

Research article

Explaining Match Outcome during The Men's Basketball Tournament at The Olympic Games

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Abstract

In preparation for the Olympics, there is a limited opportunity for coaches and athletes to interact regularly with team performance indicators providing important guidance to coaches for enhanced match success at the elite level. This study examined the relationship between match outcome and team performance indicators during men's basketball tournaments at the Olympic Games. Twelve team performance indicators were collated from all men's teams and matches during the basketball tournament of the 2004-2016 Olympic Games (n = 156). Linear and non-linear analyses examined the relationship between match outcome and team performance indicator characteristics; namely, binary logistic regression and a conditional interference (CI) classification tree. The most parsimonious logistic regression model retained 'assists', 'defensive rebounds', 'field-goal percentage', 'fouls', 'fouls against', 'steals' and 'turnovers' (delta AIC <0.01; Akaike weight = 0.28) with a classification accuracy of 85.5%. Conversely, four performance indicators were retained with the CI classification tree with an average classification accuracy of 81.4%. However, it was the combination of 'field-goal percentage' and 'defensive rebounds' that provided the greatest probability of winning (93.2%). Match outcome during the men's basketball tournaments at the Olympic Games was identified by a unique combination of performance indicators. Despite the average model accuracy being marginally higher for the logistic regression analysis, the CI classification tree offered a greater practical utility for coaches through its resolution of non-linear phenomena to guide team success.

Key words: Team sport, classification tree, machine learning, performance analysis, non-linear analysis; athlete.

Introduction

Basketball is an intermittent, anaerobic-dominant, team sport that is played by athletes across a range of levels (Scanlan et al., 2012; Tessitore et al., 2006). Several studies have reported on the key physical and physiological characteristics of basketball athletes (Hoare, 2000; Koklu et al., 2011). While these characteristics contribute to individual performance, the combination of all individual performances in a coherent manner ultimately results in team success (Gomez et al., 2009). Subsequently, team performance indicators during matches may provide a holistic foundation for coaches in the development of training and match strategies to enhance success.

Basketball match success has been associated with a range of team performance indicators including successful 3-point (Ibanez et al., 2009; Jukic et al., 2000; Lorenzo et al., 2010), 2-point (Ibanez et al., 2009; Jukic et al.,

2000; Lorenzo et al., 2010) and 1-point (free-throw) (Jukic et al., 2000; Sampaio et al., 2006; Trninic et al., 2002) shots, 'defensive rebounds' (Gomez et al., 2008; Ibanez et al., 2009; Trninic et al., 2002), 'fouls' (Sampaio et al., 2006), 'turnovers' (Lorenzo et al., 2010) and 'assists' (Gomez et al., 2008; Ibanez et al., 2009; Trninic et al., 2002). Gomez and colleagues (2008) reported that 'defensive rebounds' and 'assists' discriminated all wins and losses during the 2004-2005 Spanish Men's Professional League. Other studies focussing on European basketball matches have also reported the importance of 'defensive rebounds', 'assists' and 'field-goal percentage' for team match success (Jukic et al., 2000; Trninic et al., 2002). During short-term, junior tournaments, a range of performance indicators including '2-point field-goal' accuracy, 'defensive rebounds', 'turnovers' and 'assists' were acknowledged as discriminatory for wins or losses (Ibanez et al., 2009; Lorenzo et al., 2010). Despite this quantity of work, the contribution of similar team performance indicators to match success during the men's basketball tournament at the Olympic Games has yet to be examined. Unlike season long competitions, players within teams for the Olympics have a limited opportunity to interact regularly with identification of these team performance indicators expected to provide vital direction to coaches in the design of training programs and match strategies to enhance match success likelihood.

To identify performance indicators explanatory of a predetermined response (e.g. match outcome), sports performance analysts have become increasingly proficient with the use of machine learning techniques (Gomez et al., 2015a; Gomez et al., 2015b; Robertson et al., 2015). One of the benefits of machine learning techniques is its capability to resolve meaningful, non-linear interactions within multivariate datasets in contrast to traditional linear techniques (Morgan et al., 2013; Robertson et al., 2015). Accordingly, machine learning may assist coaches with the identification of flexible targets or performance indicator combinations that enhance the likelihood of team success. Classification trees have been shown to be an effective, machine learning technique to explain match outcome in elite Australian Football (AF) (Robertson et al., 2015) and rugby league (Woods et al., In press), as well as explaining the effectiveness of ball screens and inside passes in basketball (Courel-Ibáñez et al., 2016; Gomez et al., 2015a). However, such an approach has yet to be employed for team performance indicator combinations and match outcome during an elite basketball tournament.

The aims of the current study were: 1) to examine the relationship between team performance indicator characteristics and match outcome during the men's basketball tournament at the Olympic Games; 2) to compare the utility of linear and non-linear statistical approaches in the resolution of this relationship. Given the findings of others (Courel-Ibáñez et al., 2016; Gomez et al., 2015a; Robertson et al., 2015), it was hypothesised that: 1) distinctive performance indicator combinations would be explanatory of match outcome; and 2) the classification accuracy of both statistical approaches would yield similarity, however, the non-linear approach would offer greater practical utility given the non-linear interactions between team performance indicators.

Methods

Study design

This study was a retrospective analysis of publically available data from the official Olympic websites with all procedures considered in line with local, institutional, ethical approval. All matches ($n = 156$) undertaken within the men's basketball tournament at the 2004 (Athens, $n = 42$), 2008 (Beijing, $n = 38$), 2012 (London, $n = 38$) and 2016 (Rio de Janeiro, $n = 38$) Olympic Games were examined. The team performance indicators for each match were downloaded and collated (Table 1) and *a priori* classified according to match outcome (win/loss). All team performance indicators were normalised for the number of ball possessions by each team per match, as previously described (Gomez et al., 2013; Lorenzo et al., 2010; Sampaio and Janeira, 2003). Briefly, ball possessions were calculated using the following equation: field-goal attempts – 'offensive rebounds' + 'turnovers' – (0.4 x free-throw attempts) (Oliver, 2004). Each match provided two datasets or observations (one per team) with a total of 312 observations (84 from 2004, 76 from 2008, 76 from 2012 and 76 from 2016) examined in the current study.

Statistical analysis

Descriptive statistics (mean \pm SD) were calculated for each team performance indicator relative to match outcome (win/loss). All analyses and visualisations were conducted using R (version 3.2.2, Vienna, Austria). Prior to hypothesis testing, a Spearman's correlation matrix was built to assess the level of collinearity between the team performance indicators. This screening process revealed collinearity between 'field goal percentage', '3-point percentage', and '2-point percentage' ($r > 0.4$). Accordingly, the latter two indicators were removed from further analyses. A multivariate analysis of variance (MANOVA) examined the main effect of match outcome on each performance indicator. Additionally, the effect size (and 90% confidence interval) of match outcome on the team performance indicators was calculated using Cohen's d statistic, where an effect size (d) of < 0.2 was considered trivial, $d = 0.20$ – 0.49 considered small, $d = 0.50$ – 0.79 considered medium, and $d > 0.79$ large (Cohen, 1992).

Binary logistic regression was then used to build linear probability models. Match outcome was coded as the response variable (0 = win, 1 = loss), while each performance indicator that was significantly different according to the MANOVA, was coded as explanatory variables. Model selection was performed using the delta Akaike Information Criterion (AIC) and Akaike weights (Burnham and Anderson, 2002). The delta AIC provides a measure of relative model parsimony with a value < 2 indicating high parsimony (Burnham and Anderson, 2002). Conversely, Akaike weights indicate the probability that the selected model is the best among the model set with a value closer to 1 indicating greater probability (Burnham and Anderson, 2002). Both delta AIC and Akaike weights were ascertained via the 'dredge' function in the MuMIn package (Burnham and Anderson, 2002).

A recursively, partitioned, conditional interference (CI), classification tree was then grown to model the relationship between the same response and explanatory variables. This classification analysis enables the

Table 1. Description of team performance indicators examined within this study.

Performance Indicator	Description
Field-goal percentage	Success (%) for all 2- and 3-point shots; calculated as a percentage of 2- and 3-point shots made from all 2- and 3-point shots attempted
3-point percentage	Success (%) for all 3-point shots; calculated as a percentage of 3-point shots made from all 3-point shots attempted
2-point percentage	Success (%) for all 2-point shots; calculated as a percentage of 2-point shots made from all 2-point shots attempted
Free-throw (1-point) percentage	Success (%) for all 1-point shots; calculated as a percentage of 1-point shots made from all 1-point shots attempted
Offensive rebounds	Total number of ball possessions obtained by the offensive team after a missed-shot
Defensive rebounds	Total number of ball possessions obtained by the defensive team after a missed-shot
Assists	Total number of times when a player provided the ball to a teammate who immediately made a successful shot
Turnovers	Total number of times (not including shots) when the ball was lost by the offensive team
Steals	Total number of times (not including shots) when the ball was seized by the defensive team from the opposition
Blocked shots	Total number of scoring shots that were physically prevented from scoring by the defensive team
Fouls committed	Total number of personal contact and technical infractions (fouls) that were committed by the team
Fouls against	Total number of personal contact and technical infractions (fouls) that were committed by the opposition

resolution of non-linear phenomena (Robertson and Joyce, 2015). A CI classification tree was chosen as its fitting algorithm estimated a regressive relationship through binary partitioning by testing the null hypothesis between a set of explanatory variables and a response variable (Hothorn et al., 2006). To prune the tree, a minimum node size of ten observations was chosen with partitioning occurring for the explanatory variables that had the greatest association with the response variable (i.e. estimated in accordance with a ‘P-value’). Thus, the partitioning stopped when the null hypothesis could not be rejected (i.e. $p > 0.05$). This analysis was performed via the ‘ctree’ function in the party package (Hothorn et al., 2006).

Results

The descriptive statistics for each normalised, team performance indicator relative to match outcome are presented in Table 2 with most indicators significantly greater during wins compared to losses. ‘Field-goal percentage’ had the largest effect on match outcome ($d > 1.1$) with ‘defensive rebounds’ and ‘assists’ also exhibiting large effects (Table 2).

As shown in Table 3, the best linear model retained ‘assists’, ‘defensive rebounds’, ‘field-goal percentage’, ‘fouls’, ‘fouls against’, ‘steals’ and ‘turnovers’. This reduced linear model successfully classified 85.2% and 85.8% of the *a priori* classified wins and losses, respectively, for an average model accuracy of 85.5%.

The subsequent output from the CI classification tree is illustrated in Figure 1. As shown, four performance

indicators were retained within the tree with an average classification accuracy of 81.4%. Seven terminal nodes were grown (numbers 5, 6, 7, 8, 11, 12 and 13) with the root node (number 1) partitioning the dataset based on ‘field-goal percentage’. The subsequent branching to the left of the tree denotes a loss (≤ 63.9 ‘field-goal percentage’) and the branching to the right denotes a win (> 63.9 ‘field-goal percentage’).

Following the branch to the right of the tree, node number 9 partitioned the data based on ‘defensive rebounds’. Of the 59 observations in terminal node 13 ($> 63.9\%$ ‘field-goal’ and > 34.7 ‘defensive rebounds’), the probability of winning was higher (93.2%) than the probability of losing (6.8%). This combination offered the greatest probability of winning from the performance indicator combinations for both linear and non-linear approaches. Node number 10 (≤ 34.7 ‘defensive rebounds’) split the data based on ‘steals’ with two terminal nodes generated (numbers 11 and 12).

Following the branch to the left of the tree, node number 2 partitioned the data based on ‘defensive rebounds’, growing terminal node 8. Progressing further down the branch (≤ 40.8 ‘defensive rebounds’), node number 3 partitioned the data based on ‘turnovers’, growing terminal node 7. Lastly, node number 4 partitioned the data based on the number of ‘defensive rebounds’, resulting in the growth of two terminal nodes, numbered 5 and 6. Of the 61 observations in terminal node 5, the probability of losing (73.8%) was higher than the probability of winning (26.2%). This combination offered the lowest probability of winning from the performance indicator combinations.

Table 2. Descriptive statistics for each team performance indicator relative to match outcome. Values are mean (\pm SD) with all being normalized to ball possessions.

Performance Indicator	Wins	Losses	<i>d</i> (90% CI)	Interpretation
Field-goal percentage	67.1 (10.0)	55.7 (9.1) *	1.19 (0.98, 1.39)	Large
Free-throw (1-point) percentage	98.9 (17.1)	95.3 (18.2)	0.20 (0.01, 0.39)	Small
Offensive rebounds	14.7 (5.7)	13.3 (5.0) *	0.26 (0.07, 0.45)	Small
Defensive rebounds	35.9 (6.8)	29.9 (6.4) *	0.92 (0.72, 1.11)	Large
Assists	24.2 (8.4)	16.7 (6.8) *	0.99 (0.79, 1.19)	Large
Turnovers	17.3 (4.8)	20.6 (5.2) *	-0.65 (-0.84, -0.45)	Medium
Steals	10.5 (4.2)	8.2 (4.0) *	0.57 (0.38, 0.76)	Medium
Blocked shots	4.2 (2.5)	3.0 (2.3) *	0.48 (0.29, 0.67)	Small
Fouls committed	27.9 (5.8)	30.2 (6.5) *	-0.37 (-0.55, -0.18)	Small
Fouls against	30.1 (6.7)	27.7 (6.0) *	0.39 (0.20, 0.58).	Small

$n = 312$; * $p < 0.05$ vs. Wins; *d* – effect size; CI – confidence interval.

Table 3. Model summary for the binary logistic regression analysis ranked according to the delta Akaike Information Criterion and Akaike weights

Predictors	LL	df	AICc	Δ AIC	w_i
~ assists + def_reb + field_goal + fouls + fouls against + steals + turnovers	-103.61	8	223.69	<0.01	0.28
~ assists + blocked_shots + def_reb + field_goal + fouls + fouls against + steals + turnovers	-102.97	9	224.53	0.83	0.18
~ assists + def_reb + field_goal + fouls + fouls against + off_reb + steals + turnovers	103.17	9	224.95	1.25	0.15
~ assists + blocked_shots + def_reb + field_goal + fouls + fouls against + off_reb + steals + turnovers	-102.60	10	225.94	2.24	0.09
~ blocked_shots + def_reb + field_goal + fouls + fouls against + steals + turnovers	-105.07	8	226.63	2.93	0.06
~ def_reb + field_goal + fouls + fouls against + off_reb + steals + turnovers	-105.1	8	226.67	2.97	0.06
Null (~1)	-216.26	1	434.53	210.830	<0.01

LL, log likelihood; df, degrees of freedom; AICc, Akaike Information Criterion; Δ AIC, delta AIC; w_i , Akaike weight; def_reb, defensive rebounds; field_goal, field goal percentage; off_reb, offensive rebounds.

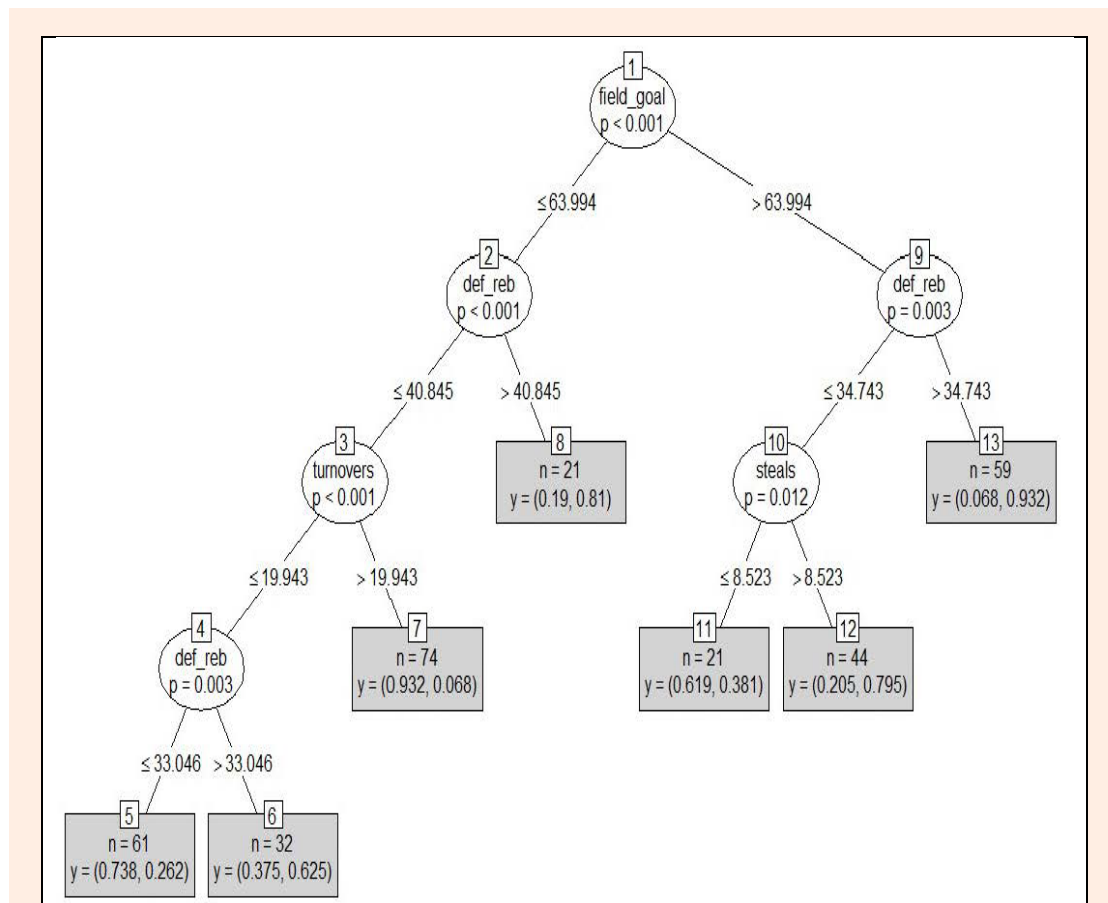


Figure 1. The conditional interference classification tree showing the probability of wins and losses during Olympic men's basketball tournaments. Note: "n" denotes the number of observations in each node (minimum of 10). The first y value denotes the probability of losing and the second y value denotes the probability of winning (e.g. 0.8 = 80%). field_goal = 'field-goal percentage', def_reb = 'defensive rebounds'; values for each team performance indicators were normalized to ball possessions.

Discussion

The current study identified key-indicators of performance that were explanatory of success in men's basketball at the Olympic Games. The best logistic regression model resolved a relatively higher classification accuracy in contrast to the CI classification tree. Although, the CI classification tree revealed a range of performance indicator combinations for match outcome in contrast to the outputs of the linear regression model. Of considerable note was the combination of 'field-goal percentage' and 'defensive rebounds' that explained 93.2% of the winning observations in terminal node 13. Conversely, a unique combination of 'field-goal percentage', 'defensive rebounds' and 'turnovers' offered the lowest probability of winning (6.8%) and the greatest probability of losing (93.2%, terminal node 7). Despite the average model accuracy being only marginally higher for the logistic regression analysis, the output from the CI classification tree offers coaches and analysts with greater practical utility. Further, it offers flexible and non-linear insights into the unique combinations of performance indicators required to increase (or decrease) a team's probability of success within an Olympic basketball tournament. This practical model provides coaches with the capability to devise multiple game plans or strategies to enhance their

likelihood of winning based upon the accumulation of these performance indicators. For example, if a team was unable to generate a 'field-goal percentage' of ~64%, then a coach could shift strategic focus toward the generation of more than 40 'defensive rebounds' to preserve a higher than chance probability of winning (Figure 1). The results of this study have demonstrated the utility of non-linear, machine learning techniques to explain patterns within multivariate datasets in sport science.

The resolution of 'field-goal percentage', 'defensive rebounds', 'steals' and 'turnovers' in both linear and non-linear models emphasizes their importance for match outcome during these Olympic basketball tournaments. These findings were in general agreement with those reported for other basketball competitions with Gomez et al. (2008) demonstrating that 'defensive rebounds' were a key contributor to winning basketball matches in the elite Spanish Men's Professional League. Specifically 'defensive rebounds' was the essential discriminatory variable for balanced (final score difference of ≤ 12 points) and unbalanced (final score difference of > 12 points) matches (Gomez et al., 2008). This indicator represents a substantial defensive action that decreases the number of possessions and subsequent shots for the opposition while increasing the number of possessions and shot opportunities for the securing team (Sampaio and Janeira, 2003). Others

have also identified 'defensive rebounds' as a crucial performance indicator for wins in junior (Ibanez et al., 2009; Lorenzo et al., 2010) and senior (Garcia et al., 2013; Gomez et al., 2014; Sampaio et al., 2006) competitions. However, to our knowledge, the current study was the first to identify 'steals' as a key performance indicator for winning in an elite basketball competition. This performance indicator again reflects a defensive action that decreases the number of possessions and subsequent shots for the opposition, while increasing the number of possessions and shot opportunities for the team in possession. Accordingly, in addition to identifying and then selecting players capable of accruing a high field goal accuracy, coaches and analysts should focus on devising defensive strategies (i.e. 'defensive rebounds' and 'steals') during their preparation of national basketball teams during the limited, pre-Olympic stage. Such preparations would likely lead to enhanced team possessions and the probability of match success during the Olympic Games.

The current study has provided promising findings but was not without limitations that requires acknowledgement. Firstly, the results were de-limited to men's basketball matches of the most recent Olympic Games. Others have identified significant gender differences in performance indicators for elite basketball matches (Gomez et al., 2014; Sampaio et al., 2004) with further examination of female elite competition warranted. Secondly, data was retrieved from the last four Olympic Games only with this sample examined to enhance the robustness of modelling performed. Future studies may clarify the capability of the identified performance indicators to explain match outcome in prospective basketball tournaments at the Olympic Games. Next, both regular and playoff tournament matches were included into the modelling with potential differences possible between stages of competition. Previously, style of play and subsequent team performance indicators for winning varied with stage of competition during a full season (Garcia et al., 2013). The impact of such stage differences though may be minimal during short-term tournaments where match victory may have greater impact on progression through the tournament and ultimate tournament success. Finally, measures of athlete physical performance (Robertson et al., 2015) were not examined presently in conjunction with team match performance indicators. Future work examining the physical activity profiles of teams may clarify the impact of accumulated fatigue during Olympic tournaments (i.e. multiple matches over short durations) on the relationship between performance indicators and match outcome. Such future work may integrate the use of microtechnology (e.g. local positioning systems) to enable 'multidimensional' insight into successful and less successful team profiles during elite basketball competition when coupled with the current results.

Conclusions

Using both linear and non-linear analyses, this study showed that: 1) distinctive combinations of 'field-goal percentage', 'defensive rebounds', 'turnovers' and 'steals'

were explanatory of match outcome during a men's Olympic basketball tournament; and 2) the classification accuracy of both statistical approaches yielded similarity, however, the non-linear approach (CI classification tree) was likely to offer coaches and analysts with greater practical utility given the interactions between multiple team performance indicators. Such analyses may provide important guidance when devising training and game strategies to increase the probability of winning during a men's Olympic basketball tournament.

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Key points

- A unique combination of team performance indicators explained 93.2% of winning observations in men's basketball at the Olympics.
- Monitoring of these team performance indicators may provide coaches with the capability to devise multiple game plans or strategies to enhance their likelihood of winning.
- Incorporation of machine learning techniques with team performance indicators may provide a valuable and strategic approach to explain patterns within multivariate datasets in sport science.

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