TITLE:
Predicting Weight Category Specific Performance Zones for Olympic, World and European Weightlifting Competitions.

AUTHORS:
Mr Shyam Chavda – MSc, PGCHE, CSCS*D, ASCC, CES[1], Dr Paul Comfort – PhD, CSCS*D, ASCC[2], Dr Jason P Lake – PhD[4], Dr Chris Bishop –MSc, PGCHE, ASCC [1], Dr Anthony N Turner – PhD, CSCS*D[1]

[1.] London Sports Institute, Middlesex University, Stone X Stadium, Greenlands Lane, NW4 1RL

[2.] Directorate of Psychology & Sport, University of Salford, Salford, Greater Manchester, UK

[3.] Chichester Institute of Sport, University of Chichester, College Lane, Chichester, PO19 6PE.

Corresponding Author
Shyam Chavda
Middlesex University
The Burroughs
Hendon
NW4 4BT
e-mail: s.chavda@mdx.ac.uk

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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.

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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

94   through the use of stepwise multiple regression. Additionally, the authors also suggested that

95   91.8 and 95.1% of variance in the SN and CJ, respectively, could also be explained by IMTP

96   PF and CMJ PP. While this information is highly valuable when collecting physical

97   performance measures, a gap still exists in trying to predict which Ptot are required to achieve

98   a specific rank at a specific competition, within a specific weight category, and therefore needs

99   to be explored.

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101   A unique issue that exists in trying to predict future weightlifting performances is that as of

102   July 2018, the IWF announced 10 new weight categories for women and men, which

103   consequently also changed the contested weight categories at the next Olympic (Tokyo 2020).

104   Therefore, the data sample available for the newly contested weight categories would not be

105   sufficient enough to develop a predictive model, and therefore the utilising performance data

106   from the old weight categories would need to be used in developing predictive models.

107   Though, one can try to predict future performances, a clear method of data organisation and

108   analysis must be conducted to ensure the model best reflects the trend of the data in which the

109   performance teams are interested in. An inherent issue with using historical data is that

110   differences in performances between competition year and single athlete reoccurrence may

111   affect predictive ability. These can present themselves as outliers thus affecting the fit of the

112   model. Therefore prior to any regression analysis being made, one must account for this by

113   exploring such differences and deciding whether the inclusion of outliers will be deleterious to

114   the development of the predictive model at the expense of utilising data that truly represents

115   the population. Once accounted for, this may help with; i) reducing the noise by being able to

116   exclude specific data that may not be representative of the normal trend and ii) provide an

117   opportunity to pool data to increase its utility within the predictive model. The aforementioned

118   considerations help to ensure the model is not under or over fitted, thus presenting a trade-off

119   between bias and variance. This allows for appropriate predictive ability, while also ensuring

120   the generalizability of the model for future data sets (5).

121

122   To the authors' knowledge, predicting future performances of major weightlifting competitions

123   is yet to be explored within the published literature, particularly given the weight class changes

124   in 2018, therefore presenting a novel challenge of predicting future performance zones of the

125   new weight categories utilising the historic data of previous categories. The primary objective

126   of this investigation, therefore, is to predict the Ptot required within specific performance zones

127   in major weightlifting competitions within the newly adopted weight categories. A secondary

128 objective of this investigation is to compare the predicted Ptot to current available

129 performances achieved within the new weight categories.
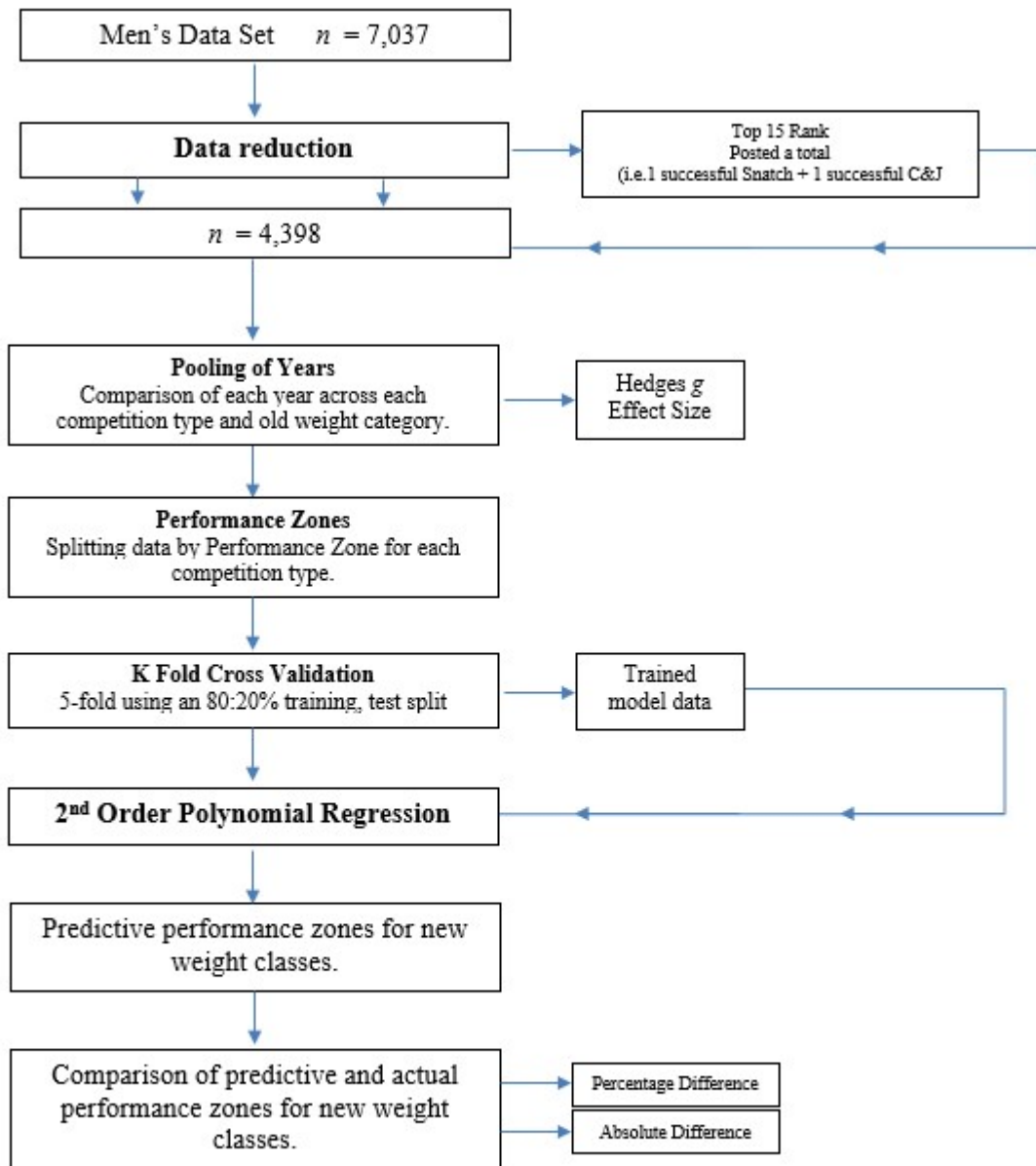
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131 **METHODS**

132 *Experimental Approach*

133 Men's performance totals of the OG, WC, and EC (referred to as competition type) from 1998

134 to 2021 were obtained from the IWF website. All data were organised by competition type,

135 year, and rank, based on the Ptot of the top 15 athletes using the old weight category

136 classifications (pre-November 2018). To ensure enough data was available to develop the

137 predictive model, Ptot from each competition type across each year was pooled and averaged

138 followed by a Hedges *g* effect size analysis to identify if any meaningful differences existed

139 between competition year. The Ptot data was then split into five performance zones for each

140 competition type. A second order Polynomial regression was conducted using the individual

141 Ptot and bodyweights for each performance zone. The *y* intercept was used to extrapolate the

142 predicted Ptot for each Performance Zone across each competition type for the new weight

143 categories. The prediction was then compared to existing performance zones using percentage

144 and absolute differences to provide insight into the efficacy of the models.

145

146 *Sample*

147 Men's Ptot data was obtained from the old weight categories, for a total of 7,037 samples from

148 the official IWF webpage using a custom data scrapping script developed in Python (v3.8, Van

149 Rossum, Amsterdam) (see Supplemental Digital Content 1) accessed 27th May 2020. The data

150 was organised so that only the top 15 athletes within each weight category across all

151 competitions were considered. This range was selected as this was the maximum number of

152 athletes contested at the 2020 OG, which is considered the pinnacle of the sport. Following the

153 above reductions, a total of 4,011 samples from old weight category data was utilised to

154 develop the performance zone predictive models. New weight category data was obtained

155 manually between July and August 2021, following the 2020 Olympic games, providing an

156 additional 639 samples. Ethics was granted via an institutional review board.

157

158 *Statistical Analysis*

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┌─────────────────────────────────────┐
│     Men's Data Set    n = 7,037      │
└─────────────────────────────────────┘
                  │
                  ▼
┌─────────────────────────────────────┐        ┌──────────────────────────────────┐
│          Data reduction             │───────▶│           Top 15 Rank            │
│                                     │        │          Posted a total          │
└─────────────────────────────────────┘        │ (i.e.1 successful Snatch + 1 successful C&J) │
          │           │                        └──────────────────────────────────┘
          ▼           ▼
┌─────────────────────────────────────┐
│            n = 4,398                 │◀───────────────────────────────
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                  │
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┌─────────────────────────────────────┐        ┌──────────────────┐
│          Pooling of Years           │───────▶│    Hedges g      │
│  Comparison of each year across each │        │   Effect Size    │
│ competition type and old weight category. │    └──────────────────┘
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                  │
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┌─────────────────────────────────────┐
│         Performance Zones           │
│ Splitting data by Performance Zone for each │
│         competition type.           │
└─────────────────────────────────────┘
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┌─────────────────────────────────────┐        ┌──────────────────┐
│       K Fold Cross Validation       │───────▶│     Trained      │
│  5-fold using an 80:20% training, test split │ │   model data     │
└─────────────────────────────────────┘        └──────────────────┘
                  │
                  ▼
┌─────────────────────────────────────┐
│    2ⁿᵈ Order Polynomial Regression  │◀────────────────────
└─────────────────────────────────────┘
                  │
                  ▼
┌─────────────────────────────────────┐
│  Predictive performance zones for new │
│          weight classes.            │
└─────────────────────────────────────┘
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┌─────────────────────────────────────┐        ┌──────────────────────┐
│   Comparison of predictive and actual │─────▶│ Percentage Difference │
│   performance zones for new weight   │      └──────────────────────┘
│             classes.                │       ┌──────────────────────┐
│                                     │─────▶│  Absolute Difference  │
└─────────────────────────────────────┘       └──────────────────────┘
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Figure 1 – schematic outlining the data analysis process.

159

160 *Pooling of Data*

161 A Hedges *g* effect size analysis was used to determine the magnitude of differences between

162 each year within each competition type using a custom Microsoft Excel spreadsheet (15, 17).

163 Descriptors for effect sizes were as follows; <0.2 '*Trivial*', 0.21-0.5 '*Small*', 0.51-0.8

164 '*Moderate*', >0.8 '*Large*' (Cohen, 1988). All effect sizes were calculated with 95% confidence

165 intervals (CI) (16). Checking for year-to-year differences enabled the pooling of Ptot based on

166 competition type, should no *moderate to large* differences be present. This provides a larger

167 sample size in which the predictive model can be developed and would also enable the

168 exclusion of specific competition years that are not representative of the typical trend, thus

169 avoiding dilution of the data and is comparable to removing outliers within data sets.

170

171 As the second objective of the investigation was to compare the predictions to actual outcomes,

172 all new weight categories that had been contested at the WC and EC from 2018 – 2021, had

173 been pooled, of which the average of each performance zone ± SD was calculated. The

174 exception to this was the OG, which only had one instance of which the new weight categories

175 were contested (July-August 2021), compared to the two of the WC and EC (November 2018

176 and September 2019, and April 2019 and 2021, respectively).

177

178 *Rank Zone Definitions*

179 In phase 3, the data for each weight category and competition type was divided into five rank

180 Zones: Medal Zone (1st - 3rd), Zone 2 (4th – 5th), Zone 3 (6th – 8th), Zone 4 (9th - 10th) and Zone

181 5 (11th – 15th). Although performance zone grouping can arguably be approached using many

182 variations, these performance zones were chosen for the following reasons: The Medal Zone

183 provides a Zone in which all athletes aspire to and is the pinnacle of performance, Zone 2 serves

184 as an 'outside shot' of a medal opportunity as there is a likelihood of crossover due to the

185 variation of Ptot achieved in the Medal Zone and Zone 2. Current qualification for the OG

186 provides the top eight ranked athletes within a weight class to automatically gain a spot at the

187 Olympics. Furthermore, Zone 3 provides the lower echelon of the minimum rank required (8th)

188 to attain an Olympic diploma and is often associated with higher funding potential within

189 national Olympic committees (NOC's). Like Zone 2, Zone 4 is an 'outside shot' of achieving

190 atop 8 finish. Zone 5 is the lower echelon of the ranking system and is the maximum number

191 of athletes within a given weight category at the OG.

192

193 *Predictive Model*

194 It has been well established that the relationship between strength and body size is nonlinear

195 (3, 6) specifically, a parabola relationship between weightlifting performance and bodyweight

196 has previously been reported (3, 5, 11). It was therefore determined appropriate to use a second

197 order Polynomial model of regression. The regression was used to predict Ptot at the newly

198 contested weight classes using the equation $\hat{y}^* = ax^2 + bx + c$, where $\hat{y}^*$ is the prediction (Ptot),

199 x is the known value of bodyweight, and a, b and c are the coefficients.

200

201 Confidence intervals of 95% were calculated using the equation $\hat{y}^* \pm t_{a/2}S_{\hat{y}*}$, where $\hat{y}^*$ is the

202 predicted point estimate, t_a is the t distribution given alpha, and $S_{\hat{y}*}$ is the estimated SD of the

203 mean of $\hat{y}^*$. The calculation of $S_{\hat{y}*}$, was as follows.

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

204

205 Where S is the standard error of the regression model, n is the sample size, x is the known value

206 of bodyweight and $\tilde{x}$ is the mean of all known x values. The 95% CI provides an upper and

207 lower boundary in which one could expect that the populations line of best fit would likely fall

208 between. Like the above, a 95% predictive interval (95% PI) was calculated as $\hat{y}^* \pm t_{a/2}S_{Pred}$,

209 with it's estimated SD calculated as:

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

210

211

212 The 95% PI provides a boundary in which 95% of future predictions (or Ptot) for a single value

213 of x (bodyweight) would likely fall between. Prediction intervals must account for both the

214 uncertainty in estimating the population mean, plus the random variation of the individual

215 values and is therefore wider than a confidence interval (14). Since the new weight categories

216 had been contested during WC and EC from 2018, the mean bodyweight for each class was

217 used to intercept the y slope. All polynomial analysis was conducted using a custom Matlab

218 script (v.9.6.0, R2019a, Natick Massachusetts: The Mathworks Inc) (see Supplemental Digital

219 Content 2).

220

221

222

223 *Predictive Model Validation*

224 A 5-fold k-cross internal validation method was used to evaluate the quality of each

225 performance zone model, using the Regression Learner application in Matlab (v.9.6.0, R2019a,

226 Regression Learner, Natick Massachusetts: The Mathworks Inc). The old weight category data

227 set was compartmentalised as 80% training data and 20% test data randomly assigned across 5

228 iterations. Root mean square error (RMSE), mean squared error (MSE) and mean absolute error

229 (MAE) are presented in the supplementary material for each performance zone (see

230 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 ($\pm$SD) can be seen in table 2 a-c. Graphical data can be referred to in the supplementary material (see Supplemental Digital Content 5).

Table 1 – Men's Polynomial Regression outputs

	Zone	Equation	Coefficient 95% Confidence Interval			R^2
			Coefficient 1	*Coefficient 2*	*Coefficient 3*	
OG	Medal Zone	$-0.019x^2 + 5.623x + 41.730$	[-0.021 - -0.017]	[5.217 - 6.028]	[22.290 - 61.180]	0.97
	Zone 2	$-0.023x^2 + 6.448x + -7.257$	[-0.026 - -0.021]	[5.928 - 6.969]	[-31.910 - 17.390]	0.97
	Zone 3	$-0.022x^2 + 6.250x + -6.446$	[-0.025 - -0.019]	[5.658 - 6.842]	[-33.940 - 21.050]	0.96
	Zone 4	$-0.023x^2 + 6.293x + -15.190$	[-0.027 - -0.019]	[5.562 - 7.025]	[-50.180 - 19.790]	0.92
	Zone 5	$-0.021x^2 + 5.811x + -6.373$	[-0.026 - -0.016]	[4.772 - 6.850]	[-54.460 - 41.720]	0.79
WC	Medal Zone	$-0.019x^2 + 5.599x + 37.060$	[-0.020 - -0.018]	[5.363 - 5.835]	[25.530 - 48.590]	0.96
	Zone 2	$-0.022x^2 + 6.151x + 4.186$	[-0.023 - -0.021]	[5.869 - 6.432]	[-9.376 - 17.750]	0.96
	Zone 3	$-0.024x^2 + 6.521x + -19.380$	[-0.025 - -0.023]	[6.232 - 6.810]	[-32.980 - -5.788]	0.95
	Zone 4	$-0.025x^2 + 6.753x + -36.040$	[-0.027 - -0.023]	[6.350 - 7.156]	[-54.860 - -17.220]	0.94
	Zone 5	$-0.026x^2 + 6.803x + -44.880$	[-0.028 - -0.024]	[6.444 - 7.162]	[-61.480 - -28.270]	0.90
EC	Medal Zone	$-0.020x^2 + 6.035x + -4.710$	[-0.022 - -0.019]	[5.690- 6.379]	[-21.570 - 12.150]	0.94
	Zone 2	$-0.024x^2 + 6.625x + -40.230$	[-0.026 - -0.022]	[6.236 - 7.014]	[-58.420 - -22.040]	0.96
	Zone 3	$-0.027x^2 + 7.091x + -67.680$	[-0.029 - -0.024]	[6.664 - 7.518]	[-87.690 - -47.670]	0.93
	Zone 4	$-0.021x^2 + 5.834x + -18.340$	[-0.024 - -0.018]	[5.211 - 6.456]	[-48.210 - 11.530]	0.87
	Zone 5	$-0.022x^2 + 5.968x + -32.620$	[-0.026 - -0.019]	[5.198 - 6.738]	[-69.150 - 3.898]	0.75

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

256   within each competition type carried low error rates (RMSE). This suggests that the models
257   perform well on unseen data (Test data). However, what becomes apparent is that the error
258   increases the lower down the performance zone (i.e. 11th -15th). This is evidence and discussed
259   further below within the context of performance zones and their practical interpretations.
260

261   *Olympic Games*

262   The performance zones for the OG displayed R^2 values ranging from 0.79 to 0.97 to suggesting
263   a variance of 79 to 97% of the Ptot could be explained by the weight category. Average
264   predictive ability of all the performance zones was 3.65 ± 2.51% (12.46 ± 9.16kg). The
265   predictions for the Medal Zones averaged a 2.15 ± 1.20% (8.10 ± 4.53kg) difference from the
266   Tokyo 2020 performances across all new weight categories. The best prediction occurred in
267   the 73kg weight category, which had a 0.16% (0kg) difference to the actual Medal Zone (351
268   vs 351kg). This can be deemed a perfect prediction, but it's important to state that the
269   interpretation of this should consider that this prediction would provide a silver medal
270   performance as it is an average of 1st, 2nd and 3rd. The men's 96kg weight category displayed
271   the biggest difference between the prediction and actual outcome, with a value of 3.71%
272   (15kg). The actual outcome achieved was 392 ± 9kg, with the prediction being 407kg. This
273   over prediction would in fact achieve a gold medal, however, the LLPI of 380kg encapsulates
274   the actual outcome ± the SD (401 – 383kg) and therefore it is suggested in this instance that
275   performance teams aim for anything above the LLPI to increase medal potential. The Medal
276   Zone for all other categories displayed prediction to actual outcome differences of between
277   1.17 – 3.71%. When analysing all other performance zones within the OG, it becomes apparent
278   that the differences between the prediction to the actual outcome generally ascend down the
279   performance zones, with the largest differences existing in Zone 5 (11th – 15th). This is likely
280   due to multiple reasons, 1) this performance zone has the largest number of athletes within it,
281   compared to the other performance zones which is likely to increase the variance of Ptot and
282   2) this Zone likely contains athletes who qualified outside of top 8 automatic qualification spots
283   in the lead up to the OG.
284

285   *World Championship*

286   The WC contested all 10 new weight categories. The R^2 values for the regression models
287   ranged from 0.90 to 0.96, suggesting each model had the ability for bodyweight to strongly
288   account for the variance of Ptot. The average predictive ability for the WC across all

289   performance zones was 0.78±3.29% (2.26±10.08kg). The average prediction for the Medal

290   Zone was 1.02 ± 2.71% (3.28 ± 8.78kg) across all new weight categories. The best predictive

291   ability in the Medal Zone was the <109kg weight category, with a near perfect prediction of -

292   0.06% (0kg) compared to the actual Medal Zone (457 vs 457kg, respectively). Interestingly,

293   the actual Ptot had a SD of 20kg (457 ± 20kg), suggesting that the Medal Zone is large. The

294   likely reason behind this is that in both the 2018 and 2019 WC from which this data has been

295   formulated, the differences between each medal zone ranged from 14 to 24kg, averaging 20kg.

296   Although the absolute value of 20kg may seem large, the SD as a percentage of the actual

297   outcome is <5%. As the actual results could be between 437 and 477kg, it is suggested that

298   performance teams aim to achieve a Ptot close to or above the LLCI of 453kg, as the LLPI of

299   426kg may results in a rank outside of the Medal Zone.

300

301   The worse predictive model for the WC Medal Zone was the 55kg weight category, displaying

302   a 6.91% (19kg) overprediction. Interestingly, this was followed by the 102kg and 89kg weight

303   category which also showed overpredictions of 4.25% (17kg) and 3.42% (13kg), respectively.

304   A likely reason for this is that the data used to analyse the WC was prior to the OG, in which

305   the aforementioned weight categories were not contested. Therefore, it is likely that athletes

306   moved to Olympic weight categories therefore affecting these, Medal Zones. All other Medal

307   Zones had predictions ranging from -1.64% to 0.64% (-6 – 3kg) relative to the actual Ptot. All

308   other performance zones showed a range of predictive ability, with the best being Zone 5 in

309   the 96kg weight category showing a near perfect predictive Ptot with no difference (0.08%

310   ,0kg) to the actual Ptot (366 vs 366kg). On average the predictive models for the 96kg weight

311   category showed a difference across performance zones of only 0.55 ± 0.75%, suggesting this

312   model may be useful for those working with athletes preparing for the WC in this weight

313   category.

314

315   *European Championships*

316   The EC predictive models displayed R^2 values ranging from 0.75 to 0.96, with the lowest

317   variance observed for performance zone 5. The average predictive ability for the EC across all

318   performance zones was -1.13±3.46% (-4.32±11.10kg). The average prediction for the Medal

319   Zone across all new weight categories was -0.25 ± 3.47% (-1.93 ± 12.51kg). The best predictive

320   ability in the Medal Zone was the 61kg weight category, with a -0.02% (0kg) prediction

321   compared to the actual Medal Zone (287 vs 287kg, respectively). The worst predictive model

322   in the Medal Zone was for the 55kg weight category, overpredicting the actual Ptot by 6.04%
323   (15kg). The actual Ptot had a SD of 9kg (251 ± 9kg), which means a 1st place finish would be
324   a total of ~260kg, which is 2kg less than that of the LLCI (262kg). Interestingly, the 2019 and
325   2021 EC 1st place finish achieved a total of 261 and 258kg respectively, therefore, performance
326   teams should consider aiming for the LLCI of 262kg to increase their chance of a gold medal.

328   All other Medal Zones had varying under- and over- predictions ranging from -6.02% to 4.66%
329   (-26.45 – 17.78kg). Much like the WC, on average, the best predicted weight category was the
330   96kg category with a small over prediction of Ptot by 0.41% (1.67kg) across all performance
331   zones. Suggesting this model may be useful for those working with athletes preparing for the
332   EC in this weight category.

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

343   *Re-occurrences (same athlete data)*
344   The old weight category data obtained from the IWF website spanned over a period of 20 years
345   (1998 – 2018) across 3 major competitions. Data re-occurrences of individuals and their
346   performances within these competitions must be considered. Although we acknowledge the
347   concern of possible limiting of model generalisability arising from the use of recurring athletes,
348   we believe that the methodologies used throughout this investigation maximise the
349   generalisability of the models given the unique case of the sport weightlifting.

350   Firstly, individual performance totals were considered to be observed within the study design,
351   as opposed to individual athletes. This is because performance can vary over time and across
352   competitions which is important information that should be captured. Furthermore, selecting
353   only one out of several performance totals could introduce the issue of selection bias.
354   Additionally, this would significantly reduce the sample size for modelling which in turn would

355 result in lower generalisability of predictions. For future analysis, using a larger database of

356 athletes (which would naturally expand over time) would help to further tackle this potential

357 issue.

358

359 *Outliers (individuals)*

360 Often, outliers within data sets can skew the dispersion around the mean. In high performance

361 sport it is not uncommon to come across statistical outliers which may distort the calculated

362 outcome (2), in this case the predicted Ptot within performance zones. It is important to state

363 that performance teams would need to consider whether they are willing to accept an increase

364 in predictive variance keeping in known outliers, or removing outliers at the risk of not

365 capturing performances reflective of what is actually achieved within competition. The

366 practical ramifications of the latter can be explained when looking at medal zones. If an athlete

367 who achieves a Gold medal Ptot considerably more than that of 2nd place was removed, the

368 medal zone would reduce in both its mean and SD (as well as 95% CI and PI), telling us that

369 the total required to achieved a medal is artificially lower than it would be having kept in the

370 outlier. As this practical example shows, given the consequences of underprediction and by

371 extension incorrectly classifying an athlete as a potential medallist or OG qualifier (i.e False

372 Positive) it is clear that we would be willing to accept overprediction if this ensures we

373 minimise the number of false positives.

374

375 *Performance Zone grouping*

376 The performance zones utilised in this investigation were based on current processes and

377 requirements for qualifying for the Olympic games (top 8) and/or predicting outside

378 opportunities for medals (zone 2 4-5th) across major competitions. While this may carry

379 ecological utility, some issues may exist in developing the predictive model given that some

380 performance zones are so closely grouped together (i.e. zone 2, 4-5th). This reduces the sample

381 size and consequently may lead to models with low bias and higher levels of variance. This

382 potential of overfitting is one we have attempted to address through the use of lower model

383 complexity alongside K-Fold Cross validation. Future analysis using an expanding database

384 over time will further help address the issue of low samples within performance zones.

385

386 *Doping*

387 At the time of data extraction from the IWF database all athletes who had Anti-Doping rule

388 violations (ADRVS) were marked as "DNF" (did not finish) and were therefore excluded from

389 the analysis. However, many bans within weightlifting occur retrospectively following re-
390 analysis of samples collected during major competitions. For example, Kollari-Turner et al
391 (13) reported that a total of 61 weightlifters were identified to have adverse analytical findings
392 of prohibited substances during the 2008 and 2012 OG. From this sample a total of 34 of them
393 were medallists. The relevance of this within the present study is that it highlights the need to
394 update the data used in developing the predictive models as and when doping violations are
395 announced to ensure higher levels of efficacy.
396

397 **PRACTICAL APPLICATION**
398 This study provides outcomes for predictive models for major competitions in the sport of
399 weightlifting. The tables provided in this manuscript can be used by performance teams to aid
400 in the long- and short- term preparation for the Olympic Games and World and European
401 Championships. Furthermore, the results from this study may also provide a more objective
402 selection process for the analysed competition types to enhance the chance of achieving the
403 highest possible rank. While the predictive models generally carried low percentage differences
404 relative to the actual Ptot, some consideration around interpretation and utility must be
405 considered. It is evident that the predictive models carried variation throughout each
406 competition type and performance zone. Given that there were both over and underpredictions
407 throughout the models, it is suggested that performance teams manage expectation and use
408 these predictions in conjunction with a coach's intuition and knowledge of the field of play. It
409 is also worth highlighting that crossover between performance zones will be likely, and
410 therefore should be explored further. Future investigation should also look to apply this as a
411 proof of concept within women's weightlifting, which was introduced to the Olympics and the
412 World Championships at later time points than the men, thus having less data over the years.
413 As for immediate utility, coaches or performance teams can use the equations provided to
414 identify specific Ptot within specific weight categories and performance zones. Furthermore,
415 with the freely available Ptot data, performance teams may also repeat the proposed
416 methodology for other weightlifting demographics (i.e. women, junior and youth), for different
417 performance zones they deem relevant and also for the individual lifts of the snatch and jerk,
418 given medals opportunities are available for each of these at WC and EC.
419

422

Declaration of Interest

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

425

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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