Evaluating strategic periodisation in team sport

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Abstract

The planned peaking for matches or events of perceived greatest priority or difficulty throughout a competitive season is commonplace in high-level team sports. Despite this prevalence in the field, little research exists on the practice. This study aimed to provide a framework for strategic periodisation which team sport organisations can use to evaluate the efficacy of such plans. Data relating to factors potentially influencing the difficulty of matches were obtained for games played in the 2014 Australian Football League season. These included the match location, opposition rank, between-match break and team ‘form’. Binary logistic regression models were developed to determine the level of association between these factors and match outcome (win/loss). Models were constructed using ‘fixed’ factors available to clubs prior to commencement of the season, and then also ‘dynamic’ factors obtained at monthly intervals throughout the in-season period. The influence of playing away from home on match difficulty became stronger as the season progressed, whilst the opposition rank from the preceding season was the strongest indicator of difficulty across all models. The approaches demonstrated in this paper can be used practically to evaluate both the long and short term efficacy of strategic periodisation plans in team sports as well as inform and influence coach programming.

Key words:

Match difficulty, performance analysis, training, Australian Rules football, logistic regression

Introduction

In team sports, strategic periodisation can be defined as the intentional peaking for matches or events of perceived greatest priority or difficulty throughout a competitive season (Robertson & Joyce, 2015). In practical terms, this typically consists of the deliberate manipulation of training volumes and intensities over a discrete time period in order to optimise athlete preparedness for an upcoming competition schedule. Given the myriad of factors that can influence athlete preparedness, effective implementation of strategic periodisation is seen as a useful tool in managing the heavy travel schedule, fatigue and injuries that often accompany a competitive team sport season. Despite anecdotal evidence of widespread use in many team sports, strategic periodisation has experienced limited attention to date in the literature, with single examples from rugby league and union (Kelly & Coutts, 2007; Robertson & Joyce, 2015 for respective instances).

A number of key advancements are therefore important to develop in order to further improve the specificity and validity of this practice. Obtaining evidence relating to the influence certain factors exert on team performance presents a pragmatic initial approach. By obtaining such evidence, the design of strategic periodisation plans could then be informed and subsequently evaluated based on their ability to account for these factors. Of relevance, previous work by Robertson & Joyce (2015) proposed a match difficulty index (MDI) for use in informing strategic periodisation (initially defined as 'tactical periodisation') for elite rugby union. The index assigned individual weightings to a range of factors based on their influence in determining the difficulty of matches. These weightings were each determined retrospectively by assessing their influence on match outcome during a known season schedule. Examples included both fixed (those factors set prior to the start of the season) and dynamic (those which are subject to change throughout the in-season) factors. Previously reported examples of fixed factors include the number of days between matches (Moreira, Kempton, Saldanha Aoki, Sirotic, & Coutts, 2015), match location (Clarke, 2005; Hugh, 2006), and previous season rankings of opposing sides (Kelly & Coutts, 2007), whilst the opposition team rank at a given point of the season has been used as a dynamic factor influencing the difficulty of an upcoming match (Robertson & Joyce, 2015).

However, a number of other quantifiable factors may also warrant consideration when developing strategic periodisation plans. Specifically, rather than solely considering opposition ranking, the difference in ladder position between the two teams could be considered as it may provide a greater insight into the difficulty of an upcoming match. Components relating to team dynamics may also be relevant, such as the number of first year 'rookie' players competing, and the number of changes to team selection from preceding matches. Further, the performance of a team over a given time period preceding the match of interest (colloquially known as 'form') may also be of interest. Form (also referred to as 'momentum') may potentially be associated with the difficulty of a match, based on the notion that a preceding series of wins or losses by a team provides some influence over the likely outcome of future matches. However the influence of form on sporting outcomes (as well as confirmation of its very existence) has not reached agreement in the research to date (Arkes & Martinze, 2011; Bar-Eli, Avugos & Raab, 2006; Vergin, 2000). Factors shown as influential in previous related research could also be considered, such as the crowd size (Nevill & Holder, 1999; Nevill, Newell & Gale, 1996), altitude at which the match is played (McSharry, 2007) and combined experience levels of the team/s (McLean, Coutts, Kelly, McGuigan & Cormack, 2010).

In informing the strategic periodisation plan, it is of practical use to determine whether the influence of these factors on match difficulty displays meaningful variation throughout different stages of a competitive schedule. For instance, in the abovementioned example from rugby, a 'short' number of turnaround days between matches did not meaningfully contribute to match difficulty for teams when compared to a normal or longer break (Robertson & Joyce, 2015). This is somewhat surprising, given the mixed findings shown relating to such factors in previous literature in other sports (Fowler, Duffield, Waterson & Vaile, 2015; Smith, Efron, Mah & Malhotra, 2013). However, it is possible that different factors may exert an accumulation effect as the season progresses, which may not be evident when analysing the season as a single time period. For instance, by analysing the influence of turnaround days between matches at incremental (i.e., monthly) stages during the season, its influence may alter as the year progresses. Or for example, the difficulty of playing matches away from home may increase as the season progresses, due to the fatigue and injuries that are accumulated by many teams over this period (Heisterberg, Fahrenkrug, Krustrup, Storskov, Kjær, & Andersen, 2013; Silva, Rebelo, Marques, Pereira, Seabra, Ascensão, & Magalhães, 2013).

Despite only limited scientific support, it is evident that elite Australian Rules football (AF) teams utilise strategic periodisation as part of their macro and micro planning (McNicol, 2014). In particular, AF differs to previously investigated sports in the literature with respect to areas such as fixture, travel requirements and season length (Bilton, 2015). For instance, in the elite Australian Football League (AFL), teams do not play each other an equal number of times within a season and also face unequal amounts of interstate travel each year. Consequently, AF represents an especially appropriate team sport in which to investigate strategic periodisation further.

Using previous work as a starting point, this study aimed to develop a match difficulty index for use in strategic periodisation for elite AF. Primarily, this was undertaken by quantifying the influence of various fixed and dynamic factors on match difficulty at monthly time points throughout an AFL season. It was hypothesised that these factors would fluctuate with respect to their influence on match difficulty at each of these stages. This would provide further supporting evidence of the dynamic nature of the competitive team sport season and as a result, its inclusion in any strategic periodisation framework.

Methods

Data Collection and Analysis

Data was collected from a total of 198 regular season games played during the 2014 AFL regular season. This included one drawn match, which was removed from all analyses. A range of fixed (n = 3) and dynamic (n = 6) factors relating to each match were recorded for initial consideration in the MDI. Table I provides a list of each of these along with their corresponding operational definitions. All data was obtained from either open access sources (www.afl.com.au/stats) or directly from Champion Data (Champion Data Pty Ltd, Melbourne, Australia). Prior to analysis of the data, ethics clearance to conduct the study was granted by the relevant institutional Human Research Ethics Committee.

Pre-season MDI

Analyses were undertaken considering the data from two different time periods. The first MDI incorporated only factors available prior to the commencement of the AFL season (the pre-season) and included all 198 games. These fixed factors were opposition rank – previous year, match location and between-match break; as per those considered previously by Robertson & Joyce (2015) in Super Rugby.

****INSERT TABLE I ABOUT HERE****

In-season MDI

The second analysis incorporated six dynamic factors (obtained whilst the regular season was in progress) in addition to those from the pre-season analysis. Specifically, MDIs were developed following the final AFL match played in each period ending by April, May, June and July and the end of the season. This resulted in a total of 45, 81, 117, 153 and all 197 matches included in each sample respectively, thereby allowing for examination into whether the influence of each factor varied as the season progressed. The factors included opposition rank – current year (the opposition team's ladder position at the time of the match), the difference in ladder position (between the two teams at the time of match), the number of team changes from one match to the next and the number of first year players selected in the side. A further dynamic factor, 'team form' was also included. This metric was considered as the performance of a team over a *k*-week period preceding the match of interest. In specifically defining this factor, eight separate approaches were trialled in the modelling (further information is provided below). The first included considering the number of wins recorded by the team in the preceding weeks before a given match; whereby the last 3, 4, 5 and 6 matches were considered as separate scenarios in the analysis (n = 4). In place of the number of wins, the sum of the team margins was also trialled over the same four different time periods (n = 4). For example, if a team recorded match margins of 45, -13 & 12 points over a three week period, then their form margin would be deemed to be 44 points.

Statistical Analysis

Descriptive statistics (mean ± s) for each of the factors and match outcome were calculated for each club for all 197 games included from the 2014 AFL season. For the pre-season MDI, binary logistic regression was used to develop a linear probability model using the three fixed factors, with the dependent variable of match outcome set as WIN = 1 and LOSS = 0. All assumptions relating to the use of this statistical approach were met. Odds ratios (OR) and corresponding 95% confidence intervals (95% CI) were outputted in order to provide a standardised measure of the influence of each factor included in the models. Performance of each model was evaluated as the percentage of match outcomes correctly classified. In implementing a logistic regression approach, an assumption of independence between matches was assumed. In addition to the definition shown in Table I, between-match break was also considered as the difference between games as a day differential between the two opposing teams as part of the modelling process. A 'normal' between-match break was assumed for each team to start the season, in order to allow for the inclusion of Round One matches.

For the in-season MDIs, additional logistic regression models were run at each of the five abovementioned stages of the in-season period. In addition to the three fixed factors, these models also included the six dynamic factors. Each model was run following the completion of the final game of each calendar month during the regular season, meaning that separate models were generated for April (Round 6), May (Round 11), June (Round 15) & July (Round 19). For this process, preliminary models were constructed considering the factor 'team form' in each of the eight abovementioned formats. The format by which the factor most improved the model (with respect to overall classification accuracy) was selected for use in the final version.

Outputted predicted probabilities from all models run were then used to determine separate MDI values for all matches included in the sample. This was undertaken by subtracting the logit probability value of WIN from 1 and then multiplying by 10. The resulting outputs provided values for the MDI, thereby utilising a scale reported in arbitrary units between 0 and 10. All analyses were undertaken using SPSS V20 (Armonk, NY: IBM Corp) and level of significance was accepted at $P \leq 0.05$, unless otherwise indicated.

Results

Results from the pre-season as well as the fifth and final in-season model are reported in Table II. The pre-season model revealed that opposition rank - previous year was the strongest indicator of match difficulty, whilst the match location also exerted a meaningful influence. Specifically, matches played away but intra-state were more difficult than home games (OR ± 95%CI = 0.61 [0.34, 1.12]), whereas interstate away matches were harder still (OR = 0.53 [0.33, 0.86]).

****INSERT TABLE II ABOUT HERE****

In defining team form, preliminary modelling revealed that the number of matches won by a team over the past four attempts represented the most appropriate definition for use in this context (based on its relative increase in model classification accuracy). Thus, this definition was used in all five models. Figure 1 shows the changes in odds ratios for each of the fixed factors at the five defined stages of the season. For instance, the influence of opposition rank – previous year on match difficulty remains a relatively constant, positive influence on match difficulty throughout the models. However the odds ratios associated with playing away from home drop substantially below 1.0 as the season progresses, suggesting that matches played away from home (both inter- and intra-state) later in the season are linked with increased match difficulty in the AFL for this particular season. Figure 2 shows the changes in odds ratios throughout the season for the six dynamic factors. Notably, team form contributes strongly to all in-season models, thereby confirming its importance in defining match difficulty throughout the competitive period.

****INSERT FIGURES 1 & 2 ABOUT HERE****

Full results from the fifth and final in-season model (including the logistic regression output) are shown in Table II. As discussed, team form as well as the difference in ladder position meaningfully contributed. Specifically, for each game won by a team over a four-week period equated to a meaningful decrease in match difficulty (OR = 1.35 [1.06, 1.73]). Further, each positional difference in ladder positions between opposing sides resulted in a small decrease in match difficulty (Table II). With respect to performance, the pre-season model reported a classification accuracy of 65.5% Small improvements in performance of the five in-season models were generally noted as the season progressed (and the sample increased). Specifically, classification accuracies were 60.0%, 67.9%, 67.5%, 69.6% & 69.7% for the April, May, June, July and full in-season models respectively.

Figure 3 displays the mean match difficulty for each of the 18 teams across all 22 matches they participated in across the 2014 AFL season. Hawthorn reported the highest mean MDI (5.27 ± 1.79) based on the pre-season model; whilst the Western Bulldogs experienced the lowest mean pre-season MDI at 4.71 ± 1.8. Given the lack of dynamic factors in this model, these MDI values should be considered as a measure of draw difficulty; given they are all under the control of those responsible for the design of the fixture. When the dynamic factors are introduced, dramatic changes in mean MDI values are seen across the 18 teams. Specifically, Geelong’s mean match difficulty was substantially easier when considering the dynamic factors, changing from 5.21 in the pre-season (the second hardest) to 3.56 in-season (the easiest). In contrast, Brisbane’s mean match difficulty changed from 5.01 (the 11th easiest) to 7.35 (the hardest) over the same time comparison.

****INSERT FIGURE 3 ABOUT HERE****

Discussion

This study aimed to develop a match difficulty index for use in strategic periodisation for elite AF. It also aimed to provide a means whereby the efficacy of strategic periodisation can be specifically refined and evaluated by organisations using this approach.

Strategic periodisation is used by technical and performance coaches to ensure athletes arrive at a competitive fixture with a pre-planned level of training and fatigue in their system. Occasionally, the coaching team may sacrifice a certain amount of 'freshness' for a particular event, opting instead to train the athletes harder leading into an event with the strategic aim of targeting a 'higher value' event in the future. The planning of these training loads forms the basis of strategic periodisation. In order to implement this process effectively, it is critical that the coaches have a good understanding of the competitive events for which they wish to peak. In a typical team sport competitive season, this is commonly the forthcoming match, since victory in all matches is rewarded with the same number of points. Despite this, it appears that each match possesses a unique difficulty profile based on the external factors (such as those accounted for in this study) that accompany it.

By quantifying the influence of fixed and dynamic factors on match difficulty, the specificity by which strategic periodisation plans can be prescribed can be refined. Previous research in this area has considered the influence of external factors on match difficulty as fixed throughout a competitive season (Robertson & Joyce, 2015). However, this study contended that factors such as team form and player selections are dynamic in nature; not only in the manner in which they change throughout the course of a season, but also the extent to which they influence subsequent team performance. This is important, as strategic periodisation plans are often updated in high-level team sports on semi-regular (i.e., monthly) basis. Therefore, the ability to obtain information as to how these factors alter their influence throughout the course of a competitive season is of practical use.

In the pre-season models, opposition strength and match location were shown to be the most influential factors contributing to the match difficulty. This is in general accordance with the findings of Robertson & Joyce (2015), who developed a similar match difficulty index for rugby union. Also of pertinence, the number of days between consecutive matches does not seem to exert a particularly meaningful influence on the MDI in either sport.

For the in-season models, team form and the difference in ladder position between competing teams were shown to be particularly important. Evidence of the changing influence of these factors over time justifies the approach taken in this paper. For instance, the influence of playing away from home on match difficulty becomes more pronounced as the season progresses. There may be a number of factors that contribute to this phenomenon. Fatigue accumulation in players is likely to exert some influence, meaning that the ‘tax’ that travelling to play a match imposes is progressively larger later in the season (Heisterberg et al., 2013; Silva et al., 2013). It is advised that coaches take account of the increasing difficulty of this factor as the season progresses in their training (and potentially) travel plans. Further, although not a primary aim of the work the superior classification accuracy of the final in-season model comparative to the pre-season shows the importance of their inclusion in understanding what contributes to match difficulty.

A novel finding from this investigation was the defining of the term ‘team form’. Although not well defined as a construct, form is widely used to refer to how well an athlete or team is performing over a recent period of time. Here, various metrics were trialled to define the construct, with the number of wins achieved by a team over a four-week period selected as the most appropriate measure based on its improvement to model accuracy. Notably, this period of time roughly corresponds with the regularity in which the in-season models were iterated. Therefore it is recommended that strategic periodisation plans be considered on approximately a monthly basis in order to maximise the accuracy of both prescription and evaluation. The approach will be of particular benefit to teams competing in finals or playoff series in order to optimise physical training and load prescription, as athlete physiological and psychological optimisation is of particular importance at this stage of the season.

The results from this study are delimited to the 2014 AFL season. The strength in which the factors included in this study exert on match difficulty over subsequent AFL seasons and for that matter in other team sports can be a source for further investigation in future. For instance, it would be useful to determine the presence of a cumulative effect on an MDI in a competition such as the National Hockey League or National Basketball Association, where teams may compete in upwards of 90 matches in a season. Furthermore, it would be of benefit to determine whether the same fixed factors that contribute most strongly to an MDI in one sport are stable in all others. This would enable practitioners to generate an MDI of their own and then enhance it by including factors specific to their sport. A number of further fixed and dynamic factors could also be considered in developing models for a similar purpose in future. For instance, historical head-to-head records between teams, or specific information relating to team structure or personnel were not considered here. Equally, the authors have not sought to determine the effect of certain 'marquee' clashes, such as local derbies where a poorly performing team may perform above expectation against a traditional rival (see Lenor, Lenten & McKenzie, 2016 for examples of such analyses). Whilst likely to improve model accuracy, the inclusion of additional and sometimes complex factors in the models needs to be offset against the increased demand on practitioners to collect and report such data (see Coutts, 2016 for a relevant commentary on Occam's Razor and model parsimony in sports science practice).

We anticipate that follow up work in this area may look to determine alternate metrics of team performance, based on a team's ability to outperform the MDI. As discussed earlier, uneven fixtures in the AFL can make it difficult to assess team performance from one year to the next based solely on wins and losses. To this end, developing an ability to evaluate performances relative to the match difficulty may provide a truer picture of how a team has fared throughout the season, rather than simply looking at the competition ladder. It is also opportune to note, that the MDI concept should not only be of use to team sports. It could be expanded upon for use in individual sports such as golf and tennis, to help the athlete and their support team select the most appropriate competitions to enter. Further, it may evolve that the model could be incorporated into the current ranking schema in sports such as tennis to quantify the number of ranking points that should be awarded for victory in a particular tour event.

Conclusions

Results from this study build upon previous research to refine the concept of the match difficulty index in team sport. Specifically, this study demonstrates that the influence various factors exert on match difficulty change over the course of a season and therefore the most effective way of determining the difficulty of upcoming fixtures are to re-run the model every month. This ensures that the form of the team and their opposition are taking into account, a construct that the authors have demonstrated is best demonstrated as a 4-week trend of match results. Finally, this paper provides further impetus for more advanced applications of the MDI in other domains such as fixturing, strategic competition targeting (in sports such as golf and tennis), awarding of prize money or ranking points, and evaluation of competitive performance.

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Figure Captions

Figure 1. Changes in odds ratios for fixed factors relating to the four in-season logistic regression models run throughout the 2014 AFL season. In the interest of figure scaling, 95% confidence intervals are not shown, however are included in the full in-season model in Table II.

Figure 2. Changes in odds ratios for dynamic factors relating to the four in-season logistic regression models run throughout the 2014 AFL season. In the interest of figure scaling, 95% confidence intervals are not shown, however are included in the full in-season model in Table II.

Figure 3. Mean (± SD) MDI values for each of the 18 clubs participating in the 2014 AFL season. Both pre-season and in-season MDI values are shown.

Table I. Operational definitions relating to factors considered in developing the match difficulty index models

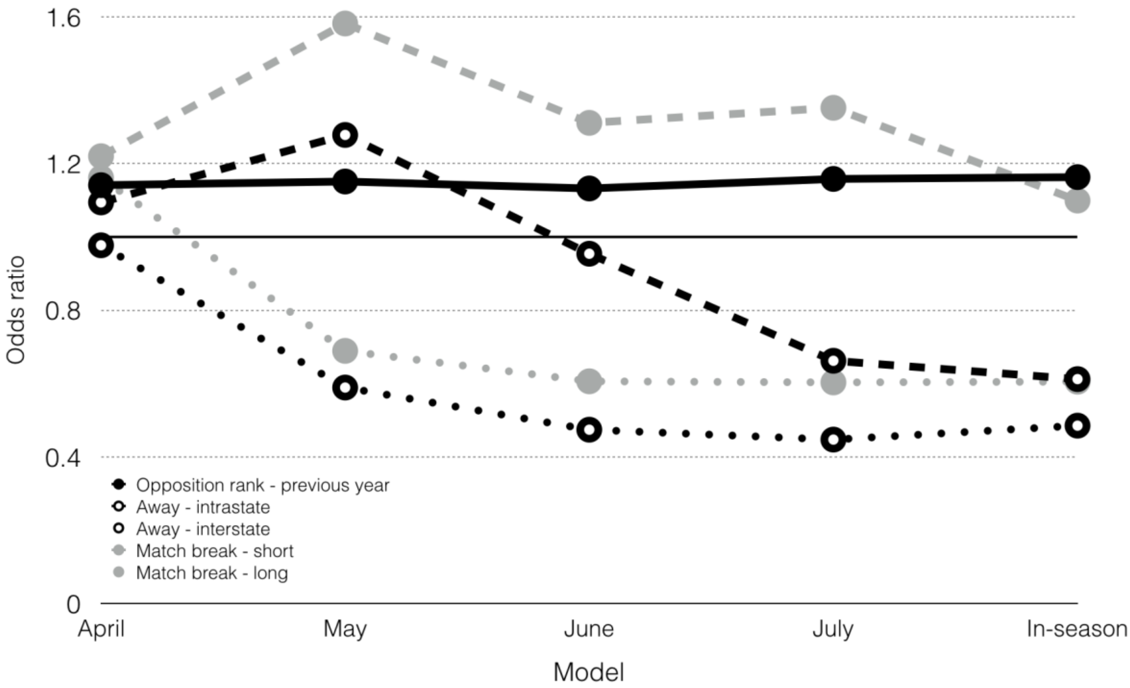
Term	Operational definition
Fixed factors	
Opposition rank-previous year	Rank of the opposing club based on their final ladder position from the previous year's competition. For example, a rank of 1 indicates that the club won the competition in the year prior, whereas a rank of 18 refers to a club finishing on the bottom of the table.
Match location (home)	Refers to the location of the match with relation to both home and away games. Away-intrastate refers to a match played away but in the same state as where the club is based; away interstate refers to an away match played in another state.
Between-match break	Length of the interval between matches. A normal break refers to 7 days between matches; 6 days or less was considered short whereas 8 days or longer was considered a long between-match break.
Dynamic factors	
Opposition rank-current year	Rank of the opposing club based on their ladder position at the time of relevant game. For example, when competing in a round 6 match, this value refers to the opposing side's ladder position at the completion of all round 5 matches.
Team form	Number of wins recorded by the team in the previous *k*-week period
Difference in ladder position	Difference in ladder position of opposing team at the time of a match subtracted from team's current ladder position. For example, for a team ranked 5th on the ladder meeting an opposing team ranked 10th, the difference would be -5 positions.
Team changes-previous week	The number of player changes made to a team from the previous match
Team changes-previous *k*-weeks	The number of player changes made to a team from the previous *k* matches
Number of first year players	The number of players selected in the first team for the given week participating in their first senior year of AFL football.

Table II. Results relating to the two logistic regression models run for the pre-season and in-season period of the 2014 AFL season data (dependent variable is "match outcome = WIN")

Factor	Pre-season				In-season			
	β (S.E.)	χ^2	OR (95% CI)	*P*	β (S.E.)	χ^2	OR (95% CI)	*P*
Constant	-1.195 (0.285)	17.514	0.40	<0.001	-0.546 (0.554)	3.792	0.58	0.325
Opposition rank previous year	0.137 (0.022)	38.787	1.15 (1.10, 1.20)	<0.001	0.144 (0.033)	21.066	1.16 (1.08, 1.23)	<0.001
Match location (home)		7.127		0.028		8.193		0.017
Away – intrastate	-0.488 (0.309)	2.500	0.61 (0.34, 1.12)	0.114	-0.431 (0.337)	1.635	0.65 (0.34, 1.26)	0.201
Away – interstate	-0.619 (0.243)	6.472	0.53 (0.33, 0.86)	0.011	-0.756 (0.267)	8.009	0.47 (0.28, 0.79)	0.005
Between-match break (long)		1.340		0.720		4.233		0.120
Normal	-0.276 (0.259)	1.128	0.98 (0.58, 1.64)	0.288	-0.063 (0.285)	0.049	1.07 (0.61, 1.86)	0.825
Short	-0.260 (0.270)	0.880	0.75 (0.46. 1.26)	0.348	-0.520 (0.291)	3.205	0.59 (0.34, 1.05)	0.073
Team form					0.303 (0.126)	5.788	1.35 (1.06, 1.73)	0.016
Difference in ladder position					-0.078 (0.030)	6.892	0.93 (0.87, 0.98)	0.009
Opposition rank current year					-0.051 (0.041)	1.562	0.95 (0.88, 1.03)	0.211
Team changes-previous week					0.115 (0.100)	1.330	1.12 (0.92, 1.36)	0.249
Team changes-previous 4-wk					-0.055 (0.031)	3.118	0.95 (0.89, 1.01)	0.077
Number first year players					-0.143 (0.096)	2.215	0.87 (0.71, 1.05)	0.137

Model performance		
Chi-square	54.275 [df=6]	94.934 [df=11]
Cases correctly classified	65.5%	69.7%

β is the beta coefficient, SE is the standard error, Wald's χ^2 is Wald's chi-square, OR is the odds ratio. Statistical significance accepted at ≤0.05



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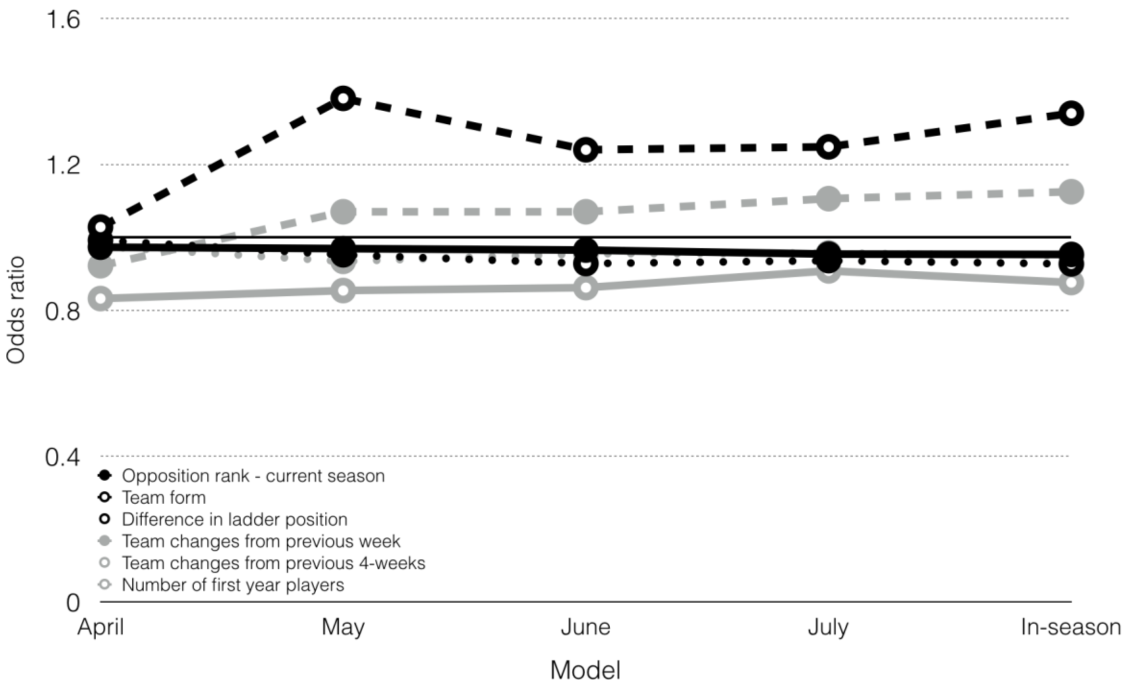
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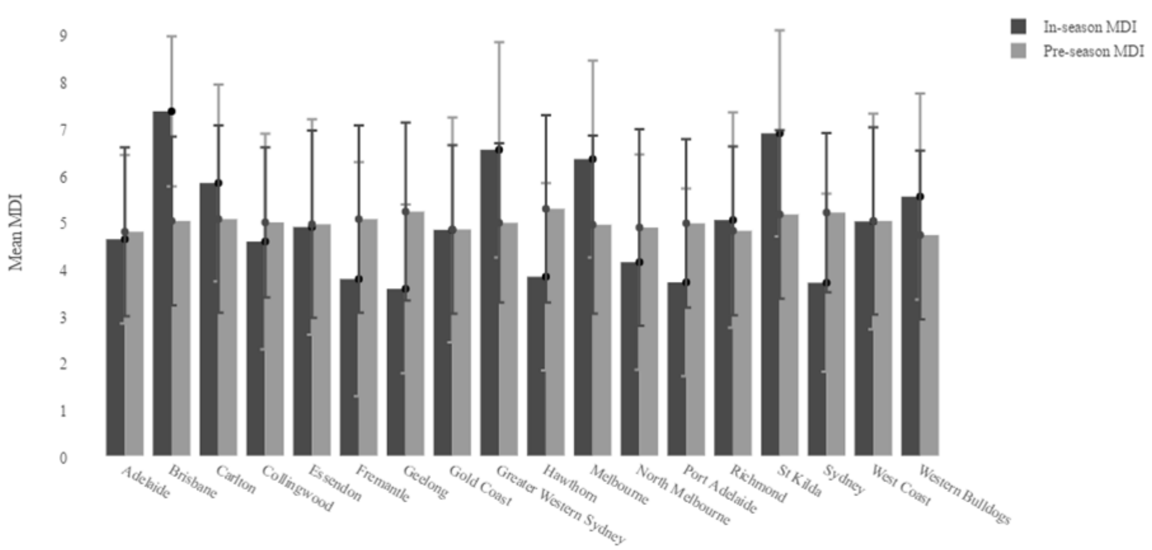
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Port Adelaide
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St Kilda
Sydney
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