# Longitudinal growth modelling of strength adaptations in powerlifting athletes across ages in males and females

Supplementary materials:
www.osf.io/23qth

For correspondence:
c.latella@ecu.edu.au

Christopher Latella[1,2], Daniel van den Hoek[3], Milo Wolf[4], Patroklos Androulakis-Korakakis[4], James P. Fisher[4], James Steele[4]

[1] School of Medical and Health Sciences, Centre for Human Performance, Edith Cowan University, Joondalup, Western Australia, Australia.

[2] School of Medical and Health Sciences, Neurophysiology Research Laboratory, Edith Cowan University, Joondalup, Western Australia, Australia.

[3] School of Behavioural and Health Sciences, Australian Catholic University, Banyo, Queensland, Australia.

[4] Faculty of Sport, Health and Social Sciences, Solent University, Southampton, UK

*Please cite as*: Latella, C., van den Hoek, D., Wolf, M., Androulakis Korakakis., P, Fisher, JP & Steele., J. (2022). Longitudinal growth modelling of strength adaptations in powerlifting athletes across ages in males and females. *SportRχiv*.

## ABSTRACT

Introduction: Several retrospective studies of strength sport athletes have reported strength adaptations over months to years, however, such adaptations are not linear. Methods: We explored changes in strength over time in a large, retrospective sample of powerlifting (PL) athletes. Specifically, we examined the rate and magnitude of strength adaptation based on age category and weight class for total strength, and the squat, bench press, and deadlift, respectively. Mixed effects growth modelling was performed for each operationalised performance outcome (squat, bench press, deadlift, and total) as the dependent variables with outcomes presented on both the raw untransformed time scale, and on the common logarithmic scale. Additionally, the fitted values were rescaled as a percentage. Results: Collectively, the greatest strength gains were in the earliest phase of PL participation (~7.5-12.5% increase in the first year, with only an ~12.5-20% increase after 10 years). Females tended to display faster progression, possibly because of lower baseline strength. Additionally, female Masters 3 and 4 athletes (>59 years) still displayed ~2.5-5.0% strength improvement, and only slight strength loss was observed in Masters 4 (>69 years) males (~0.35%/year). Conclusion: Although directly applicable to PL, these findings provide population level support for the role of consistent and continued strength training to improve strength across individuals, and importantly, to mitigate, or at least largely attenuate age-related declines in strength compared to established general population norms. This information should be used to encourage participation in strength sports, resistance training more generally, and to support future public health messaging.

## Introduction

Muscle strength is positively associated with health and physical function across the lifespan (5). Indeed, greater muscle strength displays an inverse relationship with many co-morbidities and all-cause mortality (40). Moreover, strength declines with advancing age at a rate of ~1% per year, with more rapid loss occurring in the lower limbs and after 60 years of age (10, 12, 16, 38). Importantly, regular participation in resistance training can improve muscle strength throughout the lifespan, or at least attenuate the rate of decline in older adults compared to more sedentary individuals (27). Hence, resistance training is recommended in global health and physical activity guidelines (33).

Despite the known benefits of regular participation in resistance training it is difficult to prospectively study the associated chronic effects (e.g., several years or longer) due to logistical, time, and financial constraints, as well as participant retention issues. Indeed, resistance training interventions ≥12 months are uncommon. One way to overcome these difficulties is to conduct retrospective and/or cross-sectional analyses of large databases to understand strength adaptation (see (19, 20, 22, 45)). For example, Steele et al. (45) recently reported that strength increases by ~50-60% over an approximate 6-year period, but that ~30-50% of this occurs within the first year. Importantly, these results are in response to minimal dose resistance training (i.e., one training session per week, comprising six exercises and only one set to momentary muscle failure for each) in a general, non-athletic population. Given the deliberate prescription of minimal dose resistance training it is not clear whether this is indicative of the greatest (or even typical) amount of strength adaptation that can occur in response to resistance training. To answer these questions, the investigation of alternative populations such as strength sport athletes may be more appropriate. For example, powerlifting (PL) athletes train solely to improve maximum upper-and lower-body strength which is then expressed by lifting as much weight as possible in the squat, bench press, and deadlift during competition. Indeed, competitive PL athletes dedicate large amounts of time to training, as much as 90-120 minutes per session on 5-6 days per week (43), usually to the exclusion of concurrent physical activities (e.g., endurance training). This affords a unique opportunity to examine the chronic effects of larger amounts of high-intensity strength training that has the specific and primary aim of improving maximum strength. As maximum strength is then determined using the same rules and regulations each time during competition (including data capture of athlete age and bodyweight), it can provide a robust measure of maximal strength that can be tracked within athletes and compared across large samples of athletes across time.

Several retrospective studies of PL and weightlifting athletes have reported strength adaptations over periods ranging from 10-15 years (19, 20, 29, 34). In PL specifically, similar rates of whole-body strength adaptation have been reported between sexes, however, the strongest males gained strength more slowly than the least strong males (20). Recent expansion of this work also suggests that differences in strength gain occur between the upper- and lower-body lifts (19). Importantly though, and as noted by Latella et al. (19), strength gain does not occur linearly. As recently suggested by Steele et al. (45) certain statistical approaches hold inherent limitations. Thus, alternative statistical approaches such as mixed effects growth modelling (as used to explore the effects of minimal dose resistance training [(45)]), may provide more robust information in this area. Indeed, in the same paper by Steele and colleagues (45), mixed effects growth modelling was also used to test a randomly selected sample of 10,000 PL athletes. The results indicate that the magnitude of strength gain is less than that of the general population (likely due to prior experience with resistance training), and that strength adaptations still plateau after approximately 1-year. However, likely differences in strength adaptation between age categories, lift-types, and weight classes are yet to be explored using this approach.

The purpose of this investigation was to explore changes in strength over time in a large, retrospective sample of PL athletes. Specifically, we aimed to identify differences in the rate and magnitude of strength adaptation based on age category and weight class for overall strength, and the squat, bench press and deadlift, respectively. Based on general ageing population evidence, we hypothesize that older PL athletes will display less strength adaptation compared to younger counterparts. Conversely, based on previous work in PL athletes (19, 20), we hypothesize that there will be no differences between sexes. The findings of this investigation are intended to serve two purposes. The first is to provide detailed information about changes in strength of PL athletes over time. The second, with a view towards wider generalisation and advocation of muscular strength, is to help provide a better understanding of adaptive potential across the lifespan in response to chronic participation in strength training.

## Materials and methods

### *Study design*

This study was a retrospective longitudinal growth modelling analysis of performance data from the Open Powerlifting dataset (https://openpowerlifting.gitlab.io/opl-csv/; accessed 4th August 2021, see file version in online supplementary materials https://osf.io/ruwda/). Considering the retrospective nature of the study design evaluating existing public domain data, that all data was handled in accordance with Global Data Protection Regulations (GDPR), and guidance from the Health Research Authority and Research Ethics Committee section 11 of Standard Operating Procedures, *a priori* ethical/IRB approval was not required for this research.

### *Data Preparation*

We limited our study to the International Powerlifting Federation (IPF) dataset including all IPF affiliates, filtered to include only open raw (i.e., unequipped) “Squat, Bench, and Deadlift” events. We also removed any observations where a lifter failed all attempts for a given lift (and was subsequently disqualified) such that total was always the sum of the greatest successful attempt in each of the three lifts, and limited our analysis to lifters who had competed at a minimum of three competitions to be suitable for growth model analyses (11)[1]. We chose to use the IPF dataset for our primary analysis as competitions in this federation are drug tested; however, we also refit our statistical models (described below) to the overall Open Powerlifting dataset to explore the

---

[6] Though notably partial pooling effects enable the estimation of effects for even those with missing data in mixed effects models (Gelman and Hill, 2006).

sensitivity of our results in a (likely) more heterogenous powerlifting sample. This filtering resulted in a dataset including 46,066 observations (rows) over 9,259 unique lifters up to a maximum of ~17 years of competition. Performance was operationalized as the best of all attempts for squat, bench press, and deadlift in addition to the PL total (sum of best attempts across all three lifts) for each competition. We considered both age and bodyweight as continuous variables for the purposes of statistical modelling, but also operationalized age category and bodyweight class according to the IPF categories for the purposes of model visualization (see below). Age categories were Sub-junior (≤18 years), Junior (>18 ≤23 years), Open (>23 ≤39 years), Masters 1 (>39 ≤49 years), Masters 2 (>49 ≤59 years), Masters 3 (>59 ≤69 years), and Masters 4 (>69 years). Bodyweight classes for women were 47 kg, 52 kg, 57 kg, 63 kg, 69 kg, 76 kg, 84 kg, and >84 kg; and for men were 59 kg, 66 kg, 74 kg, 83 kg, 93 kg, 105 kg, 120 kg, and >120 kg. Full data on all covariates for analyses described below were available for 6,968 lifters and 35,244 observations.

### *Statistical Analysis*

Analysis for this study was not pre-registered and was treated as exploratory. Thus, inferential statistics from the analysis of the dataset generated from our participants should be treated as highly unstable local descriptions of the relations between model assumptions and data to acknowledge the inherent uncertainty in drawing generalised inferences from single samples (3). However, considering the sample size for this present study, we consider our results well generalisable to the sampled population of competitive PL athletes. For all analyses, we opted to avoid dichotomising the existence of effects and therefore did not employ traditional null hypothesis significance testing, which has been extensively critiqued (2, 28). Instead, though we present *p* values for model summaries, we consider the implications of all results compatible with these data, from the lower limit to the upper limit of interval estimates, with the greatest interpretive emphasis placed on the point estimates. Further, we focus primarily on qualitative description of our results based on visualisation of the data and models. All analysis was conducted in R (v 4.0.2; R Core Team, https://www.r-project.org/) and all data and code utilised is presented in the supplementary materials (https://osf.io/23qth/).

Mixed effects growth modelling was performed for each operationalised performance outcome (i.e., squat, bench press, deadlift, and total) as the dependent variables. Time was defined continuously as the natural logarithmic transformation of 'time' in weeks based on the conversion of competition dates from the first competition date for each individual. Random intercepts and slopes for time for individual participants were included and we also included the fixed effects and full interactions of time with age, sex, and bodyweight. We initially visually explored several models where raw time (in weeks) and log(time) were treated linearly, or as a second order polynomial. A random sample of 100 lifters were drawn and PL total explored. Models were fitted on this sample and the respective model predicted values were plot and compared with the raw values. The difference in fit when inspected visually (see https://osf.io/7w83f/) was negligible between the two models. Considering the respective model indices (compared using the package 'performance'(23)) for both the small (see https://osf.io/3g7mx/), and full datasets (see https://osf.io/9y27u/) though the polynomial-log model had a better fit this was marginal (see https://osf.io/xt7ca). Thus, we opted to utilise the linear-log model formulation to facilitate easier interpretation of model coefficients and comparison to similar analyses in prior studies (45). Model formulation in Pinheiro-Bates modified Wilkinson-Rogers notation (37, 48) was thus:

Performance ~ log(Time) * Age * Sex * Bodyweight + (log(Time) | ID)

All models were fit using the ‘lme4’ package (4) with Restricted Maximum Likelihood Estimation and Nelder-Mead optimisation (31)). Model summary tables were produced using the ‘sjPlot’ package (6). Standardised beta coefficients using Gelman’s (1) standardisation by two standard deviations were also produced and included in model summary tables to allow for comparison across models and to any past and future longitudinal growth models for strength/performance from different datasets. Model diagnostics were inspected using the ‘performance’ package, and correlation matrices for fixed effects multi-collinearity.

Data visualisation for the main model included calculation of model predicted values and 95% prediction intervals using the ‘ggeffects’ package (24) to communicate the model uncertainty. We calculated predicted values and intervals for the fixed effects from our models up to the maximum time for which data was available in the main sample. For all interaction effect plots we show confidence intervals bands. Both age class and bodyweight class were visualised for the median of each as continuous variables. When exploring the interaction of time with bodyweight as noted we visualised this across bodyweight classes. Thus, for these visualisations, given that males and females have different weight classes we refit the models to male and female data separately to extract marginal effects for visualisation. All plots are presented on both the raw untransformed time scale, and on the common logarithmic scale. Additionally, the fitted values were rescaled as a percentage value normalised to the fitted value at time = 1 and each individual curve re-plotted for visual comparison of strength change magnitudes. All figures show the models presented in Pinheiro-Bates modified Wilkinson-Rogers notation.

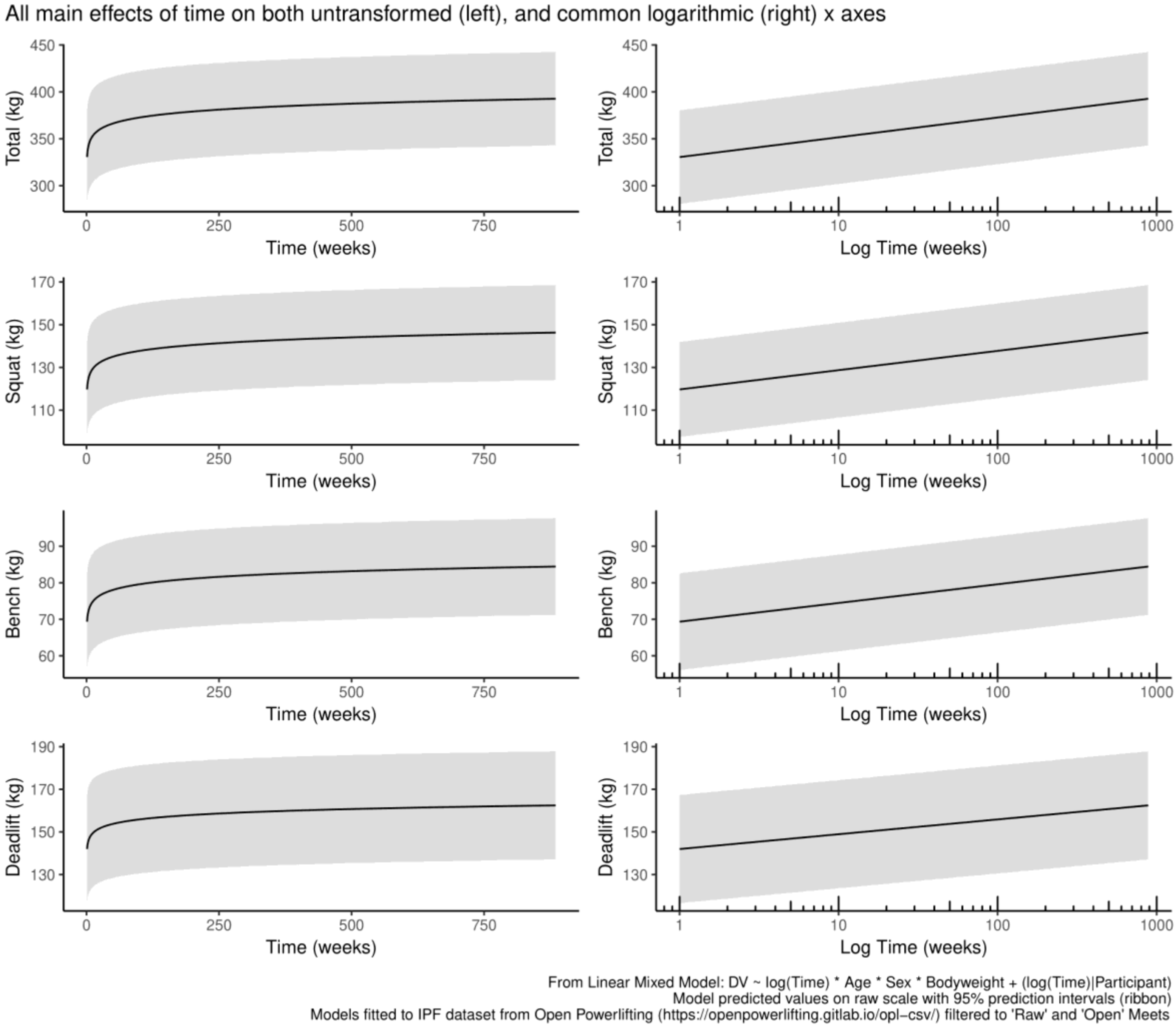
Lastly, given the longitudinal model employed we attempted to rule out the possible explanation that, given a larger proportion of participants had data for fewer competitions (see supplementary materials https://osf.io/uhz2e/), weaker individuals dropping out of competing over time may account for any apparent plateau in performance with time (i.e., survivorship bias). We explored whether there was any correlation between the random effects by lifters from the main model and time duration for which they had data available.

## Results

All model diagnostic plots and the correlation matrix for fixed effects are available in the online supplementary materials (see https://osf.io/23qth/ > Outputs > Model checks and diagnostics). Briefly, all relevant model assumptions were met except for some deviation from normality of distribution in the residuals at the tails. However, we were unconcerned with this given that both linear regression models with large samples (25, 42), and mixed models (18, 41) are typically robust to deviation from normality assumptions, particularly where simple growth models with a single random intercept and slope are employed such as we have used here (15).

### *Main Effects of Time*

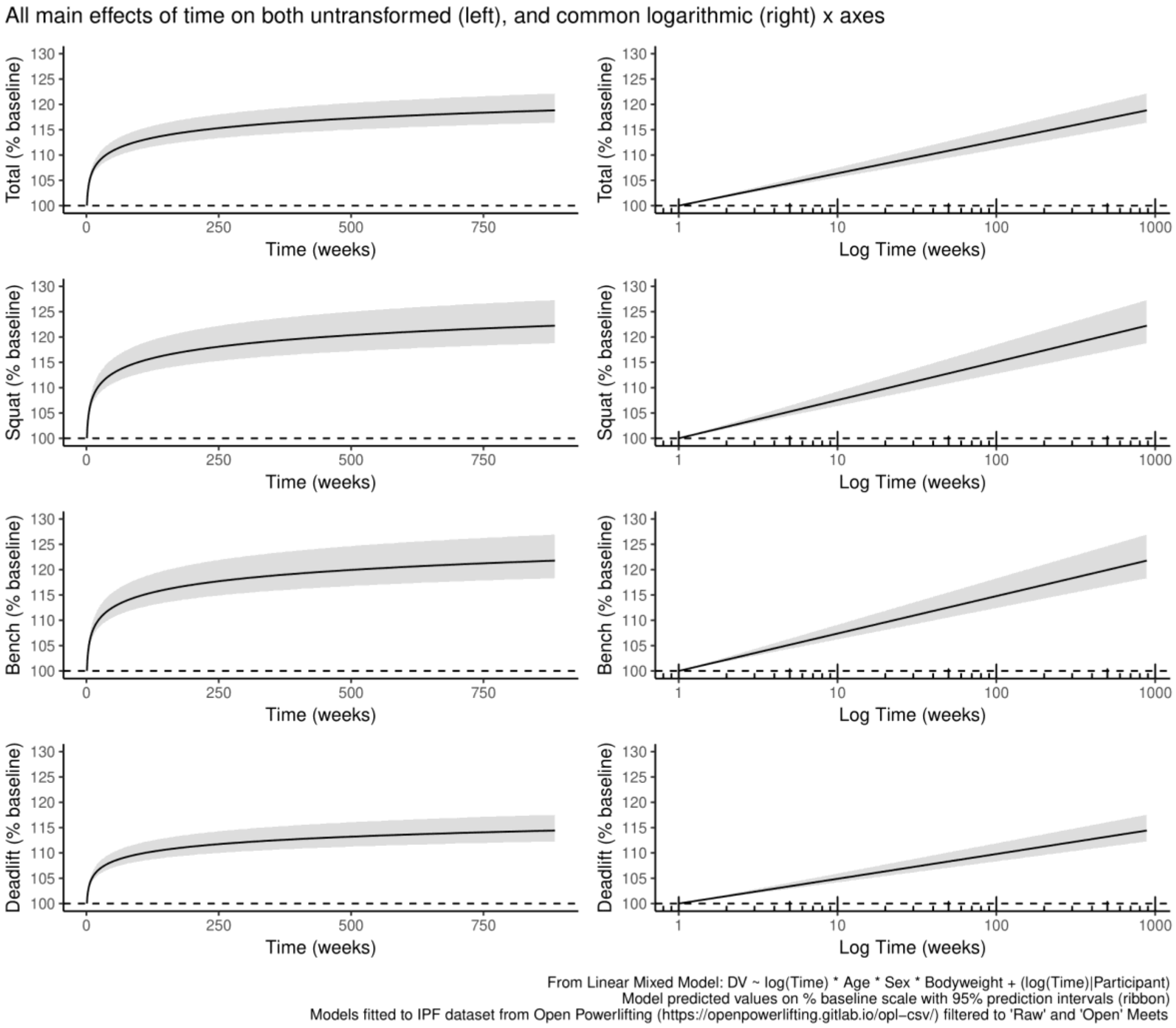
Across all lifts, similar patterns of performance growth were observed (figure 1). Our models demonstrated a robust linear-log relationship between performance and the main effect of time indicating that as time progressed the magnitude of performance changes diminished (right panels in figure 1). Examining the fitted models on the untransformed time scale (left panels in figure 1) clearly indicates that rapid strength adaptation occurs within the first year of competition before beginning to plateau. Standardized beta coefficients for log(time) indicated that strength progression was relatively small across lifts and occurred most rapidly for the squat. Rescaling performance as percentage of baseline showed approximately ~7.5-12.5% gains over the first year, yet 10 years later gains had only reached ~12.5-20% of baseline (figure 2). Full model summaries for each lift are presented in table 1. The following sub sections describe the findings for other fixed effects (sex, age, bodyweight) and their interactions.



All main effects of time on both untransformed (left), and common logarithmic (right) x axes

From Linear Mixed Model: DV ~ log(Time) * Age * Sex * Bodyweight + (log(Time)|Participant)
Model predicted values on raw scale with 95% prediction intervals (ribbon)
Models fitted to IPF dataset from Open Powerlifting (https://openpowerlifting.gitlab.io/opl-csv/) filtered to 'Raw' and 'Open' Meets

**Figure 1.** Main model fitted values (solid line) and 95% prediction intervals (dashed lines).



All main effects of time on both untransformed (left), and common logarithmic (right) x axes

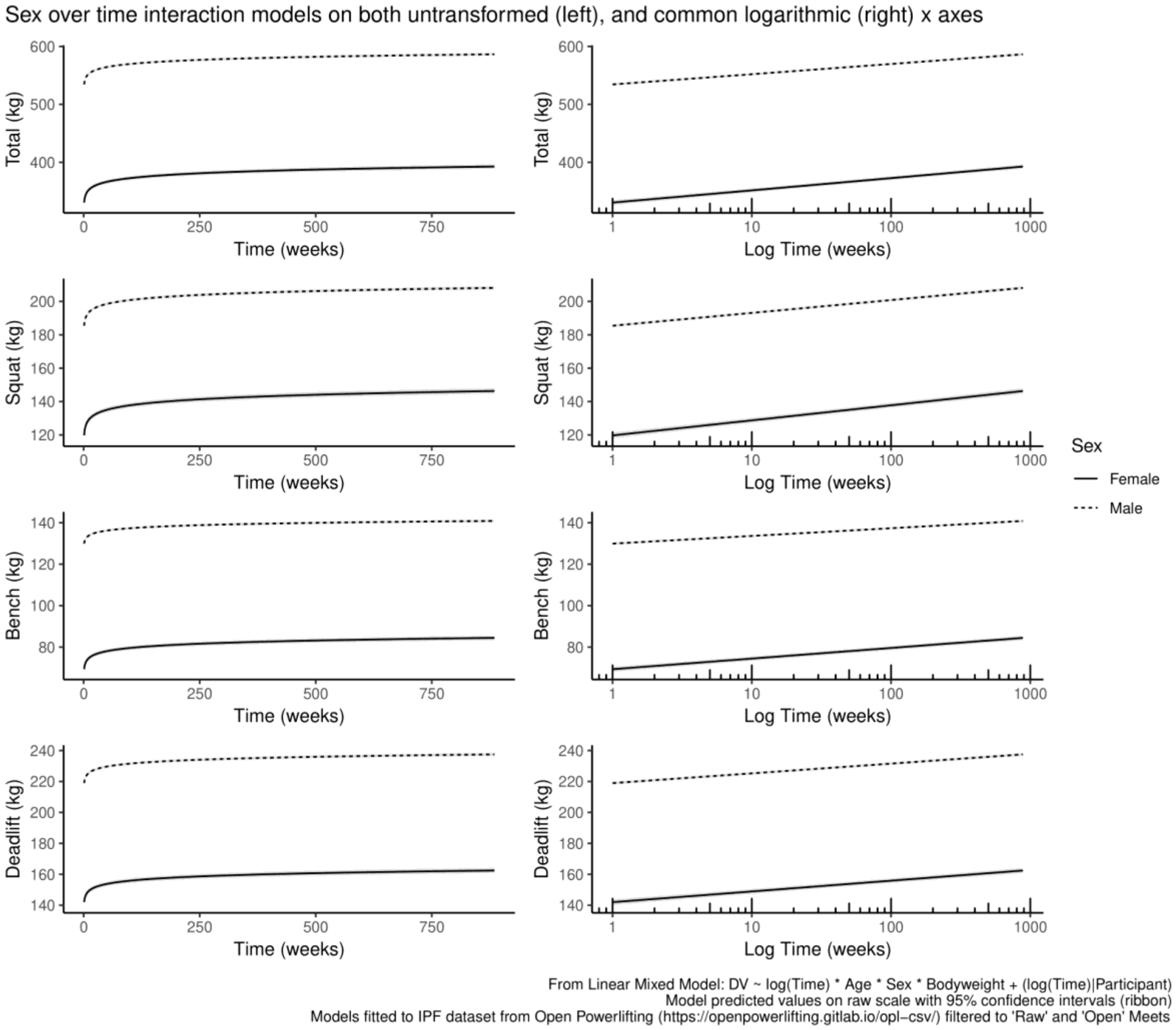
From Linear Mixed Model: DV ~ log(Time) * Age * Sex * Bodyweight + (log(Time)|Participant)
Model predicted values on % baseline scale with 95% prediction intervals (ribbon)
Models fitted to IPF dataset from Open Powerlifting (https://openpowerlifting.gitlab.io/opl-csv/) filtered to 'Raw' and 'Open' Meets

**Figure 2.** Main model fitted values rescaled as a percentage of baseline performance values.

| | Total (kg) | | | | | | Squat (kg) | | | | | | Bench Press (kg) | | | | | | Deadlift (kg) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Predictors* | *Estimates* | *std. Beta* | *CI* | *standardized CI* | *p* | *std. p* | *Estimates* | *std. Beta* | *CI* | *standardized CI* | *p* | *std. p* | *Estimates* | *std. Beta* | *CI* | *standardized CI* | *p* | *std. p* | *Estimates* | *std. Beta* | *CI* | *standardized CI* | *p* | *std. p* |
| (Intercept) | 102.47 | -1.11 | 59.46 – 145.48 | -1.14 – -1.08 | **<0.001** | **<0.001** | 30.12 | -1.01 | 12.10 – 48.14 | -1.04 – -0.98 | **0.001** | **<0.001** | 23.84 | -1.15 | 12.02 – 35.67 | -1.18 – -1.12 | **<0.001** | **<0.001** | 45.33 | -1.08 | 26.58 – 64.07 | -1.11 – -1.05 | **<0.001** | **<0.001** |
| Time [log] | 6.20 | 0.32 | 0.10 – 12.30 | 0.30 – 0.34 | **0.046** | **<0.001** | 0.45 | 0.35 | -2.25 – 3.14 | 0.33 – 0.38 | 0.746 | **<0.001** | 1.63 | 0.29 | 0.03 – 3.23 | 0.27 – 0.31 | **0.046** | **<0.001** | 4.41 | 0.27 | 1.64 – 7.19 | 0.24 – 0.30 | **0.002** | **<0.001** |
| Age | 1.94 | -0.02 | 0.54 – 3.34 | -0.04 – 0.01 | **0.007** | 0.214 | 0.65 | -0.05 | 0.06 – 1.23 | -0.07 – -0.02 | **0.031** | **0.002** | 0.27 | 0.02 | -0.12 – 0.65 | -0.01 – 0.05 | 0.176 | 0.166 | 1.07 | -0.02 | 0.46 – 1.68 | -0.05 – 0.01 | **0.001** | 0.235 |
| Sex [Male] | -15.24 | 1.26 | -66.63 – 36.15 | 1.23 – 1.30 | 0.561 | **<0.001** | -7.08 | 1.08 | -28.73 – 14.56 | 1.05 – 1.11 | 0.521 | **<0.001** | -12.27 | 1.35 | -26.33 – 1.80 | 1.32 – 1.38 | 0.087 | **<0.001** | 3.90 | 1.26 | -18.67 – 26.48 | 1.23 – 1.30 | 0.735 | **<0.001** |
| Bodyweight | 2.91 | 0.26 | 2.26 – 3.55 | 0.24 – 0.28 | **<0.001** | **<0.001** | 1.21 | 0.30 | 0.94 – 1.48 | 0.27 – 0.33 | **<0.001** | **<0.001** | 0.53 | 0.19 | 0.35 – 0.71 | 0.17 – 0.21 | **<0.001** | **<0.001** | 1.22 | 0.28 | 0.94 – 1.50 | 0.25 – 0.30 | **<0.001** | **<0.001** |
| Time [log] * Age | -0.05 | -0.06 | -0.25 – 0.15 | -0.08 – -0.04 | 0.616 | **<0.001** | 0.02 | -0.07 | -0.07 – 0.11 | -0.09 – -0.05 | 0.635 | **<0.001** | -0.03 | -0.07 | -0.08 – 0.02 | -0.09 – -0.05 | 0.277 | **<0.001** | -0.05 | -0.04 | -0.14 – 0.04 | -0.06 – -0.01 | 0.297 | **0.002** |
| Time [log] * Sex [Male] | 13.94 | -0.05 | 6.24 – 21.63 | -0.08 – -0.03 | **<0.001** | **<0.001** | 6.62 | -0.05 | 3.22 – 10.02 | -0.07 – -0.02 | **<0.001** | **0.001** | 1.46 | -0.09 | -0.56 – 3.47 | -0.11 – -0.07 | 0.157 | **<0.001** | 6.02 | -0.03 | 2.52 – 9.53 | -0.06 – 0.00 | **0.001** | 0.065 |
| Age * Sex [Male] | 2.18 | 0.03 | 0.50 – 3.86 | 0.00 – 0.06 | **0.011** | **0.028** | 0.40 | 0.04 | -0.30 – 1.11 | 0.00 – 0.07 | 0.265 | **0.026** | 0.71 | 0.03 | 0.25 – 1.17 | 0.00 – 0.06 | **0.003** | **0.040** | 1.12 | 0.03 | 0.38 – 1.86 | 0.00 – 0.07 | **0.003** | **0.049** |
| Time [log] * Bodyweight | 0.09 | 0.03 | 0.00 – 0.19 | 0.01 – 0.05 | **0.047** | **0.004** | 0.07 | 0.05 | 0.03 – 0.11 | 0.03 – 0.07 | **0.001** | **<0.001** | 0.03 | 0.05 | 0.00 – 0.05 | 0.03 – 0.07 | **0.030** | **<0.001** | -0.00 | -0.01 | -0.05 – 0.04 | -0.04 – 0.01 | 0.852 | 0.359 |
| Age * Bodyweight | -0.03 | -0.02 | -0.05 – -0.01 | -0.04 – -0.00 | **0.005** | **0.044** | -0.01 | -0.03 | -0.02 – -0.00 | -0.06 – -0.01 | **0.005** | **0.015** | -0.00 | 0.00 | -0.01 – 0.00 | -0.02 – 0.03 | 0.337 | 0.665 | -0.02 | -0.04 | -0.02 – -0.01 | -0.06 – -0.01 | **0.001** | **0.004** |
| Sex [Male] * Bodyweight | 2.28 | 0.27 | 1.56 – 2.99 | 0.25 – 0.30 | **<0.001** | **<0.001** | 0.75 | 0.28 | 0.44 – 1.05 | 0.25 – 0.31 | **<0.001** | **<0.001** | 0.77 | 0.33 | 0.57 – 0.97 | 0.31 – 0.36 | **<0.001** | **<0.001** | 0.75 | 0.19 | 0.43 – 1.06 | 0.16 – 0.22 | **<0.001** | **<0.001** |
| (Time [log] * Age) * Sex [Male] | -0.32 | -0.02 | -0.57 – -0.07 | -0.04 – 0.00 | **0.012** | 0.077 | -0.15 | -0.00 | -0.26 – -0.04 | -0.03 – 0.02 | **0.006** | 0.807 | -0.02 | -0.01 | -0.08 – 0.05 | -0.03 – 0.01 | 0.592 | 0.236 | -0.15 | -0.04 | -0.27 – -0.04 | -0.07 – -0.01 | **0.007** | **0.003** |
| (Time [log] * Age) * Bodyweight | -0.00 | -0.01 | -0.00 – 0.00 | -0.03 – 0.01 | 0.358 | 0.195 | -0.00 | -0.02 | -0.00 – 0.00 | -0.04 – -0.00 | 0.083 | **0.045** | -0.00 | -0.01 | -0.00 – 0.00 | -0.03 – 0.00 | 0.411 | 0.100 | 0.00 | 0.00 | -0.00 – 0.00 | -0.02 – 0.02 | 0.841 | 0.875 |
| (Time [log] * Sex [Male]) * Bodyweight | -0.15 | -0.06 | -0.26 – -0.04 | -0.08 – -0.03 | **0.006** | **<0.001** | -0.08 | -0.07 | -0.13 – -0.03 | -0.09 – -0.04 | **0.001** | **<0.001** | -0.02 | -0.06 | -0.04 – 0.01 | -0.08 – -0.04 | 0.241 | **<0.001** | -0.05 | -0.04 | -0.10 – -0.01 | -0.07 – -0.01 | **0.030** | **0.005** |
| (Age * Sex [Male]) * Bodyweight | -0.01 | -0.02 | -0.04 – 0.01 | -0.05 – 0.00 | 0.215 | 0.059 | -0.00 | -0.01 | -0.01 – 0.01 | -0.03 – 0.02 | 0.898 | 0.667 | -0.01 | -0.04 | -0.01 – 0.00 | -0.06 – -0.01 | 0.111 | **0.002** | -0.01 | -0.03 | -0.02 – 0.00 | -0.06 – 0.00 | 0.074 | 0.058 |
| (Time [log] * Age * Sex [Male]) * Bodyweight | 0.00 | 0.02 | -0.00 – 0.01 | -0.00 – 0.04 | 0.126 | 0.057 | 0.00 | 0.03 | 0.00 – 0.00 | 0.01 – 0.06 | **0.027** | **0.009** | -0.00 | 0.01 | -0.00 – 0.00 | -0.01 – 0.03 | 0.899 | 0.437 | 0.00 | 0.02 | -0.00 – 0.00 | -0.01 – 0.04 | 0.157 | 0.186 |
| **Random Effects** | | | | | | | | | | | | | | | | | | | | | | | | |
| $\sigma^2$ | 647.28 | | | | | | 128.77 | | | | | | 45.68 | | | | | | 167.96 | | | | | |
| $\tau_{00}$ | $5901.40_{\text{Lifter}}$ | | | | | | $945.52_{\text{Lifter}}$ | | | | | | $490.50_{\text{Lifter}}$ | | | | | | $954.36_{\text{Lifter}}$ | | | | | |
| $\tau_{11}$ | $49.14_{\text{Lifter.log(Time)}}$ | | | | | | $9.60_{\text{Lifter.log(Time)}}$ | | | | | | $3.30_{\text{Lifter.log(Time)}}$ | | | | | | $8.09_{\text{Lifter.log(Time)}}$ | | | | | |
| $\rho_{01}$ | $-0.32_{\text{Lifter}}$ | | | | | | $-0.30_{\text{Lifter}}$ | | | | | | $-0.28_{\text{Lifter}}$ | | | | | | $-0.30_{\text{Lifter}}$ | | | | | |
| ICC | 0.89 | | | | | | 0.87 | | | | | | 0.91 | | | | | | 0.84 | | | | | |
| N | $6968_{\text{Lifter}}$ | | | | | | $6968_{\text{Lifter}}$ | | | | | | $6968_{\text{Lifter}}$ | | | | | | $6968_{\text{Lifter}}$ | | | | | |
| Observations | 35211 | | | | | | 35244 | | | | | | 35244 | | | | | | 35244 | | | | | |
| Marginal $R^2$ / Conditional $R^2$ | 0.769 / 0.976 | | | | | | 0.726 / 0.966 | | | | | | 0.759 / 0.978 | | | | | | 0.709 / 0.954 | | | | | |

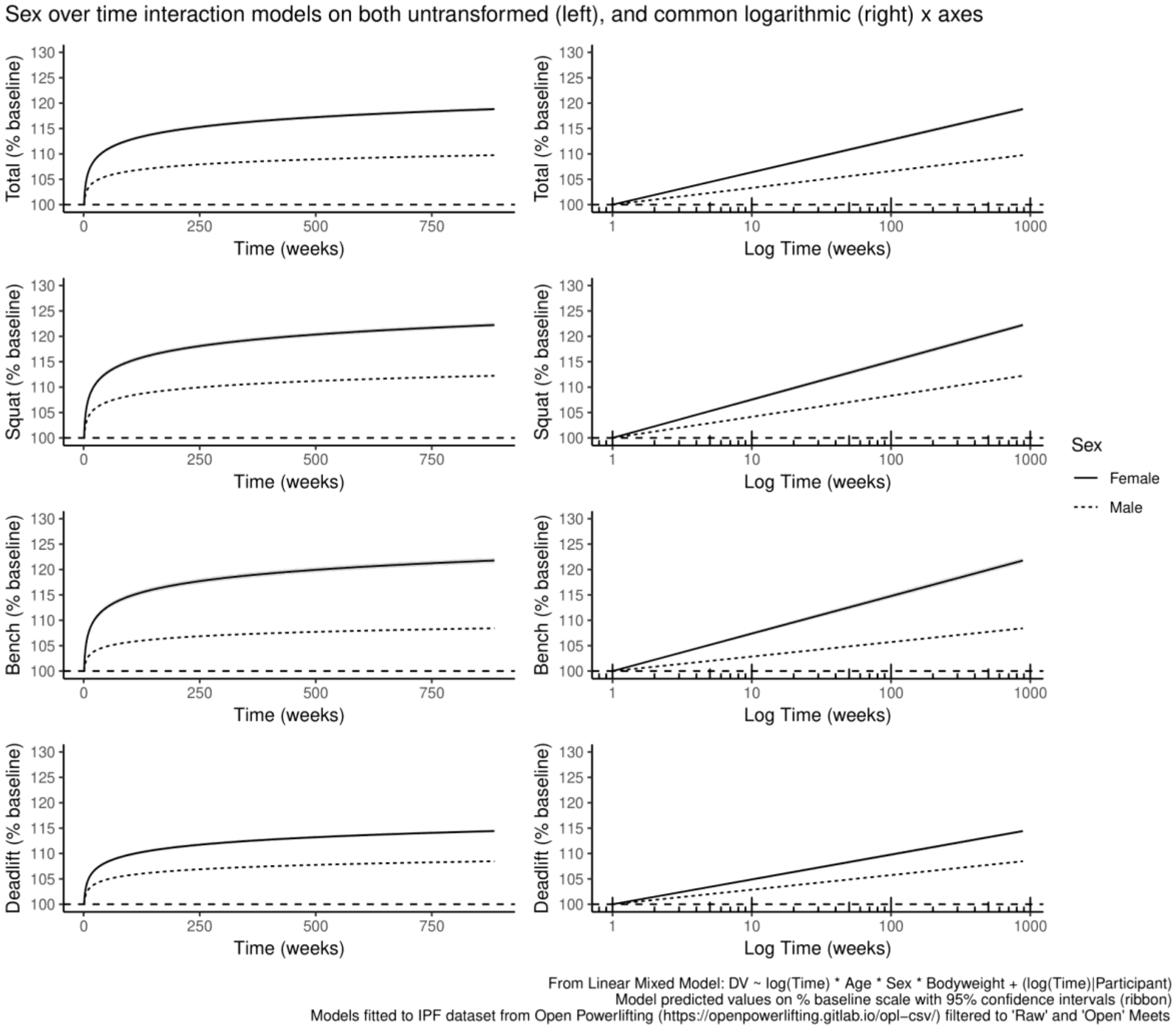
*Sex Interaction*

As might be expected, sex impacted model intercepts across all lifts with males having greater strength at baseline and continuing across time (figure 3). Standardised intercepts showed a large effect of sex, though standardised beta coefficients suggested that the interaction effect with log(time) was trivial though females had slightly steeper slopes indicating faster strength progression over time (see table 1). When rescaling performance as percentage of baseline though the steeper increase in strength for females was more obvious (figure 4).


Sex over time interaction models on both untransformed (left), and common logarithmic (right) x axes

From Linear Mixed Model: DV ~ log(Time) * Age * Sex * Bodyweight + (log(Time)|Participant)
Model predicted values on raw scale with 95% confidence intervals (ribbon)
Models fitted to IPF dataset from Open Powerlifting (https://openpowerlifting.gitlab.io/opl-csv/) filtered to 'Raw' and 'Open' Meets

**Figure 3.** Sex interaction model fitted values and 95% compatibility (confidence) intervals.



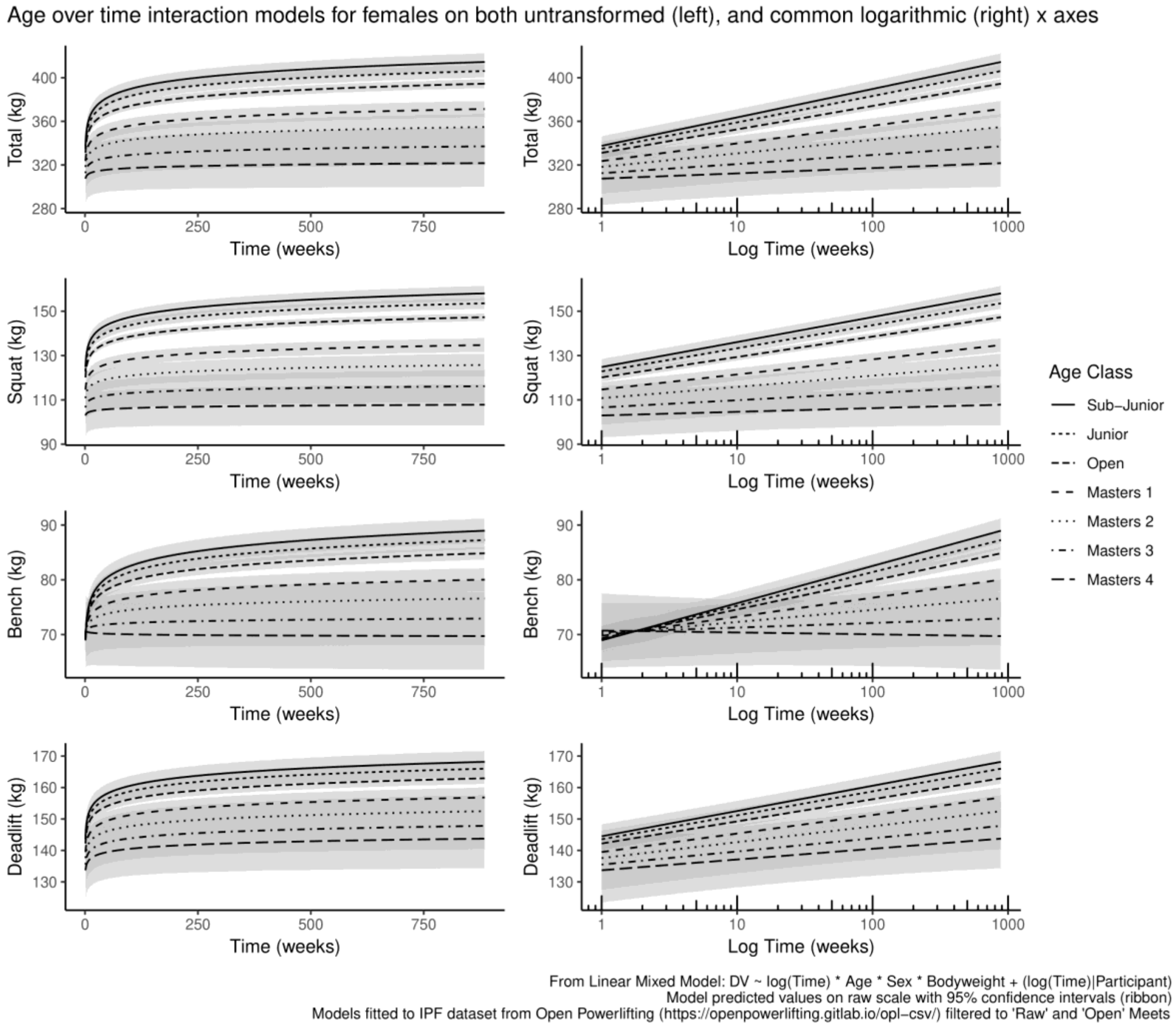
Sex over time interaction models on both untransformed (left), and common logarithmic (right) x axes

From Linear Mixed Model: DV ~ log(Time) * Age * Sex * Bodyweight + (log(Time)|Participant)
Model predicted values on % baseline scale with 95% confidence intervals (ribbon)
Models fitted to IPF dataset from Open Powerlifting (https://openpowerlifting.gitlab.io/opl-csv/) filtered to 'Raw' and 'Open' Meets

**Figure 4**. Sex interaction model fitted values rescaled as a percentage of baseline performance values.

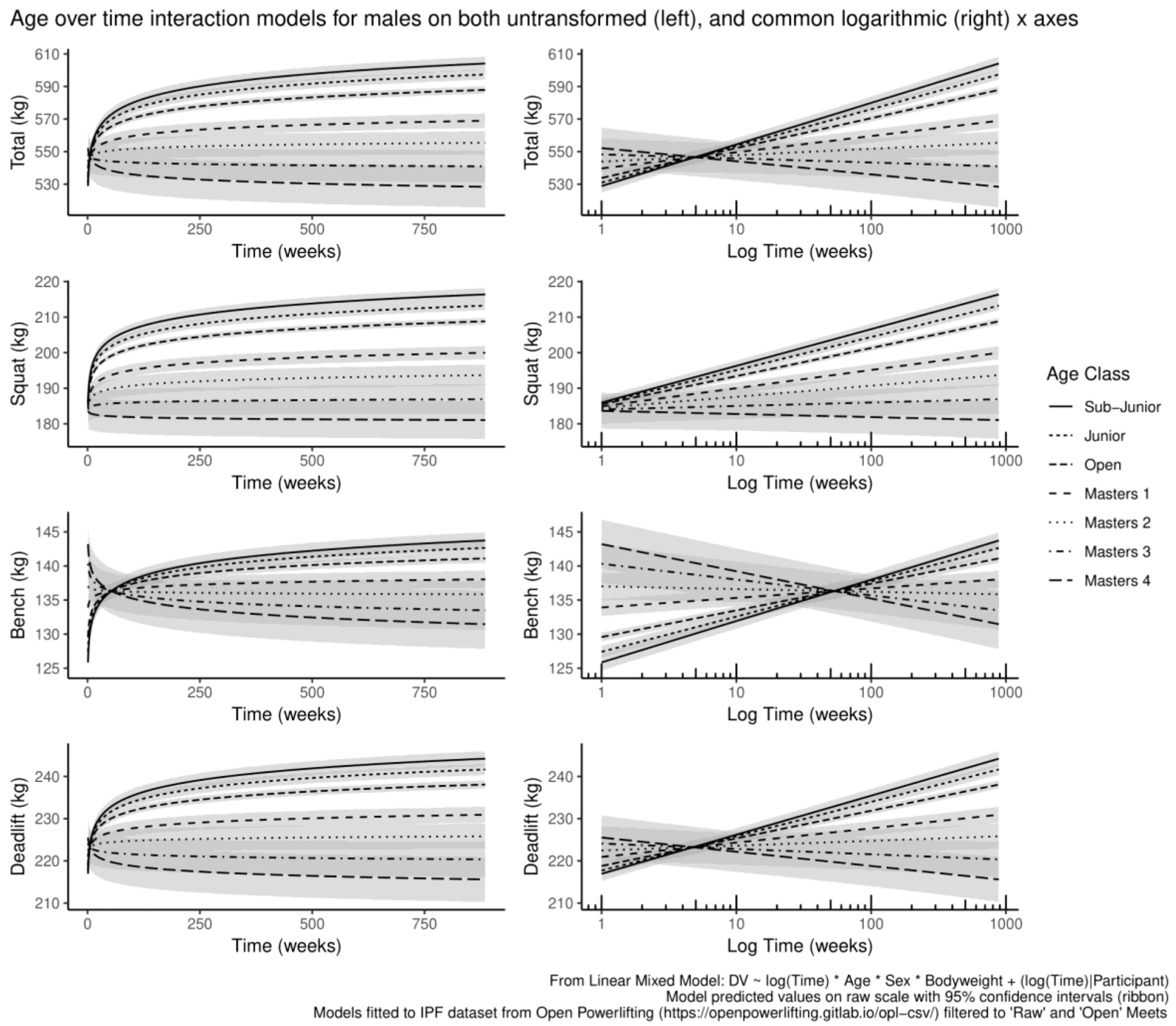
*Age Interaction*

Age also impacted model intercepts across all lifts with reduced strength gain observed with increased baseline (i.e., age) and this observation continued across time (figures 5 and 6). Standardised beta coefficients also suggested that the interaction effect with log(time) revealed younger individuals had slightly steeper slopes indicating faster strength progression over time (see table 1). Sex also seemed to impact upon this interaction with older males in fact displaying negative slopes (i.e., a loss of strength over time; see figure 6). Again, when rescaling strength as percentage of baseline the interactions between age, time, and sex were more obvious (figures 7 and 8).


Age over time interaction models for females on both untransformed (left), and common logarithmic (right) x axes

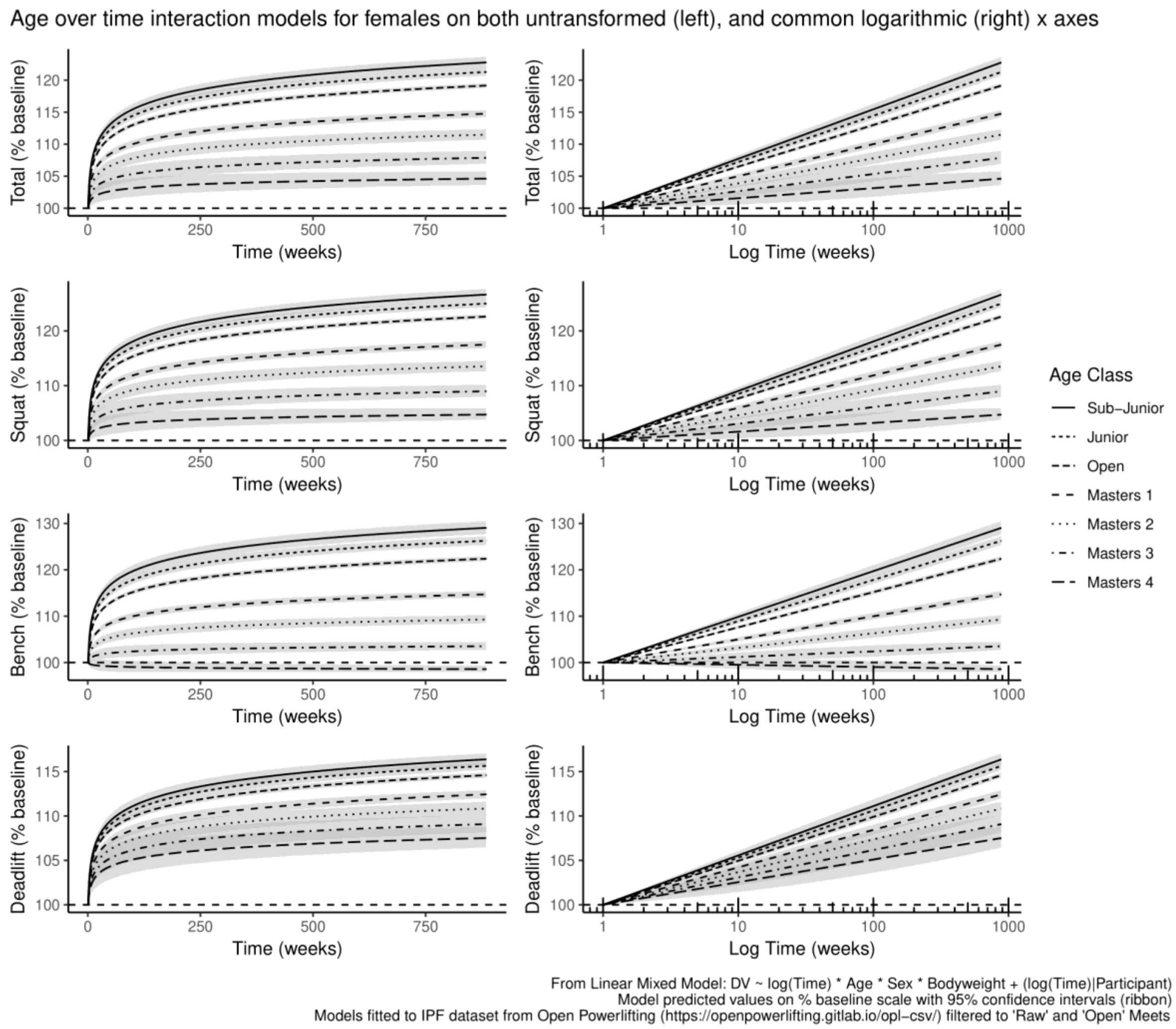
From Linear Mixed Model: DV ~ log(Time) * Age * Sex * Bodyweight + (log(Time)|Participant)
Model predicted values on raw scale with 95% confidence intervals (ribbon)
Models fitted to IPF dataset from Open Powerlifting (https://openpowerlifting.gitlab.io/opl–csv/) filtered to 'Raw' and 'Open' Meets

**Figure 5.** Age interaction model for females fitted values and 95% compatibility (confidence) intervals.


Age over time interaction models for males on both untransformed (left), and common logarithmic (right) x axes

From Linear Mixed Model: DV ~ log(Time) * Age * Sex * Bodyweight + (log(Time)|Participant)
Model predicted values on raw scale with 95% confidence intervals (ribbon)
Models fitted to IPF dataset from Open Powerlifting (https://openpowerlifting.gitlab.io/opl−csv/) filtered to 'Raw' and 'Open' Meets

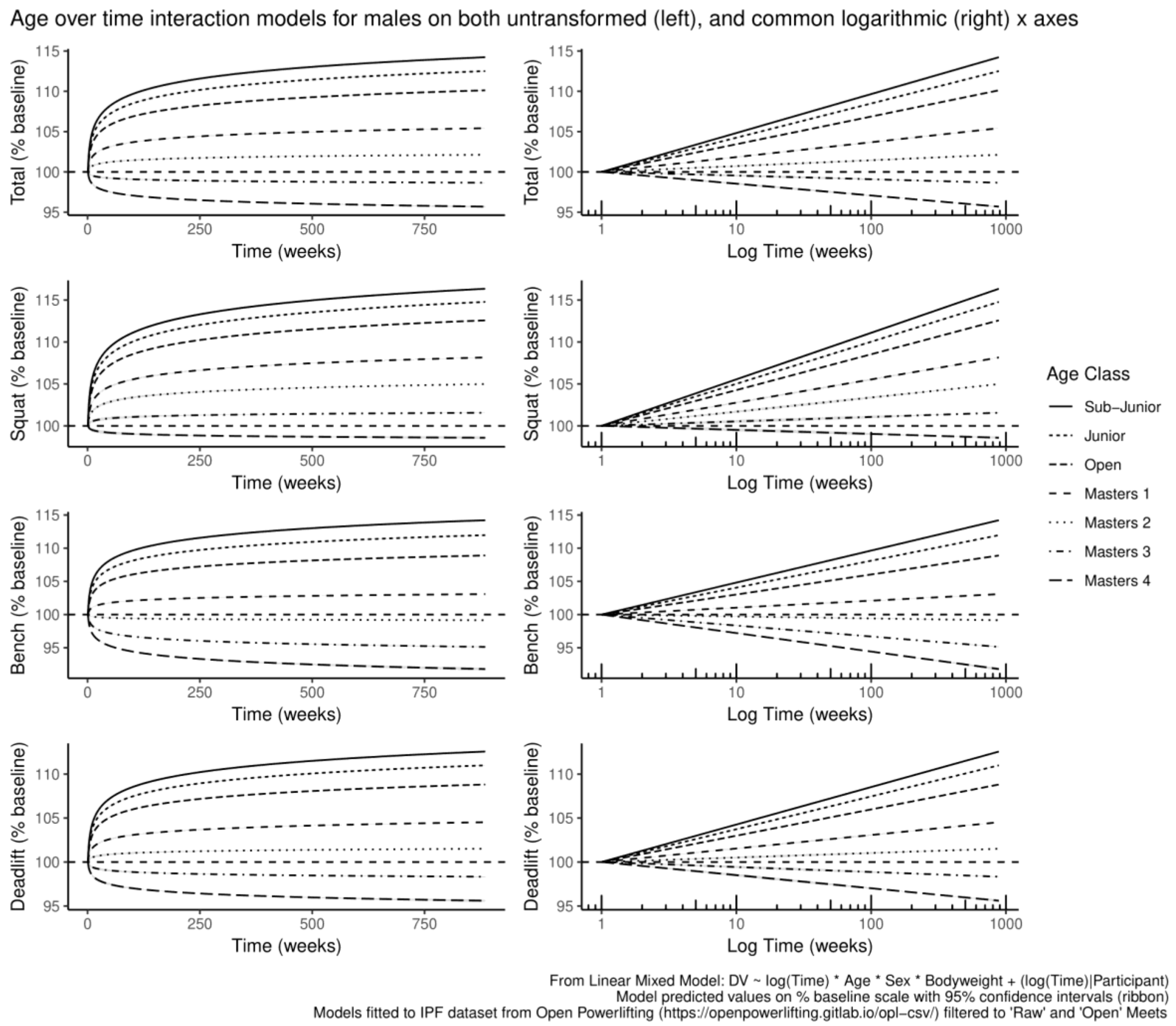
**Figure 6.** Age interaction model for males fitted values and 95% compatibility (confidence) intervals.



Age over time interaction models for females on both untransformed (left), and common logarithmic (right) x axes

From Linear Mixed Model: DV ~ log(Time) * Age * Sex * Bodyweight + (log(Time)|Participant)
Model predicted values on % baseline scale with 95% confidence intervals (ribbon)
Models fitted to IPF dataset from Open Powerlifting (https://openpowerlifting.gitlab.io/opl–csv/) filtered to 'Raw' and 'Open' Meets

**Figure 7.** Age interaction model for females fitted values rescaled as a percentage of baseline performance values.

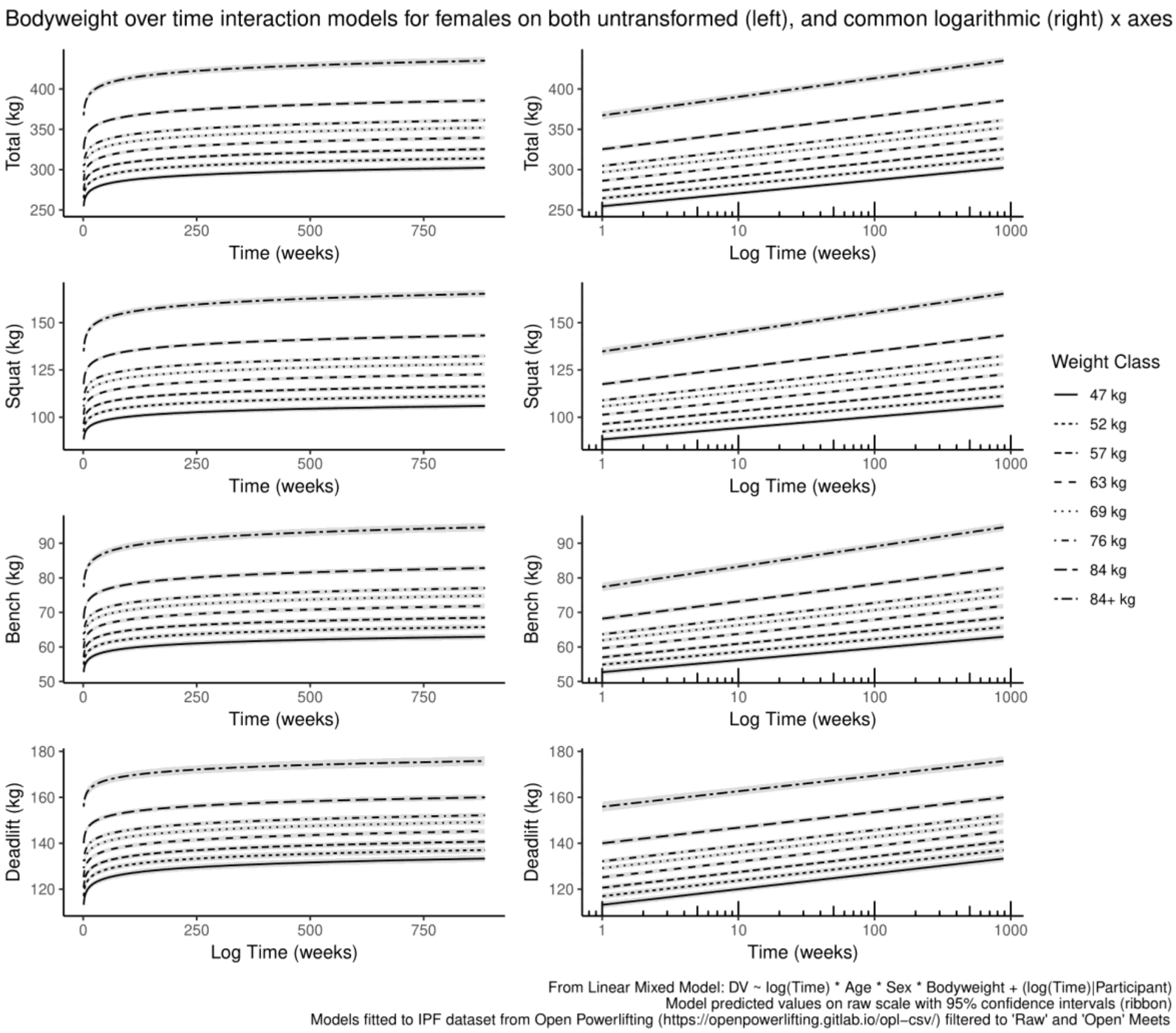

Age over time interaction models for males on both untransformed (left), and common logarithmic (right) x axes

From Linear Mixed Model: DV ~ log(Time) * Age * Sex * Bodyweight + (log(Time)|Participant)
Model predicted values on % baseline scale with 95% confidence intervals (ribbon)
Models fitted to IPF dataset from Open Powerlifting (https://openpowerlifting.gitlab.io/opl−csv/) filtered to 'Raw' and 'Open' Meets

**Figure 8.** Age interaction model for males fitted values rescaled as percentage of baseline performance values.

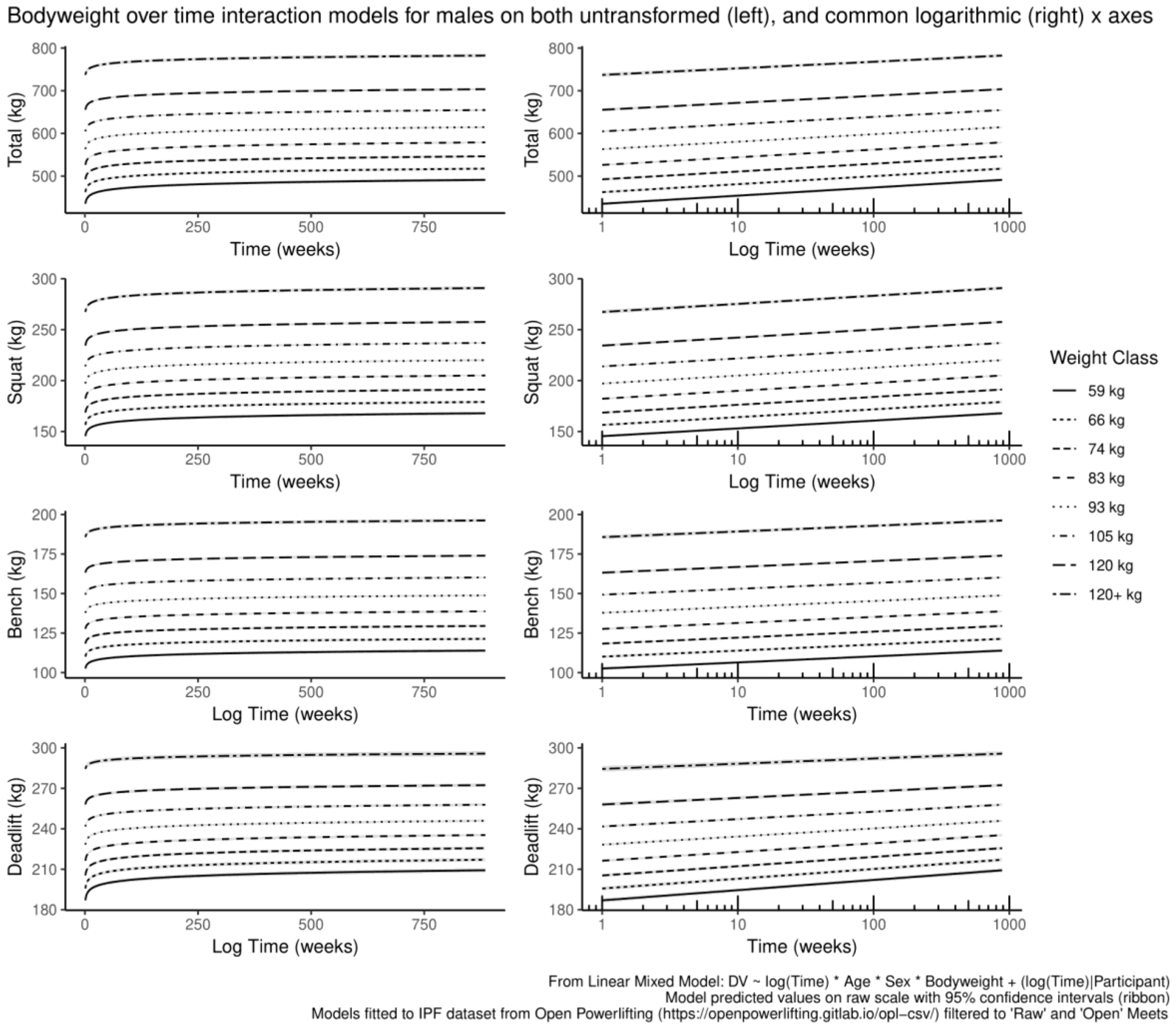
### *Bodyweight Interaction*

Bodyweight also impacted model intercepts across all lifts with greater strength gain with increased bodyweight at baseline and this observation continued across time (figures 9 and 10). Standardised beta coefficients also suggested that the interaction effect with log(time) revealed heavier individuals had slightly steeper slopes indicating faster strength progression over time (see table 1). Sex seemed to impact upon this interaction however, with males displaying slightly decreasing slopes with increasing bodyweight. When rescaling performance as percent bodyweight of baseline the interactions between bodyweight, time, and sex were more obvious (figures 11 and 12).


Bodyweight over time interaction models for females on both untransformed (left), and common logarithmic (right) x axes

From Linear Mixed Model: DV ~ log(Time) * Age * Sex * Bodyweight + (log(Time)|Participant)
Model predicted values on raw scale with 95% confidence intervals (ribbon)
Models fitted to IPF dataset from Open Powerlifting (https://openpowerlifting.gitlab.io/opl-csv/) filtered to 'Raw' and 'Open' Meets

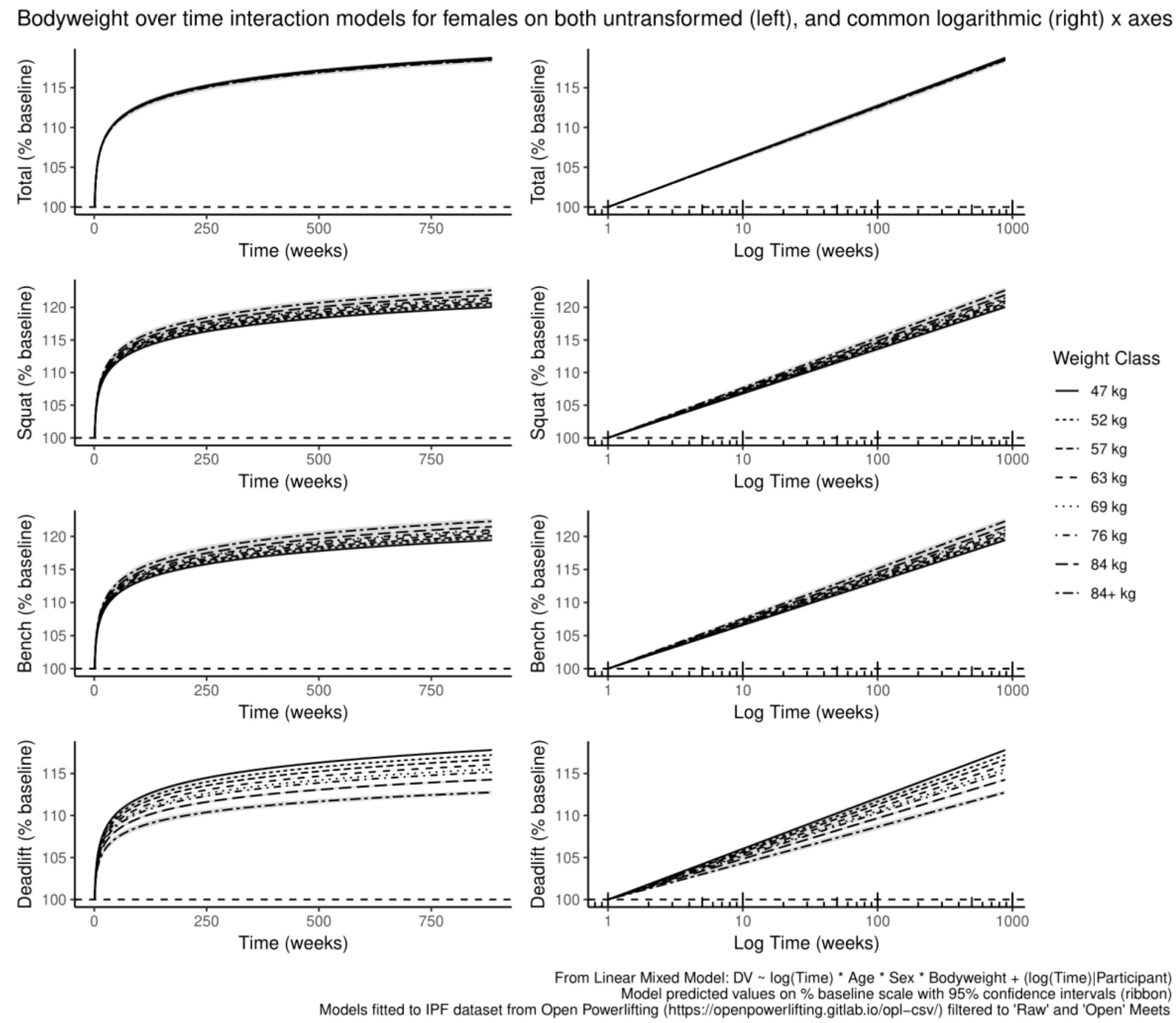
**Figure 9.** Bodyweight interaction model for females fitted values and 95% compatibility (confidence) intervals



Bodyweight over time interaction models for males on both untransformed (left), and common logarithmic (right) x axes

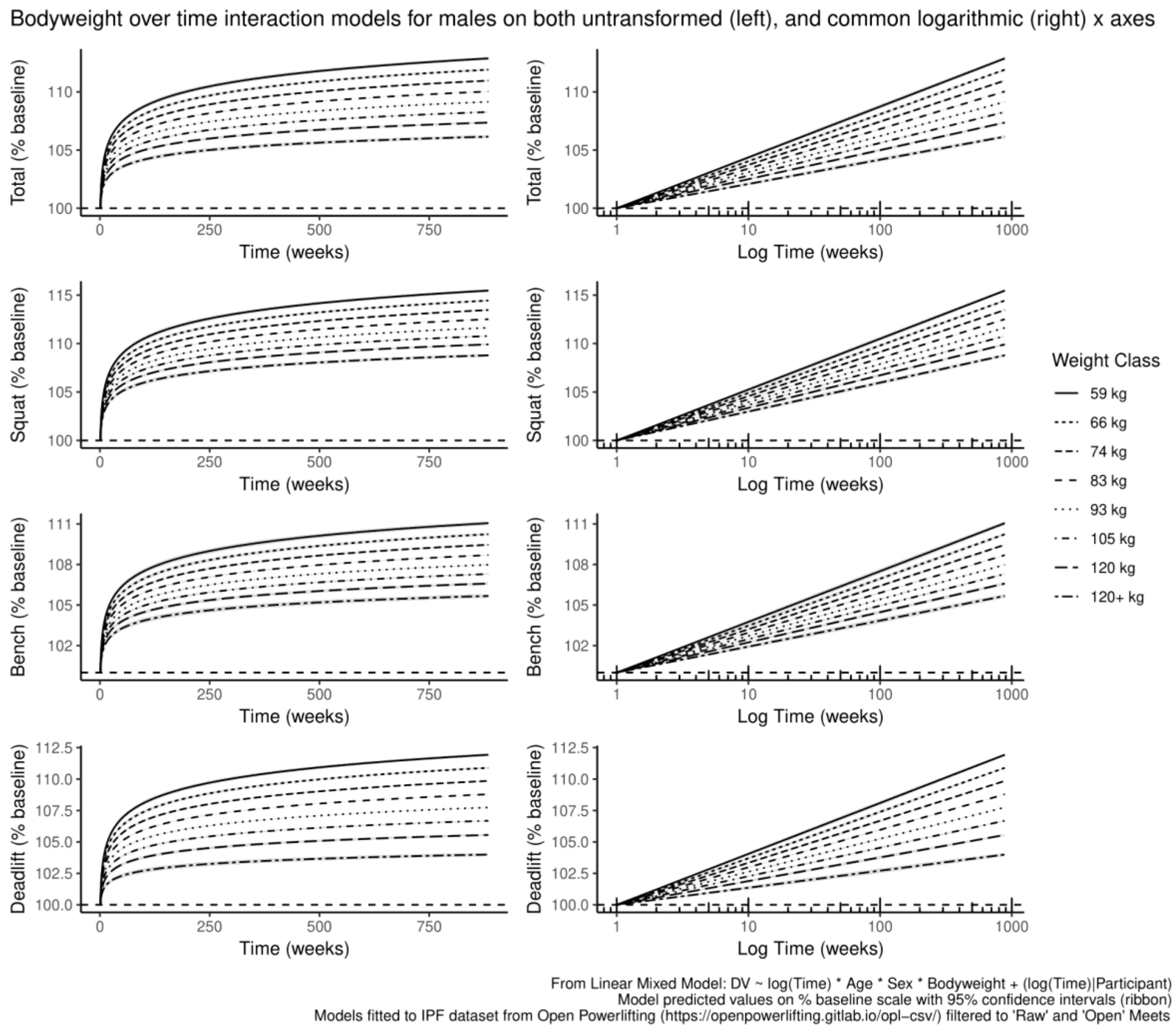
From Linear Mixed Model: DV ~ log(Time) * Age * Sex * Bodyweight + (log(Time)|Participant)
Model predicted values on raw scale with 95% confidence intervals (ribbon)
Models fitted to IPF dataset from Open Powerlifting (https://openpowerlifting.gitlab.io/opl−csv/) filtered to 'Raw' and 'Open' Meets

**Figure 10.** Bodyweight interaction model for males fitted values and 95% compatibility (confidence) intervals.


Bodyweight over time interaction models for females on both untransformed (left), and common logarithmic (right) x axes

From Linear Mixed Model: DV ~ log(Time) * Age * Sex * Bodyweight + (log(Time)|Participant)
Model predicted values on % baseline scale with 95% confidence intervals (ribbon)
Models fitted to IPF dataset from Open Powerlifting (https://openpowerlifting.gitlab.io/opl-csv/) filtered to 'Raw' and 'Open' Meets

**Figure 11.** Bodyweight interaction model for females fitted values rescaled as percentage of baseline performance values.



Bodyweight over time interaction models for males on both untransformed (left), and common logarithmic (right) x axes

From Linear Mixed Model: DV ~ log(Time) * Age * Sex * Bodyweight + (log(Time)|Participant)
Model predicted values on % baseline scale with 95% confidence intervals (ribbon)
Models fitted to IPF dataset from Open Powerlifting (https://openpowerlifting.gitlab.io/opl-csv/) filtered to 'Raw' and 'Open' Meets

**Figure 12.** Bodyweight interaction model for males fitted values rescaled as percentage of baseline performance values.

*Survivorship Bias?*

Examination of relationships between random effects and length of time for which participants had been competing displayed slight tendencies towards higher random intercepts when over the untransformed timescale (i.e., higher baseline values for those who had been competing for longer), but for log(time) there were essentially no relationships for either intercepts or slopes (see supplementary materials https://osf.io/8bwqt/). Thus, we were confident that our models appropriately reflected the effects of strength change over time of participation in competitive powerlifting absent survivorship bias.

## Discussion

To our knowledge, this is the first study to investigate strength adaptations, and associated age and sex effects, in PL athletes using mixed effects growth modelling. These analyses demonstrate that females appear to have a steeper trajectory of strength gain (when expressed as a percentage of their baseline) than males, possibly due to lower starting strength. With increased age (e.g., Masters athletes), associated strength changes for females were still generally positive, but they tended to decline for the eldest two Masters categories (>59 and >69 years) for males. For younger athletes of both sexes, strength improvements appear steeper than for their older counterparts. In addition, athletes with increased bodyweight at baseline were the strongest. However, athletes with lesser bodyweight at baseline showed greater rates of strength gain. Collectively, this study has reported comprehensive data on strength changes in a large sample of PL athletes over a maximum period of 17 years. The effects of age, sex, and bodyweight provide novel insight into strength adaptive potential across the lifespan in males and females.

### *The effect of time on strength trajectory*

The rate of strength adaptation slows with time. This concept is demonstrated by previous work showing diminishing returns with long-term exercise training and participation (19, 20, 45). Indeed, the greatest strength gains are noted in the earliest phase of PL participation (~7.5-12.5% strength increase above baseline in first year, yet only ~12.5-20% above baseline after 10 years) (see Figure 1). This finding is similar to previous research that has reported greater strength gains during the early phase of resistance training before improvements moderate with continuing duration (i.e., diminishing returns) (45) and other evidence that suggests that the required dose and magnitude of response is dependent upon training status (35). Whilst the findings in relation to initial strength gains are consistent with previous literature, it is the continued improvement (or at least maintenance) in strength across the lifespan that may be most important to overall population health. This is because of the deleterious effects of poor strength on physical and social functioning. In particular, regular resistance exercise can counteract the effects of muscle weakness on physical frailty (9), and improve physical performance (14), quality of life (7), and psychological wellbeing (49), as well as reduce the risk of falls and fractures for older adults (44). Therefore, participation in a strength sport such as PL, regardless of age, may prove to be a beneficial tool to promote population physical and psychological health.

### *Age effects on strength trajectory*

Advancing age is known to have negative effects on muscle fibre function (13) and strength (10, 16, 38). Given the associated health risks of poor muscle strength, resistance training is advocated for in global public health messaging (33). Our results demonstrate that strength still improved for Masters 1 and 2 athletes of both sexes (age range: 40-59), and that this positive trend continued over the 750-week period (~14.4 years later). Of particular interest, females displayed continued strength increases despite more advanced age (e.g., ~5% and ~2.5% for Master 3 and 4 categories, respectively; age range:

>59 years) over the data period. It could be argued that this improvement is due to lower starting strength and hence better adaptive potential for females. Nonetheless, this may be somewhat representative of the training and physical status of the wider population as it is known that older females generally participate in less physical activity than male counterparts (46). Importantly, these results reinforce the role that ongoing participation in strength training can have for advancing age in females and is in contrast with typical age-related declines noted for older individuals, e.g., (10, 16, 38). For males, strength declines were noted with advanced age (i.e., Masters 3 and 4 categories). Again however, considering the minimal decline in strength over ~750 weeks for Masters 4 males of ~5% (~0.35%/year), we note that this is a substantial attenuation of expected strength declines in this demographic. Supporting evidence has shown that participation in lifelong resistance training appears to protect against age-related declines in strength and maintains of efferent neural drive compared to habitual recreational activity (47). These benefits become increasingly important when we consider that 10-20% of all older adults are classified as having poor muscle strength (8). Consequently, this poor muscle strength is a major contributor to secondary adverse health outcomes and death (26, 30) with an estimated ~$47 billion economic health care cost per annum (36). Indeed, poor muscular strength is a leading predictor of mortality amongst elderly individuals (26, 30). Hence, the current results in ageing support the benefits of regular, chronic strength training through PL and provide strengthened rationale for its promotion and subsequent adoption amongst older adult populations.

### *The effects of sex and time on strength trajectory*

Previous research reports that male and female PL gain strength similarly when expressed in relative (to bodyweight) or absolute terms (19, 20). The only apparent discrepancy between sexes is that the rate of strength adaptation for females did not differ between starting strength quartiles while the strongest males gained strength more slowly than their counterparts in the lowest quartile for starting strength (20). In contrast, the results of the current analysis demonstrate that the trajectory of strength gains is greater for females (when considered as a percentage of baseline). The consideration of change from baseline allows a type of normalisation in the interpretation of the data, but we acknowledge that absolute strength and associated increases in actual weight lifted might still be greater for males. When analysing strength adaptation trajectories more closely by lift type (squat, bench press and deadlift) (see figure 4), our analyses show that the trend of females gaining strength more rapidly holds true across all three lift disciplines (again, when considered as a percentage of baseline). Thus, females may have greater potential to improve relative strength but less potential to increase absolute strength on average. Interestingly, previous research has found that sex does not affect muscle hypertrophy responses in individuals engaging in lower body (17) or whole-body strength training (39). Some support for our findings stems from O'Hagan et al. (32), who report that females have greater relative increases in strength compared to males. However, we do acknowledge that this study was performed in the elbow flexors only, and so cannot be directly compared to the whole-body strength increases observed in the current study.

### *Limitations*

The limitations of this analysis relates to the information available from the data set itself and are the same points that we have previously discussed elsewhere (19, 20). Briefly, these relate to the limited information available about each individual included in the analysis that may/may not have affected their strength performance over the data period. Such factors may include, but not be limited to poor performance at competition, the level of competition for a given event (motivation/need to lift as much as possible), and injury and training records. Despite this, we are confident that the large amount of data and adoption of a mixed effects growth modelling approach (as recently used to explore other longitudinal training data sets [(45)]), provides an accurate, novel and detailed insight into the strength changes occurring over time. Prospective efforts may seek to employ remote data collection strategies to capture additional training or injury information and minimise logistical problems to better understand training-related variables that impact strength adaptations (21).

### *Conclusion*

Collectively, the results presented in this paper provide insight into human strength adaptations and several biological and morphologic factors (age, sex, and bodyweight) that may influence this strength change. The use of a large sample of competitive PL athletes and modelling of strength trajectories provides further confidence of these findings. Although directly applicable to the sport of PL, we argue that these findings provide population level support for the role of consistent and continued strength training to improve strength across demographics, and importantly, to mitigate, or at least largely attenuate age-related declines in strength compared to established general population norms. This information should be used to encourage participation in strength sports, resistance training more generally, and to support future public health messaging. Further research may wish to establish other, health-related outcomes associated with long term strength sport participation.

**References:**

1. A. G. Scaling regression inputs by dividing by two standard deviations. *Stat Med* 27: 2865-2873, 2008.
2. Amrhein V GS, McShane B. Scientists rise up against statistical significance. *Nature* 567: 305-307, 2019.
3. Amrhein V TD, Greenland S. Inferential statistics as descriptive statistics: there is no replication crisis if we don't expect replication. *Am Stat* 73: 262-270, 2019.
4. Bates D MM, Bolker B, Walker S. Fitting Linear Mixed-Effects Models Using lme4. *J Stat Software* 67: 1-48, 2015.
5. Brill PA MC, Davis DR, Blair SN, Gordon N. Muscular Strength and Physical Function. *Med Sci Sports Exerc*: 412-416, 2000.
6. https://CRAN.R-project.org/package=sjPlot.
7. de Vreede PL VMN, Samson MM, Wittink HM, Duursma SA, Verhaar HJ. The effect of functional tasks exercise and resistance exercise on health-related quality of life and physical activity. A randomised controlled trial. *Gerontol* 53: 12-20, 2007.
8. Ethgen O BC, Buckinx F, et al. The future prevalence of sarcopenia in Europe: a claim for public health action. *Calcified Tissue Int* 100: 229-234, 2017.
9. Fiatarone MA ONE, Ryan ND, Clements KM, Solares GR, Nelson ME, Roberts SB, Kehayias JJ, Lipsitz LA, Evans WJ. Exercise training and nutritional supplementation for physical frailty in very elderly people. *N Engl J Med* 330: 1769–1775, 1994.
10. Frontera WR HV, Fielding RA, Fiatarone MA, Evans WJ, Roubenoff R. Aging of skeletal muscle: a 12-yr longitudinal study. *J Appl Physiol* 88: 1321-1326, 2000.
11. Gelman A HJ. Data Analysis Using Regression and Multilevel/Hierarchical Models (Analytical Methods for Social Research). *Cambridge: Cambridge University Press doi:101017/CBO9780511790942*, 2006.
12. Goodpaster BH PS, Harris TB, Kritchevsky SB, Nevitt M, Schwartz AV, Simonsick EM, Tylavsky FA, Visser M, Newman AB. The loss of skeletal muscle strength, mass, and quality in older adults: The health, aging and body composition study. *J Gerontol A Biol Sci Med Sci* 61: 1059–1064, 2006.
13. Grosicki GJ ZC, Sundberg CW. Single Muscle Fibre Contractile Function with Ageing. *J Physiol*, 2022.
14. Häkkinen K KW, Pakarinen A, et al. Effects of heavy resistance/power training on maximal strength, muscle morphology, and hormonal response patterns in 60-75-year-old men and women. *Can J Appl Physiol* 27: 213-231, 2002.
15. Jacqmin-Gadda H SS, Proust C, Molina JM, Thiebaut R. Robustness of the linear mixed model to misspecified error distribution. *Comp Stat Data Analysis* 51: 5142-5154, 2007.
16. Kemmler W vS, Schoene D, Kohl M. Changes of Maximum Leg Strength Indices During Adulthood a Cross-Sectional Study With Non-athletic Men Aged 19–91. *Frontiers Physiol* 9: 1524, 2018.
17. Kittilsen HT G-FS, Freberg BI, Nicolaisen I, Stoa EM, Bratland-Sanda S, Helgerud J, Wang E, Saebo M, Storen O. Responses to Maximal Strength Training in Different Age and Gender Groups. *Front Physiol*, 2021.
18. Knief E FW. Violating the normality assumption may be the lesser of two evils. *Behavior Res Methods* 53: 2576-2590, 2021.

19. Latella C OP, Davies T, Spathis J, Mallard A, van den Hoek D. Long-Term Adaptations in the Squat, Bench Press, and Deadlift: Assessing Strength Gain in Powerlifting Athletes. *Med Sci Sports Exerc* 54: 841-850, 2022.
20. Latella C TW-P, Spathis J, van den Hoek D. Long-Term Strength Adaptation: A 15-Year Analysis of Powerlifting Athletes. *J Strength Cond Res* 34: 2412-2418, 2020.
21. Latella C vD, Mallard A, Spathis J. Not just a pandemic possibility: The push toward remote data collection can complement existing big data sets in sport science *J Appl Physiol*, In Press.
22. Latella C vD, Teo W-P. Factors affecting powerlifting performance: an analysis of age- and weight-based determinants of relative strength. *Int Journal of Perform Anal Sport* 18: 532-544, 2018.
23. Lüdecke D B-SM, Patil I, Waggoner P, Makowski D. performance: An R Package for Assessment, Comparison and Testing of Statistical Models. *J Open Source Software* 6: 3139, 2021.
24. Lüdecke. D. ggeffects: Tidy Data Frames of Marginal Effects from Regression Models. *J Open Source Software* 3: 772, 2018.
25. Lumley T DP, Emerson S, Chen L. The importance of the normality assumption in large public health data sets. *Annu Rev Public Health* 23: 151-169, 2002.
26. McGrath RP KW, Snih SA, et al. Handgrip strength in health and aging adults. *Sports Med* 48: 1993-2000, 2018.
27. McKendry J BL, Shad BJ, Greig CA. Muscle morphology and performance in master athletes: A systematic review and meta-analyses. *Ageing Res Rev* 45: 62-82, 2018.
28. McShane BB GD, Gelman A, Robert C, Tackett JL. Abandon statistical significance. *Am Stat* 73: 235-245, 2019.
29. Miller JD VH, Bracken LE. Rate of Performance Change in American Female Weightlifters Over Ten Years of Competition. *Int J Exerc Sci* 11: 290-307, 2018.
30. Moreland JD RJ, Goldsmith CH, et al. Muscle weakness and falls in older adults: A systematic review and meta-analysis. *J Am Geriatric Soc* 52: 1121-1129, 2004.
31. Nelder JA MR. A simplex method for function minimization. *Computer J* 7: 308-313, 1965.
32. O'Hagan FT SD, MacDougall JD, Garner SH. Response to resistance training in young women and men. *Int J Sports Med* 16: 314-321, 1995.
33. Organization GWH. WHO guidelines on physical activity and sedentary behaviour. 2020.

34. Pearson J SJ, van den Hoek DJ, Owen PJ, Weakley J, Latella C. Effect of Competition Frequency on Strength Performance of Powerlifting Athletes. *J Strength Cond Res* 34: 1213-1219, 2020.
35. Peterson MD RM, Alvar BA. Applications of the dose-response for muscular strength development: a review of meta-analytic efficacy and reliability for designing training prescription. *J Strength Cond Res* 19: 950-980, 2005.
36. Pinedo-Villanueva R WL, Syddall HE, et al. Health care costs associated with muscle weakness: A UK population-based estimate. *Calcified Tissue Int* 104: 137-144, 2019.
37. Pinheiro JC BD. Linear mixed-effects models: Basic concepts and examples. Springer, Springer, New York, NY. https://doi.org/10.1007/978-1-4419-0318-1_1.
38. Rantanen T MK, Foley D, Izmirlian G, White L, Guralnik JM. Grip strength changes over 27yr in Japanese-American men. *J Appl Physiol* 85: 2047-2053, 1998.

39. Roth SM IF, Martel GF, Lemmer JT, Hurlbut DE, Siegel EL, Metter EJ, Fleg JL, Fozard JL, Kostek MC, Wernick DM, Hurley BF. . Muscle size responses to strength training in young and older men and women. *J Am Geriatric Soc* 49: 1428-1433, 2001.
40. Ruiz JR SX, Lobelo F, Morrow JR, Jackson AW, Sjostrom M, Blair SN. Association between muscular strength and mortality in men: prospective cohort study. *BMJ* 337: 439, 2008.
41. Schielzeth H DN, Nakagawa S, Westneat DF, Allegue H, Teplitsky C, Reale D, Dochtermann NA, Garamszegi LZ, Araya-Ajoy YG. Robustness of linear mixed-effects models to violations of distributional assumptions. *Methods Ecol Evol* 11: 1141-1152, 2020.
42. Schmidt AF and C. F. Linear regression and the normality assumption. *J Clin Epidemiol* 98: 146-151, 2018.
43. Shaw MP AV, Saeterbakken AH, Pulsen G, Samnoy LE, Solsatd TEJ. Contemporary Training Practices of Norwegian Powerlifters. *J Strength Cond Res* 36: 2544-2551, 2022.
44. Silva RB EG, Duque G. Exercise for falls and fracture prevention in long term care facilities: A systematic review and meta-analysis. *J Am Med Dir Assoc* 14: 685–689, 2013.
45. Steele J FJ, Giessing J, Androulakis-Korakakis P, Wolf M, Kroeske B, Reuters R. Long-Term Time-Course of Strength Adaptation to Minimal Dose Resistance Training Through Retrospective Longitudinal Growth Modeling. *Res Q Exerc Sport*, 2022, 10.1080/02701367.2022.2070592.
46. Sun F NI, While AE. Physical activity in older people: a systematic review. *BMC Public Health* 13: 449, 2013.
47. Unhjem R. NM, vandenHoven LT, Sidhu SK, Hoff J, Wang E. Lifelong strength training mitigates the age-related decline in efferent drive. *J Appl Physiol* 121: 415-423, 2016.
48. Wilkinson GN RC. Symbolic description of factorial models for analysis of variance. *J Appl Stat* 22: 392-399, 1973.
49. Zanuso S SJ, Smith N, Carraro A, Bergamin M. The effect of a strength training program on affect, mood, anxiety, and strength performance in older individuals. *Int J Sport Psychol* 43: 53-56, 2012.