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Biological sex minimally affects the free-weight back squat load-velocity profile when accounting for relative strength: An exploratory study

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Abstract

Research suggests that biological sex and strength level influence the load-velocity profile. However, existing research have not appropriately statistically accounted for the interdependencies between sex and relative strength. This exploratory study investigated load-velocity profiles of 24 resistance-trained participants (14 males, 10 females; back squat 1.69 × and 1.28 × body mass, respectively) using mixed-effects modelling to account for relative strength and individual variability. Participants completed 2–3 incremental back squat loading tests (20 kg to one-repetition maximum [1RM]). 1RM assessments showed excellent reliability, while mean concentric velocity (MCV) at 0–40% of 1RM demonstrated good-to-excellent reliability, with reliability systematically declining at higher relative loads. Small effects of biological sex on load-velocity profiles was found at 0–40% of 1RM (0.07–0.13 m/s, BF = 10.702–47.682, *pd* = 91–98%), while the effects of relative strength were more pronounced at 0–70% of 1RM (0.18–0.44 m/s, BF = 26.972–2399.000, *pd* = 96–100%), both with diminishing differences as relative load increased. These findings challenge assumptions about sex as a major load-velocity profile moderator when accounting for relative strength and individual variability. While exploratory and requiring replication, the study recommends future research employ more nuanced statistical methods, recruit homogeneously trained samples, and minimise measurement noise to avoid potential type-I errors.

Keywords

Body composition, gender, resistance training, smartphone-based wearable device

Introduction

When programming resistance training, strength and conditioning coaches typically prescribe and manipulate training variables such as volume,[1] relative load (% of one-repetition maximum [1RM]),[2] proximity-to-failure,[3] among others to elicit desired adaptations within their athletes. These variables have traditionally undergone pre-planned manipulations based on prior maximal strength tests.[4,5] However, pre-planned and percentage-based training has been critiqued[5,6] for not necessarily accounting for individual progression rates, subtle day-to-day variations in performance, or the interindividual variability in the number repetitions performed to failure at a given relative-load.[5,7,8] Although it remains unclear whether velocity-based training adequately addresses these concerns–given the greater variability in velocity compared to maximal strength tests[9]–it has gained popularity for monitoring acute changes in lifting performance,[10] enabling high-frequency strength estimations,[11,12] particularly in contexts where maximal strength testing is considered undesirable or logistically infeasible,[11,13] as well as prescribing and autoregulating training variables like relative-load, proximity-to-failure and volume,[14] and regulating motivation and attentional focus.[9,15]

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Velocity-based training leverages the strong relationship between mean concentric velocity (MCV) and relative load when lifts are performed with maximal intent, a relationship known as the load–velocity profile.[11] On average, velocity-based 1RM predictions tend to overestimate true 1RM by approximately 3.6%,[11] which, if applied uncritically, may result in inappropriate training loads. Nevertheless, when athletes are sufficiently familiarised, velocities at 20–90% of 1RM[13,16,17] and 1RM predictions based on low to high loads[16–18] appear to demonstrate high reliability. Additionally, changes in velocity at submaximal loads have been associated with changes in 1RM across a mesocycle in powerlifters, even without explicit familiarisation.[19] Therefore, while velocity-based 1RM predictions should not replace direct 1RM testing–given the variability of load–velocity profiles across micro-, meso-, and macrocycles[16,18–20]–the combination of simultaneous 1RM testing and load–velocity profiling, where individual systematic prediction biases may be accounted for may be valuable. Tracking relative changes in 1RM estimation or velocities at given relative loads that exceed the associated smallest detectable change[13] may allow for more objective and precise decision-making regarding the autoregulation of volume and loads compared to subjective ratings of perceived exertion or repetitions in reserve[21] and may enable higher frequency estimation of maximal strength throughout a training block, which shows promise for utility in both practice and research for relative strength changes over time.[11,12] However, further research is needed to determine how–and whether–velocity metrics can be effectively implemented in practice to improve athlete monitoring and training prescription, and whether prediction biases can be reliably accounted for within individuals. Also, basing an athlete's training on an inaccurate load–velocity profile may lead to the misestimation of relative load and other variables, potentially compromising the desired training adaptations.[22]

Generally, males exhibit load-velocity profiles with higher intercepts and steeper slopes compared to females (i.e., males are typically capable of moving faster with lighter relative loads, though this difference diminishes as relative loads increase), across exercises like the free-weight[23] and Smith-rack back squat,[24,25] deadlift,[26] leg press,[27] various upper body pressing[20,25,28–31] and pulling exercises.[32] This could potentially be due to sex differences in muscle fibre-type distributions.[33,34] However, many of these studies lack ecological validity and generalisability to athletic populations due to their use of Smith machines,[24,25,30] imposed pauses between eccentric and concentric phases,[24,25] the use of the relatively weaker participants,[25] or non-strength-matched cohorts.[10] As such, further research is needed to examine sex differences in load-velocity profiles using regular free-weight back squats to enhance the applicability of findings to athletic training contexts.

The training status of the athlete may also affect the shape of load-velocity.[20,23,24,31] Given the typically different levels of RT participation and preferences between sexes (i.e., males tend to prefer training with higher relative loads than females),[35,36] it is reasonable to suspect that mixed-sex samples may not adequately account for differences in training status. This is an issue, as previous studies examining the effects of strength levels on sex differences in load-velocity profiles have relied on arbitrary cut-offs between weaker and stronger participants, based on within-sex sample medians.[23,24,31] Except for its statistical simplicity, little rationale exist for this approach, and comes with substantial drawbacks, including[37] i) substantial loss of statistical power, ii) characterising individuals near the cut-off as different, despite being very similar, and iii) by not accounting for all predictors in the same model, the risk of observing patterns that may not be there and is just a result of uncontrolled variables increase (i.e., increased type-I error).[38,39]

Thus, the aim of this project was to explore the effects of biological sex and relative strength on the load-velocity profile in the free-weight back squat. Linear mixed-effects models were employed to appropriately account for sex and relative strength simultaneously.

Materials and methods

Participants

This project was part of a larger data collection effort, with some results previously published elsewhere[40]; however, the data presented in this paper have not been published previously. Participants comprised ten females (age = 25 ± 3 years, height = 1.63 ± 0.07 m) and 14 males (age = 28 ± 4 years, height = 1.84 ± 0.07 m). Participants were resistance-trained, defined as: i) at least six months of resistance training (RT) experience (≥3 sessions/week), and ii) a 1RM squat of ≥1 × body mass (BM). Nine of the ten females were using hormonal contraception (oral contraceptives: n = 8; intrauterine device: n = 1), and one did not use any hormonal contraception (12 days since last menstruation). Given that hormonal contraception and menstrual cycle phase on average have a trivial effect on exercise performance,[41,42] this study did not control for either. Ethical approval was granted by St Mary's University, Twickenham (SMU_ETHICS_2020–21_014). The study was conducted in line with the ethical standards of the Declaration of Helsinki, and all participants provided informed written consent.

Experimental procedures

Participants attended the facility twice in one week, with at least 48 h between sessions. All sessions included body composition testing, a standardised warm-up, and an incremental back squat loading test. Participants were instructed to refrain from training for 48 h before all testing sessions and to maintain their usual nutrition and caffeine intake throughout the study.

Due to the COVID-19 lockdown, the original data collection was interrupted, and some participants returned approximately six months later to complete the second part of the study. These participants underwent an additional baseline assessment. As a result, all participants completed two baseline sessions within the same week, while some completed a third session at a later time. All sessions were included in the analysis to i) increase statistical power,[12] (ii) account for the random error associated with load-velocity profiling[17] and the PUSH band[43] across days, and (iii) capture the effects of within-participant strength changes on the load-velocity profile if participants became meaningfully stronger or weaker between sessions two and three.

Body composition. BM, along with absolute and relative fat-free mass (FFM, FFMP) and fat mass (FM, BFP), was measured using the InBody 570 device (InBody, Cerritos, CA, USA [intraclass correlation coefficient (ICC) > 0.98, standard error of measurement (SEM) < 0.87 kg, relative to dual-energy X-ray absorptiometry[44]]), following the manufacturer's guidelines.

Incremental loading test. The procedure for the incremental free-weight back squat loading test has been detailed elsewhere.[40] In brief, participants performed the squat with the barbell positioned across their upper back, using their preferred stance and bar placement. They descended in a self-determined continuous motion[13,17,18] until the crease of the hip was below the top of the knee, as visually assessed by the lead researcher, an experienced powerlifting coach. While allowing self-selected stance and eccentric tempo without standardisation may reduce internal validity, this approach enhances ecological validity. From this position, participants were instructed to perform the concentric phase as quickly as possible without leaving the ground, with verbal encouragement and visual velocity feedback provided.[45] The measured eccentric phases were 1.32 s (99% confidence interval [CI]: 1.27 to 1.37) or 0.66 m/s (99% CI: 0.64 to 0.69) in session 1, and 1.28 s (99% CI: 1.24 to 1.33) or 0.69 m/s (99% CI: 0.67 to 0.73) in session 2. The consistency of eccentric duration across sessions was moderate (ICC = 0.61 [95% CI: 0.52 to 0.68]; coefficient of variation (CV) = 24.71% [95% CI: 22.68 to 27.48]), as was eccentric velocity (ICC = 0.57 [95% CI: 0.48 to 0.63]; CV = 28.47% [95% CI: 26.24 to 31.25]).

The initial load was set at 20 kg and increased in 10 kg increments until a MCV of <0.6 m/s was achieved, corresponding to approximately 75% of 1RM.[46] MCV was recorded for all repetitions using the PUSH Band™ 2.0 (PUSH Inc., Toronto, Canada), which was attached to the barbell according to the manufacturer's guidelines. To more precisely determine the 1RM, the load was subsequently adjusted in smaller increments (2.5–5 kg) until the lifter was unable to complete the lift. Each participant was given the option of one additional attempt at a given weight. For safety, each lift was supported by two to three spotters, all of whom were experienced lifters and coaches.

For light loads (≥1.1 m/s), participants performed three repetitions; for medium loads (0.6–1.1 m/s), two repetitions; and for heavy loads (<0.6 m/s), one repetition. Rest periods of at least 5 min, as done elsewhere,[47] were provided between sets at velocities below 0.6 m/s. All testing was conducted using a free-standing squat rack (ER Equipment, Albertslund, Denmark), a 20 kg powerlifting bar, and calibrated weight plates (Eleiko, Halmstad, Sweden). Based on the 1RM results and InBody assessments, three measures of relative strength were calculated to account for sex differences in body composition: 1RM to BM ratio (1 RM/BM), 1RM to FFM ratio (1RM/FFM), and International Powerlifting Federation Goodlift points (GLP).[48]

Instrumentation. MCV was measured using the PUSH Band™ 2.0, a smartphone-based wearable device designed to track movement velocity during various resistance exercises. The device has been shown to be reliable in the squat at velocities below 1.0 m/s.[43,49] MCV data from each repetition were transmitted via Bluetooth to the proprietary PUSH app on an Apple iPad, and all repetitions were included in the analysis.

Statistical analysis

All statistical analyses were conducted and load-velocity profiles created using RStudio (2023.06.1). Given the exploratory nature of this project, the aim was not to control the error rate or test specific hypotheses, but rather to explore the data and update beliefs about what might be worth investigating further in the future.[50,51] Therefore, except for test-retest reliability, we employed an estimation-based approach, with all results interpreted continuously and probabilistically, compatible with the data and their precision, relative to the smallest detectable effect size (SDES) within a Bayesian framework.[52] To ensure reproducibility and methodological rigor, we adhered to the WAMBS (When to Worry and how to Avoid the Misuse of Bayesian Statistics) checklist.[53]

Model comparison. Initially, individual load-velocity profiles for each session were plotted using linear regression, as polynomial regressions only add statistical complexity without improving the predictive ability of the load-velocity profile.[11] The individual load-velocity profiles were plotted using both the full dataset and a filtered dataset. The filtered dataset excluded MCVs >1.00 m/s, which are associated with lower reliability when measured using the PUSH band,[49] as well as the MCV at 1RM (MCV_{1RM}), which may be unreliably in general.[18,54] To proceed with the filtered model, support of improved model fit was required determined by the average coefficient of determination (R^2) for individual load-velocity profiles, as to not reduce the dataset and statistical power unnecessarily. This choice was made based on the mean difference, 95% credible interval (CrI) and Bayes factor (BF) from a Bayesian unpaired t-test, using the *BayesFactor*[55] and *HDInterval*[56] packages. BFs were interpreted as anecdotal (BF >1/3 to <3), moderate (BF > 1/10 to <1/3 and >3 to <10), and strong (BF <1/10 and >10).[52] Unless otherwise stated, all CrIs are extracted using the highest density interval approach. MCV predictions were extracted from individual load-velocity profiles at 0% (i.e., intercept), 40%, 70%, 90%, and 100% of 1RM for reliability analysis.

Test-retest reliability. To establish the SDES against which the effects of sex and relative strength would be interpreted, we calculated the SEM ($SEM = SD \times \sqrt{[1–ICC]}$) for body composition (BM, FM, FFM, BFP, and FFMP), strength measures (absolute 1RM, 1RM/BM, 1RM/FFM, and GLP), and predicted MCV (at 0%, 40%, 70%, 90%, and 100% of 1RM) between sessions 1 and 2. In addition, we also report ICC(1,3) and within-subject CV, including their 95% CIs. ICC values and their 95% CIs were interpreted as poor (<0.50), moderate (0.50–0.75), good (0.75–0.90), and excellent (>0.90).[57]

The effect of sex on anthropometry and strength. Between-sex differences in body composition and strength outcomes were assessed using Bayesian linear mixed-effects models with default priors using the *brms* package.[58] Each model included sex and session as fixed effects, their interaction term, a random intercept for participants, and a by-participant random slope for session to account for repeated measurements. For each outcome measure, we computed estimated marginal means (EMMs) using the *emmeans* package[59] to estimate the average response for each sex while accounting for the model's structure. Posterior distributions were extracted using the *tidybayes* package[60] to calculate between-sex contrasts and their associated 95% CrI. To quantify the evidence for sex differences, we calculated Bayes factors and directional probabilities from the posterior distributions.[61] For each outcome, we computed two probabilities: the probability of the effect being genuine (*pd*: proportion of posterior draws where the male-female contrast exceeded 0 in direction of the point estimate), and the probability of no meaningful difference (pd_{null}: proportion of posterior draws that fell within ± SDES). Results are presented as posterior means with their 95% CrI, BFs and *pd*s.

The effect of sex and relative strength on load-velocity profiles. To explore the effects of sex and relative strength on the load-velocity profile, three Bayesian linear mixed-effects model were fit with weakly informative default priors using the *brms* package.[58] The models included fixed effects for relative load, sex, relative strength, and session, along with their interactions. Following current best practices,[38,39] we implemented the maximal random effects structure given the experimental design. This included by-participant random intercepts and slopes for both session and relative load, including their interaction.[62] To determine the most appropriate measure of relative strength for analysing load-velocity profiles, three models were fit using either 1RM/BM, 1RM/FFM, or GLP as the measure of relative strength. All models performed similarly, based on the Watanabe-Akaike Information Criterion and Leave-One-Out cross-validation ($\Delta WAIC < 0.5$; $\Delta LOO < 0.2$, see Supplementary Materials). Consequently, GLP was retained in the final model given the typically higher strength of males relative to BM, and sometimes FFM.[63] Model fit, predictive accuracy, convergence and multicollinearity were assessed through R-hat statistics, visual inspection of trace and autocorrelation plots, the Geweke diagnostic, smoothness of the posterior histogram, posterior predictive checks, and re-running the model with the double amount of iterations to rule out local convergence. To compare the load-velocity profiles across sexes and relative strength levels, we extracted predicted MCV and their 95% CrIs at 0%, 40%, 70%, 90%, and 100% of 1RM using the final model. We analysed both between-sex differences and the effect of relative strength by comparing predictions at the minimum and maximum relative strength values in our sample. For each relative load, we computed the EMMs, their associated 95% CrIs, BFs and the *pd*. Following established protocols, we evaluated these differences relative to the SDES of MCV at each relative load.

Results

Load-velocity profile model comparisons

Moderate evidence (mean difference = 0.002 [95% CrI: −0.016, 0.022], BF = 0.0161) was found for no meaningful improvement in model fit with the filtered approach ($R^2 = 0.933 \pm 0.062$) compared to the whole model ($R^2 = 0.935 \pm 0.047$). Therefore, the whole model was retained for all subsequent analyses.

Measurement reliability

Test-retest reliability analyses revealed excellent reliability for all anthropometric and strength measures. MCV measurements had good-to-excellent reliability at 0% and 40% of 1RM, after which it showed a systematic decline in reliability as relative load increased (Table 1, Supplementary Materials).

Table 1. Test-retest reliability. BM, body mass. FFM, fat-free mass.

	Session 1	Session 2	ICC (1,3) [95% CI]	CV [95% CI]	SEM
BM	79.2 ± 15.2	79.0 ± 15.3	0.999 [0.998, 1.000]	0.68 [0.56, 0.85]	0.42 kg
FFM	63.8 ± 16.0	63.9 ± 16.1	0.999 [0.999, 1.000]	0.63 [0.53, 0.80]	0.35 kg
FFMP	80.1 ± 8.2	80.3 ± 8.1	0.997 [0.993, 0.999]	0.64 [0.53, 0.81]	0.4%
FM	15.3 ± 5.9	15.1 ± 5.8	0.997 [0.992, 0.999]	2.82 [2.34, 3.54]	0.34 kg
BFP	19.9 ± 8.2	19.7 ± 8.1	0.997 [0.993, 0.999]	2.34 [1.94, 2.94]	0.4%
1RM	120.6 ± 40.6	123.5 ± 41.1	0.998 [0.996, 0.999]	2.52 [2.10, 3.17]	1.6 kg
1RM/BM	1.49 ± 0.29	1.53 ± 0.28	0.994 [0.986, 0.997]	2.91 [2.41, 3.65]	0.02 kg/kg
1RM/FFM	1.86 ± 0.30	1.91 ± 0.29	0.992 [0.982, 0.997]	2.59 [2.15, 3.25]	0.03 kg/kg
GLP	18.9 ± 3.1	19.4 ± 3.0	0.993 [0.984, 0.997]	2.76 [2.29, 3.47]	0.26 pts
MCV at 0% of 1RM	1.38 ± 0.17	1.44 ± 0.15	0.842 [0.669, 0.929]	5.26 [4.37, 6.61]	0.06 m/s
MCV at 40% of 1RM	1.01 ± 0.12	1.03 ± 0.11	0.908 [0.800, 0.959]	5.31 [4.41, 6.67]	0.03 m/s
MCV at 70% of 1RM	0.74 ± 0.09	0.72 ± 0.09	0.720 [0.453, 0.868]	7.72 [6.41, 9.69]	0.05 m/s
MCV at 90% of 1RM	0.56 ± 0.08	0.51 ± 0.09	0.577 [0.235, 0.792]	13.33 [11.08, 16.75]	0.06 m/s
MCV at 100% of 1RM	0.46 ± 0.08	0.41 ± 0.09	0.504 [0.134, 0.750]	18.41 [15.30, 23.12]	0.06 m/s

FFMP, fat-free mass percentage. FM, fat mass. BFP, body fat percentage. 1RM, one-repetition maximum. 1RM/BM, 1RM normalised to BM. 1RM/FFM, 1RM normalised to FFM. GLP, Goodlift points. MCV, mean concentric velocity. ICC, intra-class correlation. CI, confidence interval. CV, coefficient of variation. SEM, standard error of measurement. Sex-specific session data can be found in supplementary materials.

Table 2. Sex differences in anthropometric and strength outcomes.

	Males (n = 14)	Females (n = 10)	Between-sex comparison	Bayes factor, directional probability
BM (kg)	88.1 ± 3.1 [82.3, 94.5]	66.6 ± 3.6 [59.6, 73.8]	21.4 ± 4.8 [11.9, 30.7]	BF = ∞, *pd* = 100%, pd_{null} = 0%
FFM (kg)	74.7 ± 2.7 [69.3, 79.9]	48.7 ± 3.3 [42.3, 55.1]	26.0 ± 4.3 [17.8, 34.7]	BF = ∞, *pd* = 100%, pd_{null} = 0%
FFMP (%)	84.8 ± 1.8 [81.3, 88.3]	73.6 ± 0.2 [69.5, 77.6]	11.3 ± 2.7 [5.9, 16.3]	BF = ∞, *pd* = 100%, pd_{null} = 0%
FM (kg)	13.2 ± 1.5 [10.1, 15.9]	17.8 ± 1.8 [14.3, 21.2]	-4.7 ± 2.3 [-9.5, -0.3]	BF = 0.023, *pd* = 98%, pd_{null} = 1%
BFP (%)	15.2 ± 1.7 [11.9, 18.7]	26.2 ± 2.1 [22.1, 30.4]	-11.1 ± 2.8 [-16.5, -5.5]	BF = 0.000, *pd* = 100%, pd_{null} = 0%
1RM (kg)	149.0 ± 7.2 [135.0, 164.0]	85.0 ± 8.3 [69.4, 102.0]	63.1 ± 11.1 [42.0, 85.9]	BF = ∞, *pd* = 100%, pd_{null} = 0%
1RM/BM (A.U.)	1.69 ± 0.06 [1.58, 1.81]	1.28 ± 0.07 [1.14, 1.41]	0.41 ± 0.09 [0.23, 0.58]	BF = 3332.333, *pd* = 100%, pd_{null} = 0%
1RM/FFM (A.U.)	2.00 ± 0.08 [1.85, 2.16]	1.74 ± 0.09 [1.56, 1.92]	0.25 ± 0.12 [0.01, 0.49]	BF = 40.841, *pd* = 98%, pd_{null} = 2%
GLP (pts)	20.0 ± 0.8 [18.4, 21.6]	18.0 ± 1.0 [16.1, 19.9]	1.9 ± 1.3 [-0.7, 4.4]	BF = 13.104, *pd* = 93%, pd_{null} = 5%

BM, body mass. FFM, fat-free mass. FFMP, fat-free mass percentage. FM, fat mass. BFP, body fat percentage. 1RM, one-repetition maximum. 1RM/BM, 1RM normalised to BM. 1RM/FFM, 1RM normalised to FFM. GLP, Goodlift points. Within-sex and between-sex statistics are reported as estimated marginal means ± SD [95% credible interval], Bayes factor (BF), and probability that the posterior distribution exceed zero in direction of the point estimate (*pd*) or falls within the SDES (pd_{null}). Positive between-sex values indicating larger values in males.

Between-sex differences in strength and body composition

Strong evidence was found (BF > 13.104, $pd \geq 93\%$) of greater BM, FFM, FFMP, 1RM, 1RM/BM, 1RM/FFM and GLP in males. Conversely, strong evidence was found (BF < 0.023, $pd \geq 98\%$) of higher FM and BFP in females (Table 2). Full model summaries and visualisations can be found in the Supplementary Materials.

The effect of sex, relative strength and individual variability of load-velocity profiles

The final model demonstrated an excellent fit (Bayesian R^2 = 0.941 [95% CrI: 0.938, 0.943]), with robust convergence diagnostics, no concerning patterns of multicollinearity, and strong predictive accuracy. Analysis of random effects revealed substantial individual variation in baseline velocities (SD = 0.17 [95% CrI: 0.12, 0.24])

Table 3. Effects of sex and relative strength of velocity at different relative loads.

	Males	Females	Comparison	Bayes factor, directional probability
$MCV_{0\%}$ (m/s)	1.50 ± 0.04 [1.41, 1.57]	1.37 ± 0.05 [1.27, 1.46]	0.13 ± 0.06 [0.01, 0.25]	BF = 47.682, *pd* = 98%, pd_{null} = 13%
$MCV_{40\%}$ (m/s)	1.06 ± 0.03 [0.99, 1.12]	0.99 ± 0.04 [0.91, 1.07]	0.07 ± 0.05 [-0.03, 0.17]	BF = 10.702, *pd* = 91%, pd_{null} = 21%
$MCV_{70\%}$ (m/s)	0.73 ± 0.03 [0.66, 0.79]	0.70 ± 0.04 [0.62, 0.78]	0.03 ± 0.05 [-0.07, 0.13]	BF = 2.316, *pd* = 70%, pd_{null} = 61%
$MCV_{90\%}$ (m/s)	0.51 ± 0.03 [0.44, 0.57]	0.51 ± 0.04 [0.43, 0.59]	-0.01 ± 0.05 [-0.11, 0.10]	BF = 0.874, *pd* = 53%, pd_{null} = 72%
$MCV_{100\%}$ (m/s)	0.40 ± 0.04 [0.33, 0.47]	0.42 ± 0.04 [0.33, 0.50]	-0.02 ± 0.06 [-0.13, 0.09]	BF = 0.551, *pd* =64%, pd_{null} = 72%
	Strongest	Weakest	Comparison	
$MCV_{0\%}$ (m/s)	1.62 ± 0.08 [1.46, 1.79]	1.18 ± 0.08 [1.02, 1.34]	0.44 ± 0.12 [0.21, 0.67]	BF = 2399.000, *pd* = 100%, pd_{null} = 0%
$MCV_{40\%}$ (m/s)	1.15 ± 0.07 [1.01, 1.29]	0.86 ± 0.07 [0.73, 1.00]	0.29 ± 0.10 [0.10, 0.48]	BF = 291.683, *pd* = 100%, pd_{null} = 1%
$MCV_{70\%}$ (m/s)	0.80 ± 0.07 [0.66, 0.94]	0.63 ± 0.07 [0.50, 0.76]	0.18 ± 0.10 [-0.02, 0.37]	BF = 26.972, *pd* = 96%, pd_{null} = 7%
$MCV_{90\%}$ (m/s)	0.57 ± 0.08 [0.43, 0.72]	0.47 ± 0.07 [0.34, 0.61]	0.10 ± 0.10 [-0.11, 0.30]	BF = 5.197, *pd* = 84%, pd_{null} = 27%
$MCV_{100\%}$ (m/s)	0.46 ± 0.08 [0.30, 0.61]	0.40 ± 0.07 [0.25, 0.55]	0.06 ± 0.11 [-0.16, 0.27]	BF = 2.580, *pd* = 72%, pd_{null} = 39%

MCV, mean concentric velocity. $MCV_{0\%}$, MCV at 0% of 1RM. $MCV_{40\%}$, MCV at 40% of 1RM. $MCV_{70\%}$, MCV at 70% of 1RM. $MCV_{90\%}$, MCV at 90% of 1RM. $MCV_{100\%}$, MCV at 100% of 1RM. Within-group and between-group statistics are reported as estimated marginal means ± SD [95% credible interval], Bayes factor (BF), and probability that the posterior distribution exceed zero in direction of the point estimate (*pd*) or falls within the SDES (pd_{null}). Positive comparison values indicating larger values in males or stronger.

and in response to relative load (SD = 0.14 [95% CrI: 0.09, 0.22]). A complete model summary, model diagnostic plots and the WAMBS checklist are provided in the Supplementary Materials.

Fixed effects of sex on load-velocity profile. The fixed effect of sex on baseline MCV (0.32, [95% CrI: −0.63, 1.32]) and its interaction with relative load (i.e., the slope of the load-velocity profile) (−0.40 [95% CrI: −1.40, 0.61]) were uncertain. Between-sex contrasts of EMMs provided strong evidence for higher velocities in males at 0% (0.13 [95% CrI: 0.01, 0.25], BF = 47.682, *pd* = 98%) and 40% (0.07 [95% CrI: −0.03, 0.17], BF = 10.702, *pd* = 91%) of 1RM. However, estimates were 13–21% compatible with random error (i.e., within the SDES). At higher intensities (70–100% of 1RM), evidence for between-sex differences was anecdotal (BF = 0.551–2.316) and was mostly compatible with random error ($pd_{null} > 61\%$) (Table 3, Figure 1).

Fixed effects of GLP on load-velocity profile. The fixed effect of GLP on baseline MCV (0.03 [95% CrI: −0.01, 0.07]) and its interaction with relative load (–0.03 [95% CrI: −0.07, 0.02]) were uncertain. However, contrasts of EMMs between GLP extremes revealed strong evidence (BF = >16.972) for higher velocities with the maximum GLP value at 0% (0.44 [95% CrI: 0.21, 0.67], BF = 2399.000, *pd* = 100%, pd_{null} = 0%), 40% (0.29 [95% CrI: 0.10, 0.44], BF = 291.683, *pd* = 100%, pd_{null} = 1%), and 70% (0.18 [95% CrI: −0.02, 0.37], BF = 26.972, *pd* = 96%, pd_{null} = 7%) of 1RM. At intensities of 90–100% of 1RM, evidence for between-GLP differences was anecdotal to moderate (Bayes Factor < 5.197), and was 27–39% compatible with random error (Table 3, Figure 1).

Discussion

This project aimed to examine the effects of biological sex and relative strength on the load-velocity profiles in the free-weight back squat using statistically robust methods. The key findings are as follows. First, contrary to previous research, little effect of biological sex on the load-velocity profile at practically relevant loads was found when accounting for relative strength and random variation within participants. Second, although associated with some uncertainty, individuals with higher relative strength, as measured by GLP, tended to have load-velocity profiles with higher intercepts and steeper slopes compared to those with lower relative strength. Third, the load-velocity profile in the free-weight back squat was strongly linear. Fourth, substantial individual variability was observed in load-velocity profiles.

Contrary to most studies on this topic, we found little effect of biological sex on load-velocity profiles. This discrepancy may be due to our inclusion of more trained

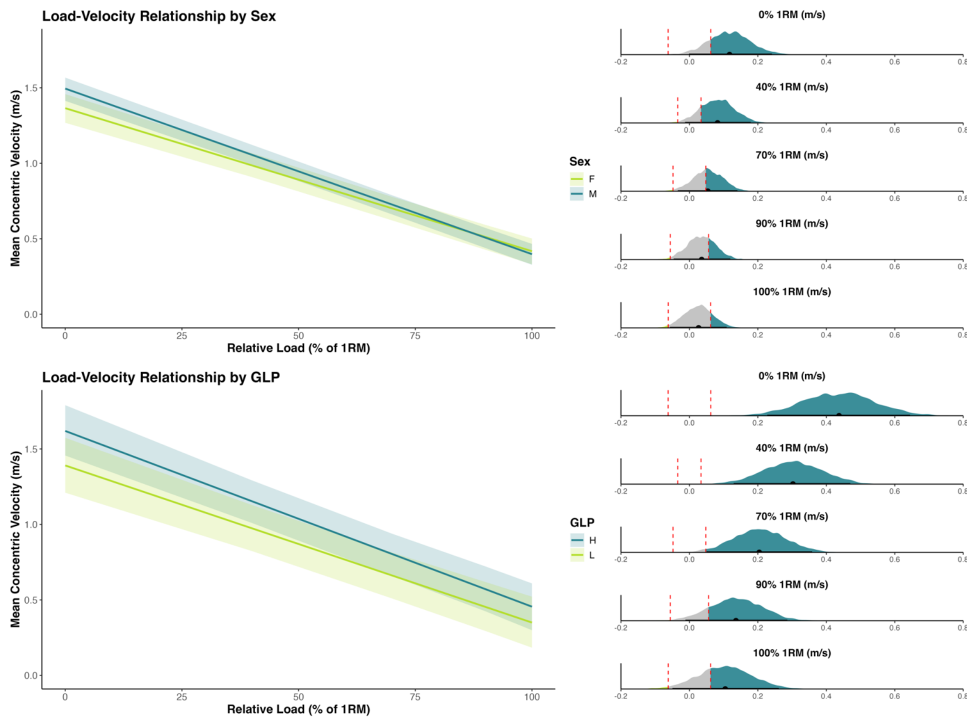

Figure 1. Load-velocity profiles and contrast analysis by sex and relative strength. The left panels demonstrate predicted load-velocity profile: the top left panel shows differences between male and female participants, while the bottom-left panel illustrates differences between participants with low and high GLP. The right panels display posterior distribution density plots of the estimated marginal differences. These density plots visualise the uncertainty and magnitude of differences between groups at each relative load, using colour coding to guide statistical inferences relative to the SDES: Blue represents posterior probability of males or stronger participants exceeding the SDES, green represents posterior probability of females or weaker participants exceeding the SDES, and gray indicates differences within the SDES. Red dashed vertical lines demarcate the upper and lower bounds of the SDES, providing a visual threshold for interpreting meaningful differences between groups.

females or our statistical approach. Unlike previous studies, which often failed to account for relative strength[20,25–30,32] or did so using within-sample median splits,[23,24,31] our approach properly controlled for both relative strength and individual variability when examining sex differences. Given that males are generally stronger and have more muscle mass, both in absolute terms and relative to BM,[36,63] have higher RT participation rates,[35] and tend to prefer heavier training than females,[36] it is likely that previous findings were, at least in part, driven by differences in training status rather than by biological sex alone. Since that most studies do employ relatively weaker participants, we recommend that future researchers: i) recruit more homogeneously trained samples of high expertise in the studied exercise (e.g., powerlifters or weightlifters), and/or ii) apply appropriate statistical methods to account for relative strength and other factors that may influence the profile, along with individual variability (when possible), when assessing sex differences. This would help avoid overly simplified conclusions based solely on biological sex.

Although associated with uncertainty, we observed that individuals with higher GLPs produced higher MCVs, particularly at lower relative loads, indicating higher intercepts and steeper slopes than relatively weaker individuals. This effect was larger and detectable across a larger spectrum of the load-velocity profile than the effect of sex. GLP is a measure of relative strength in powerlifting that corrects for body mass and sex.[48] Individuals with higher GLP may likely exhibit greater technical proficiency and ability to maximally exert force, facilitating a more efficient and consistent transfer of muscle force to barbell displacement, which enables a more accurate display of their capabilities. For context, the direct comparison in this study was based on model predictions using the minimum and maximum values of our dataset (13.6 and 26.4 GLP). Assuming an approximately 36% contribution of the squat to a powerlifting total,[64] this differences corresponds to a direct comparison between a lifter in the 10th percentile of powerlifting results against a 40th or 70th percentile lifter for males and females, respectively.[65] This indicate that while relative strength may have an effect on load-velocity profile, the magnitude of relative strength difference needed for it to become meaningful is quite substantial.

We observed strong linear relationships between relative load and individual MCVs in our strength-trained sample of males and females. These findings are consistent with previous studies, which also reported high R^2 values for the linear fit of the load-velocity profile in both free-weight[17,66] and Smith-rack back squats.[24,25] Similar to other research, we found that MCV at 1RM exhibited less than excellent reliability.[18,54] However, unlike others,[24] this did not appear to affect the linearity of our results. Collectively, these findings challenge the idea that MCV at 1RM should be excluded when developing load-velocity profiles, but whether this is best practice is unclear.

This study has several limitations. Our load–velocity data exhibited considerable individual variability and less-than-ideal test–retest reliability, which may partly explain why, unlike others,[24,25,31] we did not observe a sex-related effect. While this variability may reflect the inherent nature of load–velocity profiling, we cannot rule out the potential influence of limited familiarisation, lack of standardisation of eccentric tempo and squat stance, or the use of the PUSH Band. Although the PUSH Band demonstrates high within-unit reliability,[43] it presents 1.3 to 1.8 times greater CV% than those of linear position transducers,[43,67–69] undoubtedly increasing measurement error in our dataset. As such, our results should be interpreted with caution due to the use of the PUSH Band, and the methods should be replicated using more reliable velocity trackers. However, due to the study design, it is impossible to isolate this reduced between-session reliability to the PUSH Band alone, as biological variation (e.g., technical execution, motivation, fatigue, learning effects, sleep, and nutrition) is inherent when employing human participants for test-retest designs.[70] For example, we observed only moderate consistency in eccentric tempo between sessions. This could again relate to the PUSH Band's ability to accurately assess eccentric duration, which, to our knowledge, has not been validated. While previous research using self-selected eccentric durations has demonstrated high reliability for concentric velocity measures,[13,17,18] the absolute (0.23 s [99% CI: 0.20 to 0.27]; 0.14 m/s [99% CI: 0.12 to 0.15]) and raw differences (–0.03 s [99% CI: −0.08 to 0.01]; 0.03 m/s [99% CI: 0.01 to 0.05]) in eccentric tempo in our study were small and fell within the recommended range (0.15–0.20 m/s) provided by previous velocity-based research.[71,72] Nonetheless, it cannot be ruled out that the technical execution (both eccentric tempo and stance) of participants contributed to the observed reliability. Additionally, although our participants were resistance trained, they were not familiarised to lifting with maximal intent, increasing the likelihood of learning effects. This is supported by our findings in three ways: (i) as shown in Table 1, velocities at low and high relative loads systematically increased and decreased, respectively, in the second session, suggesting that participants improved both their ability to move the bar explosively at low loads and to express maximal strength through more *grindy* repetitions at heavier loads; (ii) R^2 values improved in session two (0.951 ± 0.022 vs. 0.919 ± 0.060), indicating better velocity consistency across the load spectrum; and (iii) individuals with higher intercepts at session 1 tended to show more consistency across sessions (Supplementary materials), suggesting that those initially unable to produce high velocities at low loads improved the most in the following session. Although we could have restricted our analysis to data from the second session, we opted to retain all data to avoid unnecessary reductions in data size. This approach also aligned with prior studies, which either did not report detailed familiarisation procedures or did not conduct extensive familiarisation,[28–31] yet still observed sex-related effects. Including both sessions allowed us to include the measurement noise introduced by the PUSH Band and any learning effects within our uncertainty estimates. We therefore recommend that future research employ velocity trackers of higher reliability (i.e., LPTs),[43,67–69] ensure thorough participant familiarisation of execution, and standardise technical execution to minimise measurement error and improve the precision of findings. It remains unclear how many familiarisation sessions are required to achieve acceptable reliability in load–velocity profiling, or whether this number varies based on training experience. The effect of standardising eccentric duration and squat stance between sessions in trained participants on test-retest reliability also remains uncertain.

Conclusion

Contrary to most research on this topic, we found little evidence that biological sex substantially affects the load-velocity profile when appropriately accounting for relative strength and individual variability. Conversely, we observed that individuals with higher relative strength, quantified by GLP, probably produce higher MCVs than those with lower relative strength at lower relative loads. However, given the exploratory nature of this project and the uncertainty associated with the estimates, these results should be interpreted with caution and need to be replicated. We recommend that future researchers investigating the effects of biological sex and relative strength (or other factors) ensure sufficient familiarisation for participants, standardisation of methodology, utilise highly valid and reliable velocity trackers, and employ mixed-effects modelling, analysis of covariance (ANCOVA) or similar to appropriately account for moderators. These approaches can improve precision and reduce the type I error rate.

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