)
First	Losing	MSR	84.20 (3.85)	90.03 (3.06)	89.78 (2.58)	82.80 (2.51)
First	Losing	HSR	88.21 (5.54)	98.19 (3.47)	96.80 (2.25)	89.77 (2.81)
First	Losing	VHSR	79.47 (3.68)	92.19 (3.58)	88.65 (2.57)	86.87 (2.98)
First	Winning	LSR	63.87 (3.32)	73.47 (2.39)	72.82 (2.12)	69.98 (2.18)
First	Winning	MSR	81.08 (3.43)	94.00 (2.56)	86.97 (2.16)	73.18 (2.72)
First	Winning	HSR	89.90 (3.79)	92.50 (2.31)	86.84 (2.21)	80.70 (2.52)
First	Winning	VHSR	76.39 (3.43)	91.07 (2.55)	79.45 (2.63)	77.80 (3.37)
Second	Draw	LSR	60.33 (4.30)	73.55 (2.73)	67.24 (2.52)	66.70 (2.22)
Second	Draw	MSR	81.13 (3.56)	90.75 (3.06)	89.05 (2.34)	79.97 (2.36)
Second	Draw	HSR	85.69 (5.54)	100.32 (2.71)	85.00 (2.61)	77.94 (2.32)
Second	Draw	VHSR	81.33 (3.54)	90.99 (2.70)	87.59 (2.60)	82.67 (2.58)
Second	Losing	LSR	54.42 (5.61)	85.49 (4.30)	79.80 (3.90)	67.73 (4.50)
Second	Losing	MSR	83.22 (5.23)	90.84 (4.13)	90.12 (7.14)	76.75 (4.12)
Second	Losing	HSR	74.28 (5.61)	82.70 (5.67)	102.69 (4.80)	79.72 (3.92)
Second	Losing	VHSR	75.25 (6.03)	87.54 (4.13)	89.35 (4.08)	81.24 (4.12)
Second	Winning	LSR	74.62 (3.11)	73.60 (2.33)	76.97 (1.90)	69.96 (2.26)
Second	Winning	MSR	86.49 (3.13)	92.38 (2.22)	92.47 (1.89)	85.10 (2.24)
Second	Winning	HSR	90.30 (3.28)	91.42 (2.33)	97.49 (1.87)	88.09 (2.26)
Second	Winning	VHSR	84.46 (3.21)	87.45 (2.37)	86.50 (1.88)	79.68 (2.35)

Table 0-4. Descriptive statistics denoting the means (SE) for max power (W) across match and position contexts.

Half	GD	Speed	CB	FB	FWD	MF
First	Draw	LSR	1141.64 (37.80)	925.56 (28.40)	983.05 (27.17)	1071.99 (27.35)
First	Draw	MSR	1093.73 (38.84)	950.75 (27.34)	984.94 (25.65)	1130.69 (26.17)
First	Draw	HSR	1135.45 (38.89)	935.80 (30.61)	1015.37 (26.02)	1082.25 (26.27)
First	Draw	VHSR	983.27 (41.50)	743.06 (27.68)	803.46 (27.37)	976.98 (28.96)
First	Losing	LSR	1099.22 (57.53)	932.31 (38.96)	973.44 (26.62)	1061.41 (33.20)
First	Losing	MSR	1152.43 (42.85)	931.83 (32.30)	996.90 (28.20)	1048.35 (27.48)
First	Losing	HSR	1097.97 (57.53)	940.54 (35.98)	954.53 (25.46)	1032.17 (30.08)
First	Losing	VHSR	949.48 (41.45)	750.88 (36.90)	829.70 (28.08)	914.75 (31.50)
First	Winning	LSR	1063.27 (38.66)	1024.55 (26.71)	940.11 (24.39)	1080.85 (24.79)
First	Winning	MSR	1164.40 (39.44)	992.72 (28.07)	962.68 (24.69)	1029.03 (29.36)
First	Winning	HSR	1144.92 (42.40)	1019.56 (26.00)	938.43 (25.10)	1080.13 (27.64)
First	Winning	VHSR	995.56 (39.44)	792.27 (28.00)	831.15 (28.60)	848.45 (34.95)
Second	Draw	LSR	1052.21 (46.76)	846.31 (29.54)	956.50 (27.66)	1062.42 (25.11)
Second	Draw	MSR	1163.73 (40.58)	941.55 (32.32)	1014.78 (26.14)	1073.32 (26.22)
Second	Draw	HSR	1165.35 (57.55)	901.09 (29.33)	1007.89 (28.40)	1057.33 (25.90)
Second	Draw	VHSR	1020.65 (40.43)	811.63 (29.22)	893.60 (28.24)	865.48 (28.08)
Second	Losing	LSR	1157.25 (55.75)	917.55 (43.45)	961.72 (39.79)	1129.47 (45.18)
Second	Losing	MSR	1055.31 (54.80)	992.26 (41.91)	1108.70 (69.79)	1150.82 (41.84)
Second	Losing	HSR	1168.06 (55.75)	952.73 (56.10)	929.70 (48.00)	1165.39 (40.05)
Second	Losing	VHSR	920.02 (61.96)	723.50 (41.93)	816.72 (41.39)	972.95 (41.84)
Second	Winning	LSR	1119.28 (37.01)	995.73 (26.22)	925.26 (22.63)	1069.10 (25.45)
Second	Winning	MSR	1134.22 (37.09)	975.20 (25.24)	950.60 (22.57)	1055.84 (25.25)
Second	Winning	HSR	1129.91 (38.33)	1012.18 (26.24)	938.52 (22.42)	1062.06 (25.39)
Second	Winning	VHSR	980.80 (37.75)	793.31 (26.52)	773.34 (22.45)	927.01 (26.19)