The accuracy of load-velocity relationships to predict 1RM: A systematic review and individual participant data meta-analysis protocol

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Review objective and research questions

The objective of this systematic review and meta-analysis is to investigate and quantify the accuracy of load-velocity models to predict 1RM performance. The following research questions will be addressed to guide the review:

1. Which variables and associated procedures have been used to predict 1RM performance based on a load-velocity relationship?

2. What is the predictive accuracy of common models, and are these moderated by factors such as modelling approaches and exercises investigated?

Keywords: Monitoring; Maximum strength; Velocity based training; Autoregulation

Introduction

The load lifted during resistance training is frequently prescribed in terms of a percentage of the maximum load that can be lifted for one repetition (1RM; González-Badillo and Sánchez-Medina 2010). This process allows for both individualisation of a training stimulus and prescription of various training zones based on the relative load lifted that can be used to target distinct physical qualities (Fleck and Kraemer 2014). Despite extensive research and practical experience supporting the use of 1RMs to prescribe resistance training, the process can also be viewed as inconvenient, time-consuming and limited by the precision of a single measurement that may fluctuate on a daily basis due to changes in readiness (Shattock and Tee 2020; Greig et al. 2020) or trend substantively over the short-to-medium term due to changes in fitness and fatigue (Dorrell, Smith and Gee 2019; Greig et al. 2020). Previous attempts to address limitations such as the time required to determine an individual's 1RM include repetition-maximum tests with a sub-maximum load that can then be used to predict 1RM (Pestaña-Melero et al. 2018). However, repeated administration of any repetition-maximum test is likely to generate undesirable levels of fatigue, thereby limiting the frequency with which the measurement process can be performed (Banyard, Nosaka and Haff 2017). More recently, alternative processes have been adopted to predict 1RM through the use of load-velocity relationships (Hughes et al. 2019). Underpinning these processes include a strong inverse linear relationships between load and velocity (González-Badillo and Sánchez-Medina 2010), and the recent proliferation of technologies that can accurately measure velocity during resistance training. The prediction of 1RM from load-velocity relationships represents an appealing alternative for practitioners, as the process does not require performance of a fatiguing repetition-maximum test, and can be completed at high frequencies including each resistance training session (Perez-Castilla et al. 2019). In addition, the process can be incorporated into pre-existing warm-up routines such that the prediction of daily 1RM requires no additional time to complete.

A range of approaches have been proposed to predict 1RM from load-velocity relationships (García-Ramos et al. 2020). In general, these include development of linear regression equations from velocity measurements made across multiple increasing sub-maximum loads. The regression equation is then extrapolated beyond the measured data to predict 1RM. Representative approaches can differ on a range of factors including the extrapolated point to represent 1RM (Jidovtseff et al. 2011; Lake et al. 2017; Hughes et al. 2019a; García-Ramos et al. 2020), the number of loads assessed (Garcia-Ramos et al. 2019), the velocity metric used (García-Ramos et al. 2019) and the use of individual or group-level data to generate measurements (Weakley 2020).

If 1RM predictions can be derived with high frequency and suitable accuracy, then load-velocity profiles could be used to compliment training-based decisions across a range of timescales. For example, practitioners could integrate load-velocity profiles into existing monitoring approaches to provide information surrounding an individual's response across the training cycle (Jovanović and Flanagan 2014; Hughes et al. 2019). In the case that observed changes in performance deviate markedly from expected changes, this information could then be used to inform the programming of subsequent training cycles or training sessions that better match the individual and their overarching training goals (Greig et al. 2020). Alternatively, load-velocity based predictions could be integrated more frequently to assist with prescription of training specific sessions. Here, practitioners have used velocity data gathered during incremental warm-ups to generate 1RM predictions for each of the core exercises to be performed on that day (Jovanović and Flanagan 2014).The predicted values can then be used to prescribe loads which correspond to the desired %1RM's for each exercise (Moore and Dorrell 2020). By integrating velocity in this manner it is thought that practitioners may be able to better account for potential fluctuations in individual's performance which may have otherwise resulted in inappropriate load prescription (Greig et al. 2020).

Despite the initial appeal of load-velocity based relationships to predict 1RM and guide training prescription, validation of approaches has demonstrated varying success across a wide range of upper and lower body exercises (Weakley et al. 2020). Additionally, based on the range of prediction approaches that can be adopted it is challenging to make clear recommendations for both practice and future research. Currently there have been limited attempts to synthesise existing evidence on the validity of load-velocity relationships for predicting 1RM in commonly performed resistance exercises (McBurnie et al. 2019; Dahlin 2018). Previous reviews have provided varying levels of detail surrounding the relevant literature; however, no quantitative synthesis of information has yet been provided. In addition, the review by Dahlin (2018) focused only on a single 1RM prediction method despite the variety of approaches that currently exist. In both reviews, the predictive capability of models was quantitively evaluated primarily through the interpretation of reported R^2 values. This statistic describes the total variance in the dependent variable accounted for by the linear combination of the predictors and is principally a measure of model fit to observed data (Paulmer and O'Connell 2009). Whilst the dimensionless nature of R^2 is effective in comparing models across different measurement scales, the practical relevance may be unclear as high R^2 values can still be obtained for models that produce prediction errors considered inappropriate in practice. In contrast, identifying the predictive validity of a model may be best established by quantifying the accuracy and stability of predictions. The accuracy of a model can be established by analysing the standard error of the estimate (SEE) and the percentage that the SEE represents of the predicted mean (SEE %; Paulmer and O'Connell 2009). The SEE provides a measure of the typical prediction error in the units of the dependent variable with the practical relevance readily interpretable. However, this statistic is influenced by a range of factors including the magnitude of the dependent variable, and therefore the SEE % may be preferred as a means of comparing prediction accuracy across models derived from different samples (Paulmer and O'Connell 2009). Calculation of R^2 and SEE from a single data set are likely to overestimate the predictive validity of a process and do not establish the stability of model predictions (Kuhn and Johnson 2013). The amount of overfitting and stability of model predictions are best assessed through cross-validation process where the prediction accuracy of a model developed on one sample is assessed on another sample from the same population (Kuhn and Johnson 2013). However, given the simplicity of most models used to develop load-velocity predictions, it is expected that overfitting may be limited.

Based on the range of proposed load-velocity approaches to predict 1RM, and the paucity of evidence synthesis research including quantitative attempts to summarise predictive validity and relevant moderating factors, the review described in this protocol will be conducted. It is expected that the findings from this review will assist in identifying the most effective and parsimonious load-velocity processes that can be used in practice to provide high frequency estimates of 1RM.

Search strategy

Searching will be performed in three stages to maximise inclusion of available evidence. Firstly, a limited search of MEDLINE and SPORTDiscus using initial keywords (Appendix 1) will be performed followed by an analysis of the text words in the title/abstract as well as keywords used to describe studies to develop a full search strategy. The resulting full search strategy will then be adapted to each database and applied systematically to MEDLINE, Web of Science, SPORTDiscus and Scopus. Searches for unpublished literature including theses and pre-prints will also be conducted by searching Google Scholar, CORE and British Ethos databases. Finally, searching of references and citations of included studies will be performed using Google Scholar and Scopus to capture any additional records not identified during the initial stages of the search. The choice to use both platforms for reference and citation tracking is based on evidence of unique listings (Bakkalbasi et al. 2006).

Inclusion criteria

Inclusion criteria for this review have been developed and reported in line with best practice guidelines (Shamseer et al. 2015; Munn et al. 2018). Given the focus of this review is to assess predictive validity, inclusion criteria have been specified according to the PIRD (Population – Index test – Reference test – Diagnosis of interest) mnemonic (Munn et al. 2018). This approach is frequently used in health evidence synthesis contexts to assess the diagnostic accuracy of clinical tests (Campbell et al. 2015) and provides a general framework for specifying inclusion criteria where the aim of a review is to compare the validity of a new or alternative method when compared with an appropriate criterion.

Population

This review will include individuals with no underlying health conditions of any gender, age and demographic that have previously engaged in resistance training.

Index Test

The index test for this review includes any variant of a load-velocity relationship used for the purposes of 1RM prediction. Broadly, load-velocity relationship will be defined as any model that takes as input to a regression equation the velocity recorded at more than one load to generate an estimated 1RM value. Studies will be restricted to those that have developed and validated a load-velocity relationship for one or more of the most performed barbell exercises including: 1) squat; 2) bench-press; 3) deadlift; 4) clean; 5) clean and jerk; 6) power clean; 7) snatch; and 8) power snatch. Both smith-machine and free-weight variants of the above exercises will be considered eligible for inclusion. However, given the substantive difference in mediolateral displacement commonly observed between smith-machine and free-weight variants of the same exercise, these will be coded separately to facilitate analyses regarding potential differences in accuracy (Hughes et al. 2020)

Reference Test

The reference test for this review includes any 1RM assessment of the specified exercises whereby the outcome is the heaviest mass that can lifted for a single repetition with appropriate technique. To be considered for inclusion, studies must have also conducted the reference test within 3 weeks of the index test. Previous research has shown that 1RM assessments remain stable for up to 3 weeks with minimal to no stimulus (Mcmaster et al. 2013), and it is expected that most studies will complete both reference and index tests in a short time-frame such that substantive changes in 1RM performance are unlikely to occur.

Target variable (diagnosis)

The target variable in this review is maximum strength as quantified by the measurement of an individual's 1RM performance during a resistance exercise commonly performed to develop strength or power and can be safely performed with a maximum load.

Types of study

This review will include any study that has directly compared measured 1RM to predicted 1RM as estimated through a load-velocity relationship. No limitation will be placed on study design and therefore both cross-sectional and longitudinal studies meeting the above criteria will be deemed eligible for inclusion. For studies that repeat the index or reference test all relevant data will be extracted each time-point and clearly coded in the extraction tool. Conference abstracts will be included where sufficient data exists and no related full text publication can be located. Opinion papers, blogs, websites and social media posts will not be considered for inclusion.

Methodology

The proposed systematic review will be conducted in alignment with best practice guidelines as outlined by the Joanna Briggs Institute JBI (Aromataris and Munn 2020) and reporting of items will follow the guidelines set out by the PRIMSA-IPD statement- a PRISMA variant specifically designed for individual participant data (IPD) meta-analyses- to enhance transparency, accessibility, and reproducibility (Stewart et al. 2013)

Study selection

Following the literature search, all records will be uploaded into the reference manager software RefWorks. Records will then undergo an initial de-duplication procedure prior to being imported into Covidence (Melbourne, Australia) for eligibility screening. All references will then undergo a second de-duplication procedure using in-built functions within Covidence software. Studies will then initially be screened for relevance based on their title and abstract prior to full-text eligibility screening. All screening will be completed independently by two researchers, and disagreements will be resolved through either discussion or by a third reviewer. All excluded studies will be coded within the PRIMSA diagram by recording the total number of studies excluded, alongside the reason for their exclusion.

Data extraction

Data extraction of qualitative information related to the studies assessed will be conducted using a bespoke tool designed for the purposes of this review under the guidance of the CHARMS checklist (Moons et al. 2014). This will undergo a pilot trial with multiple studies to ensure the tool is fit for purpose and possesses suitable transparency. Data extracted will include basic information on the population, study design and exercise(s), as well as more detailed information on the methods used to build and assess predictive models. Modifications will be made to the information collected and structure of the data extraction tool as and when necessary. Where substantial modifications are made that may affect the results generated, these will be detailed in the final written report.

This is an IPD meta-analysis, and therefore study authors will be contacted to request original data (load and velocity values). Where data cannot be obtained from authors, individual summary data (normalised or absolute differences between observed and predicted 1RM values) will be extracted directly from studies through digitisation of in-text plots. Summary of contact with authors requesting data will be recorded and made available in the full report to ensure transparency. Where data are available, comparisons between raw and digitised data will be completed to assess the reliability and accuracy of the digitisation process and detailed in the final report. Comparisons will also be made between the actual velocity recorded at each individual's 1RM load, and the velocity value defined in the specific model to represent 1RM. This analysis will aid in differentiating between various components of model error.

Risk of bias assessment

Risk of bias will be conducted based on a modified version of the Prediction Model Risk of Bias Assessment Tool (PROBAST) (Wolff et al. 2019) as no equivalent currently exists in exercise science. The PROBAST tool is designed for evaluating studies that assess predictive validity of multivariate models (Wolff et al. 2019) and will be modified to account for single predictor models expected from studies.

Data synthesis

Both one-stage and two-stage IPD meta-analysis models will be completed and their results compared (Burke et al. 2017). For both sets of models, prediction residuals (prediction – direct assessment) will be obtained. For two-stage analyses, the standard error of the estimate $\left(SEE = \sqrt{\frac{\sum residual^2}{n-2}}\ ; SEE\ \% = \frac{SEE}{Criterion\ Mean}\right)$ will be calculated for each analysis presented in a study. Within sample variance will be obtained by boot-strapping and the effect sizes pooled across studies with three-level hierarchical models used to account for covariance between multiple sets of results presented in a single study. For one-stage analyses, prediction residuals and prediction residuals scaled by the criterion value will be incorporated into random effects models. Fixed effects will be added to models to quantify the moderating effects of variables thought to influence model accuracy including the exercise assessed, the modelling approach/characteristics, extrapolation techniques used, and the devices used to measure velocity. All data will be presented in tabular and graphical format with an accompanying narrative synthesis of the literature that describes how the data relate to the objectives of this review. Data may also be presented to help further describe key findings and recommendations for future research and practice.

Appendix 1: Example search strategy

	Search string
1. Velocity	**AB/TI:** velocity
2. Prediction	**AB/TI:** predict* OR estimat*
3. 1RM	**AB/TI:** 1RM OR 1-RM OR “repetition maximum”
4. Combined string	S1 AND S2 AND S3

References

AROMATARIS, E. and MUNN, Z., 2020. Chapter 1: JBI Systematic Reviews. *JBI Manual for Evidence Synthesis*, JBI. [online]. Available from: https://wiki.jbi.global/display/MANUAL/Chapter+1%3A+JBI+Systematic+Reviews

BANYARD, H.G., NOSAKA, K. and HAFF, G.G., 2017. Reliability and Validity of the Load-Velocity Relationship to Predict the 1RM Back Squat. *Journal of Strength and Conditioning Research*, 31(7), pp. 1897–1904.

BURKE, D.L., Ensor, J. and Riley, R.D., 2017. Meta-analysis using individual participant data: One-stage and two stage approaches, and why the may differ. *Statistics in Medicine*, 36(5): 855-875.

CAMPBELL, J.M. et al., 2015. Diagnostic test accuracy: methods for systematic review and meta-analysis. *International Journal of Evidence-Based Healthcare*, 13(3), pp. 154–162.

DORRELL, H.F., SMITH, M.F. and GEE, T.I., 2019. Comparison of Velocity-Based and Traditional Percentage-Based Loading Methods on Maximal Strength and Power Adaptations. *Journal of Strength and Conditioning Research*, 34(1), pp. 46–53.

GARCIA-RAMOS, A. et al., 2019. Reliability and validity of different methods of estimating the one-repetition maximum during the free-weight prone bench pull exercise. *Journal of Sports Sciences*, 37(19), pp. 2205–2212.

GARCÍA-RAMOS, A. et al., 2019. Assessment of the load-velocity profile in the free-weight prone bench pull exercise through different velocity variables and regression models. *PLoS ONE*, 14(2), pp. 1–12.

GARCÍA-RAMOS, A. et al., 2020. Reliability of the velocity achieved during the last repetition of sets to failure and its association with the velocity of the 1-repetition maximum. *PeerJ*, 8, p. e8760.

GONZÁLEZ-BADILLO, J.J. and SÁNCHEZ-MEDINA, L., 2010. Movement velocity as a measure of loading intensity in resistance training. *International Journal of Sports Medicine*, 31(5), pp. 347–352.

GREIG, L. et al., 2020. Autoregulation in Resistance Training: Addressing the Inconsistencies. *Sports Medicine*. [online]. Available from: http://link.springer.com/article/10.1007/s40279-020-01330-8?utm_source=researcher_app&utm_medium=referral&utm_campaign=RESR_MRKT_Researcher_inbound.

HUGHES, L.J. et al., 2019. Using a load-velocity relationship to predict one repetition maximum in free-weight exercise: A comparison of the different methods. *Journal of Strength and Conditioning Research*, 33(9), pp. 2409–2419.

HUGHES, L.J. et al., 2019. Using Load-Velocity Relationships to Quantify Training-Induced Fatigue. *The Journal of Strength & Conditioning Research*, 33(3), pp. 762-773.

HUGHES, L.J. et al., 2020. Load-velocity relationship 1RM prediction: A comparison of Smith machine and free-weight exercise. *Sports Medicine and Biomechanics*. [online]. Available from: https://www.tandfonline.com/doi/full/10.1080/02640414.2020.1794235?casa_token=PP5o31mch3gAAAAA%3Aei8O05-lEWIa74FBPUf4jJkj3tOSVwdVbzEH5PKG9WCgwu6aCPkxMC6pynAf51-vhAGdwkelzDoMlA

JIDOVTSEFF, B. et al., 2011. Using the load-velocity relationship for 1RM prediction. *Journal of Strength and Conditioning Research*, 25(1), pp. 267–270.

JOVANOVIĆ, M. and FLANAGAN, D., 2014. Researched applications of velocity based strength training. *Journal of Australian Strength and Conditioning*, 22(2), pp.58-69.

LAKE, J. et al., 2017. Comparison of different minimal velocity thresholds to establish deadlift one repetition maximum. *Sports*, 5(3), p. 70.

MCBURNIE, A.J. et al., 2019. The Benefits and Limitations of Predicting One Repetition Maximum Using the Load-Velocity Relationship. *Strength and Conditioning Journal*, 41(6), pp. 28-40.

MCMASTER, D.T. et al., 2013. The Development, Retention and Decay Rates of

Strength and Power in Elite Rugby Union, Rugby League and American Football. *Sports Medicine*, 43(5), pp. 367-384

MOONS, K.G.M. et al., 2014. Critical appraisal and data extraction for systematic reviews of prediction modelling studies: the CHARMS checklist. *PLoS Med*, 11(10), p. e1001744.

MOORE, J. and DORRELL, H., 2020. Guidelines and Resources for Prescribing Load using Velocity Based Training. *IUSCA Journal*, 1(1 SE-Articles). [online]. Available from: https://journal.iusca.org/index.php/Journal/article/view/4.

MUNN, Z. et al., 2018. What kind of systematic review should I conduct? A proposed typology and guidance for systematic reviewers in the medical and health sciences. *BMC Medical Research Methodology*, 18(1), p. 5. Available from: https://pubmed.ncbi.nlm.nih.gov/29316881.

PALMER, P.B. and O'Connell, D.D. 2009. Regression analysis for prediction: Understanding the process. *Cardiopulmonary Physical Therapy Journal,* 20(3), pp. 23-26.

PEREZ-CASTILLA, A. et al., 2019. Validity of Different Velocity-Based Methods and Repetitions-to-Failure Equations for Predicting the 1 Repetition Maximum During 2 Upper-Body Pulling Exercises. *Journal of Strength and Conditioning Research*. [online]. Available from: http://ovidsp.ovid.com/ovidweb.cgi?T=JS&PAGE=reference&D=medp&NEWS=N&AN=30741875.

PESTAÑA-MELERO, F.L. et al., 2018. Reliability of the Load–Velocity Relationship Obtained Through Linear and Polynomial Regression Models to Predict the 1-Repetition Maximum Load. *Journal of Applied Biomechanics*, 34(3), pp. 184–190.

SHAMSEER, L. et al., 2015. Preferred reporting items for systematic review and meta-analysis protocols (prisma-p) 2015: Elaboration and explanation. *BMJ (Online)*.

SHATTOCK, K. and TEE, J.C., 2020. Autoregulation in Resistance Training. *Journal of Strength and Conditioning Research*. [online]. Available from: https://journals.lww.com/10.1519/JSC.0000000000003530.

STEWART, L.A. et al., 2013. Preferred reporting items for a systematic review and meta-analysis of individual participant data: the PRISMA-IPD statement. *Jama*, *313*(16), pp.1657-1665.

WEAKLEY, J. et al., 2020. Velocity-Based Training : From Theory to Application. *Strength and Conditoning Journal.* [online]. Available from: https://journals.lww.com/nsca-scj/Abstract/9000/Velocity_Based_Training__From_Theory_to.99257.aspx

WOLFF, R.F. et al., 2019. PROBAST: a tool to assess the risk of bias and applicability of prediction model studies. *Annals of Internal Medicine*, 170(1), pp. 51–58.