VELOCITY-BASED STRENGTH TRAINING: COMPARING DURATION AND MEAN VELOCITY TO PREDICT THE MAXIMUM NUMBER OF REPETITIONS IN A SET

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This study explores the relationships among various velocity parameters and the maximum number of repetitions in a set (XRM). Specifically, the predictive power of the concentric phase duration (Tconc) and other velocity parameters, such as the peak velocity, are examined against the average concentric velocity (ACV) approach. Using a preliminary dataset (n=19), various models are developed to predict the maximum number of repetitions performed. The findings indicate that Tconc significantly predicts repetitions with the adjusted model (R^2: 0.37, SEE: 2.98), outperforming the ACV model (R^2: 0.14, SEE: 3.46). However, because of its small sample size and the absence of a test group, the models necessitate further validation. This research advocates for a in-depth examination of velocity curves, which could lead to more effective and safer training methodologies.

KEYWORDS: Velocity-based Training, Resistance Training, Neuromuscular Fatigue.

INTRODUCTION: Resistance training (RT) is recognized for improving athletic performance, reducing injury risk, and enhancing daily life quality. Current challenges lie in objectively monitoring neuromuscular fatigue to adhere to RT guidelines and maximize benefits while minimizing injury risks. Velocity-based training (VBT) has emerged as an objective method for ensuring the safety and effectiveness of training outcomes. Numerous studies (Jukic et al., 2023; Miras-Moreno et al., 2022) have sought to define the relationship between the maximum number of repetitions in a set (XRM) and velocity, using the maximal average concentric velocity (ACV) of each set to failure as the predictive variable. Generalizable models are currently insufficient but there is a growing consensus for individualized ACV-XRM profiles, given the highly personal nature of %1RM-velocity relationships, as indicated in recent research (Pérez-Castilla et al., 2023).In this study, we aim to extend our analysis beyond the traditional ACV with the fastest repetition by examing various velocity parameters, as outlined in Figure 1. The aim of this study was to determine whether parameters from the velocity curve of the fastest repetition could predict repetitions performed in the back squat among trained lifters. Leveraging preliminary data, this work establishes the groundwork for a more comprehensive study, targeting a broad spectrum of velocity parameters to overcome the limitations and information loss inherent in solely ACV-based approaches. Specifically, our model includes the duration of the eccentric phase (Tecc, markers 1-2) and concentric phase (Tconc, markers 2-3), velocities at the first (PV1, marker 4) and second (PV2, marker 5) maximal barbell peaks, and ACV, markers 2-3.

METHODS: The participants were 19 (10M/9F) recreationally active RT athletes with at least 3 years of experience in free weight back squats. The study protocol complied with the Declaration of Helsinki for Human Experimentation and was approved by the regional ethics committee. Written informed consent was obtained from each participant prior to data acquisition. The participants reported to the laboratory for one testing session, where they performed a velocity profiling, 1RM testing and a set to exhaustion at 80% of the 1RM, according to VBT guidelines. Repetitions to Failure at 80% of the 1RM: The participants were explicitly instructed to lift with maximal intent; thus, the concentric velocity can be described as maximal. Volitional failure was determined as the participant either failing a repetition or recording an RPE value of 10 (maximal perceived effort) after a successful repetition. The total number of successful repetitions was recorded as the dependent variable. Parameters from the velocity curve of the fastest repetition were used as predictor variables. Repetitions prior to the fastest repetitions were excluded from the analysis. Details about the procedures, recording and data handling can be found elsewhere (Achermann et al., 2023).

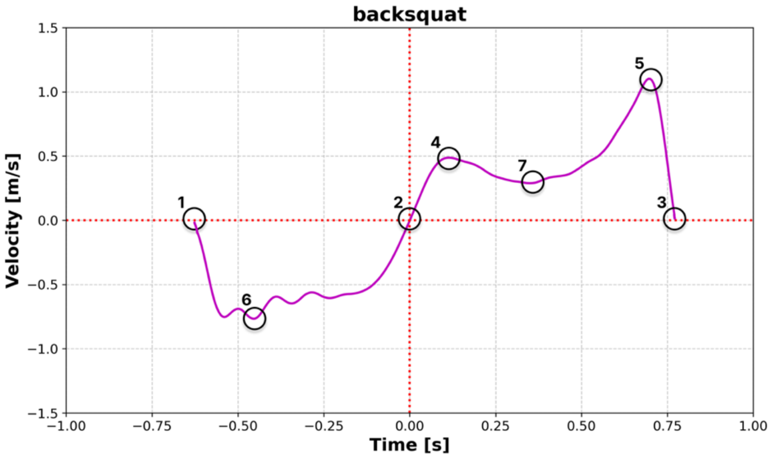

Figure 1: Representation of a typical free-weight back-squat velocity curve illustrating the eccentric phase (marker 1 to 2) and concentric phase (marker 2 to 3). Markers 4 and 5 indicate the first and second maximal barbell peak velocities, respectively. Markers 6 and 7 indicate the velocity minima in the eccentric and concentric phase, respectively.

Statistical Analysis: The predictor variables used for analysis were ACV, PV2, PV1, Tconc and Tecc, as shown in Figure 1. First, all continuous variables of interest were described. Kolmogorov–Smirnov and Shapiro–Wilk tests were used to assess normality. Furthermore, the Breusch–Pagan test was performed to investigate violations of homogeneity. A variety of model comparisons were then used to elucidate the best predictive model for the number of successful repetitions that a participant could perform. For this purpose, R squared (R2), Standard Error of Estimate (S.E.E.) and Akaike Information Criterion AIC were calculated, utilizing bootstrap (n=1000) to establish 95% confidence Intervals (CI). Initially, linear regression models were run for each of the ACV variables, with total repetitions serving as the outcome variable (simple: $Y = b_0 + b_1X + \varepsilon$). For all predictor variables, ordinary least square regression was used. According to these regressions, the Tconc variable was found to be most promising (R^2 comparison) and hence utilized in further analysis. Next, exploratory models inspired by Heischer et al. 2023 were applied to adjust for an additional predictor Z (adjusted: $Y = b_0 + b_1X + b_2Z + \varepsilon$, multiplied: $Y = b_0 + b_1X + b_2Z + b_3XZ + \varepsilon$). A comparison between the models from Heischer (X: ACV, Z: Gender) and different velocity curve parameters (X: Tconc, Z: PV1) was created. Finally, to assess the normality and homogeneity of residuals, the Kolmogorov-Smirnov and Shapiro-Wilk tests were employed, while the Breusch-Pagan test was utilized to examine potential violations of homogeneity. For all the statistical calculations, Python 3.11.7 (Python Software Foundation, https://python.org/) was used, including the modules statsmodels (https://statsmodels.org) and scipy (https://scipy.org/). The level of significance was set at $p \leq 0.05$.

RESULTS: The descriptive statistics of the 19 participants performing the Set to Exhaustion test and the descriptive statistics of the chosen velocity parameters are shown in Table 1. All the input parameters were normally distributed except for Tecc, which significantly differed according to the Shapiro–Wilk test. Furthermore, no violation of homogeneity of variance was detected by the Breusch–Pagan test. The variables ACV, PV1, Tconc and Tecc were analyzed in a simple regression model to assess their predictive ability (Table 2). Only Tconc was identified as a significant predictor of XRM and was used as a primary independent variable for further models. For comparison with the findings of other publications (Haischer et al.) and alignment with standard VBT practices, ACV was also adopted as a primary independent variable. Model comparisons were then performed between the simple, adjusted and multiplicative models. Tconc was the only predictor yielding significant models, with the multiplicative and adjusted models performing comparably and better than the simple model, although no definitive superiority was determined between the multiplicative and adjusted versions based only on the results.

Table 1: Descriptive Statistics.

N = 19 (m:11, w:8 / age: 29±5.2)	1RM	Weight (kg)	Height (cm)
	136±34	76±12	172.2±8.9
	Mean ±SD	**Minimum**	**Maximum**
XRM (80% 1RM)	9±3.5	4	16
ACV [m/s]	0.52±0.06	0.42	0.65
PV1 [m/s]	0.52±0.11	0.32	0.79
PV2 [m/s]	1.11±0.18	0.86	1.48
Tconc [s]	1.33±0.15	1.11	1.62
Tecc [s]	1.15±0.24	0.87	1.85

1RM = one repetition maximum, XRM = number of repetitions executed in a set

Table 2: Model Comparison Between Independent Variables and different ACV/Tconc Models.

	R2 (CI)	S.E.E (CI)	F	Sig.	AIC
Simple ACV	0.08(0.00-0.33)	3.48 (2.28-4.18)	1.496	0.238	103.19
Simple PV1	0.14(0.00-0.54)	3.38 (2.18-4.16)	2.654	0.122	102.04
Simple PV2	0.03(0.00-0.28)	3.58 (2.28-4.33)	0.492	0.493	104.26
Simple Tconc	0.28(0.03-0.58)	3.08 (2.04-3.55)	6.636	0.020	98.53
Simple Tecc	0.01(0.00-0.21)	3.60 (2.34-4.34)	0.245	0.627	104.52
Adjusted ACV	0.14(0.01-0.48)	3.46 (2.20-3.98)	1.332	0.292	103.87
Adjusted Tconc	0.37(0.09-0.71)	2.98 (1.76-3.52)	4.617	0.026	98.14
Multiplicative ACV	0.15(0.04-0.53)	3.57 (2.21-4.07)	0.852	0.487	105.81
Multiplicative Tconc	0.40(0.15-0.78)	2.98 (1.67-3.56)	3.390	0.046	98.96

AIC = Akaike information criterion, CI: bootstrap Confidence Interval

Table 3: Tests of Normality and Heteroscedasticity of residuals.

	Kolmo.–Smirnov		**Shapiro–Wilk**		**Breusch–Pagan**	
	Statistic	Sig.	Statistic	Sig.	Chi-Sqr.	Sig.
Simple ACV	0.16	0.662	0.94	0.306	0.44	0.509
Simple Tconc	0.20	0.38	0.88	0.023	0.67	0.412
Adjusted ACV	0.19	0.440	0.89	0.039	0.86	0.652
Adjusted Tconc	0.19	0.444	0.94	0.217	0.00	0.999
Multi. ACV	0.21	0.338	0.89	0.031	1.08	0.783
Multi. Tconc	0.20	0.368	0.90	0.056	1.31	0.726

1RM = one repetition maximum, XRM = number of repetitions executed in a set

DISCUSSION: The regression analyses revealed that, among the parameters, only the Tconc of the fastest repetition significantly predicted the number of repetitions performed (Table 2, Simple models). Consequently, Tconc was incorporated into both adjusted and multiplicative models. Nonetheless, given the prevalent application of ACV in the literature, it was also considered in subsequent models. It's important to note that the CIs for R2 and S.E.E values across all models are relatively wide, indicating a degree of uncertainty in the proportion of variance and predictive accuracy of the models. This suggests that investigating models incorporating additional predictors and alternative modeling approaches, which more accurately represent the underlying relationship, would be beneficial. These potential models should be closely analyzed regarding the residuals normal distribution, as pointed out by the Shapiro-Wilk test (Table 3). The Shapiro-Wilk test indicates that residuals from most models adhere to normality, with notable exceptions for "Tconc Simple" and to a lesser extent "Vmean Adjusted" and "Vmean Multiplicative". For Tconc, the adjusted model accounted for the addition of PV1, while the multiplicative model incorporated both PV1 and the interaction between PV1 and Tconc. Similarly, for ACV, the adjusted model was enhanced by including sex, and the multiplicative model further included both sex and the interaction between sex and ACV, as in (Haischer et al., 2023). The rationale for incorporating PV1 as an additional predictor comes from preliminary data suggesting its stronger association with technical influences, such as descent velocity potentially leading to a bounce effect, than with neuromuscular fatigue. Additionally, the AIC and the standard error of the estimate indicated that the adjusted and multiplicative models for Tconc were the most plausible (Table 2). Given their similar performance, the adjusted Tconc model was deemed superior due to its simpler structure. The adjusted Tconc model demonstrated a prediction error of 2.98(1.76-3.52) repetitions, exceeding the 2.44 error reported by Haischer et al. Similarly, the ACV models incurred prediction errors of 3.46(2.2-3.98) and 3.57(2.21-4.07). A three-repetition error margin is significant for practical use, warranting further debate on acceptable thresholds. The difference between our ACV models and Haischer's, despite utilizing the same foundational model, is noteworthy but also needs to be interpreted carefully as no CIs were reported by Heischer. Nevertheless, the results underscore the potential of examining velocity curves and integrating underexplored parameters such as Tconc and PV1, which improved the model's performance. It is notable that when squat depth is held constant, ACV and Tconc effectively measure the same variable. Additionally, our study employed the 'maximal intent' cue for each repetition, unlike Haischer et al., who reported various pacing strategies during sets to exhaustion. Concerning the influence of PV1 on the model, it might be important to evaluate whether a bouncing strategy is utilized. The primary limitation of this study is the small sample size, which might also be the cause for the large uncertainty reported for all models. Additionally, the models were developed without a test group. For subsequent research, it is advised to increase the sample size and examine additional velocity parameters to identify models that account for a greater proportion of the variance and improved predictive accuracy.

CONCLUSION: The present study expands upon previous XRM-velocity relationship studies while providing clues for future studies on XRM-velocity relationships. Therefore, Tconc during a set-to-failure at 80% of the 1RM in the back squat might be able to predict the total number of repetitions performed to failure better than the ACV. Despite these results, the limited sample size, the reported uncertainty, and the absence of a test group restrict the generalizability and robustness of our findings. These limitations highlight the need for further research to validate and confirm the proposed models. We suggest that by reducing the velocity curve to a single average value information is lost, which might be important for fully understanding the dynamics of different RT movements. By including the whole velocity curve, future research could pave the way for more personalized and safer training methodologies.

REFERENCES

Achermann, B., Oberhofer, K., Ferguson, S. J., & Lorenzetti, S. R. (2023). Velocity-Based Strength Training: The Validity and Personal Monitoring of Barbell Velocity with the Apple Watch. *Sports*, *11*(7), 125. https://doi.org/10.3390/sports11070125

Haischer, M., Carzoli, J., Cooke, D., Pelland, J., Remmert, J., & Zourdos, M. (2023). Predicting Total Back Squat Repetitions from Repetition Velocity and Velocity Loss. *Journal of Human Kinetics*, *87*, 167–178. https://doi.org/10.5114/jhk/162021

Jukic, I., Helms, E. R., & McGuigan, M. R. (2023). The Fastest Repetition in a Set Predicts the Number of Repetitions Completed to Failure During Resistance Training: The Effects of Sex, Training Status, History, And Personality Traits. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4330743

Miras-Moreno, S., Pérez-Castilla, A., & García-Ramos, A. (2022). Lifting Velocity as a Predictor of the Maximum Number of Repetitions That Can Be Performed to Failure During the Prone Bench Pull Exercise. *International Journal of Sports Physiology and Performance*, *17*(8), 1213–1221. https://doi.org/10.1123/ijspp.2021-0534

Pérez-Castilla, A., Miras-Moreno, S., Weakley, J., & García-Ramos, A. (2023). Relationship Between the Number of Repetitions in Reserve and Lifting Velocity During the Prone Bench Pull Exercise: An Alternative Approach to Control Proximity-to-Failure. *Journal of Strength and Conditioning Research*, *37*(8), 1551–1558. https://doi.org/10.1519/JSC.0000000000004448

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