



Research



Cite this article: Sadekar O, Chowdhary S, Santhanam MS, Battiston F. 2024 Individual and team performance in cricket. *R. Soc. Open Sci.* **11**: 240809.

<https://doi.org/10.1098/rsos.240809>

Received: 30 January 2024

Accepted: 8 June 2024

Subject Category:

Computer science and artificial Intelligence

Subject Areas:

complexity

Keywords:

sports analytics, cricket, team science, science of success

Authors for correspondence:

Onkar Sadekar

e-mail: sadekar_onkar@phd.ceu.edu

Federico Battiston

e-mail: battistonf@ceu.edu

Electronic supplementary material is available online at <https://doi.org/10.6084/m9.figshare.c.7303158>.

Individual and team performance in cricket

Onkar Sadekar¹, Sandeep Chowdhary¹, M. S.

Santhanam² and Federico Battiston¹

¹Department of Network and Data Science, Central European University, Vienna 1100, Austria

²Department of Physics, Indian Institute of Science Education and Research, Dr Homi Bhabha Road, Pune 411008, India

OS, 0000-0002-5177-0836; FB, 0000-0001-9646-6232

Advancements in technology have recently allowed us to collect and analyse large-scale fine-grained data about human performance, drastically changing the way we approach sports. Here, we provide the first comprehensive analysis of individual and team performance in One-Day International cricket, one of the most popular sports in the world. We investigate temporal patterns of individual success by quantifying the location of the best performance of a player and find that they can happen at any time in their career, surrounded by a burst of comparable top performances. Our analysis shows that long-term performance can be predicted from early observations and that temporary exclusions of players from teams are often due to declining performances but are also associated with strong comebacks. By computing the duration of streaks of winning performances compared to random expectations, we demonstrate that teams win and lose matches consecutively. We define the contributions of specialists such as openers, all-rounders and wicket-keepers and show that a balanced performance from multiple individuals is required to ensure team success. Finally, we measure how transitioning to captaincy in the team improves the performance of batsmen, but not that of bowlers. Our work emphasizes how individual endeavours and team dynamics interconnect and influence collective outcomes in sports.

1. Introduction

The inception of sports, notably the Olympic Games in ancient Greece, played a pivotal role in cultural and societal bonding [1,2]. As societies evolved, sports mirrored changes in social structures, becoming more organized and diverse [3,4]. Recent digital technology advancements and enhanced data acquisition capabilities have ushered in a new era of sports analytics,

providing valuable insights into athlete and team performance [5–9]. In baseball, the ‘Moneyball’ revolution popularized the strategic use of data analytics, profoundly altering team management and player evaluation [10–12]. Premier leagues in other sports such as basketball (NBA) and American football (NFL) have similarly embraced analytics to optimize player performance, team strategies and in-game decisions, leading to stylistic shifts in play [13–15]. Intellectual games like chess have also advanced with the introduction of sophisticated chess engines [8,16,17].

One-Day International (ODI) cricket, the world’s second most-followed sport after soccer [18,19], enjoys widespread popularity primarily in Commonwealth countries, including India, Australia, New Zealand, the United Kingdom, South Africa, the West Indies, Sri Lanka and Pakistan. The availability of match data, driven by amateur and professional enthusiasts, has fostered various analyses. One of the major lines of research has been predicting the match outcomes of ODI matches using a variety of techniques such as machine learning [20], logistic regression using pre-match covariates [21,22] and logistic regression using *in-game* dynamic variables [23]. Other studies have tried to uncover specific patterns based on performance such as the *hot-hand effect* [24] and ranking of the players [25] or modelling the dynamics of the game [26]. A few studies have tried to investigate in detail the batting [27,28] and bowling [29] aspects of the game. With the advent of shorter and faster formats of the game such as T20, some attention has been devoted to investigating the effect of premier leagues on social media activity [30] as well as on other formats of the game [31]. Going beyond the specificities of ODI cricket, researchers have tried to examine the role of injuries in cricket [32–34]. Despite this, there remains a substantial gap in the understanding of individual performances and their contributions to team success in ODI cricket. In this work, we track players’ careers, unveiling universal patterns of performance and identifying correlates of team-level success.

The progression of a player’s skill level enhances their likelihood of surpassing previous performance peaks [24]. Conversely, as players age, their athletic prowess may diminish, potentially impeding their ability to exceed past achievements [32]. This contrast of skill development against physical decline poses a critical question: at which point in their careers do players deliver their best performance? We address this question in §3.1 by making use of tools and methodologies from data science and extreme value theory [35,36] already deployed in diverse fields like a science of science [37–39], arts [40–42] and sports [8,43,44].

Early identification of talent and skills can provide key advantages in many competitive settings, from firm growths [45] and information spreading [46] to sports, where nurturing talent in young players can lead to higher returns [47–49]. In §3.2, we extend this inquiry to investigate the relationship between a player’s initial performance and their overall career trajectory to capture whether it is possible to see hints of future performance based on early-career display.

Fluctuations in team composition frequently arise due to injuries and variations in player performance [50]. While injuries often occur unpredictably, a decline in performance typically manifests more gradually and may not be immediately apparent. A fitting inquiry in this context is whether it is possible to discern patterns in a player’s performance preceding their expulsion from the team. We study this aspect in §3.3.

The composition of an effective team encompasses skilled players under proficient leadership. Case studies across various domains, including sports, science and business, have illustrated scenarios where moderately weak teams achieve success under adverse conditions, guided by strategic leadership [51–54]. Here, we ask the reverse question in §3.4: is a player’s performance affected by the burden of leadership? However, from a collective perspective, the strategic composition of a team is crucial for its effective functioning. The concept of using specialists—individuals who perform highly specific roles—extends beyond sports into various domains of human activity, including business organizations, scientific research, software development and even hunter–gatherer societies [55–57]. We analyse the role of three specialists—openers, all-rounders and wicket-keepers in §3.5.

So far, we have predominantly focused on individual contributions to team success in ODI cricket. We now broaden our perspective to analyse team success, setting aside specific individualistic factors that contribute to victory. Given that each cricket match culminates in a definitive outcome, our interest lies in discerning patterns of wins and losses for teams. We apply established metrics from the literature to quantify patterns in team success in §3.6. Collectively, our work presents the first comprehensive analysis of individual and team performance in ODI cricket.

2. Material and methods

2.1. Data collection

We extracted data on 4418 ODI matches in men's cricket, involving 2863 unique players by Web scrapping howstat.com [58], an open-access repository for cricket statistics, using *BeautifulSoup* and *urllib*, two python libraries. This dataset encompasses records of all ODI matches played from their inception in 1971 until March 2024. For each match, we extracted information including date, teams, runs scored, wickets taken and overs played by each team, along with player names and their contributions in terms of batting and bowling. This included details like batting position, number of balls faced, number of fours and sixes hit, number of overs bowled, number of runs conceded, number of maiden overs and number of wickets taken. Furthermore, data on the captain and wicket-keeper for each match were also collected.

Although the primary aggregation of data is at the team level for each match, the dataset is also suitable for an in-depth exploration of individual player trajectories and careers. This allows for a multi-faceted analysis of performance trends, the impact of various factors on player and team success, and the evolution of the sport over more than five decades.

2.2. Classification of players

We give a brief description of our methodology for classifying players. For interested readers, we direct them to 2024 Cricket—Wikipedia [59] for the exact role of each type of player. Note that a player can be simultaneously classified into multiple categories. For example, a batsman can be an all-rounder, a captain, an opener and a wicket-keeper.

Batsmen: We consider players as batsmen who have played at least 25 matches and batted at position seven or above in at least 50% of their matches. We have 580 batsmen in our dataset after applying this criteria.

Bowlers: We classify players as bowlers who have played at least 25 matches and bowled in at least 50% of the matches they played. We have 551 bowlers in our dataset after applying this criterion.

All-rounders: We consider all-rounders as players who have played at least 25 matches and are classified as both batsmen and bowlers using the above definitions. We have 117 all-rounders in our dataset.

Captains: In our analysis, we consider players as captains if they have captained the team in at least 15 matches. The information about captaincy is available as metadata on the website.

Openers and non-openers: we characterize openers as players who have batted at first or second position at least 10 times in their career, while non-openers as players who have batted at positions three to six at least 10 times in their career.

Wicket-keepers: In our analysis, we consider players as wicket-keepers based on the metadata available for each match on the website.

Fielders: all players on the bowling side who are not bowling or wicket-keeping are classified as *fielders* in our analysis.

2.3. Data normalization

Team scores per match have generally increased over the decades (see electronic supplementary material, SM1). This observed variation is potentially due to a confluence of factors, including modifications in game regulations (fielding rules, for example) [60], advancements or changes in the equipment used (notably the cricket bat) [61] and the reduction in the dimensions of the playing field to 65–75 m compared to 80–85 m in stadiums earlier as spectators are interested in high-scoring matches [62]. To facilitate a robust and equitable comparison of player and team performances across distinct time periods, we account for the inflation in run-scoring by implementing a normalization procedure on all batting statistics. Specifically, we multiplied runs scored by the batsmen and the runs given by a bowler in a given year by a normalization factor $nf = \frac{\langle Team\ runs \rangle_{all}}{\langle Team\ runs \rangle_{year}}$ such that the average team score is constant over the examined time period. Here, $\langle Team\ runs \rangle_{all}$ is the average team score across all years, while $\langle Team\ runs \rangle_{year}$ is the average team score in the given year. This procedure was originally introduced to correctly assess the impact of scientific papers published in different years

[63]. Our approach ensures that the comparative analysis of players' performance from different eras is conducted in an unbiased manner that controls for background temporal trends.

2.4. Statistical data analysis

2.4.1. Statistical tests

Linear regression is used to estimate the linear relationship between two variables and returns a correlation coefficient. We use it in §3.2.

Kolmogorov–Smirnov test (K–S test for short) is a non-parametric test used to determine if two *unpaired* sampled distributions come from the same underlying distribution [64]. The null hypothesis is that the two distributions are the same and the *p*-value gives the probability that the samples in question are taken from the same distribution. We use the K–S test in §§3.1 and 3.5.

Wilcoxon signed-rank test is a non-parametric test used to determine if the location of means of two *paired* distributions is the same [65]. Assuming the null hypothesis that the means are the same, it returns the probability that the null hypothesis is true. We use the Wilcoxon signed rank test in §3.1.

Mann–Whitney U test is a non-parametric test of the null hypothesis that the *unpaired* distributions underlying the two samples are the same [66]. This test checks the null hypothesis if one of the distributions is stochastically larger or smaller than the other. We use the Mann–Whitney *U* test in §§3.4–3.6.

Welch's t-test is used to determine if two populations have similar means when the variances and sample sizes may or may not be equal [67]. We use this test in §3.5.

All the above tests are conducted using the *SciPy* package of Python [68].

2.4.2. Fractional contribution

To quantitatively and equitably assess the impact of each player, we introduce the fractional contribution f_c as

$$f_c = \frac{1}{2} \times \left(\frac{\text{runs scored}}{\text{total team runs}} + \frac{\text{wickets taken}}{\text{total team wickets}} \right), \quad (2.1)$$

so that a player's maximum possible contribution (f_c) is normalized within the range of 0–1. It is important to note that, given this framework, specialized batsmen and bowlers have an upper limit of $f_c = 0.5$ in a best-case scenario. We use this definition in §§3.5 and 3.6.

2.4.3. Effective team size

We employ the concept of *effective team size*, a well-established metric in the team analysis literature [69,70] to characterize the heterogeneous contributions of individuals to the team. *Effective team size* quantifies the essential number of players in a team, effectively measuring the redundancy in team composition. Mathematically, we denote the contribution of the player to the team score as f_c such that $\sum_c f_c = 1$, as per equation (2.1). The *effective team size* S_{eff} is defined in such a way that it equals the actual team size if contributions are evenly distributed among all players and reduces to 1 if a single player is solely responsible for the entire performance. A common approach to calculate S_{eff} is to use the formula $S_{eff} = 2^H$, where $H = -\sum_c f_c \log_2 f_c$. Statistically, S_{eff} represents the entropy of the distribution of contributions f_i from team players. We use this concept in §3.6.

2.5. Null models

In our work, we analyse characteristic patterns in the performance of both players and teams. In order to control for confounding variables, one of the usual approaches is to employ null models. A null model is a concept commonly used to capture the existence (or lack thereof) of signal from noisy data. It often involves randomizing certain aspects of the data while keeping the rest of the factors constant. Comparing the differences between the randomized and true data allows us to extract statistically

significant and meaningful patterns. Here, we use two null models for detecting individual and team performance signatures.

2.5.1. Best individual performance

In §3.1, we characterize the temporal patterns of top performances. In order to establish a baseline for the measures, we shuffle the timestamps of individual performances for each player 100 times, keeping the actual values of performance the same. In this way, we are breaking the temporal correlation between different performances. For each shuffling, we find the timestamp for the best (N^*), second best (N^{**}) and third best (N^{***}) performances of a player. We compare these randomly shuffled data to the original dataset to establish the similarities and differences.

2.5.2. Hot and cold streaks for teams

In §3.6, we show the existence of *hot* and *cold* streaks for teams. We consider all the teams that have played at least 200 matches. By keeping the number of wins constant, we shuffle the timestamps of the match results 10^4 times for each team. For each reshuffling, we compute the number of consecutive wins (hot) and losses (cold) denoted by L_{streak} . By taking the average across 10^4 reshuffles, we compute N_{rand} to highlight the significance of N_{data} —the number of streaks of length l or higher in the actual dataset.

3. Results

3.1. Temporal patterns of top performances

Methods: We designate N^* , N^{**} and N^{***} as the match numbers corresponding to a player's best, second-best and third-best performances, respectively. For batsmen, this is marked as their highest run score. For bowlers, it corresponds to the highest number of wickets taken. In instances of identical runs or wickets, the performance involving respectively fewer balls played or fewer runs conceded is considered. Additionally, to account for variations in the career lengths of the individual players, we normalize the timing of peak performances (N^* , N^{**} and N^{***}) with overall career lengths (N).

We are interested in two questions: (i) does the best performance (N^*) occur at a specific time within a player's career? and (ii) are the best performances closely related in time? To answer the first question, we calculate the probability distribution function of N^* as well as N^*/N and compare it with the randomized dataset as shown in §2.5. This analysis was originally introduced in Shi *et al.* [38] to test the presence of *hot streaks* in time series data. We use the K–S test to check if the distributions obtained from the original and randomized datasets differ. On the other hand, to investigate the second question, we divide the differences between the top performances ΔN , i.e. $|N^* - N^{**}|$ and $|N^* - N^{***}|$, normalized by the career length (N) into five bins. Within each bin, we compute the ratios of the number of players in the data ($n_{\Delta N}^{data}$) and the number of players in the randomized data ($n_{\Delta N}^{rnd}$). We run the Wilcoxon signed rank test to determine if the values of the ratios differing from 1 are significant.

Results: The probability distribution function $P(N^*)$ for all players is shown in figure 1*a*. We observe that $P(N^*)$ is a monotonically decreasing function, suggesting a much higher likelihood of peak performance occurring earlier rather than later in a career. However, this analysis does not account for variations in career lengths. When normalizing the timing of peak performance relative to overall career length, we observe a uniform distribution, as shown in figure 1*a* (inset). This pattern, previously dubbed as the 'random impact rule' for scientific careers [37], suggests that the timing of peak performance is generally unpredictable and can occur at any point in a career. The K–S test comparing the data to the null model gives $p > 0.05$ in both cases, thus giving an indication that the null hypothesis of the two distributions being statistically the same cannot be rejected.

In figure 1*b*, we plot the ratios of the number of players in the bins of $\Delta N/N$ for the original and the randomized dataset. We notice that, for $\Delta N/N \in [0.0, 0.2)$ (indicating top performances closely related in time), we observe a ratio > 1 , signifying that the number of players having small gaps in their best performances is higher than expected by chance on randomized data. In other words, they exhibit *hot*

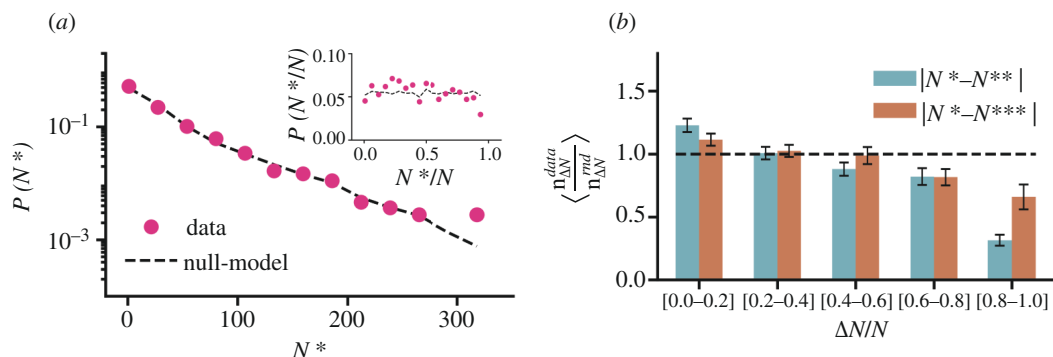


Figure 1. Time of top performance in a player's career. (a) Distribution of the match number (N^*) of the top performance for a player's career. The inset shows the distribution of the time of the top performance in a career N^* normalized by the career length N . Real data (pink circles) are consistent with a randomized null model, which removes temporal correlations (black dotted line), suggesting that the best performance can occur at any time within the career. (b) Ratio of the number of players for the original data ($n_{\Delta N}^{\text{data}}$) and randomized data ($n_{\Delta N}^{\text{rd}}$) having normalized differences ($\Delta N/N$) between best performances ($|N^* - N^{**}|$ in blue and $|N^* - N^{***}|$ in brown) in each particular bin. Values higher than 1 for small $\Delta N/N$ indicate that the best performances are clustered, highlighting the presence of *hot streaks* in cricket careers.

streaks—brief periods of time accentuated by best performances of comparable magnitude. In contrast, the ratio of the number of players for $\Delta N/N \in [0.6, 1.0]$ (indicating that best performances are far away in time) is always less than one. This implies that fewer players have long gaps between best performances compared to random expectations. The Wilcoxon signed rank test indicates a significant deviation of ratios from 1 ($p < 0.001$) for $\Delta N/N \in [0.0, 0.2]$ and $\Delta N/N \in [0.6, 1.0]$ for both $|N^* - N^{**}|$ and $|N^* - N^{***}|$. Our results are robust to the number of bins as seen in electronic supplementary material, SM2.

3.2. Long-term performance from early career observations

We are interested in determining the relationship between a player's early career trajectory and their overall career performance. *Methods:* In figure 2a,b, we correlate early and overall career statistics. Our analysis considers players who have participated in a minimum of 50 matches. We focus on their mean performance during the initial 25 matches. For batsmen, we look at the average runs scored per match in this early phase, whereas for bowlers, we look at the average number of wickets taken per match within the same period. Concurrently, we examine the full-career performance of these players.

Results: The scatter plots in figure 2 reveal a correlation between early and full career average performance metrics. We calculate the linear regression coefficients $R^2 = 0.45$ for batsmen (figure 2a) and $R^2 = 0.66$ for bowlers (figure 2b). This finding suggests that a player's initial performance may serve as an indicator of their subsequent career performance. However, notable differences emerge when comparing batsmen and bowlers. In general, approximately 55% of batsmen are observed to improve upon their early career averages, whereas this figure drops to about 45% for bowlers.

3.3. Effect of drop and re-entry

Persistence (or lack thereof) of team composition can have a substantial impact on individual as well as team performance. *Methods:* Figure 2c,d shows the average performance trajectories of batsmen and bowlers, respectively, both prior to their removal from the team and subsequent to their rejoining. We consider all players who experienced a temporary exclusion from the team for a minimum of three matches before making a return.

Results: We observe a consistent downtrend in performance during the pre-removal phase, with average runs and wickets demonstrating a monotonic decline, amounting to an approximate 19% reduction for both batsmen and bowlers compared to five matches before the exclusion. Notably, the lowest performance levels are recorded in the match just before the player's exclusion. In contrast, players tend to exhibit a strong comeback performance after reinstatement to the team. In

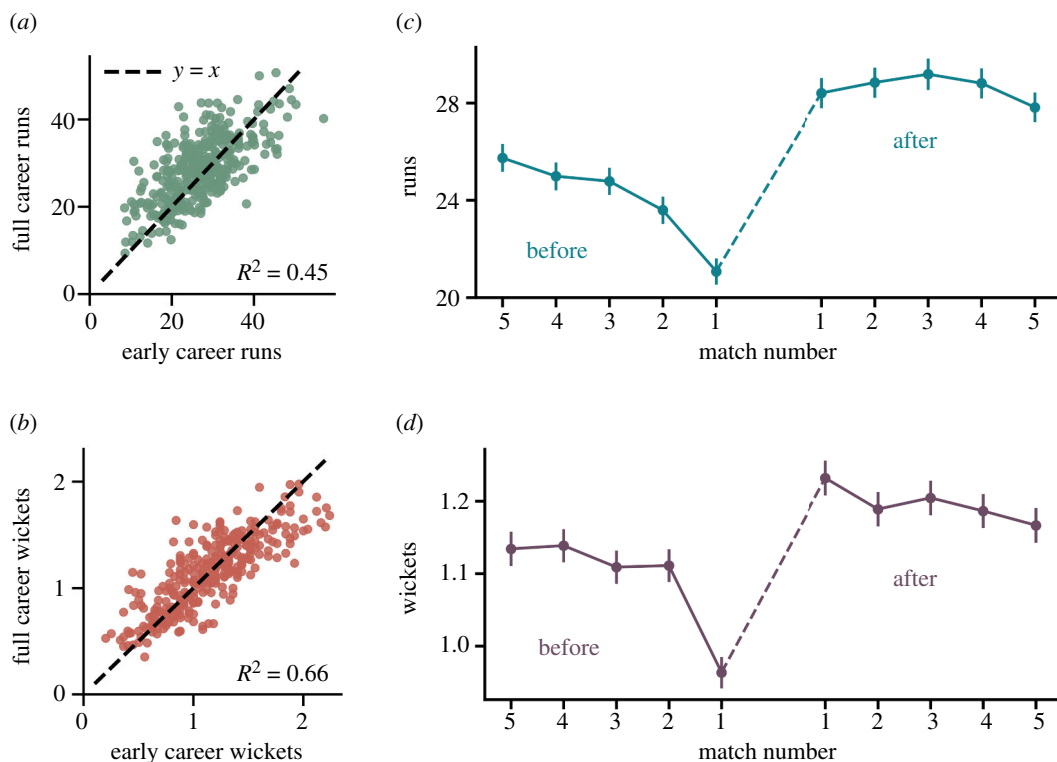


Figure 2. Early career performance and effect of drop and re-entry. (a,b) Scatter plots showing the correlation between early career and full career performance for batsmen and bowlers, respectively. The R^2 values indicate that performances in different stages of a career are correlated. (c,d) Average runs scored and average number of wickets taken by individual players (who were dropped for at least three matches) before they were dropped and after they were reinstated in the team. We observed a significant dip in the performance prior to the drop and a strong comeback in performance after re-entering the team.

particular, the initial performance post-return exhibits a substantial elevation, with batsmen registering an approximate 36% improvement and bowlers showing a 30% enhancement compared to their final pre-removal performance. This enhanced performance appears to be stable in subsequent matches, consistently displaying higher performance compared to the pre-removal, suggesting that short temporal exclusion may improve performance in the longer run.

3.4. Role of leadership

Proficient leadership can enhance performance in teams of skilled individuals. *Methods:* We consider captains who have led their team in a minimum of 15 matches (§2.2). Within our dataset, we identify 172 captains, comprising 71% batsmen and 29% bowlers, indicating a higher propensity for batsmen to be chosen as captains—more than twice as often as bowlers. Despite these differences, captain-bowlers remain in this position for longer than the batsmen on average (see electronic supplementary material, SM5). We first compare the career performance of captains with other players for both batsmen and bowlers. We use the Mann–Whitney U test to determine if the distribution of captain performances is the same as that of the players' performance distribution. To investigate the influence of leadership, we divide the career trajectories of captains into three phases: before, during and after the captainship. We are interested if the performance qualitatively changes during the three phases.

Results: Figure 3a presents a comparison of the career average performances between captains and non-captains (referred to as players). Quantitatively, the average runs scored by captain-batsmen (31) exceed those of players (26) by approximately 16%. Conversely, captain-bowlers secure, on average, 18% fewer wickets than non-captain-bowlers (0.96 versus 1.13). We have considered only the matches where players get a chance to perform. For both batsmen and bowlers, the Mann–Whitney U test yields $p < 0.001$. This disparity suggests differing pathways to captaincy, where batsmen may need to consistently outperform peers, while bowlers' captaincy seems less dependent on individual performance.

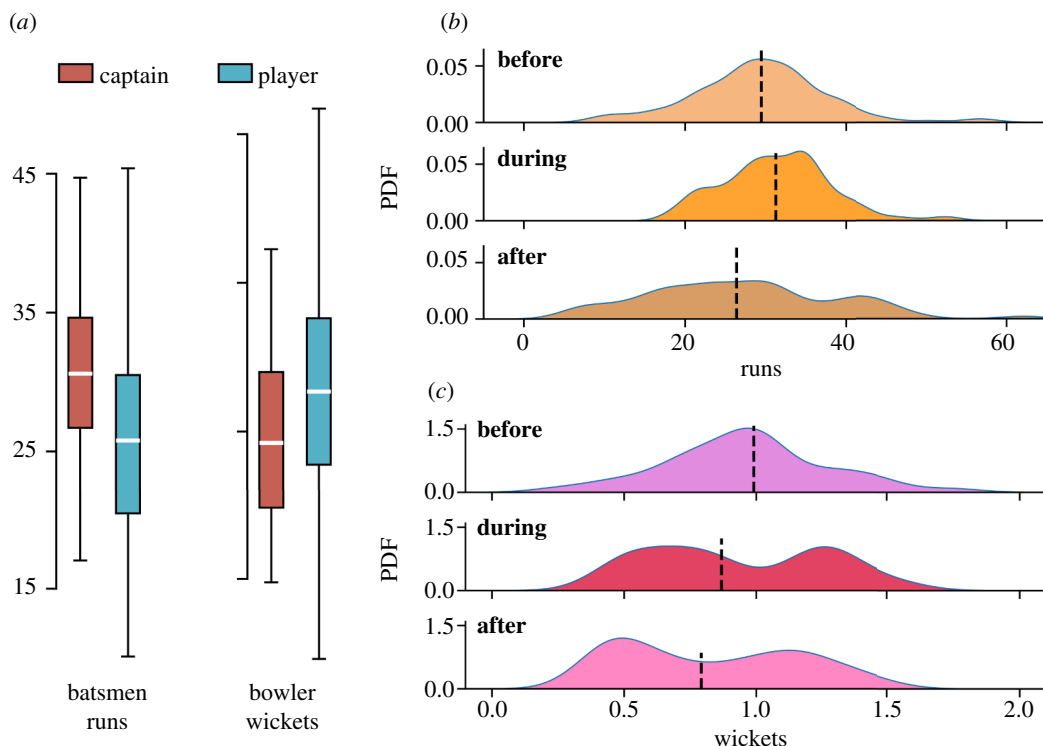


Figure 3. Leadership affects player performance. (a) Boxplot showing the average runs scored and average wickets taken by captain and non-captain players. The average trend for batsmen and bowlers is the opposite with captain-batsmen performing better than their non-captain counterparts. PDFs of performance for captains who are (b) batsmen and (c) bowlers during various phases of their career. The dotted black lines denote the median of the distribution. The performance of captain-batsmen improves during captaincy, while it declines for captain-bowlers.

For both batsmen (figure 3b) and bowlers (figure 3c), we observe that batsmen typically enhance their performance upon assuming captaincy, whereas bowlers exhibit a decline. A closer examination of figure 3c reveals a bimodal distribution during the captaincy phase for bowlers, indicating a dichotomy in skill sets among captain-bowlers. Post-captaincy, the trajectories diverge significantly for batsmen and bowlers. For batsmen, average performance markedly decreases post-captaincy, even falling below their pre-captaincy levels. The decrease is even more substantial for bowlers.

3.5. Contribution of specialists

Specialists providing focused contributions to group endeavours are often key to team success. *Methods:* Here, we consider three types of specialists—openers, all-rounders and wicket-keepers. Batsmen are categorized as openers if they occupy the first or second position in the batting lineup, while positions 3 to 6 are considered non-openers (§2.2). We focus on the pace at which they accumulate these runs. The run-scoring rate is quantified as the number of runs per 100 balls faced, commonly referred to as the *strike rate* in cricket terminology. This metric is frequently used to assess a player's defensive or aggressive playing style. We use the Mann–Whitney *U* test to compare the distributions of runs (and strike rate) scored by openers and non-openers.

All-rounders are players who make significant contributions in both aspects of the game—batting and bowling (§2.2). In contrast, specialized batsmen and bowlers are characterized by their significant contribution in only one of these areas. We quantify the fractional contribution for each type of player as shown in §2.4.2. We use the K–S test to analyse the differences between the distributions of fractional contributions of batsmen and bowlers against all-rounders.

Among various fielding roles, the wicket-keeper is considered to hold a pivotal position. Typically, a batsman can be dismissed in three primary ways: (i) if the bowler successfully hits the stumps or the batsman obstructs the stump with their leg, (ii) if a fielder catches the ball hit by the batsman before it touches the ground or (iii) if the stump is dislodged by the fielders before the completion of a run between the wickets. The first method relies exclusively on the bowler's skill, whereas the latter

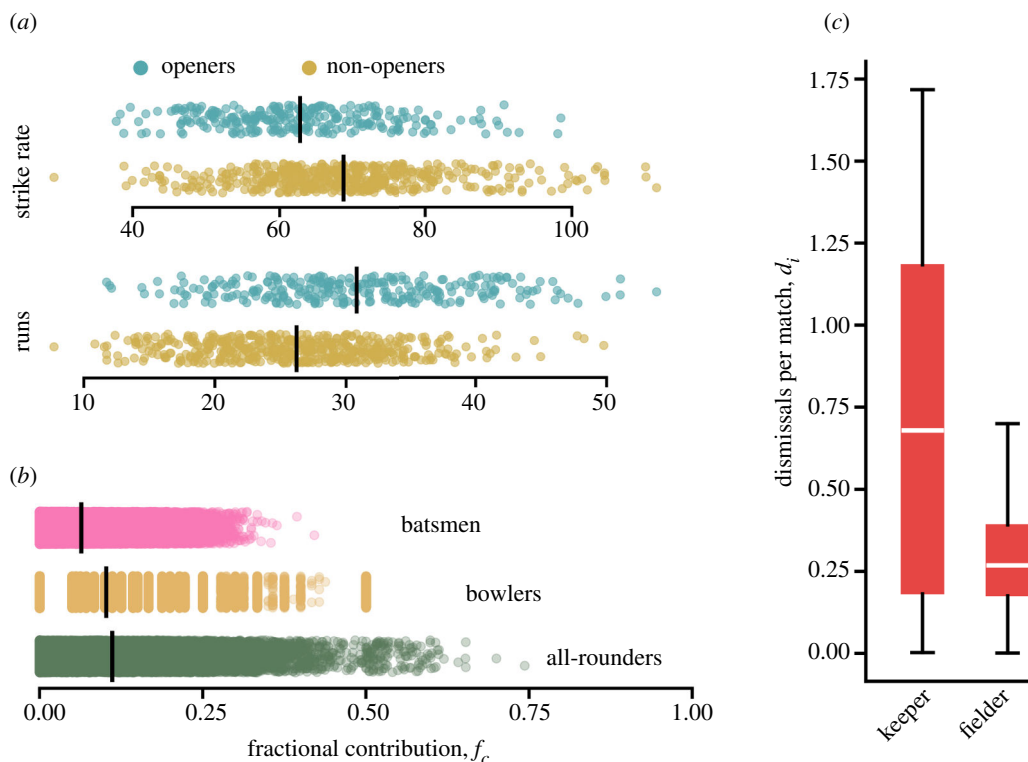


Figure 4. Contribution of specialists. (a) Runs and strike rates of opener and non-opener batsmen. The solid black lines denote the mean of the distributions. Openers score more runs at a slower pace, while non-openers play aggressively at the cost of lower contributions to team scores. (b) Fractional contribution f_c of players to the team scores for batsmen, bowlers and all-rounders. All-rounders contribute significantly higher to the team. (c) Fractional dismissals d_i per match by wicket-keepers and other fielders over the entire career. Wicket-keepers exhibit a very high tendency to contribute to team dismissals as compared to the fielders.

two require strategic collaboration between the bowler and fielders. Our interest lies in the last two dismissal types. Specifically, we define d_i as the number of dismissals executed by a fielder of type (ii) and (iii) per match. We use Welch's t -test to compute the statistical significance of differences between the number of dismissals by the wicket-keepers and fielders respectively.

Results: Figure 4a elucidates the variations in batting patterns between opening batsmen and their non-opening counterparts. Our analysis reveals that openers average a strike rate of around 63 runs per 100 balls, whereas non-openers exhibit a higher average of 69 runs per 100 balls. This suggests that non-openers score approximately 9% more rapidly than their opening counterparts. However, the average score for openers stands at approximately 31 runs, in contrast to 26 runs for non-openers, indicating a reduction of about 17% for batsmen coming later in the batting order. The Mann–Whitney U test yields statistical significance level given by $p < 0.001$.

Figure 4b presents the distribution of the contributions of all players across all matches. Among these, batsmen demonstrate the lowest mean contribution ($f_c \approx 0.06$), with bowlers exhibiting a slightly higher average contribution of $f_c \approx 0.1$. Notably, all-rounders surpass both groups with an average contribution of $f_c \approx 0.11$. Furthermore, there are instances where all-rounders singularly account for more than 50% of the team's performance, evidenced by instances of $f_c > 0.5$. The K–S test reveals that the contributions from batsmen and bowlers are significantly different ($p < 0.001$) from those of all-rounders. We also note that non-specialists contribute significantly less than the specialists in both departments (see electronic supplementary material, SM8).

Figure 4c presents a boxplot depicting the distribution of dismissal fractions attributed to wicket-keepers and fielders. Our observations reveal that wicket-keepers play a vital role in dismissals, accounting for approximately 0.7 dismissals per match. In contrast, fielders contribute to a relatively minor number of dismissals, averaging around 0.3. The Welch t -test gives $p < 0.001$ implying that wicket-keepers are consistently better than fielders when the opportunity arises.

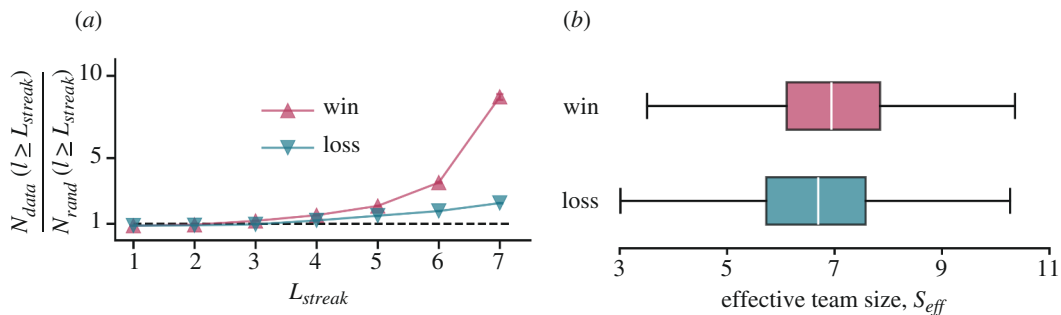


Figure 5. Patterns in team success. (a) Occurrences of hot streaks (wins denoted by red) or cold streaks (losses denoted by blue) of a given length L_{streak} compared to a null model. $N(l \geq L_{streak})$ denotes the number of times when the team had the same result for l or more matches, averaged over teams. We observe that teams demonstrate both hot and cold streaks. The fluctuations in the numbers calculated as the standard error are smaller than the symbols. (b) Differences between *effective team size* S_{eff} for winning and losing teams. Winning teams have a larger S_{eff} on average, indicating that a larger number of players contribute significantly in winning teams than in losing teams.

3.6. Patterns of team success

Methods: Similar to the bursts of exceptional performance observed in individual players (as discussed in §3.1), we assess the propensity of teams to consecutively win (or lose) a series of matches. We quantify this tendency by defining the ratio $\frac{N_{data}}{N_{rand}}$, where N_{data} represents the frequency of a team winning (or losing) l or more consecutive matches. In contrast, N_{rand} is the analogous frequency within a randomized null model (see §2.5.2). Thus, the ratio $\frac{N_{data}}{N_{rand}}$ indicates the likelihood of a team experiencing a streak of at least l consecutive wins or losses compared to a random outcome.

To gain more insight into the team composition, we employ the concept of effective size S_{eff} as discussed in §2.4.3. To compute the statistical differences between the S_{eff} of winning and losing teams, we use the Mann–Whitney U test. Additionally, we also compute the effect size $r = \frac{U}{n_1 n_2}$, where U is the test statistic and n_1 and n_2 are the sample sizes, respectively.

Results: Figure 5a reveals that teams are more prone to winning or losing matches in sequence than would be expected by chance. Notably, the probability of winning seven or more consecutive matches is nine times higher than chance, while the likelihood of losing seven or more consecutive matches is about three times the random expectation. This observation suggests that teams exhibit *hot streaks* in their winning performances. Intriguingly, we also observe *cold streaks*, where teams undergo multiple successive losses.

As illustrated in figure 5b via a boxplot, the distributions of S_{eff} for winning and losing teams differ notably. The median S_{eff} for winning teams (≈ 6.9) is approximately 4% greater than that for losing teams (≈ 6.6). This indicates that successful teams require a broader array of individual contributions. The Mann–Whitney U test indicates that the differences are significant ($p < 0.001$) and the effect size $r = 0.56$ indicates a probability that the winning side is 56% more likely to have higher S_{eff} than the losing side.

4. Discussion

In the last few years, the advent of detailed sports analytics has revolutionized our understanding of human behaviour in sports [10–12]. It offers insights into physical performance, cognitive processes and team dynamics, moving beyond traditional training methods [13,14]. This shift towards a data-driven approach in sports reflects a broader societal trend in optimizing human potential, combining historical practices with modern scientific methodologies.

In this study, we quantified the individual and team performance in ODI cricket, examining various aspects of the game. Due to the absence of quantifiable performance metrics such as the *Elo* rating system in chess, we validated the use of runs scored and wickets taken as indicators of batting and bowling performance, respectively. Our analysis revealed a significant increase in average runs scored

over time. To negate this inflation in run-scoring and facilitate fair comparisons, we implemented a normalization of all performances involving runs (see electronic supplementary material, SM1).

This rescaled data corroborated the ‘random impact rule’ observed in other domains, indicating that a player’s peak performance can occur at any point during their career [37,38]. However, this best performance often co-occurs with other comparable exemplary performances, pointing to the existence of *hot streaks* in individual cricket players. Across a range of domains such as science [38,39], arts [41,42] and sports [8,24], individual careers display *hot streaks*, where exceptional performances tend to occur in bursts that are clustered in time. Our analysis showed that, while the best performance of a cricket player’s career may manifest at any point within their career, peak performances tend to occur in rapid sequence over a short period of time. This is further confirmed by the probability of performing well in consecutive matches growing exponentially, as evidenced by the recurrence time distribution in electronic supplementary material, SM3.

Our exploration into the predictors of individual performance unveiled a strong correlation between early career achievements and overall career trajectory. However, noteworthy differences were observed between batsmen and bowlers with batsmen improving their performance from early careers more than the bowlers. Such disparities may be attributed to the distinct elements inherent in the roles of batsmen and bowlers. Batsmen, for instance, may leverage accumulated experience and refined skills to augment run-scoring, while bowlers may depend more on innovation and strategic creativity to increase their wicket tally. This distinction potentially accounts for the observed trend of a higher proportion of batsmen surpassing their initial career performance compared to bowlers. Alternatively, our observations can also be explained if some players are simply better than the rest. Thus, their performance in various stages of their careers will correlate with their full career performance. This effect is also known as the *Q-model* in the context of scientific careers [37]. Further analyses supporting this hypothesis are presented in electronic supplementary material, SM4. Additionally, we confirmed that players are often excluded from teams due to declining performances, yet they typically exhibit a sustained enhancement in performance following their comeback.

We investigated the relationship between player performance and captaincy. Our data suggested that batsmen who ascend to captaincy roles demonstrate higher performance levels, both overall and during their tenure as captain, in contrast to non-captain-batsmen. This pattern was not mirrored among bowlers, highlighting the differential impact of captaincy on distinct player types. These observations suggest a close correlation between individual performance and captaincy tenure for batsmen, where they often lead through exemplary performance. Conversely, bowlers may experience captaincy as a burden, reflected in their individual statistics. This could account for the observed differences in performance between captains and non-captains among batsmen and bowlers. We tested that this phenomenon is not because the captain-bowlers bowl for more time in electronic supplementary material, SM6. An alternative explanation might be that captains tend to bowl at the wrong time to relieve the team pressure. However, to test this hypothesis, one would need fine-grained temporal information about the progression of a match, which is not present in our data.

Focusing on the role of specialists, our findings indicated that opening batsmen typically score more runs but at a slower rate, whereas subsequent batsmen tend to adopt more aggressive strategies. Collectively, these findings illustrate a strategic balance between defensive and attacking approaches contingent on a player’s batting position. Openers tend to adopt a more conservative approach, possibly due to the initial uncertainty of the pitch conditions, while subsequent batsmen often adopt a more aggressive strategy, building upon the foundational efforts of the openers. Further analysis reveals that this disparity may be partially attributed to the differing number of balls faced by players based on their batting order (see electronic supplementary material, SM7).

All-rounders enhance the team’s score by applying their skills across both facets of the game. They were observed to contribute more to team performance compared to batsmen and bowlers. While bowlers generally contribute more towards the team’s collective efforts than batsmen, all-rounders emerge as pivotal players, often driving the team’s success with contributions that exceed 50% of the total team scores. In the realm of fielding, wicket-keepers emerged as pivotal in effecting dismissals, thereby bolstering the impact of bowlers on team success. In summary, team success depends on the successful coordination of different types of—often specialized—contributions. Although most players are predominantly recognized for their batting or bowling abilities, fielding is an integral aspect of a team’s overall success. Indeed, a commonly reiterated phrase in cricket states, ‘catches win matches’, emphasizing the significance of player dismissals through effective fielding. Wicket-keepers, by contributing to a substantial number of total dismissals, enhance the bowlers’ efforts and, consequently, the overall team performance. These findings underscore the vital role of specialists in ODI

cricket. Future research could look into a more detailed examination of their role and their strategic impact on the dynamics of the game.

Additionally, our analysis reveals that, similarly to individual performances, teams also tend to win or lose matches in clusters, thus identifying both *hot* and *cold* streaks during seasons. We observed that winning teams were characterized by more evenly distributed player performances, as indicated by higher *effective team sizes*. A lack of such collective effort often results in teams losing matches. Moreover, the data reveal a redundancy of 3 to 4 players in most teams. However, our supplementary analysis also reveals that the top performers from the winning team contribute more to their team than their top-performing counterparts from the losing team (see electronic supplementary material, SM9).

Our results might be subject to certain limitations. Cricket is a multi-faceted game, and while our analysis focuses on a wide range of indicators, it still does not consider all aspects of the game such as home advantage and differences among spinners and fast bowlers. Furthermore, the volume of ODI matches and the resulting dataset size is not fully extensive. Future research could benefit from incorporating data from diverse cricket formats such as test matches, T20 games and franchise leagues like the IPL, which might yield deeper insights into varied player performance patterns. Supplementing our analysis with data from various professional levels may reveal further patterns in players' mobility and skill levels. Additionally, our dataset focuses on end-match statistics, omitting the nuanced temporal dynamics within individual games. While the final scorecard offers substantial information, some facets of performance may only become apparent with a more granular data analysis.

All in all, our work reveals intriguing patterns of individual and team performance in ODI cricket. We believe that our methodologies developed here could be readily applied without substantial modifications to other formats of the game such as T20 and test cricket, as well as other team sports. Particularly suitable are teams with high specialization such as baseball, American football and volleyball. A comparative analysis of our results with a broader literature on sports can improve our understanding of human behaviour. We hope that our analysis motivates further research into synergistic individual efforts in sports and, more broadly, in team dynamics.

Ethics. This work did not require ethical approval from a human subject or animal welfare committee.

Data accessibility. Data and relevant code for this research work are stored in GitHub [71] and have been archived within the Zenodo repository [72].

Supplementary material is available online [73].

Declaration of AI use. We have not used AI-assisted technologies in creating this article.

Authors' contributions. O.S.: conceptualization, data curation, formal analysis, investigation, methodology, visualization, writing—original draft, writing—review and editing; S.C.: investigation, methodology, visualization, writing—review and editing; M.S.S.: investigation, methodology, writing—review and editing; F.B.: conceptualization, funding acquisition, investigation, methodology, project administration, supervision, writing—original draft, writing—review and editing.

All authors gave final approval for publication and agreed to be held accountable for the work performed therein.

Conflict of interests. We declare we have no competing interests.

Funding. F.B. acknowledges support from the Air Force Office of Scientific Research under award number FA8655-22-1-7025.

Acknowledgements. The authors thank Aanjaneya Kumar and Lorenzo Betti for the discussions which led to an improvement in the manuscript.

References

1. Roche M. 2000 *Mega-events and modernity: Olympics and Expos in the growth of global culture*, 1st edn. Oxford, UK: Routledge.
2. Guttmann A. 2002 The Olympics, a history of the modern games. In *Illinois history of sports*, 2nd edn. Urbana, IL: University of Illinois Press.
3. Bryson B. 2008 *A really short history of nearly everything*. New York, NY: Delacorte.
4. Horne J, Whannel G. 2020 *Understanding the Olympics*. Oxford, UK: Routledge.
5. Nevill A, Atkinson G, Hughes M. 2008 The growing trend of scientific interest in sports science research. *J. Sports Sci.* **26**, 413. (doi:10.1080/02640410701705108)
6. Radicchi F. 2011 Who is the best player ever? A complex network analysis of the history of professional tennis. *PLoS One* **6**, e17249. (doi:10.1371/journal.pone.0017249)

7. Pappalardo L, Cintia P, Ferragina P, Massucco E, Pedreschi D, Giannotti F. 2019 Playerank. *ACM Trans. Intell. Syst. Technol.* **10**, 1–27. (doi:10.1145/3343172)
8. Chowdhary S, Iacopini I, Battiston F. 2023 Quantifying human performance in chess. *Sci. Rep.* **13**, 2113. (doi:10.1038/s41598-023-27735-9)
9. Zappalà C, Biondo AE, Pluchino A, Rapisarda A. 2023 The paradox of talent: how chance affects success in tennis tournaments. *Chaos Soliton. Fract.* **176**, 114088. (doi:10.1016/j.chaos.2023.114088)
10. Lewis M. 2004 *Moneyball: the art of winning an unfair game*. New York, NY: W. W. Norton.
11. Brown DT, Link CR, Rubin SL. 2017 *Moneyball* after 10 years. *J. Sports Econ.* **18**, 771–786. (doi:10.1177/1527002515609665)
12. Pappalardo L, Cintia P. 2018 Quantifying the relation between performance and success in Soccer. *Adv. Complex Syst.* **21**, 1750014. (doi:10.1142/S021952591750014X)
13. Mason D, Foster W. 2007 Putting Moneyball on ice? *Int. J. Sport Finance* **2**, 206–213.
14. Dawson M. 2023 The iron cage of efficiency: analytics, basketball and the logic of modernity. *Sport Soc.* **26**, 1785–1801. (doi:10.1080/17430437.2023.2208040)
15. Neuhaus T, Thomas N. 2024 *Interdisciplinary analyses of professional basketball*, pp. 11–39. New York, NY: Springer.
16. Roring RW, Charness N. 2007 A multilevel model analysis of expertise in chess across the life span. *Psychol. Aging* **22**, 291–299. (doi:10.1037/0882-7974.22.2.291)
17. Vaci N, Bilalić M. 2017 Chess databases as a research vehicle in psychology: modeling large data. *Behav. Res. Methods* **49**, 1227–1240. (doi:10.3758/s13428-016-0782-5)
18. 2023 *The most popular sports in the world*. See <https://worldatlas.com>.
19. 2024 *Most popular Google sports trends*. See <https://topendsports.com>.
20. Subasingha S, Premaratne SC, Jayaratne KL, Sellappan P. 2019 Novel method for cricket match outcome prediction using data mining techniques. *Int. J. Eng. Adv. Technol.* **8**, 15–21. (doi:10.35940/ijeat.F1004.0986S319)
21. Bandulasiri A. 2008 Predicting the winner in One Day International cricket. *J. Math. Sci. Math. Educ.* **3**.
22. McEwan K, Pote L, Radloff S, Nicholls SB, Christie C. 2023 The role of selected pre-match covariates on the outcome of One-Day International (ODI) cricket matches. *S. Afr. J. Sports Med.* **35**, v35i1a15012. (doi:10.17159/2078-516X/2023/v35i1a15012)
23. Asif M, McHale IG. 2016 In-play forecasting of win probability in One-Day International cricket: a dynamic logistic regression model. *Int. J. Forecast.* **32**, 34–43. (doi:10.1016/j.ijforecast.2015.02.005)
24. Ram SK, Nandan S, Boulebane S, Sornette D. 2022 Synchronized bursts of productivity and success in individual careers. *Sci. Rep.* **12**, 7637. (doi:10.1038/s41598-022-10837-1)
25. Premkumar P, Chakrabarty JB, Chowdhury S. 2020 Key performance indicators for factor score based ranking in One Day International cricket. *IIMB Manag. Rev.* **32**, 85–95. (doi:10.1016/j.iimb.2019.07.008)
26. Swartz TB, Gill PS, Muthukumarana S. 2009 Modelling and simulation for one-day cricket. *Can. J. Statistics* **37**, 143–160. (doi:10.1002/cjs.10017)
27. C. G. K. 1905 Science and art of cricket. *Nature* **73**, 82–84. (doi:10.1038/073082a0)
28. Kimber AC, Hansford AR. 1993 A statistical analysis of batting in cricket. *J. R. Stat. Soc. Ser. A* **156**, 443–455. (doi:10.2307/2983068)
29. Mehta RD, Bentley K, Proudlove M, Varty P. 1983 Factors affecting cricket ball swing. *Nature New Biol.* **303**, 787–788. (doi:10.1038/303787a0)
30. Arora M, Gupta R, Kumaraguru P. 2014 Indian Premier League (IPL), cricket, online social media. (doi:https://arxiv.org/abs/1405.5009)
31. Nicholls S, Pote L, Thomson E, Theis N. 2023 The change in test cricket performance following the introduction of T20 cricket. *Sport. Innov. J.* **4**, 1–16. (doi:10.18060/26438)
32. Orchard J, James T, Alcott E, Carter S, Farhart P. 2002 Who owns the information? Databases of injuries in professional sport are valuable resources which should not suffer confidentiality restraints. *Br. J. Sports Med.* **36**, 16–18. (doi:10.1136/bjsm.36.1.16)
33. Finch CF, Elliott BC, McGrath AC. 1999 Measures to prevent cricket injuries: an overview. *Sports Med.* **28**, 263–272. (doi:10.2165/00007256-199928040-00004)
34. Orchard J, Newman D, Stretch R, Frost W, Mansingh A, Leipus A. 2005 Methods for injury surveillance in international cricket. *J. Sci. Med. Sport* **8**, 1–14. (doi:10.1016/s1440-2440(05)80019-2)
35. Coles S. 2001 *An introduction to statistical modeling of extreme values*, pp. 92–104. London, UK: Springer. (doi:10.1007/978-1-4471-3675-0_5)
36. Beirlant J, Goegebeur Y, Teugels J, Segers J. 2004 Statistics of extremes: theory and applications. In *Wiley series in probability and statistics*, 1st edn. Hoboken, NJ: Wiley. (doi:10.1002/0470012382)
37. Sinatra R, Wang D, Deville P, Song C, Barabási AL. 2016 Quantifying the evolution of individual scientific impact. *Science* **354**, aaf5239. (doi:10.1126/science.aaf5239)
38. Shi M *et al.* 2018 The evolutionary history of vertebrate RNA viruses. *Nat. New Biol.* **556**, 197–202. (doi:10.1038/s41586-018-0012-7)
39. Liu Y, Cao L, Wu B. 2022 General non-linear imitation leads to limit cycles in eco-evolutionary dynamics. *Chaos Solitons Fractals* **165**, 112817. (doi:10.1016/j.chaos.2022.112817)
40. Fraiberger SP, Sinatra R, Resch M, Riedl C, Barabási AL. 2018 Quantifying reputation and success in art. *Science* **362**, 825–829. (doi:10.1126/science.aau7224)
41. Janosov M, Battiston F, Sinatra R. 2020 Success and luck in creative careers. *EPJ Data Sci.* **9**. (doi:10.1140/epjds/s13688-020-00227-w)
42. Williams OE, Lacasa L, Latora V. 2019 Quantifying and predicting success in show business. *Nat. Commun.* **10**, 2256. (doi:10.1038/s41467-019-10213-0)

43. Bar-Eli M, Avugos S, Raab M. 2006 Twenty years of 'hot hand' research: review and critique. *Psychol. Sport Exerc. Judgm. Decis. Mak. Sport Exerc.* **7**, 525–553. (doi:[10.1016/j.psychsport.2006.03.001](https://doi.org/10.1016/j.psychsport.2006.03.001))
44. Gilovich T, Vallone R, Tversky A. 1985 The hot hand in basketball: on the misperception of random sequences. *Cogn. Psychol.* **17**, 295–314. (doi:[10.1016/0010-0285\(85\)90010-6](https://doi.org/10.1016/0010-0285(85)90010-6))
45. Golder PN, Tellis GJ. 1997 Will it ever fly? Modeling the takeoff of really new consumer durables. *Mktg. Sci.* **16**, 256–270. (doi:[10.1287/mksc.16.3.256](https://doi.org/10.1287/mksc.16.3.256))
46. Bak-Coleman JB, Kennedy I, Wack M, Beers A, Schafer JS, Spiro ES, Starbird K, West JD. 2022 Combining interventions to reduce the spread of viral misinformation. *Nat. Hum. Behav.* **6**, 1372–1380. (doi:[10.1038/s41562-022-01388-6](https://doi.org/10.1038/s41562-022-01388-6))
47. Shaw JM, Johnson DD, Nygaard IE. 2018 Engaging undergraduate kinesiology students in clinically-based research. *Quest* **70**, 292–303. (doi:[10.1080/00336297.2017.1380054](https://doi.org/10.1080/00336297.2017.1380054))
48. Till K, Baker J. 2020 Challenges and [possible] solutions to optimizing talent identification and development in sport. *Front. Psychol.* **11**, 664. (doi:[10.3389/fpsyg.2020.00664](https://doi.org/10.3389/fpsyg.2020.00664))
49. Hussain Z, Mata R, Wulff DU. 2024 Novel embeddings improve the prediction of risk perception. *EPJ Data Sci.* **13**, 38. (doi:[10.1140/epjds/s13688-024-00478-x](https://doi.org/10.1140/epjds/s13688-024-00478-x))
50. Pasarakonda S, Maynard T, Schmutz JB, Lüthold P, Grote G. 2023 How team familiarity mitigates negative consequences of team composition disruptions: an analysis of Premier League teams. *Group Organiz. Manag.* (doi:[10.1177/10596011231193176](https://doi.org/10.1177/10596011231193176))
51. Guimerà R, Uzzi B, Spiro J, Amaral LAN. 2005 Team assembly mechanisms determine collaboration network structure and team performance. *Science* **308**, 697–702. (doi:[10.1126/science.1106340](https://doi.org/10.1126/science.1106340))
52. Zhang J, Yin K, Li S. 2022 Leader extraversion and team performance: a moderated mediation model. *PLoS One* **17**, e0278769. (doi:[10.1371/journal.pone.0278769](https://doi.org/10.1371/journal.pone.0278769))
53. Hancock AJ, Gellatly IR, Walsh MM, Arnold KA, Connelly CE. 2023 Good, bad, and ugly leadership patterns: implications for followers' work-related and context-free outcomes. *J. Manage.* **49**, 640–676. (doi:[10.1177/01492063211050391](https://doi.org/10.1177/01492063211050391))
54. Betti L, Gallo L, Wachs J, Battiston F. 2024 The dynamics of leadership and success in software development teams. (doi:<https://arxiv.org/abs/2404.18833>)
55. Burke CS, Georganta E, Marlow S. 2019 A bottom up perspective to understanding the dynamics of team roles in mission critical teams. *Front. Psychol.* **10**, 1322. (doi:[10.3389/fpsyg.2019.01322](https://doi.org/10.3389/fpsyg.2019.01322))
56. Salcinovic B, Drew M, Dijkstra P, Waddington G, Serpell BG. 2022 Factors influencing team performance: what can support teams in high-performance sport learn from other industries? A systematic scoping review. *Sports Med. Open.* **8**, 25. (doi:[10.1186/s40798-021-00406-7](https://doi.org/10.1186/s40798-021-00406-7))
57. Wallrich L, Opara V, Wesołowska M, Barnoth D, Yousefi S. 2024 The relationship between team diversity and team performance: reconciling promise and reality through a comprehensive meta-analysis registered report. *PsyArXiv*. (doi:[10.31234/osf.io/nsdc4](https://doi.org/10.31234/osf.io/nsdc4))
58. 2024 HowSTAT! The cricket statisticians. See <http://howstat.com/cricket/home.asp>.
59. 2024 Cricket—Wikipedia. See <https://en.wikipedia.org/w/index.php?title=Cricket>.
60. Smyth R. 2011 *Fifteen-over field restrictions*. ESPN cricinfo. See <https://www.espnricinfo.com/story/cricket-s-turning-points-fifteen-over-field-restrictions-513169>.
61. Sankar R. 2019 *The evolution of the cricket bat: from then to now*. sportskeeda. See <https://www.sportskeeda.com/cricket/evolution-of-cricket-bats>.
62. Silgardo D. 2023 *More runs, longer careers, fewer breaks: how cricket has changed over the past 30 years*. ESPN cricinfo. See <https://www.espnricinfo.com/story/a-statistical-look-at-how-cricket-has-changed-over-the-past-30-years-more-runs-longer-careers-fewer-breaks-1367458>.
63. Radicchi F, Fortunato S, Castellano C. 2008 Universality of citation distributions: toward an objective measure of scientific impact. *Proc. Natl Acad. Sci. USA* **105**, 17268–17272. (doi:[10.1073/pnas.0806977105](https://doi.org/10.1073/pnas.0806977105))
64. Hodges JL. 1958 The significance probability of the Smirnov two-sample test. *Ark. Mat.* **3**, 469–486. (doi:[10.1007/BF02589501](https://doi.org/10.1007/BF02589501))
65. Wilcoxon F. 1945 Individual comparisons by ranking methods. *Bio. Bull.* **1**, 80. (doi:[10.2307/3001968](https://doi.org/10.2307/3001968))
66. Mann HB, Whitney DR. 1947 On a test of whether one of two random variables is stochastically larger than the other. *Ann. Math. Stat.* **18**, 50–60. (doi:[10.1214/aoms/1177730491](https://doi.org/10.1214/aoms/1177730491))
67. Welch BL. 1947 The generalisation of Student's problems when several different population variances are involved. *Biometrika* **34**, 28–35. (doi:[10.1093/biomet/34.1-2.28](https://doi.org/10.1093/biomet/34.1-2.28))
68. Virtanen P et al. 2020 Scipy 1.0: fundamental algorithms for scientific computing in Python. *Nat. Methods* **17**, 261–272. (doi:[10.1038/s41592-019-0686-2](https://doi.org/10.1038/s41592-019-0686-2))
69. Klug M, Bagrow JP. 2016 Understanding the group dynamics and success of teams. *R. Soc. Open Sci.* **3**, 160007. (doi:[10.1098/rsos.160007](https://doi.org/10.1098/rsos.160007))
70. Delice F, Rousseau M, Feitosa J. 2019 Advancing teams research: what, when, and how to measure team dynamics over time. *Front. Psychol.* **10**, 1324. (doi:[10.3389/fpsyg.2019.01324](https://doi.org/10.3389/fpsyg.2019.01324))
71. Onkar S. 2024 Cricket_Public. *GitHub*. See https://github.com/sadekar-onkar/cricket_public.
72. Onkar S. 2024 sadekar-onkar/cricket_public: individual and team performance in cricket. See <https://zenodo.org/records/11581222>.
73. Sadekar O, Chowdhary S, Santhanam MS, Battiston F. 2024 Supplementary material from: Individual and team performance in cricket. Figshare. (doi:[10.6084/m9.figshare.c.7303158](https://doi.org/10.6084/m9.figshare.c.7303158))