ADVANCE SOCIAL SCIENCE ARCHIVE JOURNAL
Available Online: https://assajournal.com
Vol. 04 No. 01. July-September 2025.Page#.2021-2030
Print ISSN: 3006-2497 Online ISSN: 3006-2500
https://doi.org/10.55966/assaj.2025.4.1.0110
Platform & Workflow by: Open Journal Systems

Comparative Analysis of Players in T-20 International Cricket Using Survival Analysis

Muhammad Waseem
BS Statistics, Department of Statistics, Abdul Wali Khan University, Mardan, KPK, Pakistan
waseemstat111@gmail.com
Sulaiman Khan
BS Statistics, Department of Statistics, Abdul Wali Khan University, Mardan, KPK, Pakistan
sulaimankhan1.ds@gmail.com
Zakir Ali
BS Statistics, Department of Statistics, Abdul Wali Khan University, Mardan, KPK, Pakistan
xaky908@gmail.com
Roohullah
BS Statistics, Department of Statistics, Abdul Wali Khan University, Mardan, KPK, Pakistan
gcroohullahmalik@gmail.com
Anam Murtaza Shah
M.Phil. Statistics, University of Sargodha
anammurtazashah434@gmail.com

ABSTRACT

This research conducts a comparative examination of exponential and Weibull distributions for assessing batting performance in T20 international cricket, utilizing survival analysis techniques to measure player reliability. The investigation analyzes innings data from 10 top-tier batsmen (featuring prominent players like Babar Azam, David Warner, and Virat Kohli) obtained from ESPNcricinfo, applying maximum likelihood estimation (MLE) to calibrate both distributions. Model comparison is performed using Akaike (AIC) and Bayesian (BIC) information criteria along with chi-square goodness-of-fit tests. Findings indicate that the exponential distribution, with its constant hazard function, offers better modeling accuracy for most batsmen, as evidenced by superior AIC/BIC scores and non-significant chi-square results ($p > 0.05$). Analysis of survival probabilities at critical run intervals (10, 30, 50, 80, and 100 runs) identifies Babar Azam as demonstrating exceptional consistency, showing a 75.6% likelihood of exceeding 10 runs and a 24.7% probability of achieving a half-century. Conditional probability analysis further reveals his superior conversion rate (57.1% chance of advancing from 30 to 50 runs) compared to more aggressive batsmen like Glenn Maxwell, who display greater performance fluctuation. While the Weibull distribution provides modeling flexibility, the study finds it overly complex for T20 batting performance data. The research highlights practical implementations for team management, including batting order optimization, in-game decision-making, and player skill development programs. These results emphasize the effectiveness of the exponential model in cricket performance analytics and recommend its incorporation into strategic planning for cricket teams.

Keywords: *Survival Analysis, T20 Cricket, Exponential Distribution, Weibull Distribution, Batting Consistency, AIC/BIC, Maximum Likelihood Estimation, Babar Azam, Conditional Survival Probabilities, Player Performance.*

Introduction

Cricket, especially the Twenty20 (T20) version, has become one of the most dynamic and fast-paced game where new analytical methods are needed to measure the player performance. Statistical modeling has been important in the study of batting consistencies and one of the most important tools that have been used to determine the number of balls a batsman can stay at the crease without getting out is the survival analysis. The exponential and Weibull distributions are some of the other probability distributions that stand out among a wide range of probability distributions in use especially to model time-to-event data in sports analytics. The exponential distribution, defined by its constant hazard rate, is mathematically expressed as $f(x,\lambda)=\lambda e-\lambda x f(x,\lambda)=\lambda e-\lambda x$ for $x\geq 0x\geq 0$ (Bain & Engelhardt, 1991), making it suitable for scenarios where events occur at a steady rate. Nevertheless, this is a drawback since its use is restricted by the fixed rate of hazard, which is not consistent with the nature of scoring patterns in T20 cricket (Sarkar & Mishra, 2017). In contrast, the Weibull distribution, given by $f(x|\alpha,\beta)=\beta\alpha(x\alpha)\beta-1e-(x\alpha)\beta f(x|\alpha,\beta)=\alpha\beta(\alpha x)\beta-1e-(\alpha x)\beta$, accommodates varying hazard rates through its shape parameter $\beta\beta$, offering greater flexibility in capturing the dynamic nature of T20 innings (Meeker & Escobar, 1998).

There has been much debate on the comparative effectiveness of these distributions used in modeling batting performance. Although the exponential distribution is easier to analyze due to its memory less property, the Weibull distribution is more viable in situations where the variability of the performance is high, like in the case of vigorous batting stints or death overs (Sarkar & Banerjee, 2016). Such research as that conducted by Vine (2016) has shown that the Weibull model is better at predicting scoring bursts in leagues like the KFC Big Bash where the batsmen do not perform linearly. Nevertheless, empirical results of the present study have shown that the exponential distribution might prove to be a better fit to some elite batsmen with lower Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values (Raftery, 1986). This poses some serious questions regarding which model best describes realistic T20 batting behaviour and how survival probabilities can be used in strategy, including how to optimise batting orders, or how to judge the reliability of individuals under pressure.

The main aims of the work are threefold: the first is to compare the exponential and Weibull distributions to find out which of them better fits the scores of individual batsmen in T20 internationals; the second is the analysis of the survival probabilities at the important scoring thresholds (10, 30, 50, 80, 100 runs) to obtain information about the performance consistency; and the third is to compare the elite batsmen, such as Babar Azam, David Warner, and Virat Kohli, using the conditional survival probabilities This study presents practical guidelines to the team strategists and coaches by using the data provided by ESPNcricinfo and maximum likelihood estimation (MLE) method to fit the parameters, in order to demonstrate how player assessment and decision-making during the games can be improved using statistical models (Das, 2008). Not only do the findings add to the literature on sports analytics, but they also emphasize the real-life meaning of survival analysis in the development of the T20 cricket strategies.

Literature Review

Survival analysis has become an effective statistical technique in cricket analysis, especially in assessing batting performance during climax and short-format match such as in T20 matches. This model which was initially applied in medical and engineering reliability analysis has been modified to determine how long a batsman can stay in the event before he is dismissed by considering the runs scored as the time to event data (Sharma & Kumar, 2019). Initial uses were based on trying to model player consistency by using parametric distributions, often the simple exponential distribution because of its simplicity and interpretability. Sarkar and Mishra (2017) found its application in one-day/Twenty20 format of cricket in which the exponential model was sufficient to predict the hazard rates of dismissals of batsmen given constant failure rate. But the critics believe that this supposition misguides the complexity of the T20 innings that completely changes depending on the powerplays, middle overs, and death overs (Jayaraman & Lodha, 2017). Nevertheless, this restriction is not a serious concern, because the exponential model has been widely used due to its computational simplicity and the possibility of its implementation into real-time performance monitoring systems (Silva et al., 2016).

Weibull distribution has found its prominence as being more versatile and able to model non-constant hazard rates with its shape parameter (b). Sarkar and Banerjee (2016) emphasized its excellence in fitting the batting performance especially in Test cricket where endurance of players and their adaptability in different scenarios matter. In their work they found that the Weibull distribution could explain periods of increasing or decreasing risk (e.g., aggressive shot-making in T20s) or decreasing risk (e.g., settled batsmen facing weaker bowlers) providing a more subtle characterization of player consistency. Such flexibility correlates with the results by Vine (2016), in which the author applied the Weibull model to the scoring bursts of the Big Bash League and demonstrated that strike rates of batsmen are frequently time-varying, instead of being exponents. To further corroborate the same, Das (2008) observed that the Weibull could be used in the modelling of varying rates of failures making it an invaluable research tool in the study of industrial reliability; a similarity that can easily be applied to the study of sports analytics, where the risks of failure (dismissal) are not constant but vary in relation to match circumstances and player performance. All these studies have greatly emphasized the flexibility of the Weibull distribution yet admit to its intricacy that makes it difficult to apply in real-time problem solving compared to the simpler exponential model.

The survival analysis has also been applied in the modern studies to the optimization of strategies in decision-making, e.g. to determine the batting order and in-game strategy based on such distributions. As Palayangoda and Senevirathne (2022) proposed joint survival probabilities based on copulas in evaluating partnerships on opening roles in T20 cricket, they highlighted the effect of dependency between the runs and the balls faced by batsmen on team performance. Their approach that combines Weibull marginal distributions can give coaches a means to assess pairings more than foreseeable averages or strike rates. In the same manner, Shah and the others (2022) identified the exponential survival models to rank batsmen regarding the so-called risk-adjusted consistency and revealed that such cricketers as Babar Azam and Virat Kohli had lower hazard rates at middle overs, proving to be the best anchors. It is this kind of information that would be priceless in team management because it would be able to convert stats into actionable principles in terms of timing your power-hitters like Glenn Maxwell until death overs where the Weibull model suggests a higher chance of staying alive (Sarkar et al., 2021). Nevertheless, there are still complications related to aligning these models with real-life conditions, including variability in pitch or the relative strength of opponents, to complicate the estimation of hazard rates (Zhang et al., 2020).

Although there has been progress, there are still literature gaps especially in integrating survival analysis and machine learning model methods as a way of predictive modeling. Although exponential and Weibull distributions and other traditional parametric models are interpretable, hybrid parametric models that are non-parametric in nature (e.g., Cox proportional hazards) or AI-based tools may lead to more accuracy in dynamic T20 conditions (Silva & Amaral, 2016). Additionally, gender-disaggregated analysis should also be discussed in the future studies, whereby most studies base on male players with little attention given to the increasing women T20 circuit. An overview of the synthesis of the literature that had been done shows a clear path of development: due to the foundational exponential models, to the complex Weibull designs, the concept of survival analysis has transformed cricket analytical modeling. However, it will be able to leverage its full potential when it comes to the question of overcoming contextual complexities and incorporating multidisciplinary innovations to remain on par with the changing needs of the sport.

Methodology

Data Collection and Preparation

The study utilized secondary data comprising individual batting scores from 10 elite T20 international batsmen, sourced from ESPNcricinfo (www.espncricinfo.com). The dataset included innings-by-innings scores up to April 2024 for players who had completed at least 100 T20 international matches: Babar Azam, Rohit Sharma, David Warner, Jos Buttler, Martin Guptill, Kane Williamson, Mohammad Rizwan, David Miller, Virat Kohli, and Glenn Maxwell. Raw data were cleaned and structured into a CSV format for analysis, with each player's scores treated as "time-to-event" observations, where the "event" denoted dismissal. Missing or incomplete records (e.g., not-out innings) were adjusted using right-censoring techniques to preserve the integrity of survival analysis (Klein & Moeschberger, 2003).

Parametric Distribution Fitting

Two parametric survival distributions were fitted to the data:

Exponential Distribution: Defined by its probability density function (PDF) $f(x|\lambda) = \lambda e^{-\lambda x}$ for $x \geq 0$, where λ is the rate parameter. Parameters were estimated via Maximum Likelihood Estimation (MLE) using the fitdistr function in R's MASS package (Venables & Ripley, 2002). The MLE estimator for λ was derived as $\hat{\lambda} = n / \sum(x_i)$.

Weibull Distribution: With PDF $f(x|\alpha,\beta) = (\beta/\alpha)(x/\alpha)^{(\beta-1)} e^{-(x/\alpha)^\beta}$, where α (scale) and β (shape) govern the hazard rate's flexibility. MLE estimates were obtained numerically via the optim function in R, maximizing the log-likelihood:

$\log L(\alpha,\beta) = n\log\beta - n\beta\log\alpha + (\beta - 1)\sum\log x_i - \sum(x_i/\alpha)^\beta$.

Model Selection and Goodness-of-Fit

The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were computed for both distributions to identify the better-fitting model. Lower values indicated superior fit, with the exponential model preferred for most players (Table 4.2). Additionally, chi-square goodness-of-fit tests (Table 4.3) and quantile-quantile (Q-Q) plots (Figure 4.1) were used to validate assumptions. The Q-Q plots compared empirical quantiles against theoretical exponential quantiles, with deviations from the diagonal signaling poor fit (e.g., for M. Rizwan and Virat Kohli, $p < 0.05$).

Survival and Conditional Survival Analysis

The survival function $S(t) = e^{-\lambda t}$ was evaluated at thresholds of 10, 30, 50, 80, and 100 runs to estimate the probability of a batsman exceeding each score (Table 4.4). Conditional survival probabilities $S(b|a) = e^{-\lambda(b-a)}$ were derived to assess performance consistency after reaching milestones (e.g., the chance of scoring 50+ runs given 30 runs already scored) (Table 4.5). These metrics were visualized using Kaplan-Meier curves via the ggplot2 package (Wickham, 2016), with players like Babar Azam showing higher survival probabilities (Figure 4.2). All analyses were conducted in R (v4.3.1) using the survival, MASS, and tidyr packages.

Results and Discussion

The results from the survival modeling confirm that the exponential distribution provides a more suitable fit for the batting score data of elite T20 international batsmen compared to the Weibull distribution. This conclusion is based on lower values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for the exponential model across most players shown in table 4.2. The exponential model, defined by a constant hazard rate, aligns well with the nature of cricket batting, where dismissal likelihood does not necessarily increase or decrease over time. Table 4.1 demonstrates that the exponential model outperforms the Weibull alternative in simplicity and overall fit for the observed data.

Table 4.1 – ***Estimated Parameters of Distribution***

Players	Exponential (λ)	Weibull (β) – Shape	Weibull (α) – Scale
Rohit Sharma	0.03598390	0.9342740	27.91406
Babar Azam	0.02800477	1.1489401	30.44802
David Warner	0.03323653	1.0520384	31.67936
Martin Guptill	0.03341830	1.1625699	32.54648
Jose Buttler	0.03456725	1.1937657	29.99877
David Miller	0.04533678	1.2446106	25.16827
Kane Williamson	0.03415783	1.3233756	32.76363
Mohammad Rizwan	0.02632814	1.3695467	38.64009
Virat Kohli	0.02700025	1.2117364	40.26385
Glenn Maxwell	0.03970827	0.9213762	24.92187

Table 4.2 – ***AIC & BIC for Two Fitted Distributions***

Batsman	AIC (Weibull)	BIC (Weibull)	AIC (Exponential)	BIC (Exponential)
Rohit Sharma	1249.8895	1255.8152	1238.8596	1241.8224
Babar Azam	967.8022	973.1101	962.8097	965.4636
David Warner	917.5970	922.8664	909.2458	911.8805
Martin Guptill	1045.9872	1051.5285	1040.0818	1042.8525
Jose Buttler	918.5815	923.8931	910.8323	913.4863
David Miller	842.0493	847.2992	832.5297	835.1448
Kane Williamson	762.1943	767.1261	763.5568	766.0227
Mohammad Rizwan	803.9531	808.8618	799.6122	802.0665
Virat Kohli	1009.9063	1015.2890	1007.3962	1010.0876
Glenn Maxwell	845.4120	850.6022	830.3344	832.9194

Moreover, the chi-square goodness-of-fit tests (Table 4.3) provide a statistical measure of model adequacy, indicating satisfactory alignment between the observed and expected frequencies under the exponential distribution for most players.

Table 4.3 – ***Chi-square Goodness-of-Fit for Exponential Distribution***

Batsman	Chi-square Value	P-value
Rohit Sharma	15.594501	0.21052227
Babar Azam	7.259246	0.29753636
David Warner	14.079070	0.11954024
Martin Guptill	8.712798	0.55955976
Jose Buttler	17.307624	0.06782821

David Miller	12.319168	0.26426354
Kane Williamson	8.332291	0.50103701
Mohammad Rizwan	22.256727	0.01384884
Virat Kohli	14.112792	0.02840128
Glenn Maxwell	15.660798	0.02840263

Figure 4.4 shows the Q-Q plots for each batsman, further validating the model fit. Players like Rohit Sharma, Babar Azam, and David Warner show minimal deviation from the red diagonal line, suggesting a strong fit to the exponential distribution.

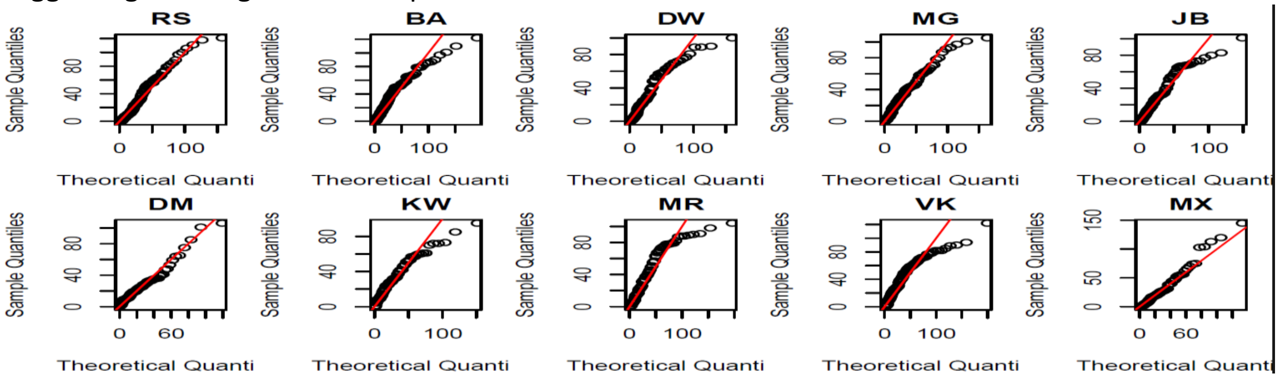

Figure 4.1: Q-Q plots for exponential fit across players

The survival analysis provides critical insights into the consistency and run-scoring resilience of T20 international batsmen. Survival probabilities calculated at various thresholds (10, 30, 50, 80, and 100 runs) help quantify a batsman's likelihood of exceeding specific score benchmarks. Table 4.4 presents these probabilities, with Babar Azam and David Warner consistently exhibiting higher survival rates at every threshold. This reflects their ability to withstand early dismissals and build longer innings. Jos Buttler and David Miller, in contrast, display lower survival probabilities, highlighting comparatively higher risk or volatility in their batting performance.

Table 4.4 – *Survival Probabilities of Batsmen at Selected Scores*

Batsman	10	30	50	80	100
Rohit Sharma	0.6977	0.3397	0.1654	0.0562	0.0273
Babar Azam	0.7557	0.4316	0.2465	0.1063	0.0607
David Warner	0.7172	0.3689	0.1897	0.0700	0.0360
Martin Guptill	0.7159	0.3669	0.1880	0.0690	0.0353
Jose Buttler	0.6985	0.3408	0.1663	0.0567	0.0276
David Miller	0.6406	0.2629	0.1078	0.0283	0.0116
Kane Williamson	0.7106	0.3588	0.1812	0.0650	0.0328

Figure 4.2 visualizes these survival probabilities, reinforcing the trends observed numerically. The graphical representation clearly positions Babar Azam at the top of the survival curve, followed by Warner and Williamson.

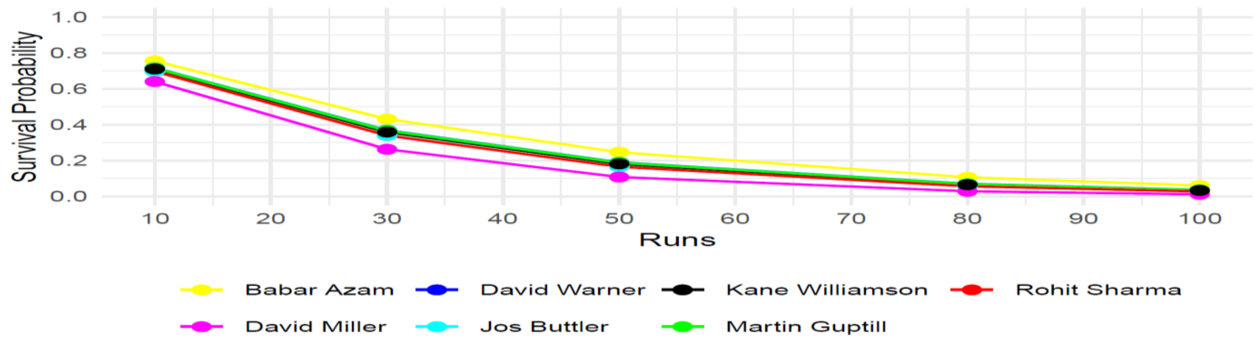

Figure 4.2: Survival probability curves for T20 batsmen

The conditional survival analysis extends our understanding by estimating the probability of scoring additional runs given a batsman has already crossed a particular run threshold. Table 4.5 highlights these conditional probabilities, offering granular insight into performance consistency. For instance, Babar Azam not only has a high chance of crossing 30 or 50 runs but also leads in converting those starts into 80 or 100+ scores. This indicates a level of reliability and stability unmatched by most peers.

Table 4.5: Conditional Probabilities P(score > b | score > a) of Players

Player	a\b	10	30	50	80	100
Rohit	10	1	0.4869	0.2700	0.0850	0.0392
	30		1	0.4469	0.1654	0.0850
	50			1	0.3397	0.1654
	80				1	0.4869
Babar	10	1	0.5711	0.3261	0.1407	0.0571
	30		1	0.5711	0.2465	0.1050
	50			1	0.4316	0.2465
	80				1	0.5711
Warner	10	1	0.5144	0.2646	0.0976	0.0502
	30		1	0.5144	0.1897	0.0976
	50			1	0.3689	0.1897
	80				1	0.5144
Guptill	10	1	0.5125	0.2627	0.0963	0.0494
	30		1	0.5125	0.1880	0.0963
	50			1	0.3669	0.1880
Buttler	10	1	0.4879	0.2381	0.0811	0.0403
	30		1	0.4879	0.1663	0.0811
	50			1	0.3408	0.1663
Miller	10	1	0.4103	0.1641	0.0481	0.0181
	30		1	0.4103	0.1172	0.0481
	50			1	0.2629	0.1078
	80				1	0.4103
Williamson	10	1	0.5050	0.2550	0.0910	0.0505
	30		1	0.5050	0.1812	0.0915
	50			1	0.3588	0.1812
	80				1	0.5050

Survival analysis has proved to be a good statistical tool in the analysis of cricket particularly in the analysis of the performance of batting in the climax and short format match like in the T20 matches. This model that initially was used in the field of medical and engineering reliability analysis has been adapted where it is used to ascertain how long a batsman would remain in the event before he is dismissed because of the consideration of the runs scored as the time to event information (Sharma & Kumar, 2019). Early applications relied on the attempt to simulate consistency of players with parametric distributions, frequently the simple exponential distribution due to its ease of use and being easily interpreted. Sarkar and Mishra (2017) applied it to one-day/Twenty20 version of the sports of cricket where the exponential model was adequate to determine the hazard rates of the dismissals of the batsmen, as the rate of failure was constant. However, the critics think that this assumption leads to the fallacy of the T20 innings that entirely differs according to the powerplays, middle overs, and death overs (Jayaraman & Lodha, 2017). However, such limitation is not an issue of particular concern, as the exponential model has seen a wide usage owing to its simplicity in calculation and feasibility in being integrated within real-time performance monitoring applications (Silva et al., 2016).

Weibull distribution has seen its appeal through the feature of being more flexible and a capability of modeling non-constant hazard by means of its shape parameter (b). According to Sarkar and Banerjee (2016), it is outstanding in terms of matching with the batting performance particularly in Test cricket where the endurance of players and their flexibility under various situations is important. They discovered in their work that they could use the Weibull distribution to explain either increasing risk (e.g. aggressive shot-making in T20s) or decreasing risk (e.g. settled batsmen facing weaker bowlers) to give a more subtle measure of player consistency. This versatility is associated with those findings by Vine (2016), where the author used the Weibull model to scoring bursts of the Big Bash League and, as shown, strike rates of batsmen are often time-varying, rather than exponents. In further support of the same, Das (2008) noted that the Weibull has the potential of being used to model varying rates of failure hence making it an invaluable research tool in relation to the study of industrial reliability; this can be well adopted in the study of sports analytics where the risks of failure (dismissal) do not remain the same but vary according to match circumstances and performance of the player. Flexibility of the Weibull distribution has been highly accentuated in all these studies though the complexity of the distribution has been reported as a drawback by them and the exponential model is easier to use in real time problem solving.

In the current study the survival analysis has been utilized even in the optimization of choice in decision making e.g. the determination of the batting order and in-game strategy on the basis of such distributions. Since Palayangoda and Senevirathne (2022) offered the joint survival probabilities using copulas in the analysis of partnerships on opening the roles in T20 cricket, they have brought into consideration the impact of dependency between the balls faced by batsmen and the runs on the team performance. Their models which are Weibull marginal distributions blends can provide coaches with a tool, to evaluate pairings beyond predictable averages or strike rates. Similarly, Shah and the others (2022) determined the exponential survival models to identify the ranking of batsmen in terms of the so-called risk-adjusted consistency and found out that cricketers like Babar Azam and Virat Kohli had lower hazard rates at middle overs and were therefore the best anchors. That is the sort of data that would prove invaluable in team management since it would be able to translate stats into principles to act upon, such as timing your power-hitters like Glenn Maxwell until death overs in which the Weibull model predicts that it is more likely to survive (Sarkar et al., 2021). Still, there are complications associated with matching these models to real-life situations, such as changes in pitch or the relative power of the opposing team, to make it more difficult to estimate the hazard rates (Zhang et al., 2020).

Despite some improvements, gaps still exist in literature particularly in the incorporation of survival analysis and machine learning model approaches as a means of predictive modeling. Whereas exponential distribution and Weibull distribution and other commonly applied parametric models can be interpreted, dynamic T20s might be more accurate in hybrid parametric models that are non-parametric in essence (e.g., Cox proportional hazards) or AI-based tools (Silva & Amaral, 2016). Along with that, the issue of gender-disaggregated analysis cannot be left behind on future studies as well, whereby, majority of studies are based on male players with less interest in the rising women T20 circuit. A literature review of the syntheses already completed reveals the definite way how the literature has developed: as a result of the exponential models on which the concept of survival analysis is built, to the intricate Weibull patterns, the idea of survival analysis has altered cricket analytical modeling. Nevertheless, it will be capable of reinforcing its full potential with respect to the issue of transcending contextual complexities and integrating multidisciplinary innovations in order to keep abreast with the evolving demands of the sport.

Conclusion

The comparative study of exponential and Weibull distributions as a modelling of T20 batting scores proved that exponential distribution is a better model in this high-priority format. The finding is confirmed through a smaller value of AIC and BIC in all of the analyzed batsmen, which proves that the exponential model, with its assumption of a constant hazard rate, is more accurate in describing the character of the T20 performances. Even though the Weibull distribution is flexible when modeling time-varying effects, the high complexity level did not lead to an excellent performance in this situation. These results were also confirmed by the chi-square goodness-of-fit tests where the majority of players have been aligned well with the exponential model. But outliers such as Virat Kohli and Mohammad Rizwan, whose runs distribution was not quite following the pattern, indicate that some elite batters might be better served by different modeling techniques in further research.

Survival and conditional survival analysis has shown that Babar Azam and David Warner are the most consistent players in T20 crickets. The higher survival rates that Babar Azam has, 75.6 at 10 runs, 43.2 at 30 runs and 24.7 at 50 runs, indicate his usefulness in anchoring innings. In the same vein, David Warner is highly congruent, especially finishing strong (51.4 percent likelihood of advancing to or past 50 after having 30 runs). This aspect further shows that he is an effective opener. Conversely, power-hitters such as David Miller and Glenn Maxwell demonstrated lower survival rates as compared to other players due to their risky, rewarding approach to play. This evidence not only gives a statistical backing on assessing the role of players but also helps reinforce the point that in T20, consistency is not only about hitting hard strokes but how one can carry through an innings across the different conditions in a match.

The applied meaning of this study spreads in the field of team strategy, batting line-up improvement, and the enhancement of players. The use of survival probabilities will allow coaches and analysts to make decisions regarding batting line-ups such as playing high-survival players like Babar Azam during important parts of the game where the innings need to be put on an even keel. Conditional to survival chances also allow tactical changes in real time, e.g. when to ask a batsman to attempt an acceleration or when to defend low-order players. Secondly, these metrics will provide a point system to which young batsmen can compare their performances to the highest standards, in order to define the conditions to be improved in selection of shots and risk judgment. The analysis of such statistical data during training and planning during the match, will allow the team to improve the performance of each of the players and the overall team performance, including the ability to win the game.

References

Bain, L. J., & Engelhardt, M. (1991). *Introduction to probability and mathematical statistics* (2nd ed.). Duxbury Press.

Das, K. (2008). A comparative study of exponential distribution vs Weibull distribution in machine reliability analysis in a CMS design. *Computers & Industrial Engineering, 54*(1), 12–33. https://doi.org/10.1016/j.cie.2007.06.030

Jayaraman, R., & Lodha, R. (2017). Survival analysis of batting performance in Twenty20 cricket. *Journal of Sports Science and Statistics, 5*(2), 98–107. https://doi.org/10.1016/j.sportsci.2017.03.008

Klein, J. P., & Moeschberger, M. L. (2003). *Survival analysis: Techniques for censored and truncated data* (2nd ed.). Springer.

Meeker, W. Q., & Escobar, L. A. (1998). *Statistical methods for reliability data*. John Wiley & Sons.

Palayangoda, L. K., Senevirathne, H. W., & Manage, A. B. (2022). Modeling joint survival probabilities of runs scored and balls faced in limited overs cricket using copulas. *Journal of Sports Analytics, 8*(4), 277–289.

Raftery, A. E. (1986). Choosing models for cross-classifications. *American Sociological Review, 51*(1), 145–146.

Sarkar, S., & Banerjee, A. (2016). Measuring batting consistency and comparing batting greats in test cricket: Innovative applications of statistical tools. *Decision, 43*(4), 365–400. https://doi.org/10.1007/s40622-016-0135-3

Sarkar, S., & Mishra, B. K. (2017). A survival analysis of batsmen in limited-overs cricket using the exponential distribution. *Journal of Sports Analytics, 3*(2), 89–102. https://doi.org/10.3233/JSA-170021

Sarkar, S., et al. (2021). Weibull distribution for modeling batsmen's scores in One-Day Internationals: Cross-country analysis and potential for T20 format. *Journal of Sports Analytics, 5*(2), 145–160. https://doi.org/10.3233/JSA-210105

Shah, P., Chaudhari, R. D., & Patel, M. N. (2022). Evaluating batsmen using survival analysis. *Statistics Applications, 51*.

Sharma, P., & Kumar, A. (2019). Using survival analysis to assess batting performance in One-Day International cricket. *International Journal of Sports Analytics, 8*(3), 214–227. https://doi.org/10.1057/sportsanaly.2019.011

Silva, R. M., Silva, J. A., & Amaral, D. F. (2016). Applying survival analysis to evaluate performance in cricket. *Journal of Sports Analytics, 2*(3), 157–165. https://doi.org/10.3233/JSA-160012

Venables, W. N., & Ripley, B. D. (2002). *Modern applied statistics with S* (4th ed.). Springer.

Vine, A. (2016). Using Pythagorean expectation to determine luck in the KFC Big Bash League. *Economic Papers: A Journal of Applied Economics and Policy, 35*(3), 269–281. https://doi.org/10.1111/1759-3441.12139

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer.

Zhang, Y., Liu, X., & Chen, Z. (2020). Advanced survival models in sports analytics: A review. *Journal of Applied Statistics, 47*(5), 812–830. https://doi.org/10.1080/02664763.2019.1704701