**The influence of pre-season training loads on in-season match activities in professional Australian football players**

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ORIGINAL INVESTIGATION

TITLE: **The influence of pre-season training loads on in-season match activities in professional Australian football players**

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**Abstract**

**Objectives:** To determine the impact of pre-season training loads on in-season match activity profiles in professional Australian football (AF) players. **Methods:** Forty-four professional AF players participated in this study. Sixty-nine pre-season training and in-season match profiles were monitored using global positioning system (GPS) microtechnology and technical statistics across two seasons. Technical performance was measured as the Player Rank score provided by Champion Data. Players were matched for position and playing experience and divided into three equal training load groups based on total distance accumulated during pre-season. **Results:** Players in the high training load (HTL) group performed more relative total and high-speed distance in matches compared with the moderate (MTL; ES = 0.73-0.86) and low (LTL; ES = 0.68-1.31) training load groups, with the differences becoming greater as the season progressed. There were no clear differences in Player Rank score between groups. There were positive relationships between pre-season high-speed running and match relative distance ($p = 0.001$; $r = 0.417$; $r^2 = 0.174$) and match relative high-speed running ($p = 0.001$; $r = 0.561$; $r^2 = 0.314$), which were greatest in the HTL group. **Conclusions:** High pre-season training loads are associated with increased physical match activities, but do not appear to impact technical performance.

KEY WORDS: team sport, training, activity profiles, performance, workloads

## Introduction

Australian football (AF) is an intermittent team sport played on a large oval field with players performing frequent technical actions throughout the game (Johnston et al. 2018). Over the course of a game, players will typically cover between 11000-13500 metres at an average speed of 110-130 $m\cdot min^{-1}$ (Varley et al. 2014). However, there are periods in a game where players may be required to cover over 220 $m\cdot min^{-1}$, with up to 50% of this distance being high-speed running (Delaney et al. 2017). With this in mind, well-developed high-intensity running ability (Mooney et al. 2011) and maximal aerobic speed is vital (Dillon et al. 2017). Furthermore, whilst match running profiles are not directly linked to match outcome (Sullivan et al. 2014b), players who cover greater distances per minute and distance at high-speed, have more involvements with the football across a game (Mooney et al. 2011; Hiscock et al. 2012; Dillon et al. 2017).

Technical actions, such as, disposals, marks, effective kicks per minute of play and goal conversion rate are vital to success in AF (Sullivan et al. 2014b). Champion Data, the official statistical provider to the Australian Football League (AFL), provides a Player Rank score which is based on the number of effective and ineffective possessions for each player and shares a relationship with individual metrics: disposals ($r = 0.511$), pressure points ($r = 0.250$), effective kicks ($r = 0.190$) and marks ($r = 0.151$) per minute of match-play (Sullivan et al. 2014b). Player Rank shares small negative correlations with a number of GPS variables (Sullivan et al. 2014b), although this is dependent on position, with high speed movements appearing to have a positive effect on Player Rank in nomadic players (Bauer et al. 2015). While the relationship between technical performance and physical output during match-play is complex, it appears evident that well-developed physical and technical qualities are required to be successful in AF.

Due to the demanding nature of AF match-play, players engage in a pre-season period, lasting approximately 3 months, where high chronic training loads and practice matches are used to develop the physical and technical abilities required (Murray, Gabbett, Townshend, et al. 2017). Previous research has shown that with sufficient, but not excessive chronic loads, players can improve physical fitness and reduce injuries over the course of the pre-season period (Harrison and Johnston 2017; Murray, Gabbett, Townshend, et al. 2017). In addition to this, higher pre-season workloads reduce injury risk and increases player availability across the competitive season in professional AF players (Murray, Gabbett, Townshend 2016; Colby et al. 2017). Some players may exhibit reductions in physical capacities as the season progresses (Hrysomallis and Buttifant 2012), which could have detrimental effects on injury and performance, particularly towards the latter stages of the season, when the most important games occur (Argus et al. 2009; Colby et al. 2017). Taken together, it appears important that players are able to complete as many scheduled pre-season training sessions and accumulate moderate-to-high chronic workloads over this period in order to improve physical qualities, reduce injury risk and maintain performance over the course of the competitive season (Johnston et al. 2018).

Despite the positive effect pre-season training has on reduced in-season injury incidence, the effect pre-season training loads have on match activity profiles across a season is unclear. It would seem likely that based on the positive relationship between training load and changes in aerobic fitness (Harrison and Johnston 2017) and performance (Mooney et al. 2011), that higher pre-season loads would lead to increased match activity profiles and technical performance, but this is yet to be elucidated. Given the importance of activity profiles on increasing technical actions in AF players during competition (Mooney et al. 2011; Hiscock et al. 2012), it would appear important to see the effect pre-season loads have on match performance. The aim of this study was to determine the impact pre-season training loads have on in-season match activity profiles in professional AF players. It was hypothesised that higher workloads over the pre-season, would lead to increased match activity profiles over the competitive season.

## Methods

### *Subjects*

Forty-four professional AF players (Table 1), competing for the same AFL club participated in this study. Twenty-five players completed both the 2016 and 2017 seasons with 19 players only completing one season (2016 n = 10; 2017 n = 9), providing a total sample of 69 (2016 n = 35; 2017 n = 34) player pre-season and match workloads. In total, 3172 pre-season sessions and 910 match files were analysed. Players were required to play at least three senior AFL games to be included in the analysis, the average number of games played was 13 ± 6 in 2016 (range = 4-22) and 14 ± 6 in 2017 (range = 3-22). The 2016 pre-season commenced on the 7th November 2015 until the 19th March 2016; the 2017 pre-season commenced on 9th November 2016 until the 15th March 2017. In the 2016 season, the team won 3 and lost 19 games; in the 2017 season, the team won 5 and lost 17 games. All procedures were approved by the Australian Catholic University Human Research Ethics Committee, conforming to the *Code of Ethics of the World Medical Association* (Declaration of Helsinki).

***TABLE 1 NEAR HERE***

### *Design*

To determine the impact of pre-season training on in-season match performance, a retrospective cohort design was used. Pre-season training and in-season match profiles were monitored using global positioning system (GPS) microtechnology and technical statistics in professional AF players across the 2016 and 2017 seasons. Both pre-season periods lasted for 21 weeks, including a 2-week break over the Christmas period; the in-season periods lasted for 23 weeks. Players were grouped into positions (fixed and nomadic) before being divided into low (LTL; n = 22; AFL games = 50 ± 54; match files = 265), moderate (MTL; n = 23; AFL games = 47 ± 49; match files = 321) and high (HTL; n = 23; AFL games = 47 ± 54; match files = 324) training load groups based on total distance accumulated over the pre-season. Pre-season training involved all field-based training sessions and trial matches up to the Monday prior to the first competitive fixture.

### *Methodology*

Training and match workloads were assessed using microtechnology devices containing a 10 Hz GPS chip and a 100 Hz tri-axial accelerometer and gyroscope (Optimeye S5, Catapult Innovations, Melbourne, Australia). Prior to each training session and match, players were fitted with a microtechnology device. Players were allocated a unit at the start of the season which remained consistent across all matches and training sessions. Units were turned on approximately 20 minutes prior to the start of each training session or match warm-up. During training, the units were worn in a vest provided by the manufacturer, worn under the players training jersey. In matches, the unit was placed within a specifically designed pouch on the playing jerseys. In both training and competition, the unit was positioned on the centre of the back between the shoulder blades. After each session, the GPS files were downloaded to a computer using proprietary software (Openfield v1.15.0, Catapult Innovations, Melbourne, Australia). Only movements that formed the scheduled, field-based training sessions were included in the analysis. During matches, non-playing minutes (i.e. bench time) were omitted from the analysis. Data were categorised into low- (0-4.9 $m \cdot s^{-1}$), and high-speed ($\geq$5.0 $m \cdot s^{-1}$) movement bands (Wisbey et al. 2010; Murray, Gabbett, Townshend 2017). PlayerLoad™ per metre was also used in the analysis, which is the square root of the sum of instantaneous accelerations in all three vectors (Boyd et al. 2011) divided by total distance, as a measure of movement efficiency (Barrett et al. 2016). All variables were also considered relative to match or training time. The units utilised in this study have been shown to have acceptable accuracy for reporting total distances and high-speed distances in team sport players (Varley et al. 2012).

Player Rank scores were gathered for each game over the 2016 and 2017 seasons using Champion Data (Champion Data, Victoria, Australia), the official statistical partner for the AFL. The ranking score is calculated based on the effectiveness of an individual's skill involvements over the course of a game, with each involvement assigned a positive or negative score depending on the outcome. The score provides an objective, global ranking for each player's skill involvements over the course of the game and has been previously used in the literature (Sullivan et al. 2014b; Graham et al. 2017).

***Statistical Analysis***

To determine the impact of pre-season load on match activity profiles, traditional null hypothesis testing and magnitude based inferences were used. A MANOVA (SPSS 22.0, SPSS Inc, Chicago, IL, USA) was used to determine the differences in pre-season training loads between groups. Differences between training load groups and match activities were assessed by linear mixed models with fixed effects of stage of season (early: matches 1-8; mid: matches

9-15; late: matches 17-22) and training load group (high, moderate and low) and random effects of player identity included in each model. Separate models were built for selected GPS metrics: relative distance, relative high-speed distance, PlayerLoad$^{TM}$ per metre per minute, and Player Rank. In addition, magnitude based inferences were used to assess the meaningfulness of any differences (Hopkins et al. 2009). Firstly, the likelihood that changes in the dependent variables were greater than the smallest worthwhile change was calculated as a small effect size of 0.20 x between subject standard deviation. Based on 90% confidence intervals, the thresholds used for assigning qualitative terms to chances were as follows: <1% almost certainly not; <5% very unlikely; <25% unlikely; <50% possibly not; >50% possibly; >75% likely; >95% very likely; >99% almost certain. The magnitude of difference was considered practically meaningful when the likelihood was ≥75%. Secondly, magnitudes of change in the dependent variables were assessed using Cohen's effect size (ES) statistic and their 90% confidence intervals. Effect sizes (ES) of 0.20-0.59, 0.60-1.19, and ≥1.20 were considered small, moderate and large respectively (Hopkins et al. 2009).

To assess the relationships between pre-season loads and in-season match activities, multiple linear regressions were used. Firstly, Pearson's correlation coefficients (r) were used to determine the relationship between variables and to determine collinearity of independent variables. Correlations of 0.10-0.29, 0.30-0.49, 0.50-0.69, 0.70-0.89 and ≥ 0.90 were considered small, moderate, large, very large, and nearly perfect (Hopkins et al. 2009). Hierarchical linear regressions were performed for each training load group using the most closely related predictor variables to match activities ($m \cdot min^{-1}$, high-speed m·min$^{-}$1, and PlayerLoad™/m) from the correlation matrix. Predictor variables with a relationship of >0.9 were removed from the regression due to collinearity. The strongest correlated variable was entered into the first block and subsequent variables entered into the second block. For each model, the Durbin-Watson statistic was used to determine the assumption that errors are independent and variance inflation factor was used to further detect collinearity between predictor variables (Field 2009). Data are reported as means ± standard deviation (SD); the significance level was set at $p<0.05$.

## Results

### *Training loads*

There were no significant differences in match experience between groups ($p = 0.887$; ES = -0.09 to 0.07). There were significantly greater pre-season training loads in the HTL group compared with the LTL ($p = 0.001$; ES = 1.14-1.67) and MTL ($p = 0.001$; ES = 0.75-1.32) groups for all training load variables. There were moderate to large differences in training load variables between MTL and LTL groups ($p = 0.001$; ES = 0.65-1.48; Table 2).

***TABLE 2 NEAR HERE***

### *Match profiles*

Across the season, greater relative distance was seen in the HTL group compared with the MTL ($p = 0.029$; ES = moderate; 0.78 ± 0.50) and LTL groups ($p = 0.053$; ES = moderate; 0.99 ± 0.51). Relative high-speed distance was also greater in the HTL group compared to the MTL ($p = 0.122$; ES = moderate; 0.93 ± 0.50) and LTL groups ($p = 0.064$; ES = moderate; 1.03 ± 0.52) during matches. There were unclear differences in relative distance ($p = 0.998$ ES = small 0.34 ± 0.49) and high-speed distance ($p = 0.593$; ES = small; 0.25 ± 0.49) between MTL and LTL groups. Despite greater relative distances, the HTL group accumulated less relative PlayerLoad™ per metre compared to the MTL ($p = 0.04$; ES = moderate; -0.89 ± 0.46) and

LTL groups (p = 0.01; ES = moderate; -0.96 ± 0.47). There was no clear difference in Player Rank scores (p = 0.445; ES = -0.15 to 0.32) between groups.

***FIGURE 1 NEAR HERE***

Across each stage of the season, the HTL group had *moderately* greater relative distance (ES = 0.70-0.75) and high-speed distance (ES = 0.83-0.91) compared with the MTL group (Figure 1A). Compared to the LTL group, the HTL group showed *moderate* to *large* greater relative distance (ES = 0.68-1.02) and high-speed running (ES = 0.91-1.31; Figure 1B). The HTL group had lower (*small* to *moderate*) relative PlayerLoad™ per metre in the early (ES: LTL = -0.72 ± 0.56; MTL = -0.54 ± 0.54), middle (ES: LTL -1.02 ± 0.54; MTL -0.48 ± 0.50), and late (ES: LTL -1.03 ± 0.60; MTL -0.49 ± 0.53) stages of the season (Figure 1A and 1B). There were little differences in match profiles between the MTL and LTL groups at any stage of the season (Figure 1C), other than, greater relative high-speed distance in the late stage of the season in the MTL group (ES = small; 0.53 ± 0.57).

Changes in relative distance, high-speed distance, PlayerLoad™ per metre and Player Ranking over the early, middle and late stages of the season are shown in Figure 2. There was little change in relative distance (Figure 2A) from early season in any group, with *small* but unclear increases in relative distance from early to middle (ES = 0.28 ± 0.50; Possibly, 60%) and early to late season (ES = 0.24 ± 0.53; Possibly, 55%) in the HTL group, *trivial* differences in the LTL (ES = 0.02 and -0.07) and *small* and *trivial* differences in the MTL (ES = 0.26 and 0.14) group (Figure 1A). In the HTL group, relative high-speed distance showed *small* increases in the middle (ES = 0.34 ± 0.51; Possibly, 67%) and *moderate* increases in the late (ES = 0.62 ±

0.51; Likely, 91%) stages of the season. There were only *trivial* and *small* unclear changes in relative high-speed distance in the LTL (ES = -0.06 to 0.11) or MTL (ES = 0.14 to 0.26) groups across the season (Figure 1B). There was also no change in PlayerLoad™ per metre from early season in the HTL (ES = 0.13 ± 0.52; 0.25± 0.55) or MTL groups (ES = 0.08 ± 0.55; -0.12 ± 0.56). There was however a *small* reduction in middle (ES = -0.35 ± 0.61; Possibly ,67%) and late (ES = -0.47 ± 0.57; Likely, 79%) season in the LTL group (Figure 1D). There were no clear changes in Player Ranking other than a *small* increase in the HTL group in the middle stage of the season compared to the early stage (Figure 1D: HTL ES: Middle = 0.42; Late = 0.10; MTL ES: Middle = 0.06; Late = 0.03; LTL ES: Middle = 0.13, Late = -0.14).

***FIGURE 2 NEAR HERE***

***Pre-season and in-season relationships***

Across all players, high-speed distance was the only predictor of match relative distance (r = 0.417; p = 0.001) and relative high-speed distance (r = 0.560; p = 0.001), explaining 17% and 31% of these match variables, respectively.

For match relative high-speed distance, there was a significant effect of pre-season high-speed distance for the HTL group, explaining 35% (r = 0.591; p = 0.001); but non-significant associations for the MTL (r = 0.322; p = 0.013) and LTL groups (r = 0.355; p = 0.011), explaining 10% and 12% of match high-speed running respectively. For relative match distance, pre-season high-speed distance was only a significant predictor for the HTL group (r = 0.374; p = 0.003), explaining 14% of match relative distance.

## Discussion

This study aimed to investigate the influence of pre-season load on match activities in a group of professional AF players. The results of this study show that players who accumulate more pre-season training load have greater physical match activities, but no difference in skill related match performance compared to players with lower pre-season loads. The relationships between pre-season load and match high-speed running is greatest in players who accumulated high pre-season workloads, highlighting the need for players to complete the majority of pre-season (>90%). In addition, players with higher training load showed increases in physical match activities as the season progressed. Collectively, to maximise player work-rates during match-play that can be sustained across the competitive season, players must accumulate high chronic loads during the pre-season period.

This study shows that high pre-season loads lead to increased physical match activity profiles through relative total and high-speed distance. Previously, AF studies have shown that players who accumulate high pre-season loads have fewer in-season injuries (Colby et al. 2017) and are available for more games and training sessions (Murray, Gabbett, Townshend 2016). Higher pre-season loads are associated with greater increases in fitness across the pre-season period (Harrison and Johnston 2017), leading to increased high-speed running during match-play (Mooney et al. 2011; Mooney, Cormack, O'Brien, et al. 2013). Although increased match activity profiles are not directly linked to team success, they do appear to play a role. Increases in high-speed running results in more technical involvements (Mooney et al. 2011; Hiscock et al. 2012; Dillon et al. 2017) and in some (Mooney et al. 2011; Bauer et al. 2015), but not all instances (Sullivan et al. 2014b), increased coaches ratings of performance. Some studies have shown that relative distance is greater during matches won and against stronger opposition (Black et al. 2017; Ryan et al. 2017), although this is not always the case (Sullivan et al. 2014a).

During a winning quarter, players have higher work-rates when not in possession of the football (Sullivan et al. 2014a). Therefore, having the capacity to elevate work rates is important. Maximising participation in pre-season training, through gradual increases in workloads, is likely to minimise injury risk (Murray, Gabbett, Townshend, et al. 2016; Colby et al. 2017), increase fitness (Harrison and Johnston 2017), and increase player work-rates during competition.

The influence of pre-season load on match activities was greatest in the HTL group, with very large relationships shared between match activities and pre-season high-speed distances. Given that only very large associations were seen in the HTL group suggests that players need a high volume of training, in order to see the benefits of pre-season across the entire 7-month competitive period. Although large volumes are required to induce improvements in fitness, the only significant predictor of in-game match activities was the proportion of pre-season loads accumulated at high-speeds demonstrates the need for a certain amount of training at high intensities (Castagna et al. 2013). Due to collinearity, there were a number of training load variables that were not included in the model, although they are likely to have had some effect on match activities. In addition, internal load was not assessed in the current study and is clearly vital in determining the training response and adaptations (Delaney et al. 2018), this warrant further investigation. Based on the current findings, players should be exposed to an adequate amount of training volume and intensity. In the present study, ~19% of total pre-season distance was spent at high-speeds in the high training load group, with a range of 25-18%.

The greatest changes in match activities as the season progressed were seen in the HTL group with smaller increases in the MTL group, and no change in the LTL group (Figure 2). This suggests a minimum amount of training is required to see a positive effect of pre-season across the prolonged competitive period. Whilst fitness was not assessed in the current study, pre-season fitness has been shown to positively influence performance (Gastin et al. 2013) and players with lower pre-season training load likely had smaller changes in fitness (Harrison and Johnston 2017), which were not high enough to sustain performance across a 7 month competitive period. Firstly, lower fitness levels are associated with higher post-match fatigue and muscle damage (Hunkin et al. 2014; Johnston, Gabbett, Jenkins, et al. 2015); over a season, this may cause increased cumulative fatigue which can reduce activity profiles (Johnston et al. 2013; Mooney, Cormack, O'Brien B, et al. 2013; Johnston, Gabbett, Jenkins 2015). Secondly, reductions in physical qualities have been observed over the season (Hrysomallis and Buttifant 2012); therefore, commencing the season with a lower chronic load may mean players are unable to cope with increased match demands as the season progresses (Ryan et al. 2017), or during finals matches (Aughey 2011). Collectively, these results show that pre-season influences match activity profiles, which becomes more important as the season progresses. Players who only accumulate moderate or low training loads do not see positive effects on match activity profiles; these players may benefit from additional physical training in the early stages of the competitive season.

The higher relative PlayerLoad™ per metre values seen in the MTL and LTL groups during matches, may suggest lower locomotor efficiency (or a disparity in how they accumulate load), with these players potentially becoming more fatigued during matches (Barrett et al. 2016). Whilst speculative, this increase may be due to reductions in stride length and concomitant increases in stride frequency and mediolateral (Le Bris et al. 2006) movement as players become fatigued. However, inferences of lower limb activity from an accelerometer positioned at the shoulders should be made with caution (Barrett et al. 2014). Further research should be conducted to ascertain the relationship between movement efficiency, physical capacity and PlayerLoad$^{TM}$. Potentially, high training loads result in improved movement efficiency seen through reductions in accelerometer load per metre.

The influence of pre-season loads explains a large proportion of match high-speed running, with increases in the HTL group as the season progresses. Players need to accumulate high loads to see the benefit of pre-season across the entire season. Despite this, there are some limitations to this study that are worth noting and areas for future research. There was no consistent measure of fitness between the two seasons that could be included in the analysis, so it is difficult to determine the true positive effect of training between groups. Only field based sessions were used as pre-season load and players may have accumulated large load during *off-feet* conditioning that could have influenced the findings. In addition, the reason for different loads between players was not considered; some players missed training through injury, whereas others were managed due to age. Notwithstanding this, the clear difference in match profiles between groups, highlights the positive impact pre-season can have. The study was conducted in just one club who finished towards the bottom of the ladder in both seasons, meaning the results may not reflect more successful teams. The lack of relationship between skill profiles and pre-season loads warrants further research. Quantifying the nature of skills training and skill involvements in players and the impact that has on in-match skill profiles.

**Practical Implications**

In order to increase high-speed running during matches, players must accumulate high training loads during pre-season training. Coaching staff must develop training programs that maximise a player’s ability to participate in as much of pre-season training as possible through careful planning of loads and monitoring of individual responses to training. Players who miss large amounts of pre-season may need to have their pre-season extended into the in-season period until comparable running loads compared to the rest of the squad during the pre-season period.

**What are the main findings?**

- Players with higher pre-season training loads cover more distance and high-speed distance per minute of play during in-season matches
- The greatest increases in match intensities are seen in players with the greatest pre-season workloads
- Pre-season training has a positive influence on match activities throughout the season which is greatest in players with high pre-season training loads

**Disclosure Statement**

The authors would like to thank the players and club for participating in this study. The authors report no conflicts of interest with the findings of this study.

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**Figure Legends**

Figure 1. Effect size differences and 90% confidence intervals for differences in match physical and technical profiles for (A) high *vs.* moderate training load groups; (B) high *vs.* low training load groups and (C) moderate *vs.* low training load groups. ES of 0.20-0.59, 0.60-1.19, and ≥1.20 were considered small, moderate and large, respectively. Early season = matches 1-8, mid-season = matches 9-15, and late season = matches 17-22. All variables are expressed relative to playing time.

Figure 2. Physical activity profiles for (A) relative distance (B) relative high-speed distance (C) PlayerLoad$^{TM}$ per metre and (D) relative Player Ranking score in the three training load groups during the early, middle, and late stages of the season. *M* = Moderate, *S* = Small effect size differences; subscript letters, $_e$ = early season. ES of 0.20-0.59, 0.60-1.19, and ≥1.20 were considered small, moderate and large, respectively. Early season = matches 1-8, mid-season = matches 9-15, and late season = matches 17-22.

## Tables

Table 1. Player characteristics of all players at the beginning of the 2016 and 2017 seasons.

| Season | AFL matches | Age (years) | Height (cm) | Weight (kg) |
|---|---|---|---|---|
| 2016 | 53.9 ± 47.4 | 22.5 ± 3.2 | 189.3 ± 7.9 | 89.5 ± 8.4 |
| 2017 | 48.1 ± 46.7 | 22.8 ± 3.1 | 189.4 ± 7.4 | 89.1 ± 8.0 |

Table 2. Total pre-season loads for high, moderate and low training load groups based on total pre-season distance.†

| | AFL matches | Training time (min) | Sessions trained (%) | Distance (km) | HSR (km) | HSR (%) | PlayerLoad$^{TM}$ (AU) |
|---|---|---|---|---|---|---|---|
| High Load | 47 ± 54 | 3545 ± 482 $^{Ll,Mm}$ | 90 ± 6 $^{Ll, Lm}$ | 365 ± 38 $^{Ll, Lm}$ | 69 ± 14 $^{Ll, Mm}$ | 19 ± 3 $^{Ml,Mm}$ | 32981 ± 4063 $^{Ll, Mm}$ |
| Moderate Load | 47 ± 49 | 3070 ± 623 $^{Ll}$ | 81 ± 7 $^{Ml}$ | 307 ± 63 $^{Ll}$ | 53 ± 16 $^{Ll}$ | 17 ± 4 | 28251 ± 6010 $^{Ll}$ |
| Low Load | 50 ± 54 | 2145 ± 588 | 67 ± 15 | 224 ± 55 | 35 ± 12 | 15 ± 3 | 20105 ± 5292 |

All data are mean ± SD. AFL = Australian Football League HSR = high-speed running. $^{Mm}$ = moderate effect size (ES) difference to moderate group; $^{Lm}$ = large ES difference to moderate group; $^{Ml}$ = moderate ES difference to low group; $^{Ll}$ = large effect size difference to low group. ES of 0.20-0.59, 0.60-1.19, and ≥1.20 were considered small, moderate and large, respectively.

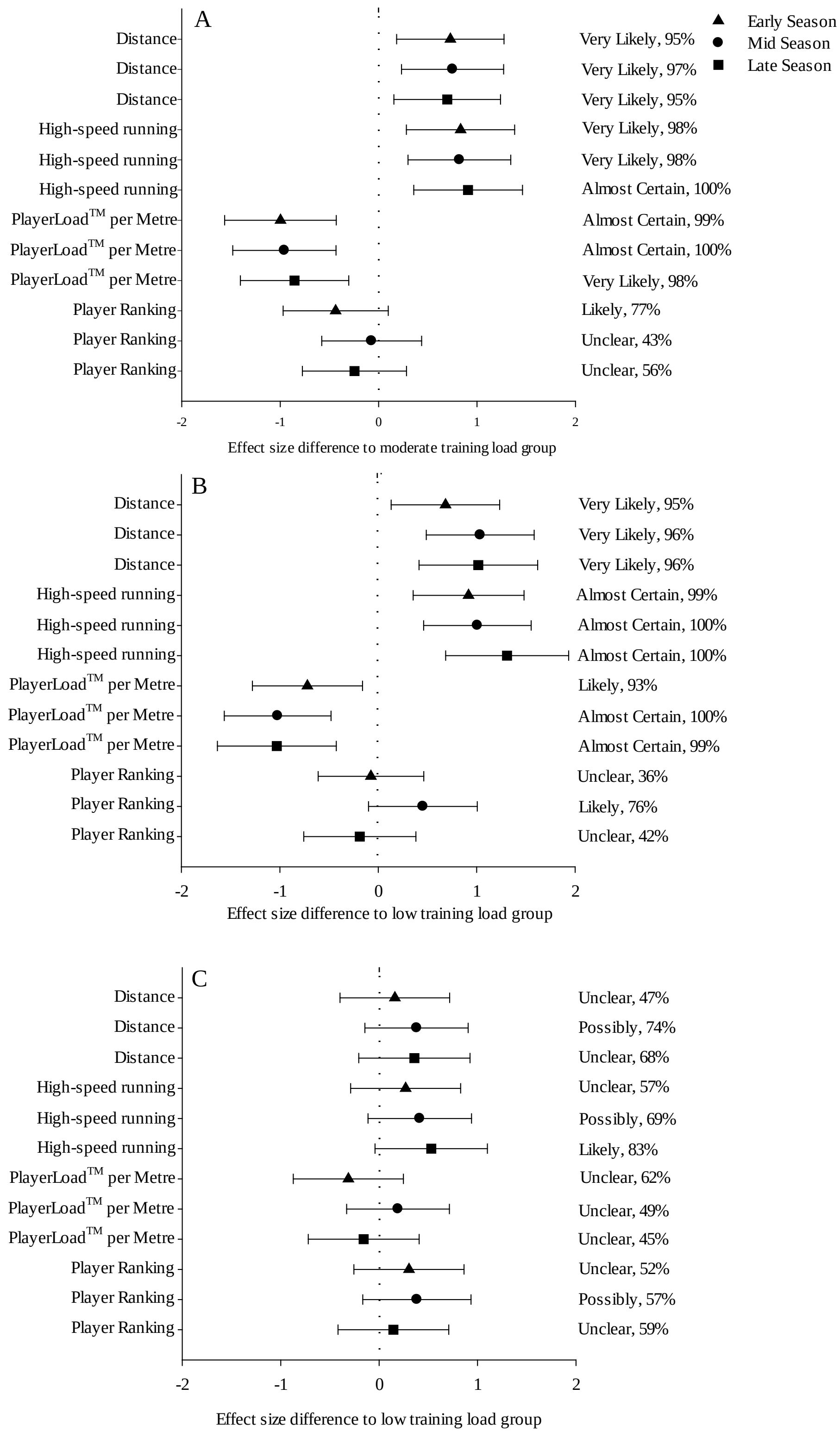
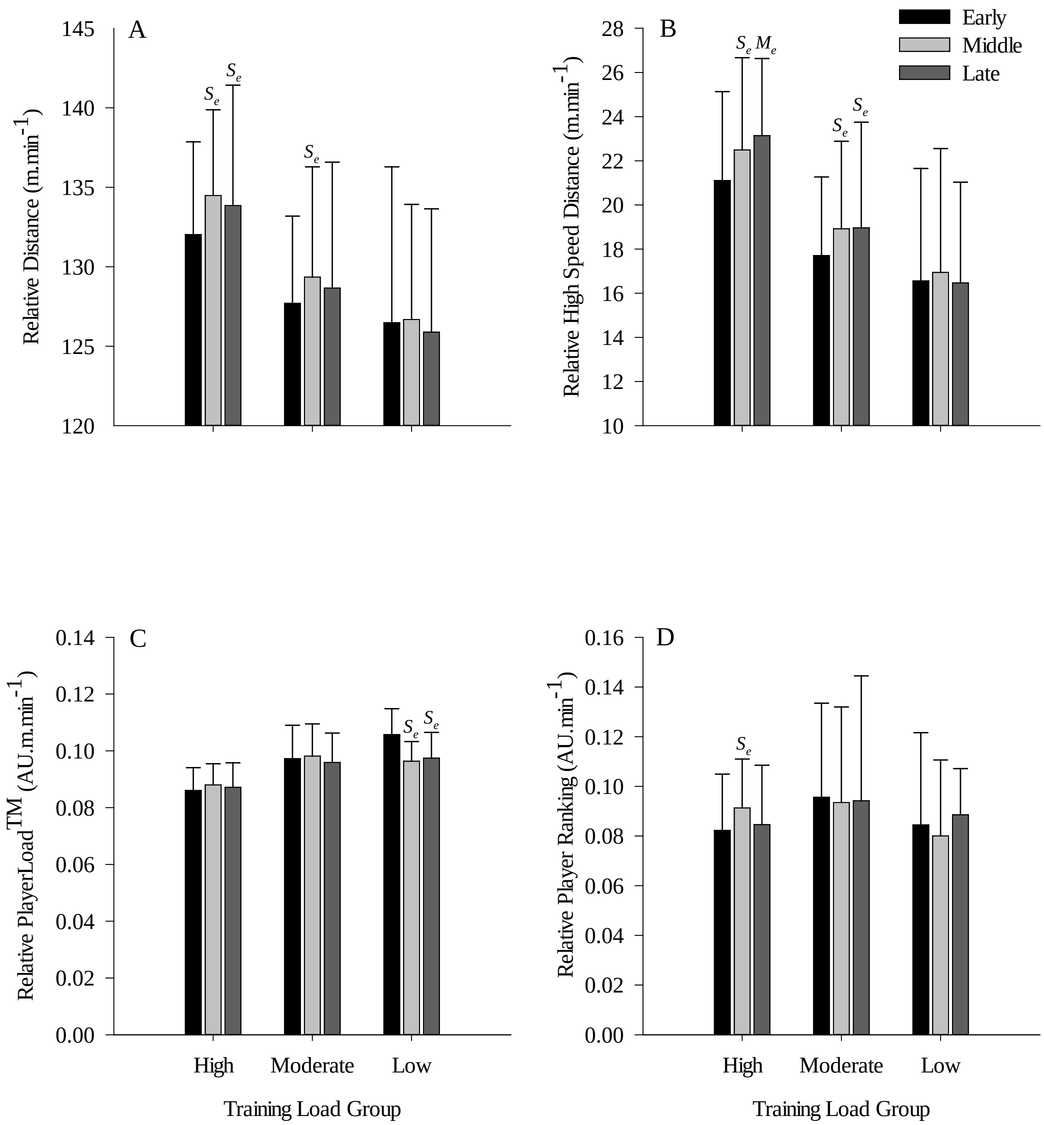

A
Distance
Distance
Distance
High-speed running
High-speed running
High-speed running
PlayerLoad™ per Metre
PlayerLoad™ per Metre
PlayerLoad™ per Metre
Player Ranking
Player Ranking
Player Ranking
Very Likely, 95%
Very Likely, 97%
Very Likely, 95%
Very Likely, 98%
Very Likely, 98%
Almost Certain, 100%
Almost Certain, 99%
Almost Certain, 100%
Very Likely, 98%
Likely, 77%
Unclear, 43%
Unclear, 56%
Early Season
Mid Season
Late Season
-2
-1
0
1
2
Effect size difference to moderate training load group
B
Distance
Distance
Distance
High-speed running
High-speed running
High-speed running
PlayerLoad™ per Metre
PlayerLoad™ per Metre
PlayerLoad™ per Metre
Player Ranking
Player Ranking
Player Ranking
Very Likely, 95%
Very Likely, 96%
Very Likely, 96%
Almost Certain, 99%
Almost Certain, 100%
Almost Certain, 100%
Likely, 93%
Almost Certain, 100%
Almost Certain, 99%
Unclear, 36%
Likely, 76%
Unclear, 42%
-2
-1
0
1
2
Effect size difference to low training load group
C
Distance
Distance
Distance
High-speed running
High-speed running
High-speed running
PlayerLoad™ per Metre
PlayerLoad™ per Metre
PlayerLoad™ per Metre
Player Ranking
Player Ranking
Player Ranking
Unclear, 47%
Possibly, 74%
Unclear, 68%
Unclear, 57%
Possibly, 69%
Likely, 83%
Unclear, 62%
Unclear, 49%
Unclear, 45%
Unclear, 52%
Possibly, 57%
Unclear, 59%
-2
-1
0
1
2
Effect size difference to low training load group

Figure 1



A
B
C
D
Early
Middle
Late
Relative Distance (m.min-1)
Relative High Speed Distance (m.min-1)
Relative PlayerLoadTM (AU.m.min-1)
Relative Player Ranking (AU.min-1)
145
140
135
130
125
120
28
26
24
22
20
18
16
14
12
10
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
0.16
Se
Me
High
Moderate
Low
Training Load Group


Figure 2