**TITLE: Using Microtechnology to Evaluate the Between- and Within-Match Variability of Professional Twenty20 Cricket Fast Bowlers**

SUBMISSION TYPE: Original Investigation

AUTHORS: James W. Bray, [1] Mark Fogarty, [1] Steve Barrett, [1] Ric Lovell, [2] and Grant Abt[1]

AUTHORS' INSTITUTIONS:

[1]School of Life Sciences, The University of Hull, Kingston-Upon-Hull, England, UK.

[2]School of Science and Health, University of Western Sydney, Penrith, Australia.

CORRESPONDING AUTHOR:

Grant Abt, PhD.

School of Life Sciences

The University of Hull

Kingston-Upon-Hull, England, UK.

Phone: +441482 463397 Fax: +441482 463855

E-mail: G.Abt@hull.ac.uk

RUNNING HEAD: Variability in Twenty20 cricket: A Case Study

# Using Microtechnology to Evaluate the Between- and Within-Match Variability of Professional Twenty20 Cricket Fast Bowlers

**ABSTRACT**

This study assessed the between- and within-match variability of external training load measures during two consecutive Twenty20 cricket seasons in professional fast bowlers. Global positioning system (GPS) and accelerometer data (PlayerLoad™) were collected from eight fast bowlers in 17 matches of domestic Twenty20 competition. Using GPS-accelerometry systems the variables selected for analysis were; total distance, low speed running distance (≤14.4 $km{\cdot}h^{-1}$), high-speed running distance (≥14.4 $km{\cdot}h^{-1}$), total sprint distance (≥18 $km{\cdot}h^{-1}$), number of sprint efforts (*n*), peak speed ($km{\cdot}h^{-1}$) and PlayerLoad™ (arbitrary units; AU). These variables were further categorised into specific reference periods; between-match (overall and bowling only) and within-match (between-over). Data were log transformed and the coefficient of variation (CV) and between-subject standard deviation determined (both expressed as percentages). The data shows that between-match variability was greatest in high-speed running distance (32.9% CV), total sprint distance (49.0% CV) and number of sprint efforts (48.0% CV). Similarly, within-match between-over data was greatest in high-speed running distance (12.8% CV), total sprint distance (17.1% CV) and number of sprint efforts (12.3% CV), yet this variability was markedly reduced compared to between-match observations. The results show that global measures of external training load (total distance and PlayerLoad™; 5.5-13.3% CV) are relatively stable, yet high-speed locomotive activities exhibit a larger degree of variability both between- and within-match. These findings have importance for practitioners, who seek to facilitate performance by informed training prescription based on replicating match demands.

**Key Words:** GPS; training load; team sport; PlayerLoad™; time-motion analysis

## INTRODUCTION

Cricket is a popular team sport, comprised of 2 teams of 11 players, typically played within Commonwealth countries (21, 22). Players are classified into specific roles, which include batsmen, fast bowlers, spin bowlers and wicket keepers. Although each player has a specific role within the team, all are required to field throughout the course of the oppositions batting innings (22). Unlike many other professional team sports, players will compete in three different match formats consisting of limited overs (Twenty20 [T20] and 50-over) and multiday (4 or 5 day) cricket (13, 21, 22, 34). Consequently, bowling load (overs and balls bowled) will vary dependant on match format. Fast bowlers usually account for 3 to 5 of the 11 players on each team (21) and have been shown to have the highest physical load of this population (21, 33). Moreover, the prevalence of injuries within this population has risen in recent years, which has been attributed to the inclusion of more T20 cricket (13, 27-29).

Given the differences in match format, there is an increasing interest in quantifying the physical demands experienced by cricketers during training and competition (31, 33, 37). Such interest has elicited the use of time-motion analysis as an objective tool to measure the physical demands as valadited in other team sports (4). Recent developments in time motion analysis, now integrate the wearable athlete tracking technology of global positioning systems (GPS) and tri-axial accelerometers, allowing for a more practical, time efficient approach to traditional time motion analysis (16). This integrated technology is now typically referred to as micromechanical-electrical systems (MEMS) and provides a further means of capturing movement patterns and quantifying the training load within sporting environments (6, 9, 21, 22, 37). Measures of training load are further characterised into physiological and psycho-biological responses (internal training load) and player movement patterns and activity profiles (external training load) (6). Monitoring enables sport scientists and/or those working with cricketers to objectively quantify the level of physical exertion and stress each player endures relative to their specific playing role in both training and competition (6, 7, 38), thus informing training prescription and recovery strategies, which may facilitate performance gains (4) and reduce injury risk (13).

Within cricket, specifically fast bowling, time motion analysis research incorporating MEMS technology has contributed to an increased understanding of the differences in match load and intensity across the different forms of competition and training (30, 32-34). These studies have reported on the variability in movement patterns during One-day Internationals (32) and T20 cricket (30). These findings highlight that international fast bowlers covered the greatest total distances of any position (32). Aside from total distance, a global measure of training load, fast bowlers also covered the greatest distances in high-speed locomotive activities across all formats of competition (33). Specifically, Petersen and colleagues (33) highlighted that during T20 cricket there were a 22% and 43% increase in hourly sprint distances for fast bowlers than during limited overs and multiday cricket, respectively (36). Moreover, in a T20 innings, fast bowlers spent 9% of the total time sprinting (30, 33), which is comparable to findings in other team sports (7, 10, 18, 20). Recently, studies have also reported on tri-axial accelerometry (PlayerLoad™) within team sport environments (3-5, 9, 22). PlayerLoad™ is a movement variable that uses the accelerometer embedded within the MEMS device to measure the frequency and magnitude of forward, sideways and upward accelerations to determine a players external training load (4, 16). Additionally, this measure allows for an increased understanding of the physical demands that are not based on running activities, such as the fast bowling action. Furthermore, these accelerometers measure at 100 Hz making them more sensitive to subtle movements compared to GPS, which typically measures global displacement at only 1-10 Hz (26). Research has reported on the reliability of PlayerLoad™ (4) and how it can quantify external load in competition and simulated team sport activity (3, 5, 16). Knowledge on this technology for monitoring cricket match play (specifically fast bowling) is limited to one study on elite age-group cricketers (22). McNamara and colleagues (22) provide comparisons for key external training load variables between fast- and non-fast bowlers in training and competition, respectively. Specifically, fast bowlers accumulated a greater PlayerLoad™ during both training (703 vs 598 arbitrary units [AU]) and competition (912 vs 679 AU), respectively. However these findings are likely due to the strong relationship with total distance (1, 5) and running kinematics (2).

The complex and intermittent characteristics typically experienced in team sport performance are unstable and subject to variation between matches (10, 17, 20). During competition the physical demands of fast bowling depend on both match type and the team strategy employed by the captain (21). While few studies have reported the movement demands of cricket match play (6, 30), the majority of published work has focused on quantifying physiological responses to simulated fast bowling (8, 23, 24). Between-match variation in physical activity has been reported in professional soccer competition (10) and more recently in both codes of professional rugby (9, 17, 20). However, data on the between-match variability specific to T20 fast bowling is limited to Australian national cricketers (30, 33). Indeed this research highlights the variability in player movement patterns, yet more importantly the results show that T20 cricket imposes greater high-speed locomotive demands compared to multiday and one-day cricket, respectively (33, 36). Moreover, given the notable differences in match format and the recent global development of domestic T20 competitions, the variability of physical performance and bowling demands are likely to differ from this published data. Consequently, quantification of both within- and between-match variability data will contribute to enhancing the methods and accuracy of monitoring fast bowling loads within competition.

Therefore, the aims of this investigation were to (1) profile fast bowling and investigate the between-match variability of key external training load variables with the use of MEMS devices during a competitive block of T20 cricket, which is now typically experienced by professional cricketers, and (2) to use the same technology and external training load variables to profile and investigate the within-match between-over variability.

## METHODS

### Experimental Approach to the Problem

Eight professional fast bowlers from an English County Cricket Club were used to examine both; between-match and within-match between-over variability of player movement characteristics in the Natwest T20 Blast competition. The movement characteristics were measured using a portable MEMS device comprising of GPS (5 Hz) and tri-axial accelerometer (100 Hz) technology. The movement parameters and locomotive classifications analysed were selected based on previous team sport research (16, 20, 30, 31, 33).

### Participants

During the 2014 and 2015 seasons, eight professional male fast bowlers (mean ± *SD*; age 24.9 ± 6.5 years; body mass 86.5 ± 8.5 kg; height 187.9 ± 4.1 cm) from the same County Cricket Club volunteered to participate in this study. Of the total number of participants, up to four fast bowlers wore a MEMS device during any given match. The Department of Sport, Health and Exercise Science Ethics Committee approved all experimental procedures and the study conformed to the declaration of Helsinki (41). All players were free from injury or any other medical condition that would prohibit participation. Before participating in this study, players were informed of all testing procedures and written informed consent was obtained. All bowlers had previously been familiarised with the MEMS device by wearing it during training sessions or non-competition matches.

**Procedures**

Data were measured during all Natwest T20 Blast fixtures. Fifty-three match files were collected from 18 matches during the 2014 (n = 10) and 2015 (n = 8) seasons, respectively. During these two consecutive seasons; 11 matches were played at home and 7 matches were played away from home, with 5 matches won, 11 lost and 1 tied. All matches were played on a professionally prepared first-class county cricket oval within the United Kingdom conforming to, and meeting the requirements of, Law 7 (The Pitch) and Law 10 (Preparation and Maintenance of the Playing Area) of the Marylebone Cricket Club (MCC) Laws of Cricket (19).

Players wore an individual MEMS device (MinimaxX Team Sports v2.5, Catapult Innovations, Melbourne, Australia; mass 64.5 g; size 0.9 x 0.5 x 0.2 cm) encased within a neoprene vest, which housed the device between the scapulae (Figure 1). The MEMS device included a GPS device sampling at 5 Hz and a tri-axial piezoelectric linear accelerometer (Kionix, KXP94) sampling at 100 Hz. As recommended, each bowler wore the same MEMS device throughout all testing procedures (15, 31). Approximately 30 minutes before each match, the units were switched on to ensure they were able to establish a satellite lock (≥4 satellites for ≥ 15 minutes). The measurement error (typical error of measurement [TEM]) in the MEMS devices used for total distance, low-speed (mean running speed ≤14.4 $km{\cdot}h^{-1}$) and high-speed (mean running speed ≥14.4 $km{\cdot}h^{-1}$) running distance during simulated team sport activities is reported to be 2.0%, 4.3% and 10.8%, respectively (16, 31). However, caution is required when interpreting shorter, higher speed locomotive activities as these devices have been reported to underestimate sprint distance (16, 31). Moreover the tri-axial accelerometer embedded within the MinimaxX devices have been reported to provide a highly reliable (< 2% CV) measure of PlayerLoad™ in both laboratory (4) and team sport simulations (3, 16).


**Figure 1.** Portable MEMS device (**L**) and fast bowler wearing a bespoke neoprene vest (**R**). The red arrow indicates unit placement, between the scapulae within a custom made pouch as part of the bespoke neoprene vest.

Throughout the testing period the mean number of satellites that were found to be available for signal transmission using Catapult Sprint software (Sprint, Version 5.1.0, Catapult Innovations, Melbourne, Australia) was 9 ± 3, which is similar to that previously reported for the optimal use of GPS technology for assessment of human movement (14, 38). The mean horizontal dilution of precision (HDOP) was 2.2 ± 2.0. A HDOP of 1 indicates an optimal geometrical positioning of orbiting satellites for accurate monitoring of position, while larger values (up to 50) are considered to provide unreliable results (14, 38, 40). No data were omitted due to poor signal quality.

Movement demands were quantified using total distance, which were further characterised into arbitrary speed zones and descriptors, in line with previous studies (30, 31, 33) (Table 1). The aim of our study was not to validate these speed zones, but to use them in order to compare our data to previous studies. Furthermore, we also reclassified the speed zones into a broader range allowing for further comparisons with existing literature (17, 18, 20). The zones included; low-speed (LSRD ≤14.4 $km{\cdot}h^{-1}$) and high-speed (HSRD ≥14.4 $km{\cdot}h^{-1}$) running distance, respectively. High-speed locomotive efforts are reported with a dwell time of 0.2 s in an attempt to reduce errors that can occur in the smoothing of data used by the software (31). In addition to GPS parameters, PlayerLoad™, expressed in arbitratry units (AU) was calculated in Sprint (Catapult Innovations, Melbourne, Australia), which is a modified vector magnitude expressed as the square root of the sum, as previously described (4, 25).

**Table 1.** Movement Category Speeds, as reported by Petersen, Portus and Dawson (30), Petersen, Pyne, Portus and Dawson (31), and Petersen, Pyne, Dawson, Portus and Kellett (33).

| Movement classification | Speed ($km{\cdot}h^{-1}$) |
|---|---|
| Standing/Walking | 0.0 – 7.2 |
| Jogging | 7.2 – 12.6 |
| Running | 12.6 – 14.4 |
| Striding | 14.4 – 18.0 |
| Sprinting | >18.0 |

Data were downloaded post-match using Sprint software (V5.1.0, Catapult Innovations, Melbourne, Australia) and subsequently analysed and processed by applying the proprietary intelligent motion filter. Each match file was subsequently split into specific reference periods, which were then used to construct performance profiles for the whole match and bowling only periods. All external training load variables were represented in absolute and relative terms, indicative of volume and intensity, respectively. Relative measures were calculated as the absolute measure divided by the on-field playing time. The minimum number of matches per player was set at three (20), giving a total of 53 match observations.

*Between-Match Variation*

To calculate the between-match variation for all fast bowlers the following external training load variables were used; total distance, low-speed running distance (mean running speed ≤14.4 $km \cdot h^{-1}$), high-speed running distance (mean running speed ≥14.4 $km \cdot h^{-1}$), total sprint distance (mean running speed ≥18 $km \cdot h^{-1}$), total number of sprints completed (*n*), peak speed ($km \cdot h^{-1}$) and PlayerLoad™ (AU).

*Within-Match Between-Over Variation*

Within-match between-over variation was calculated for all fast bowlers using the same external training load variables. However, this analysis included the bowling only periods. To construct these periods each individual match file was split into each individual over. An individual over was cropped, so that data obtained included the initial run-up of the first delivery and all subsequent movements and actions until cessation of the final delivery (typically six deliveries). In every instance the initial run-up was identfied by viewing the GPS map in parallel with the accelerometer data. The minimum number of completed overs bowled per match was set at two (up to 4-overs bowled). This resulted in a total of 172 specific over observations totalling 1070 deliveries (including extras).

**Statistical Analyses**

Raw match training load data are presented as the mean ± *SD*. Prior to statistical analysis, all data were log-transformed to reduce the error occurring from non-uninform residuals, typically experienced in athletic performance (20). Subsequently, data were analysed using a mixed effects linear model (SPSS V22, Armonk, NY: IBM Corp) to estimate the between-match and within-match between-over variability. Variability was expressed using the coefficient of variation (CV%; typical error expressed as a percentage of the mean) (11). CV's were also presented with 90% confidence intervals (90% CI) as markers of the uncertainty of the estimates (20). The smallest worthwhile change (SWC%) in external training load measures was calculated as 0.2 x between-player SD (12, 17, 20).

## RESULTS

The environmental conditions of all completed matches were 22.9 ± 4.6 °C and 56.9 ± 19.1% relative humidity (RH), respectively. The mean match duration was 72.6 ± 12.0 min with 18.1 ± 2.9 overs bowled. Individually, the mean bowling spell length was 3.2 ± 1.0 overs. Absolute and relative descriptive data summarising movement categories contributing to total distance covered are reported in Table 2. This data is further categorised to include the bowling only period.

**Table 2.** Descriptive fast bowlers ($n$ = 8) external training load data (mean ± *SD*)

| External training load variable | Whole match | Bowling only period |
|---|---|---|
| **Absolute measures** | | |
| TD (m) | 4878 ± 1190 | 1206 ± 438 |
| LSRD (m) | 4199 ± 1017 | 845 ± 309 |
| HSRD (m) | 692 ± 250 | 364 ± 154 |

| | | |
|---|---|---|
| TSD (m) | 384 ± 164 | 251 ± 131 |
| Total Sprint Number (*n*) | 30 ± 13 | 18 ± 7 |
| Peak Speed (km·h$^{-1}$) | 29 ± 4 | 28 ± 4 |
| PL (AU) | 359 ± 91 | 95 ± 33 |
| **Relative measures** | | |
| TS (m·min$^{-1}$) | 65.7 ± 11.5 | 104.9 ± 15.7 |
| LSR (m·min$^{-1}$) | 56.5 ± 9.5 | 73.9 ± 10.6 |
| HSR (m·min$^{-1}$) | 9.3 ± 3.1 | 31.9 ± 7.9 |
| TSS (m·min$^{-1}$) | 5.2 ± 2.3 | 21.7 ± 8.6 |
| Sprint Number (*n*·min$^{-1}$) | 0.4 ± 0.2 | 1.6 ± 0.4 |
| PL (AU·min$^{-1}$) | 4.8 ± 0.9 | 8.3 ± 0.9 |

TD = Total distance; LSRD = Low-speed running distance (≤14.4 km·h$^{-1}$); HSRD = High-speed running distance (≥14.4 km·h$^{-1}$); TSD = Total sprint distance (≥18 km·h$^{-1}$); PL = PlayerLoad™; TS = Total speed; LSR = Low-speed running; HSR = High-speed running; TSS = Total sprint speed

*Between-Match Variability*

The whole match and the bowling only period CVs (± 90% CI) are reported in Table 3, along with reference values for the SWC. The whole match data shows a clear increase in the mean variability from LSRD to HSRD (9.6 to 32.9), with the 90% confidence intervals not overlapping. While there is also an increase in the mean variability from HSRD to TSD (32.9 to 49.0), there is an overlap in the confidence intervals. Similarly, within the bowling only period, there is a notable increase in the mean variability from LSRD to HSRD (47.9 to 60.4) and from HSRD to TSD (60.4 to 83.2), respectively. However, there is an overlap in all of the confidence intervals. Moreover, the same observations are apparent within the relative, between-match variability data.

**Table 3.** Between-Match variation of external training load measures

| External training load variable | Whole match | | Bowling only period | |
|---|---|---|---|---|
| | CV (%; 90% CI) | SWC (%) | CV (%; 90% CI) | SWC (%) |
| **Absolute measures** | | | | |
| TD (m) | 10.6 (8.5 to 14.7) | 3.1 | 48.2 (37.5 to 70.6) | 14.9 |
| LSRD (m) | 9.6 (7.7 to 13.2) | 2.8 | 47.9 (37.2 to 70.0) | 14.8 |
| HSRD (m) | 32.9 (25.9 to 47.2) | 9.9 | 60.4 (46.5 to 89.9) | 19.0 |
| TSD (m) | 49.0 (38.1 to 71.9) | 15.2 | 83.2 (63.1 to 127.4) | 27.1 |
| Total Sprint Number (*n*) | 48.0 (37.3 to 70.2) | 14.8 | 84.4 (64.0 to 129.5) | 27.5 |
| Peak Speed ($km \cdot h^{-1}$) | 12.1 (9.7 to 16.8) | 3.5 | 15.0 (12.0 to 20.9) | 4.4 |
| PL (AU) | 12.3 (9.8 to 17.0) | 3.6 | 52.6 (40.8 to 77.5) | 16.4 |
| **Relative measures** | | | | |
| TD ($m \cdot min^{-1}$) | 11.2 (8.9 to 15.4) | 3.2 | 21.9 (17.4 to 30.9) | 6.5 |
| LSR ($m \cdot min^{-1}$) | 10.0 (8.0 to 13.7) | 2.9 | 18.7 (14.9 to 26.2) | 5.5 |
| HSR ($m \cdot min^{-1}$) | 33.6 (26.4 to 48.2) | 10.1 | 33.2 (26.1 to 47.6) | 10.0 |
| TSS ($m \cdot min^{-1}$) | 49.6 (38.5 to 72.7) | 15.3 | 54.3 (42.0 to 80.2) | 16.9 |
| Sprint Number ($n \cdot min^{-1}$) | 48.5 (37.7 to 71.0) | 15.0 | 36.8 (28.9 to 53.1) | 11.2 |
| PL ($AU \cdot min^{-1}$) | 13.3 (10.6 to 18.4) | 3.9 | 8.5 (6.8 to 11.7) | 2.4 |

TD = Total distance; LSRD = Low-speed running distance (≤14.4 $km \cdot h^{-1}$); HSRD = High-speed running distance (≥14.4 $km \cdot h^{-1}$); TSD = Total sprint distance (≥18 $km \cdot h^{-1}$); PL = PlayerLoad™; LSR = Low-speed running; HSR = High-speed running; TSS = Total sprint speed. CV%: coefficient of variation and 90% confidence interval; SWC%: smallest worthwhile change (0.2 x between subject standard deviation)

*Within-Match Between-Over Variability*

The within-match between-over CVs (± 90% CI) along with SWC values are reported in Table 4. There is a clear increase in the mean variability from LSRD to HSRD (8.2 to 12.8) and from HSRD to TSD (12.8 to 17.1), with an overlap in confidence intervals. Likewise, within the relative variability data, there is also a clear increase in the mean variability from LSR to HSR (6.4 to 13.9), however the confidence intervals do not overlap. Moreover, there is a clear increase in the mean variability from HSR to TSS (13.9 to 18.6), however the confidence intervals overlap. Global measures of match activity; total distance and PlayerLoad™ were subject to the least variability throughout.

**Table 4.** Within-Match Between-Over variation (overs 2, 3 & 4, respectively) of external training load measures

| External training load variable | Overall | |
|---|---|---|
| | CV (%; 90% CI) | SWC (%) |
| **Absolute measures** | | |
| TD (m) | 7.0 (5.5 to 10.2) | 2.0 |
| LSRD (m) | 8.2 (6.5 to 12.0) | 2.4 |
| HSRD (m) | 12.8 (10.0 to 18.9) | 3.7 |
| TSD (m) | 17.1 (13.3 to 25.4) | 5.0 |
| Total Sprint Number (*n*) | 12.3 (9.6 to 18.1) | 3.6 |
| Peak Speed ($km{\cdot}h^{-1}$) | 5.9 (4.6 to 8.5) | 1.7 |
| PL (AU) | 6.6 (5.2 to 9.6) | 1.9 |
| **Relative measures** | | |

| | | |
|---|---|---|
| TS ($m \cdot min^{-1}$) | 5.9 (4.6 to 8.6) | 1.7 |
| LSR ($m \cdot min^{-1}$) | 6.4 (5.0 to 9.3) | 1.8 |
| HSR ($m \cdot min^{-1}$) | 13.9 (10.8 to 20.5) | 4.0 |
| TSS ($m \cdot min^{-1}$) | 18.6 (14.4 to 27.7) | 5.5 |
| Sprint Number ($n \cdot min^{-1}$) | 12.0 (9.3 to 17.6) | 3.5 |
| PL ($AU \cdot min^{-1}$) | 5.5 (4.3 to 8.0) | 1.6 |

TD = Total distance; LSRD = Low-speed running distance (≤14.4 $km \cdot h^{-1}$); HSRD = High-speed running distance (≥14.4 $km \cdot h^{-1}$); TSD = Total sprint distance (≥18 $km \cdot h^{-1}$); PL = PlayerLoad™; TS = Total speed; LSR = Low-speed running; HSR = High-speed running; TSS = Total sprint speed. CV%: coefficient of variation and 90% confidence interval; SWC%: smallest worthwhile change (0.2 x between subject standard deviation)

**DISCUSSION**

This study is the first to report on the between-match and within-match between-over variability of domestic T20 competition fast bowling using MEMS technology. The main findings of this study indicates that high-speed locomotive activity (high-speed running distance, total sprint distance and number of sprints performed) is highly variable both between-matches and within-match between-overs. In addition, when the between-match reference period was reduced in time (bowling only period), variability typically increased. These findings highlight the difficulties when interpreting high-speed locomotive match data. Comparatively, total distance and PlayerLoad™ were more stable both between- and within-match between-over. These findings indicate that changes in more global measures in match loads may be interpreted with more accuracy than high-speed locomotive measures.

The descriptive match play data presented, provide conflicting findings to the existing cricket literature that quantified movement patterns in professional cricket (30, 33). While our data show a similar proportion of total time spent sprinting (8% vs 8.5%, respectively) compared with those reported (30), we also highlight large differences in the total distance covered (5.0 km vs 8.5 km, respectively). These findings are somewhat surprising due to the similarities in sample size and playing standard, however the number of match observations in this study were far greater than those previously reported (30).

The between-match CVs for high-speed locomotive activities reported in this study are similar to those previously reported in both professional cricket (33) and other team sports, where it has been reported that high-speed running parameters elicit the highest degree of variability between-matches (9, 10, 17, 20). In contrast, total distance was the parameter that displayed the least variability, which agrees with the existing literature (33). However, these authors only provide a CV range (9-17%) and fail to distinguish between playing position and game format. Furthermore, when the between-match data is split from the whole match to the bowling only period the variability in external training load measures typically increase substantially, with the exception of PlayerLoad™·$min^{-1}$. The increased variability in external training load measures as the length of reference period decreased was an expected outcome. This is a result of the length of observation period, which in turn reflects the amount of time points included in the analysis, which are likely to stabilise when more data points are included (17).

A novel aspect of this study was the focus on within-match between-over variability. As before, our data indicates that high-speed locomotive activity was the most variable parameter. However, lower variability was observed in the more global measures of external training load, total distance and PlayerLoad™. Moreover, this observed low degree of variability in PlayerLoad™ could provide an additional consideration when quantifying external training load, further supporting earlier research (16). Considerable reductions in the degree of variability across all parameters occur when comparisons are made with between-match data. Exploration of the data in this way has the potential to exclude constraints imposed by fielding position, which may be responsible for the differences in between-match variability (18). Such findings might be of particular practical relevance for sport scientists and practitioners when attempting to quantify the competitive demands of fast bowling. Therefore, by acknowledging this information it may lead to an increased specificity when designing and planning appropriate training sessions, that aim to replicate physical performance and match demands (17, 20). Moreover, by understanding true changes in both between and within-match data, sport scientists and practitioners have the ability to effectively evaluate the demands of training within competition to highlight the effectiveness of certain performance interventions (17, 20).

The large between-match variability, specifically for high-speed running distance and total sprint distance, has important practical implications for interpreting physical match play data (17, 20). Our data supports previous findings from both cricket and other team sports (9, 10, 17, 20, 33), that high-speed locomotive activities are inconsistent between- and within-matches (17, 35). While a single match observation will provide a snap shot of that match, multiple observations from many matches are needed to accurately describe the physical demands (17, 35). Ultimately, this data provide further evidence to suggest that several repeated measures are required to identify a true change in time motion analysis parameters. Specifically, practitioners should establish CVs specific to the athlete population in consideration. In contrast to high-speed locomotive activities, total distance, low-speed running distance, peak speed and PlayerLoad™ were more stable both between-match and within-match between-over. Our data suggest that the loads obtained from these variables, may appear to allow for a more informed interpretation of competition demands, compared to high-speed locomotive activities. However, when interpreting these findings, it is important to remember that fast bowlers within the same team can experience substantially different physical demands, dependant on the team strategy employed (21) and the length of bowling spell or number of deliveries bowled.

While this study provides a baseline for comprehensive analysis of fast bowling variability in professional T20 cricket, it is important to acknowledge that there are some general limitations. We accept that the sample size and number of match observations are small. However, this is unavoidable as the number of fast bowlers competing within each match are limited. Secondly, while we acknowledge that the 5 Hz GPS embedded in our MEMS device has been shown to provide an acceptable measure of both total distance and longer distances at the slower speeds (< 18 $km \cdot h^{-1}$), these units have been reported to underestimate sprint distance and time spent sprinting (16, 17, 31, 38). Recent improvements in the sampling rate of GPS technology (10 Hz or 15 Hz; supplementing with accelerometer data) may assist in providing a more accurate reflection and variability of competition loads in the future. Finally, this study has not attempted to quantify the influence of a range of contextual factors contributing to the variability of match performance, such as opposition strength, match outcome, match location, player fitness and specific role within each match (10, 17, 35, 36).

## PRACTICAL APPLICATIONS

Understanding variability in different load characteristics enables conditioning coaches to objectively quantify training and competition demands (6, 7, 38), thus informing training prescription and recovery strategies which may facilitate performance (4) and reduce injury risk (13). This study highlights the difficulties in using high-speed running parameters for conducting analysis of T20 competition. However the between-match variability of global measures of training load (total distance and PlayerLoad™) within this cohort are relatively stable and therefore may be used to monitor load in fast bowlers during T20 cricket. Total distance may initially appear of interest given its low degree of variability, yet its importance as a sport-specific dependant variable is questionable (39) as it fails to distinguish between hard and easy matches. A possible solution to combat this might be to focus specifically on within-match between-over analysis, as the variability in all external training load variables are reduced markedly. A further consideration is to utilise PlayerLoad™, as the low degree of variability irrespective of analysis method would allow coaches and conditioning staff to be confident that this measure can accurately quantify the physical match demands. Although, the dose-response validity of PlayerLoad™ for quantifying training load in cricket players is yet to be established. Finally, researchers and practitioners should establish between- and within-match CVs specific to their athlete population in consideration.

**REFERENCES**


1. Aughey RJ. Applications of GPS technologies to field sports. *Int J Sports Physiol Perform* 6: 295-310, 2011.
2. Barrett S, Midgley A, and Lovell R. PlayerLoad: reliability, convergent validity, and influence of unit position during treadmill running. *Int J Sports Physiol Perform* 9: 945-952, 2014.
3. Barrett S, Midgley A, Towlson C, Garrett A, Portas M, and Lovell R. Within-Match PlayerLoad™ Patterns During a Simulated Soccer Match (SAFT90): Potential Implications for Unit Positioning and Fatigue Management. *International journal of sports physiology and performance*, 2015.

4. Boyd LJ, Ball K, and Aughey RJ. The reliability of MinimaxX accelerometers for measuring physical activity in Australian football. *Int J Sports Physiol Perform* 6: 311-321, 2011.
5. Boyd LJ, Ball K, and Aughey RJ. Quantifying External Load in Australian Football Matches and Training Using Accelerometers. *International Journal of Sports Physiology and Performance* 8: 44-51, 2013.
6. Cummins C, Orr R, O'Connor H, and West C. Global positioning systems (GPS) and microtechnology sensors in team sports: a systematic review. *Sports Med* 43: 1025-1042, 2013.
7. Cunniffe B, Proctor W, Baker JS, and Davies B. An evaluation of the physiological demands of elite rugby union using global positioning system tracking software. *The Journal of Strength & Conditioning Research* 23: 1195-1203, 2009.
8. Duffield R, Carney M, and Karppinen S. Physiological responses and bowling performance during repeated spells of medium-fast bowling. *J Sports Sci* 27: 27-35, 2009.
9. Gastin PB, McLean O, Spittle M, and Breed RVP. Quantification of tackling demands in professional Australian football using integrated wearable athlete tracking technology. *Journal of Science and Medicine in Sport* 16: 589-593, 2013.
10. Gregson W, Drust B, Atkinson G, and Salvo VD. Match-to-match variability of high-speed activities in premier league soccer. *Int J Sports Med* 31: 237-242, 2010.
11. Hopkins WG. Measures of reliability in sports medicine and science. *Sports Med* 30: 1-15, 2000.
12. Hopkins WG, Marshall SW, Batterham AM, and Hanin J. Progressive statistics for studies in sports medicine and exercise science. *Med Sci Sports Exerc* 41: 3-13, 2009.

13. Hulin BT, Gabbett TJ, Blanch P, Chapman P, Bailey D, and Orchard JW. Spikes in acute workload are associated with increased injury risk in elite cricket fast bowlers. *British journal of sports medicine* 48: 708-712, 2014.

14. Jennings D, Cormack S, Coutts AJ, Boyd L, and Aughey RJ. The validity and reliability of GPS units for measuring distance in team sport specific running patterns. *Int J Sports Physiol Perform* 5: 328-341, 2010.

15. Johnston RJ, Watsford ML, Austin DJ, Pine MJ, and Spurrs RW. Movement Demands and Metabolic Power Comparisons Between Elite and Subelite Australian Footballers. *Journal of strength and conditioning research / National Strength & Conditioning Association* 29: 2738-2744, 2015.

16. Johnston RJ, Watsford ML, Pine MJ, Spurrs RW, Murphy AJ, and Pruyn EC. The validity and reliability of 5-Hz global positioning system units to measure team sport movement demands. *Journal of strength and conditioning research / National Strength & Conditioning Association* 26: 758-765, 2012.

17. Kempton T, Sirotic AC, and Coutts AJ. Between match variation in professional rugby league competition. *Journal of science and medicine in sport / Sports Medicine Australia* 17: 404-407, 2014.

18. Kempton T, Sullivan C, Bilsborough JC, Cordy J, and Coutts AJ. Match-to-match variation in physical activity and technical skill measures in professional Australian Football. *Journal of science and medicine in sport / Sports Medicine Australia* 18: 109-113, 2015.

19. MCC. The Laws of Cricket, in: *http://wwwlordsorg/laws-and-spirit/laws-of-cricket/*. 2013, pp 1 - 63.

20. McLaren SJ, Weston M, Smith A, Cramb R, and Portas MD. Variability of physical performance and player match loads in professional rugby union. *Journal of science and medicine in sport / Sports Medicine Australia* 19: 493-497, 2016.
21. McNamara DJ, Gabbett TJ, Chapman P, Naughton G, and Farhart P. The validity of microsensors to automatically detect bowling events and counts in cricket fast bowlers. *Int J Sports Physiol Perform* 10: 71-75, 2015.
22. McNamara DJ, Gabbett TJ, Naughton G, Farhart P, and Chapman P. Training and competition workloads and fatigue responses of elite junior cricket players. *Int J Sports Physiol Perform* 8: 517-526, 2013.
23. Minett GM, Duffield R, Kellett A, and Portus M. Effects of mixed-method cooling on recovery of medium-fast bowling performance in hot conditions on consecutive days. *J Sports Sci* 30: 1387-1396, 2012.
24. Minett GM, Duffield R, Kellett A, and Portus M. Mixed-method pre-cooling reduces physiological demand without improving performance of medium-fast bowling in the heat. *J Sports Sci* 30: 907-915, 2012.
25. Montgomery PG, Pyne DB, and Minahan CL. The physical and physiological demands of basketball training and competition. *Int J Sports Physiol Perform* 5: 75-86, 2010.
26. Mooney MG, Cormack S, O'Brien B J, Morgan WM, and McGuigan M. Impact of neuromuscular fatigue on match exercise intensity and performance in elite Australian football. *Journal of strength and conditioning research / National Strength & Conditioning Association* 27: 166-173, 2013.
27. Orchard J, James T, Kountouris A, and Portus M. Changes to injury profile (and recommended cricket injury definitions) based on the increased frequency of Twenty20 cricket matches. *Open access journal of sports medicine* 1: 63-76, 2010.

28. Orchard JW, Blanch P, Paoloni J, Kountouris A, Sims K, Orchard JJ, and Brukner P. Fast bowling match workloads over 5–26 days and risk of injury in the following month. *Journal of Science and Medicine in Sport* 18: 26-30, 2015.

29. Orchard JW, James T, Portus M, Kountouris A, and Dennis R. Fast bowlers in cricket demonstrate up to 3- to 4-week delay between high workloads and increased risk of injury. *The American journal of sports medicine* 37: 1186-1192, 2009.

30. Petersen C, Portus DB, and Dawson MR. Quantifying positional movement patterns in Twenty20 cricket. *International Journal of Performance Analysis in Sport* 9: 165-170, 2009.

31. Petersen C, Pyne D, Portus M, and Dawson B. Validity and reliability of GPS units to monitor cricket-specific movement patterns. *Int J Sports Physiol Perform* 4: 381-393, 2009.

32. Petersen C, Pyne DB, Portus MR, Karppinen S, and Dawson B. Variability in movement patterns during One Day Internationals by a cricket fast bowler. *Int J Sports Physiol Perform* 4: 278-281, 2009.

33. Petersen CJ, Pyne D, Dawson B, Portus M, and Kellett A. Movement patterns in cricket vary by both position and game format. *J Sports Sci* 28: 45-52, 2010.

34. Petersen CJ, Pyne DB, Portus MR, and Dawson BT. Comparison of player movement patterns between 1-day and test cricket. *Journal of strength and conditioning research / National Strength & Conditioning Association* 25: 1368-1373, 2011.

35. Rampinini E, Coutts AJ, Castagna C, Sassi R, and Impellizzeri FM. Variation in top level soccer match performance. *Int J Sports Med* 28: 1018-1024, 2007.

36. Stronach BJ, Cronin JB, and Portus MR. Part 2: Mechanical and Anthropometric Factors of Fast Bowling for Cricket, and Implications for Strength and Conditioning. *Strength Cond J* 36: 53-60, 2014.

37. Vickery WM, Dascombe BJ, Baker JD, Higham DG, Spratford WA, and Duffield R. Accuracy and reliability of GPS devices for measurement of sports-specific movement patterns related to cricket, tennis, and field-based team sports. *Journal of strength and conditioning research / National Strength & Conditioning Association* 28: 1697-1705, 2014.
38. Waldron M, Twist C, Highton J, Worsfold P, and Daniels M. Movement and physiological match demands of elite rugby league using portable global positioning systems. *Journal of Sports Sciences* 29: 1223-1230, 2011.
39. Weston M, Drust B, Atkinson G, and Gregson W. Variability of soccer referees' match performances. *Int J Sports Med* 32: 190-194, 2011.
40. Witte TH and Wilson AM. Accuracy of WAAS-enabled GPS for the determination of position and speed over ground. *J Biomech* 38: 1717-1722, 2005.
41. World Medical A. World medical association declaration of helsinki: Ethical principles for medical research involving human subjects. *JAMA* 310: 2191-2194, 2013.

**ACKNOWLEDGEMENTS**

The authors would like to thank all at The Yorkshire County Cricket Club for their efforts and support during the data collection period. We would like to make a special acknowledgement to Mr William M Bray who sadly passed away while this paper was written. No external sources of funding were provided for this study.