Predicting Weight Category–Specific Performance Zones for Olympic, World, and European Weightlifting Competitions

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ABSTRACT

Understanding the total likely required to achieve a specific rank within a specific competition can aid in the long- and short-term preparation and tactics for performance teams. The primary objective of this investigation was to develop a set of predictive models for new weight categories across five performance zones for 3 major weightlifting competitions. Performance total (Ptot) data for top 15 male athletes were obtained from the IWF website from 1998-2020 across the Olympics, and World and European Championships. A second order polynomial regression was conducted with 95% confidence and predictive intervals calculated. The average of the newly contested bodyweights was then used as the intercept. Predictions were compared against current performances of the new weight categories up to the 2020 Olympics. Results revealed that the models for all competition types varied in their predictive ability for each performance zone, across each new weight category. On average, predicted Ptot displayed a difference from actual Ptot of 3.65±2.51% (12.46±9.16kg), 0.78±3.29% (2.26±10.08kg) and -1.13±3.46% (-4.32±11.10kg) for the Olympics and World and European Championships, respectively. The results suggest that the predictive models may be a good indicator of future performances, however, the models may have greater efficacy in some weight categories and performance zones than others.

Key Words: prediction, performance, preparation

INTRODUCTION

Practitioners in high performance sport often look to gain a competitive advantage by better understanding trends in performance data which may help direct the development and selection of athletes at major sporting events. Furthermore, this information can help with tactical decisions to best position the athlete within the rankings of the sport which is often associated to increased funding opportunities and other incentives provided by relevant governing bodies and key stake holders. One way of utilising trends is to use historic performance data to forecast future performances. While predicting medal zones is a primary objective for many performance teams working in Olympic sports, opportunities outside of this zone, such as 4th place and below may also provide valuable information in ensuring that the athletes selected to represent their nation will be those who bring the greatest chance of success. These can be termed performance zones, where the medal zone is 1st -3rd and all subsequent performance zones can be context specific to the sport.

The sport of weightlifting is contested across two lifts: the snatch (SN) and clean and jerk (CJ), of which the highest successful performance (load lifted) of each is totalled (Ptot). It is currently contested at the Olympic games (OG), as well as hosting its own World and European championships (WC and EC, respectively) by the International Weightlifting Federation (IWF), with these three competitions carrying the most importance, particularly for European competitors. Within these competitions, there can be up to 300+ athletes competing across 10+ weight categories for both men and women, therefore predicting performance zones based on competition type and weight category, may provide useful insights into what to expect at such competitions, enabling better tactical decisions to be made in the selection of athletes. Predicting performance zones particularly to the granularity of competition type and weight class, requires large quantities of historical data which are often publicly available and has been a preferred method for many investigations of this type (4, 7, 8). This information can then be used to forecast future performances using regression analysis, which estimates the relationship between a dependent and an independent variable by presenting the proportionality of variance in which the dependent variable is explained by the independent variable. Prior use of regression analysis in weightlifting has helped to identify surrogate measures of weightlifting performance (9, 10, 12), helping performance scientists identify key physical indicators that underpin weightlifting success. For example, Joffe and Tallent (10) found that isometric mid-thigh pull peak force (IMTP PF) and countermovement jump peak power (CMJ PP), could statistically significantly predict 94.2% of variance in Ptot in international female weightlifters through the use of stepwise multiple regression. Additionally, the authors also suggested that 91.8 and 95.1% of variance in the SN and CJ, respectively, could also be explained by IMTP PF and CMJ PP. While this information is highly valuable when collecting physical performance measures, a gap still exists in trying to predict which Ptot are required to achieve a specific rank at a specific competition, within a specific weight category, and therefore needs to be explored.

A unique issue that exists in trying to predict future weightlifting performances is that as of July 2018, the IWF announced 10 new weight categories for women and men, which consequently also changed the contested weight categories at the next Olympic (Tokyo 2020). Therefore, the data sample available for the newly contested weight categories would not be sufficient enough to develop a predictive model, and therefore the utilising performance data from the old weight categories would need to be used in developing predictive models. Though, one can try to predict future performances, a clear method of data organisation and analysis must be conducted to ensure the model best reflects the trend of the data in which the performance teams are interested in. An inherent issue with using historical data is that differences in performances between competition year and single athlete reoccurrence may affect predictive ability. These can present themselves as outliers thus affecting the fit of the model. Therefore prior to any regression analysis being made, one must account for this by exploring such differences and deciding whether the inclusion of outliers will be deleterious to the development of the predictive model at the expense of utilising data that truly represents the population. Once accounted for, this may help with; i) reducing the noise by being able to exclude specific data that may not be representative of the normal trend and ii) provide an opportunity to pool data to increase its utility within the predictive model. The aforementioned considerations help to ensure the model is not under or over fitted, thus presenting a trade-off between bias and variance. This allows for appropriate predictive ability, while also ensuring the generalizability of the model for future data sets (5).

To the authors' knowledge, predicting future performances of major weightlifting competitions is yet to be explored within the published literature, particularly given the weight class changes in 2018, therefore presenting a novel challenge of predicting future performance zones of the new weight categories utilising the historic data of previous categories. The primary objective of this investigation, therefore, is to predict the Ptot required within specific performance zones in major weightlifting competitions within the newly adopted weight categories. A secondary objective of this investigation is to compare the predicted Ptot to current available performances achieved within the new weight categories.

METHODS

Experimental Approach

Men's performance totals of the OG, WC, and EC (referred to as competition type) from 1998 to 2021 were obtained from the IWF website. All data were organised by competition type, year, and rank, based on the Ptot of the top 15 athletes using the old weight category classifications (pre-November 2018). To ensure enough data was available to develop the predictive model, Ptot from each competition type across each year was pooled and averaged followed by a Hedges *g* effect size analysis to identify if any meaningful differences existed between competition year. The Ptot data was then split into five performance zones for each competition type. A second order Polynomial regression was conducted using the individual Ptot and bodyweights for each performance zone. The *y* intercept was used to extrapolate the predicted Ptot for each Performance Zone across each competition type for the new weight categories. The prediction was then compared to existing performance zones using percentage and absolute differences to provide insight into the efficacy of the models.

Sample

Men's Ptot data was obtained from the old weight categories, for a total of 7,037 samples from the official IWF webpage using a custom data scrapping script developed in Python (v3.8, Van

Rossum, Amsterdam) (see Supplemental Digital Content 1) accessed 27th May 2020. The data was organised so that only the top 15 athletes within each weight category across all competitions were considered. This range was selected as this was the maximum number of athletes contested at the 2020 OG, which is considered the pinnacle of the sport. Following the above reductions, a total of 4,011 samples from old weight category data was utilised to develop the performance zone predictive models. New weight category data was obtained manually between July and August 2021, following the 2020 Olympic games, providing an additional 639 samples. Ethics was granted via an institutional board.

Statistical Analysis

Figure 1 outlines the sequence of analysis conducted.

INSERT FIGURE 1 AROUND HERE

Pooling of Data

A Hedges *g* effect size analysis was used to determine the magnitude of differences between each year within each competition type using a custom Microsoft Excel spreadsheet (15, 17). Descriptors for effect sizes were as follows; <0.2 '*Trivial'*, 0.21-0.5 '*Small'*, 0.51-0.8 '*Moderate'*, >0.8 '*Large'* (Cohen, 1988). All effect sizes were calculated with 95% confidence intervals (CI) (16). Checking for year-to-year differences enabled the pooling of Ptot based on competition type, should no *moderate to large* differences be present. This provides a larger sample size in which the predictive model can be developed and would also enable the exclusion of specific competition years that are not representative of the typical trend, thus avoiding dilution of the data and is comparable to removing outliers within data sets.

As the second objective of the investigation was to compare the predictions to actual outcomes, all new weight categories that had been contested at the WC and EC from 2018 – 2021, had been pooled, of which the average of each performance zone ± SD was calculated. The exception to this was the OG, which only had one instance of which the new weight categories were contested (July-August 2021), compared to the two of the WC and EC (November 2018 and September 2019, and April 2019 and 2021, respectively).

Rank Zone Definitions

In phase 3, the data for each weight category and competition type was divided into five rank Zones: Medal Zone (1st - 3rd), Zone 2 (4th – 5th), Zone 3 (6th – 8th), Zone 4 (9th - 10th) and Zone

5 (11^{th} – 15^{th}). Although performance zone grouping can arguably be approached using many variations, these performance zones were chosen for the following reasons: The Medal Zone provides a Zone in which all athletes aspire to and is the pinnacle of performance, Zone 2 serves as an 'outside shot' of a medal opportunity as there is a likelihood of crossover due to the variation of Ptot achieved in the Medal Zone and Zone 2. Current qualification for the OG provides the top eight ranked athletes within a weight class to automatically gain a spot at the Olympics. Furthermore, Zone 3 provides the lower echelon of the minimum rank required (8^{th}) to attain an Olympic diploma and is often associated with higher funding potential within national Olympic committees (NOC's). Like Zone 2, Zone 4 is an 'outside shot' of achieving atop 8 finish. Zone 5 is the lower echelon of the ranking system and is the maximum number of athletes within a given weight category at the OG.

Predictive Model

It has been well established that the relationship between strength and body size is nonlinear (3, 6) specifically, a parabola relationship between weightlifting performance and bodyweight has previously been reported (3, 5, 11). It was therefore determined appropriate to use a second order Polynomial model of regression. The regression was used to predict Ptot at the newly contested weight classes using the equation $\hat{y}^* = ax^2 + bx + c$, where $\hat{y}^*$ is the prediction (Ptot), x is the known value of bodyweight, and a, b and c are the coefficients.

Confidence intervals of 95% were calculated using the equation $\hat{y}^* \pm \mathrm{t}a/2S_{\hat{y}*}$, where $\hat{y}^*$ is the predicted point estimate, ta is the t distribution given alpha, and $S_{\hat{y}*}$ is the estimated SD of the mean of $\hat{y}^*$. The calculation of $S_{\hat{y}*}$, was as follows.

$$\mathrm{S}_{\hat{y}*} = S * \sqrt{\frac{1}{n} + \frac{(x^* - \tilde{x})^2}{(n-1)S_x^2}}$$

Where S is the standard error of the regression model, n is the sample size, x is the known value of bodyweight and $\tilde{x}$ is the mean of all known x values. The 95% CI provides an upper and lower boundary in which one could expect that the populations line of best fit would likely fall between. Like the above, a 95% predictive interval (95% PI) was calculated as $\hat{y}^* \pm \mathrm{t}a/2S_{Pred}$, with it's estimated SD calculated as:

$$\mathrm{S}_{\hat{y}*} = S * \sqrt{1 + \frac{1}{n} + \frac{(x^* - \tilde{x})^2}{(n-1)S_x^2}}$$

The 95% PI provides a boundary in which 95% of future predictions (or Ptot) for a single value of x (bodyweight) would likely fall between. Prediction intervals must account for both the uncertainty in estimating the population mean, plus the random variation of the individual values and is therefore wider than a confidence interval (14). Since the new weight categories had been contested during WC and EC from 2018, the mean bodyweight for each class was used to intercept the *y* slope. All polynomial analysis was conducted using a custom Matlab script (v.9.6.0, R2019a, Natick Massachusetts: The Mathworks Inc) (see Supplemental Digital Content 2).

Predictive Model Validation

A 5-fold k-cross internal validation method was used to evaluate the quality of each performance zone model, using the Regression Learner application in Matlab (v.9.6.0, R2019a, Regression Learner, Natick Massachusetts: The Mathworks Inc). The old weight category data set was compartmentalised as 80% training data and 20% test data randomly assigned across 5 iterations. Root mean square error (RMSE), mean squared error (MSE) and mean absolute error (MAE) are presented in the supplementary material for each performance zone (see Supplemental Digital Content 3). Although preferred (1), utilising newly contested weight categories performances for external validation was not conducted as the sample size would not have been sufficient enough to use as a test model and was therefore the primary reason internal validation utilising the 80:20 split of the old weight category data was used.

RESULTS

Pooling of data

All Ptot data within each competition type displayed primarily *trivial* differences between years (see Supplemental Digital Content 4) with only 36/224 (16%) observations showing small differences, therefore all Ptot's were pooled for each competition type. Performance total data was then subdivided into their respective performance zones in preparation for the regression analysis.

Predictive Model

The regression model outputs can be seen in Table 1. Differences between the predicted Ptot and actual Ptot outcome (±SD) can be seen in table 2 a-c. Graphical data can be referred to in the supplementary material (see Supplemental Digital Content 5).

INSERT TABLE 1 and 2 a-c AROUND HERE

DISCUSSION

The primary objective of this investigation was to predict performance zones of newly contested weight categories within major competitions using historic data. The findings from this investigation indicate that predicting performance zones for major weightlifting competitions can be achieved depending on the competition type, performance zone and weight category. Data validation showed that the final model performance of each performance zone within each competition type carried low error rates (RMSE). This suggests that the models perform well on unseen data (Test data). However, what becomes apparent is that the error increases the lower down the performance zone (i.e. 11th -15th). This is evidence and discussed further below within the context of performance zones and their practical interpretations.

Olympic Games

The performance zones for the OG displayed R^2 values ranging from 0.79 to 0.97 to suggesting a variance of 79 to 97% of the Ptot could be explained by the weight category. Average predictive ability of all the performance zones was 3.65 ± 2.51% (12.46 ± 9.16kg). The predictions for the Medal Zones averaged a 2.15 ± 1.20% (8.10 ± 4.53kg) difference from the Tokyo 2020 performances across all new weight categories. The best prediction occurred in the 73kg weight category, which had a 0.16% (0kg) difference to the actual Medal Zone (351 vs 351kg). This can be deemed a perfect prediction, but it’s important to state that the interpretation of this should consider that this prediction would provide a silver medal performance as it is an average of 1st, 2nd and 3rd. The men’s 96kg weight category displayed the biggest difference between the prediction and actual outcome, with a value of 3.71% (15kg). The actual outcome achieved was 392 ± 9kg, with the prediction being 407kg. This over prediction would in fact achieve a gold medal, however, the LLPI of 380kg encapsulates the actual outcome ± the SD (401 – 383kg) and therefore it is suggested in this instance that performance teams aim for anything above the LLPI to increase medal potential. The Medal Zone for all other categories displayed prediction to actual outcome differences of between

1.17 – 3.71%. When analysing all other performance zones within the OG, it becomes apparent that the differences between the prediction to the actual outcome generally ascend down the performance zones, with the largest differences existing in Zone 5 (11^{th} – 15^{th}). This is likely due to multiple reasons, 1) this performance zone has the largest number of athletes within it, compared to the other performance zones which is likely to increase the variance of Ptot and 2) this Zone likely contains athletes who qualified outside of top 8 automatic qualification spots in the lead up to the OG.

World Championship

The WC contested all 10 new weight categories. The R^2 values for the regression models ranged from 0.90 to 0.96, suggesting each model had the ability for bodyweight to strongly account for the variance of Ptot. The average predictive ability for the WC across all performance zones was 0.78±3.29% (2.26±10.08kg). The average prediction for the Medal Zone was 1.02 ± 2.71% (3.28 ± 8.78kg) across all new weight categories. The best predictive ability in the Medal Zone was the <109kg weight category, with a near perfect prediction of -0.06% (0kg) compared to the actual Medal Zone (457 vs 457kg, respectively). Interestingly, the actual Ptot had a SD of 20kg (457 ± 20kg), suggesting that the Medal Zone is large. The likely reason behind this is that in both the 2018 and 2019 WC from which this data has been formulated, the differences between each medal zone ranged from 14 to 24kg, averaging 20kg. Although the absolute value of 20kg may seem large, the SD as a percentage of the actual outcome is <5%. As the actual results could be between 437 and 477kg, it is suggested that performance teams aim to achieve a Ptot close to or above the LLCI of 453kg, as the LLPI of 426kg may results in a rank outside of the Medal Zone.

The worse predictive model for the WC Medal Zone was the 55kg weight category, displaying a 6.91% (19kg) overprediction. Interestingly, this was followed by the 102kg and 89kg weight category which also showed overpredictions of 4.25% (17kg) and 3.42% (13kg), respectively. A likely reason for this is that the data used to analyse the WC was prior to the OG, in which the aforementioned weight categories were not contested. Therefore, it is likely that athletes moved to Olympic weight categories therefore affecting these, Medal Zones. All other Medal Zones had predictions ranging from -1.64% to 0.64% (-6 – 3kg) relative to the actual Ptot. All other performance zones showed a range of predictive ability, with the best being Zone 5 in the 96kg weight category showing a near perfect predictive Ptot with no difference (0.08%

,0kg) to the actual Ptot (366 vs 366kg). On average the predictive models for the 96kg weight category showed a difference across performance zones of only 0.55 ± 0.75%, suggesting this model may be useful for those working with athletes preparing for the WC in this weight category.

European Championships

The EC predictive models displayed R^2 values ranging from 0.75 to 0.96, with the lowest variance observed for performance zone 5. The average predictive ability for the EC across all performance zones was -1.13±3.46% (-4.32±11.10kg). The average prediction for the Medal Zone across all new weight categories was -0.25 ± 3.47% (-1.93 ± 12.51kg). The best predictive ability in the Medal Zone was the 61kg weight category, with a -0.02% (0kg) prediction compared to the actual Medal Zone (287 vs 287kg, respectively). The worst predictive model in the Medal Zone was for the 55kg weight category, overpredicting the actual Ptot by 6.04% (15kg). The actual Ptot had a SD of 9kg (251 ± 9kg), which means a 1st place finish would be a total of ~260kg, which is 2kg less than that of the LLCI (262kg). Interestingly, the 2019 and 2021 EC 1st place finish achieved a total of 261 and 258kg respectively, therefore, performance teams should consider aiming for the LLCI of 262kg to increase their chance of a gold medal.

All other Medal Zones had varying under- and over- predictions ranging from -6.02% to 4.66% (-26.45 – 17.78kg). Much like the WC, on average, the best predicted weight category was the 96kg category with a small over prediction of Ptot by 0.41% (1.67kg) across all performance zones. Suggesting this model may be useful for those working with athletes preparing for the EC in this weight category.

The primary objective of this investigation was to develop a set of predictive models for specific performance zones within the newly contested weight categories in the sport of weightlifting. While our findings suggest that some predictive models maybe able to better predict performance zones within specific weight categories than others, discussion around limitations that may have influenced the model development should be made, therefore enabling those who wish to replicate this study the ability to do so within their own context and environment whilst also understanding the constraints and philosophical decision around data analysis that may need to be made based on context.

Re-occurrences (same athlete data)

The old weight category data obtained from the IWF website spanned over a period of 20 years (1998 – 2018) across 3 major competitions. Data re-occurrences of individuals and their performances within these competitions must be considered. Although we acknowledge the concern of possible limiting of model generalisability arising from the use of recurring athletes, we believe that the methodologies used throughout this investigation maximise the generalisability of the models given the unique case of the sport weightlifting.

Firstly, individual performance totals were considered to be observed within the study design, as opposed to individual athletes. This is because performance can vary over time and across competitions which is important information that should be captured. Furthermore, selecting only one out of several performance totals could introduce the issue of selection bias. Additionally, this would significantly reduce the sample size for modelling which in turn would result in lower generalisability of predictions. For future analysis, using a larger database of athletes (which would naturally expand over time) would help to further tackle this potential issue.

Outliers (individuals)

Often, outliers within data sets can skew the dispersion around the mean. In high performance sport it is not uncommon to come across statistical outliers which may distort the calculated outcome (2), in this case the predicted Ptot within performance zones. It is important to state that performance teams would need to consider whether they are willing to accept an increase in predictive variance keeping in known outliers, or removing outliers at the risk of not capturing performances reflective of what is actually achieved within competition. The practical ramifications of the latter can be explained when looking at medal zones. If an athlete who achieves a Gold medal Ptot considerably more than that of 2nd place was removed, the medal zone would reduce in both its mean and SD (as well as 95% CI and PI), telling us that the total required to achieved a medal is artificially lower than it would be having kept in the outlier. As this practical example shows, given the consequences of underprediction and by extension incorrectly classifying an athlete as a potential medallist or OG qualifier (i.e False Positive) it is clear that we would be willing to accept overprediction if this ensures we minimise the number of false positives.

Performance Zone grouping

The performance zones utilised in this investigation were based on current processes and requirements for qualifying for the Olympic games (top 8) and/or predicting outside opportunities for medals (zone 2 4-5th) across major competitions. While this may carry ecological utility, some issues may exist in developing the predictive model given that some performance zones are so closely grouped together (i.e. zone 2, 4-5th). This reduces the sample size and consequently may lead to models with low bias and higher levels of variance. This potential of overfitting is one we have attempted to address through the use of lower model complexity alongside K-Fold Cross validation. Future analysis using an expanding database over time will further help address the issue of low samples within performance zones.

Doping

At the time of data extraction from the IWF database all athletes who had Anti-Doping rule violations (ADRVS) were marked as "DNF" (did not finish) and were therefore excluded from the analysis. However, many bans within weightlifting occur retrospectively following re-analysis of samples collected during major competitions. For example, Kollari-Turner et al (13) reported that a total of 61 weightlifters were identified to have adverse analytical findings of prohibited substances during the 2008 and 2012 OG. From this sample a total of 34 of them were medallists. The relevance of this within the present study is that it highlights the need to update the data used in developing the predictive models as and when doping violations are announced to ensure higher levels of efficacy.

PRACTICAL APPLICATION

This study provides outcomes for predictive models for major competitions in the sport of weightlifting. The tables provided in this manuscript can be used by performance teams to aid in the long- and short- term preparation for the Olympic Games and World and European Championships. Furthermore, the results from this study may also provide a more objective selection process for the analysed competition types to enhance the chance of achieving the highest possible rank. While the predictive models generally carried low percentage differences relative to the actual Ptot, some consideration around interpretation and utility must be considered. It is evident that the predictive models carried variation throughout each competition type and performance zone. Given that there were both over and underpredictions throughout the models, it is suggested that performance teams manage expectation and use these predictions in conjunction with a coach's intuition and knowledge of the field of play. It is also worth highlighting that crossover between performance zones will be likely, and therefore should be explored further. Future investigation should also look to apply this as a proof of concept within women's weightlifting, which was introduced to the Olympics and the World Championships at later time points than the men, thus having less data over the years. As for immediate utility, coaches or performance teams can use the equations provided to identify specific Ptot within specific weight categories and performance zones. Furthermore, with the freely available Ptot data, performance teams may also repeat the proposed methodology for other weightlifting demographics (i.e. women, junior and youth), for different performance zones they deem relevant and also for the individual lifts of the snatch and jerk, given medals opportunities are available for each of these at WC and EC.

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Excluded for anonymity.

Declaration of Interest

There were no conflicts of interest during the development of this manuscript.

Supplemental Digital Content

Supplemental Digital Content 1 – Python data scrape script

Supplemental Digital Content 2 – Matlab data analysis script

Supplemental Digital Content 3 – Data validation table

Supplemental Digital Content 4 – Hedges G effect size tables

Supplemental Digital Content 5 – Performance zone graphs comparing predicted and actual performance totals for each competition with 95% predictive and confidence intervals.

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