

# Reliability and validity of velocity measures and regression methods to predict maximal strength ability in the back-squat using a novel linear position transducer

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Jonathan Kilgallon<sup>1</sup> , Emily Cushion<sup>1</sup>, Shaun Joffe<sup>1,2</sup> and Jamie Tallent<sup>3,4</sup>

## Abstract

The purpose of this study was to examine the reliability of load-velocity profiles (LVPs) and validity of 1-repetition maximum (1-RM) prediction methods in the back-squat using the novel Vitruve linear position transducer (LPT). Twenty-five men completed a back-squat 1-RM assessment followed by 2 LVP trials using five incremental loads (20%–40%–60%–80%–90% 1-RM). Mean propulsive velocity (MPV), mean velocity (MV) and peak velocity (PV) were measured via a (LPT). Linear and polynomial regression models were applied to the data. The reliability and validity criteria were defined a priori as intraclass correlation coefficient (ICC) or Pearson correlation coefficient ( $r$ ) > 0.70, coefficient of variation (CV) ≤ 10%, and effect size (ES) < 0.60. Bland-Altman analysis and heteroscedasticity of errors ( $r^2$ ) were also assessed. The main findings indicated MPV, MV and PV were reliable across 20%–90% 1-RM (CV < 8.8%). The secondary findings inferred all prediction models had acceptable reliability (CV < 8.0%). While the MPV linear and MV linear models demonstrated the best estimation of 1-RM (CV < 5.9%), all prediction models displayed unacceptable validity and a tendency to overestimate or underestimate 1-RM. Mean systematic bias (−7.29 to 2.83 kg) was detected for all prediction models, along with little to no heteroscedasticity of errors for linear ( $r^2$  < 0.04) and polynomial models ( $r^2$  < 0.08). Furthermore, all 1-RM estimations were significantly different from each other ( $p$  < 0.03). Concludingly, MPV, MV and PV can provide reliable LVPs and repeatable 1-RM predictions. However, prediction methods may not be sensitive enough to replace direct assessment of 1-RM. Polynomial regression is not suitable for 1-RM prediction.

## Keywords

Velocity-based training, load-velocity relationship, relative load, regression, linear position transducer

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## Introduction

Ongoing collaboration between coaches, engineers and scientists has brought about a multitude of technology that aids athletes in training and preparation for the demands of competition.<sup>1</sup> The ability to objectively quantify, monitor and analyse resistance training variables is an essential component for practitioners aiming to maximise adaptations.<sup>2</sup> One of the most important variables for programme design is training volume as it influences neural and morphological adaptations.<sup>3,4</sup> Velocity-based training (VBT) uses velocity to inform or enhance training practice,<sup>5</sup> and has received considerable interest in recent years for the regulation of training volume.<sup>6,7</sup> VBT utilises the well-established

inverse linear relationship between relative load and movement velocity to produce a load-velocity profile

<sup>1</sup>Faculty of Sport, Allied Health and Performance Science, St Mary's University, Twickenham, UK

<sup>2</sup>British Weightlifting, Leeds, UK

<sup>3</sup>School of Sport, Rehabilitation and Exercise Sciences, University of Essex, Colchester, UK

<sup>4</sup>Department of Physiotherapy, School of Primary and Allied Health Care, Faculty of Medicine, Nursing and Health Science, Monash University, Melbourne, Australia

### Corresponding author:

Jonathan Kilgallon, Faculty of Sport, Allied Health and Performance Science, St Mary's University, Waldegrave Road, Twickenham TW1 4SX, UK.

Email: jkperformance.info@gmail.com

(LVP) which provides insights into an individual's current physiological status.<sup>8–10</sup> Applications of VBT include the provision of feedback during resistance training,<sup>11–14</sup> autoregulatory prescriptive methods,<sup>15,16</sup> fatigue monitoring<sup>17</sup> and prediction of 1-repetition maximum (1-RM) from submaximal loads.<sup>18,19</sup> The successful implementation of VBT relies on instruments which are reliable and valid.<sup>20</sup> While it is widely accepted that linear position transducers (LPTs) outperform other technologies including accelerometers and optic laser devices,<sup>21–29</sup> the price of an LPT presents a barrier of entry for practitioners.<sup>30</sup>

Cost concerns may be alleviated by the Vitruve (previously Speed4Lifts), which is the cheapest commercially available LPT. Real-time feedback is provided via a digital display on the device and a smartphone application, the latter of which also generates a wider range of features including load summary reports. When compared to six other devices, the Vitruve displayed the highest validity ( $r^2 = 0.95–0.96$ ) and the lowest levels of variability (coefficient of variation [CV] = 2.61%) during the Smith machine bench press exercise.<sup>31</sup> Very high intra-device reliability for the Vitruve was also found during Smith machine back-squat exercise.<sup>32</sup> However, previous studies' reliance on untrained participants and Smith machine modalities limit the transferability of findings to strength-trained populations.<sup>31,32</sup> This is because stronger participants exhibit different LVPs due to an increased capacity to overcome the sticking region associated with heavy loads at a lower concentric velocity.<sup>33</sup>

The Vitruve can also be distinguished from other LPTs for its ability to calculate all three commonly used variables: mean propulsive velocity (MPV), mean velocity (MV) and peak velocity (PV). MPV is the average velocity from the start of the concentric phase until acceleration is less than gravity ( $-9.81 \text{ m}\cdot\text{s}^{-2}$ ),<sup>10,34</sup> whereas MV is the average velocity across the entire concentric phase.<sup>35</sup> PV is the highest recorded velocity attained from the concentric phase.<sup>36</sup> MPV accounts for the breaking phase of the movement, whereas MV does not. Historically, MV has been the most commonly reported variable on a number of devices,<sup>5</sup> and has featured in considerably more research as a result.<sup>37</sup> Nonetheless, while both MPV and MV have been used to generate LVPs of nonaerial movements, inconsistent findings have made it unclear which measure is best for training prescription.<sup>38,39</sup> This inconsistency may be associated with variations in research methodologies in relation to sample size and strength ability, exercise type and statistical approaches. Hence, a comprehensive comparison of these velocity measures would help coaches to understand and monitor the performance potential of their athletes.

Research has not examined the test-retest reliability of velocity measures from the Vitruve during free-weight exercise. The back-squat is a closed kinetic chain exercise often used by practitioners to enable the

transfer of strength adaptations into athletic performance.<sup>40</sup> Unlike Smith machine modalities, the back-squat can involve greater horizontal movement of the barbell which is known to affect velocity measures calculated by LPTs.<sup>41</sup> Therefore, the findings from Smith machine investigations of the Vitruve should not be used to infer the LPTs reliability during free-weight exercise. While a plethora of studies have investigated the reliability of LPTs during lower body free-weight exercises,<sup>42–44</sup> the reliability of the Vitruve during back-squat exercise is not known. Given the Vitruve's substantially lower retail value, this is worthy of further investigation.

Movement velocity has received increasing attention as an alternative approach for assessing an individual's 1-RM strength ability.<sup>10</sup> This is because the 1-RM assessment presents numerous challenges. Primarily, maximal strength is known to change within short time frames,<sup>45</sup> but frequent testing can take valuable time away from training and induce unwanted fatigue which heightens the risk of injury. The explanatory mechanisms of injury stem from a breakdown of technique at the sticking point of the movement.<sup>46</sup> Considering that biomechanical principles, injury mechanisms and human tolerance are central to the design of sports technology,<sup>47</sup> any potential improvements to the precision of 1-RM predictions should be of importance to engineers.

To date, lower body Smith machine protocols have generated accurate predictions of 1-RM ( $R^2 = 0.94–0.96$ ) using submaximal loads during full-depth squat exercise.<sup>8,48</sup> However, Banyard et al.<sup>38</sup> found back-squat 1-RM predictions were not only different to measured 1-RM (effect size [ES] = 0.71–1.04), but all 1-RM prediction equations were different from each other. This result was attributed to high between-session variability of the velocity used to predict 1-RM. Subsequently, the authors suggested the validity of back-squat 1-RM predictions could be improved using MPV or second order polynomial regression. Interestingly, recent research reported no differences between back-squat LVPs derived from linear or nonlinear regression using MPV, MV and PV.<sup>49,50</sup> Furthermore, Thompson et al.<sup>50</sup> found individualised back-squat LVPs for MV ( $r = 0.98–0.99$ ) and PV ( $r = 0.98–0.99$ ) were stable and displayed improved goodness of fit when using nonlinear regression. However, neither Banyard et al.<sup>49</sup> nor Thompson et al.<sup>50</sup> published any data relating to 1-RM prediction. This may be attributed to the added complexity of applying nonlinear regression fits outside of dedicated software platforms.<sup>49</sup> Collectively, while the usefulness of different regression models and velocity measures have previously been examined, their precision in estimating back-squat 1-RM has not been compared within the same study. Further examination would also be useful for engineers. For instance, in the event polynomial models are shown to be more accurate than their linear counterparts, this could guide future innovations to

software development which may enhance the efficiency of training programmes.

The primary objective of this study was to investigate the reliability of MPV, MV and PV to develop LVPs using the Vitruve LPT during back-squat exercise. The secondary aim of this study was to determine the reliability and validity of 1-RM back-squat predictions derived from MPV, MV and PV using linear and polynomial regression. It was hypothesised that (1) all velocity measures would display acceptable reliability, (2) all estimations of 1-RM would be reliable and (3) all estimations of 1-RM would be different to 1-RM.

## Materials and methods

### Subjects

Twenty-five strength-trained males (mean  $\pm$  SD; age =  $25.2 \pm 2.8$  years; body mass =  $91.2 \pm 14.0$  kg; stature =  $180.0 \pm 9.7$  cm; back-squat = 1-RM  $178.0 \pm 28.0$  kg; relative 1-RM =  $2.0 \pm 0.4$  x/body mass) were recruited for this study. All subjects had at least 4 years' experience of resistance training and trained approximately  $8.6 \pm 2.5$  h per week. A-priori sample size estimation was calculated using G\*Power software (Version 3.1.9.3).<sup>51</sup> Twenty-four subjects were needed to identify differences between two dependant means using a Cohen  $d_z$  of 0.59,<sup>38,49</sup> a two-sided  $\alpha$  level of 0.05, and  $1-\beta$  of 0.80. Informed consent was provided prior to data collection with ethical approval granted by the St Mary's University, Twickenham's ethics committee in accordance with the seventh revision of the Declaration of Helsinki (2013). All sessions were performed at a similar time of day ( $\pm 1$  h) and were separated by 48-72 h. Subjects were instructed to refrain from strenuous exercise, and to avoid alcohol and caffeine consumption within 24 and 12 h of testing respectively.

### Design

A repeated-measures within-subject design was used. Each participant's back-squat 1-RM was assessed, followed by 2 LVP trials utilising incremental loads. The 1-RM assessment provided accurate relative loads in the subsequent sessions.

### Maximum strength assessment

All sessions were initiated with a standardised warm-up protocol. The warm-up consisted of 5 min cycling at 60 RPM and 60 W using an air-braked cycle ergometer (Wattbike Pro, Wattbike Ltd, Nottingham, UK) followed by 5 mobility exercises and 10 repetitions with an unloaded barbell. All repetitions were performed using a squat stand, calibrated 20 kg barbell, and bumper plates (Eleiko<sup>®</sup>, Halmstad, Sweden). Back-squat 1-RM was assessed via an established protocol, as used previously.<sup>42,43</sup> Participants completed five repetitions at 50% 1-RM, three repetitions at 70% and 80% 1-

RM, and one repetition at 90% 1-RM. A maximum of five 1-RM attempts were allowed, with loads increasing by 1-10 kg between attempts. Rest periods were 3 min between warm-up sets and up to 5 min between 1-RM attempts. Adequate squat depth was confirmed by video capture and a strength and conditioning coach with more than 5 years' experience. Participants were also familiarised with the performance of light loads with maximal intent.<sup>50</sup>

### Load-velocity profile assessment

Sessions 2 and 3 assessed each participant's individual LVP. Participants performed 3 repetitions at 20%, 40%, 60% and 80% 1-RM and two repetitions at 90% 1-RM. These intensity zones were chosen based on their high reliability to predict 1-RM using MPV.<sup>49</sup> Up to 3 min rest was provided between sets. All relative loads were rounded up to the nearest 1 kg. Participants were instructed to control the eccentric portion of the back-squat at a self-selected pace until full knee flexion was achieved, followed by execution of the concentric portion with maximal intent until full hip and knee extension was achieved.<sup>38</sup> Participants were told to keep their feet in contact with the ground and to apply constant downward pressure on the barbell onto the superior aspect of the trapezius muscle.<sup>30,49</sup> Visual feedback of velocity scores and verbal encouragement were provided throughout. Adequate squat depth was retrospectively confirmed using validated motion-capture software (Coach's Eye, TechSmith Corporation, USA, version 6.5.3.0)<sup>52,53</sup> via a smartphone camera system (iPhone 11, version iOS 14.4.2; Apple, Cupertino, CA) which captured video footage at 60 fps and 1080p. The smartphone was rigged onto a tripod set at a height of 62 cm (floor to camera) and distance of 250 cm (camera to centre of lifting area) in the sagittal plane. The setup was identical for all trials. Only repetitions with the highest mean concentric velocity outputs were analysed.

Individualised LVPs were constructed for each participant using least squares regression. Relative load was plotted as the independent variable, and velocity measures as the dependent variable. Both linear and polynomial lines were fitted to the data. Post hoc analysis was undertaken to predict 1-RM from these LVPs using the minimum velocity threshold (MVT) method. The MVT for each individual was established using the velocity from the final successful 1-RM attempt ( $1RM_{MVT}$ ). This method was employed due to its greater reliability of indicating general performance potential when compared to alternate 1-RM prediction methods.<sup>54</sup>

### Data acquisition

The Vitruve (Vitruve encoder; Madrid, Spain) was used to measure MPV, MV and PV. The unit was placed on the floor with a Velcro attachment strapped around the

inside of the barbell's right-hand collar. All data was captured at a sampling rate of 100 Hz through Bluetooth connection to a third-generation iPad tablet (iPad; Apple Inc, Cupertino, CA) using the Vitruve teams (version 1.11.2) application. The Vitruve recorded displacement-time-curve data by determining changes in the barbell position. Barbell acceleration was then obtained from double-differentiation of the displacement-time curve. MPV was calculated using average velocity data during the concentric phase until acceleration was less than gravity ( $-9.82 \text{ m}\cdot\text{s}^{-2}$ ). Whereas MV was calculated using average velocity data from the entire concentric phase. Finally, PV was determined as the maximum value in the same concentric period.

### Statistical analyses

All measures were tested for normality using the Shapiro–Wilk test at an  $\alpha$  level of 0.05. All data are presented as mean and SD unless stated otherwise. The confidence intervals (CI) for all analyses were set at 95%. Test re-test reliability of outcome measures from the LPT and 1-RM predictions were assessed at each relative intensity against the magnitude of the intraclass correlation coefficient ( $\text{ICC}_{3,1}$ ), CV and  $ES$ . The strength of the correlations were determined using the following criteria: trivial (0.00–0.09), small (0.10–0.29), moderate (0.30–0.49), large (0.50–0.69), very large (0.70–0.89) or nearly perfect (0.90–1.0).<sup>55</sup> The magnitude of the CV were categorised as poor ( $> 10\%$ ), moderate (5%–10%), or good ( $< 5\%$ ).<sup>55</sup> The magnitude of the  $ES$  were considered trivial ( $< 0.19$ ), small (0.2–0.59), moderate (0.60–1.19), large (1.20–1.99), or very large ( $> 2.0$ ).<sup>55</sup> This study considered the variables highly reliable if they met the following 3 criteria: very large correlation ( $> 0.70$ ), moderate CV ( $\leq 10\%$ ), and a small  $ES$  ( $< 0.60$ ).<sup>38,49</sup> The smallest detectable difference (SDD) was determined using the formula<sup>56</sup>:

$$\text{SDD} = 1.96 \times \sqrt{2} \times \text{SEM}$$

Where SEM is the standard error of the measurement, which was also calculated.

The relationship between relative load and velocity were examined in GraphPad Prism (GraphPad Software, San Diego, CA, USA, version 9.1.0). A one-tailed runs test was performed on all regression models to detect the presence of autocorrelation. The goodness of fit of the load-velocity relationships were assessed using the coefficient of determination ( $r^2$ ) and the standard error of the estimate (SEE). The validity of the 1-RM prediction methods in relation to measured 1-RM were assessed using Bland-Altman analysis (systematic bias and 95% limits of agreement [LOA]), heteroscedasticity of errors ( $r^2$ ), the Pearson correlation coefficient ( $r$ ), CV,  $ES$  and SEE. The threshold for acceptable validity required low heteroscedasticity of errors

( $r^2 < 0.10$ ),<sup>57</sup> a very large correlation ( $> 0.70$ ), moderate CV ( $\leq 10\%$ ) and a small  $ES$  ( $< 0.60$ ).<sup>30,38</sup> Correlations between 1-RM predictions and measured 1-RM were compared using the Fisher  $r$  to  $z$ -transformation and a 1-tailed Meng's  $z$ -test.<sup>58</sup> Finally, comparisons for reliability and validity were assessed for all measures using a two-tailed paired samples  $t$  test with Bonferroni corrections and type 1 error rate set at  $\alpha < 0.05$ . The test re-test reliability and validity analysis were performed via a custom spreadsheet.<sup>59</sup> All other analyses were performed on SPSS (version 27.0: SPSS Inc, Chicago, IL).

## Results

Results from the Shapiro–Wilk test confirmed all measures were normally distributed ( $p > 0.05$ ). Group mean peak knee flexion (20% =  $131.0 \pm 7.3^\circ$ ; 40% =  $131.2^\circ \pm 8.4^\circ$ ; 60% =  $131.3^\circ \pm 8.6^\circ$ ; 80% =  $131.3^\circ \pm 9.4^\circ$ ; 90% =  $131.4^\circ \pm 9.9^\circ$ ;) are as reported. The group mean 1-RM<sub>MVT</sub> were as follows: MPV =  $0.28 \pm 0.05 \text{ m}\cdot\text{s}^{-1}$ ; MV =  $0.26 \pm 0.05 \text{ m}\cdot\text{s}^{-1}$ ; PV =  $0.74 \pm 0.13 \text{ m}\cdot\text{s}^{-1}$ .

### Reliability of outcome measures

Group means between trials of velocity measures are presented in Table 1. Significant differences were found for PV and MV at 60% 1-RM. The test re-test reliability results of velocity measures are shown in Figure 1. MPV and MV were highly reliable at all relative intensities, while PV displayed poor reliability at 60% 1-RM. The low reliability observed at 60% 1-RM was informed by moderate  $ES$  and significant differences between trials (Table 1). The SDD of the outcome measures are shown in Table 2.

### Maximum strength prediction

All LVPs and their corresponding prediction equations can be seen in Figure 2. The runs test produced non-significant results for all linear (MPV:  $p = 0.90$ ; MV:  $p = 0.50$ ; PV:  $p = 0.50$ ) and polynomial (MPV:  $p = 0.90$ ; MV:  $p = 0.90$ ; PV:  $p = 0.90$ ) regression models. All models presented nearly perfect  $r^2$ . Both linear and polynomial regression models for MPV and MV displayed nearly perfect Pearson's correlations with relative load. Whilst PV models showed a very large correlation with relative load (Figure 2). Group mean 1-RM predictions are shown in Table 1. No significant differences were found between mean 1-RM predictions between trial 1 and trial 2 from either prediction model. The test re-test reliability of the 1-RM prediction models are displayed in Figure 3. All models exhibited acceptable reliability.

The paired samples  $t$  test revealed that all PV derived 1-RM predictions were not statistically different to measured 1-RM (PV linear:  $t_{24} = -0.23$ ,  $p = 0.82$ ; PV polynomial:  $t_{21} = 0.24$ ,  $p = 0.81$ ). All other models

**Table 1.** Paired Samples *t* test Results for Velocity Measures and 1-RM Predictions.

Variable	Trial 1	Trial 2	<i>t</i> test	<i>p</i> Value
MPV, mean (SD), m·s <sup>-1</sup>				
20% 1-RM	1.29 (0.19)	1.32 (0.19)	-1.35 <sup>b</sup>	0.19
40% 1-RM	1.06 (0.13)	1.06 (0.13)	-0.12 <sup>b</sup>	0.91
60% 1-RM	0.83 (0.11)	0.81 (0.10)	1.53 <sup>b</sup>	0.14
80% 1-RM	0.57 (0.09)	0.58 (0.09)	0.23 <sup>b</sup>	0.82
90% 1-RM	0.45 (0.10)	0.44 (0.08)	0.62 <sup>b</sup>	0.54
MV, mean (SD), m·s <sup>-1</sup>				
20% 1-RM	1.13 (0.12)	1.14 (0.11)	-1.00 <sup>c</sup>	0.33
40% 1-RM	0.97 (0.10)	0.97 (0.10)	-0.40 <sup>b</sup>	0.69
60% 1-RM	0.77 (0.10)	0.76 (0.08)	2.48 <sup>b</sup>	0.02*
80% 1-RM	0.54 (0.90)	0.54 (0.80)	-0.10 <sup>b</sup>	0.92
90% 1-RM	0.43 (0.10)	0.41 (0.70)	1.10 <sup>b</sup>	0.28
PV, mean (SD), m·s <sup>-1</sup>				
20% 1-RM	1.84 (0.19)	1.87 (0.17)	-1.03 <sup>b</sup>	0.31
40% 1-RM	1.57 (0.14)	1.56 (0.14)	0.35 <sup>b</sup>	0.73
60% 1-RM	1.29 (0.15)	1.26 (0.14)	2.41 <sup>b</sup>	0.02*
80% 1-RM	1.00 (0.15)	1.00 (0.14)	0.19 <sup>b</sup>	0.85
90% 1-RM	0.89 (0.17)	0.88 (0.15)	0.20 <sup>b</sup>	0.84
Linear regression, mean (SD), kg				
MPV	186.9 (30.2)	182.2 (29.6)	1.68 <sup>b</sup>	0.10
MV	191.1 (30.6)	186.7 (30.0)	1.28 <sup>b</sup>	0.21
PV	180.4 (28.7)	176.6 (29.2)	1.07 <sup>b</sup>	0.29
Polynomial regression, mean (SD), kg				
MPV	180.6 (27.8)	184.4 (31.4)	-1.17 <sup>e</sup>	0.25
MV	181.7 (28.1)	180.0 (28.4)	0.66 <sup>f</sup>	0.52
PV	175.5 (30.2)	179.8 (30.1)	-1.04 <sup>g</sup>	0.31

1-RM: 1-repetition maximum; MPV: mean propulsive velocity; MV: mean velocity; PV: peak velocity.

<sup>a</sup>Analyses were performed after the removal of outliers.

<sup>b</sup>The *df* = 24.

<sup>c</sup>The *df* = 23.

<sup>e</sup>The *df* = 20.

<sup>f</sup>The *df* = 22.

<sup>g</sup>The *df* = 16.

\**p* values are significant at < 0.05.

**Table 2.** Smallest detectable difference of velocity measures at 20%, 40%, 60%, 80% and 90% 1-RM.

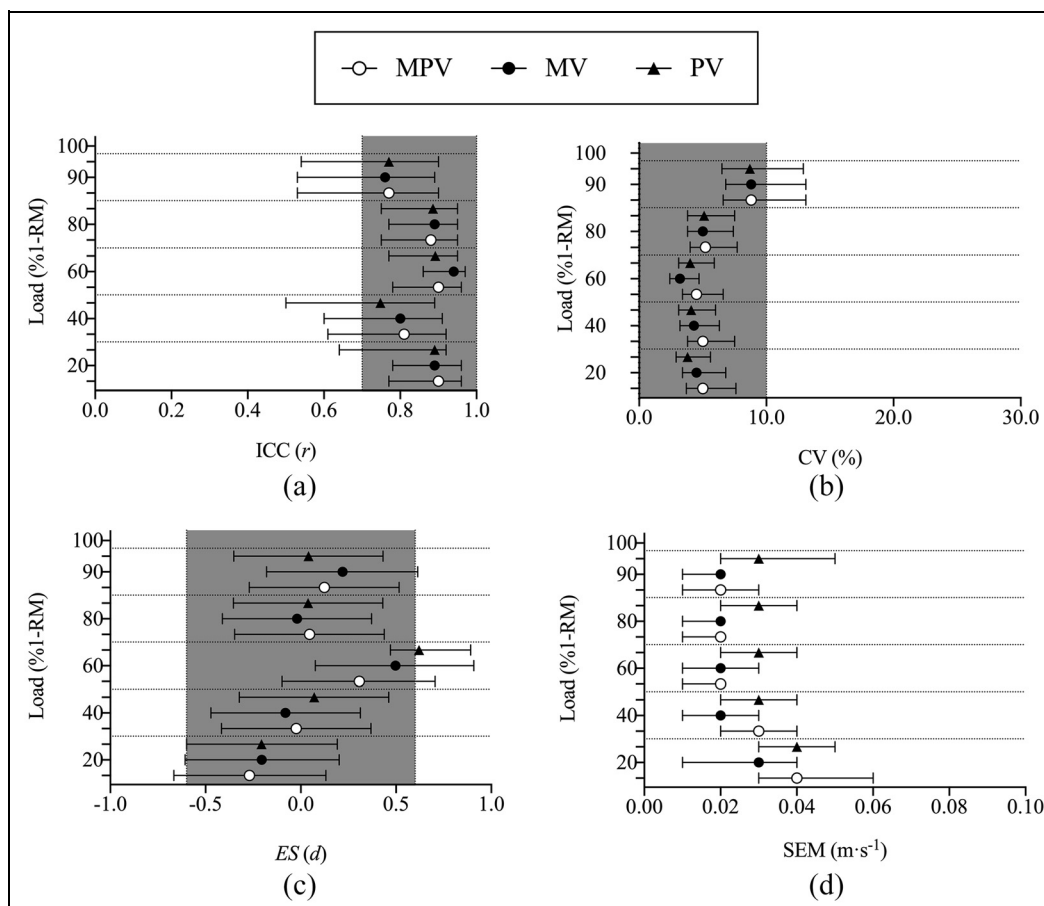
Load (%1-RM)	MPV, m·s <sup>-1</sup>	MV, m·s <sup>-1</sup>	PV, m·s <sup>-1</sup>
20	0.07	0.10	0.10
40	0.06	0.08	0.07
60	0.05	0.08	0.05 <sup>a</sup>
80	0.05	0.08	0.05
90	0.05	0.09	0.05

1-RM: 1-repetition maximum; CV: coefficient of variation; ES: effect size; ICC: intraclass correlation coefficient; MPV: mean propulsive velocity; MV: mean velocity; PV: peak velocity.

<sup>a</sup>Did not meet reliability criteria (ICC > 0.70, CV ≤ 10% and ES < 0.60).

were found to differ significantly from measured 1-RM (MPV linear:  $t_{24} = -3.23, p = 0.004$ ; MPV polynomial:  $t_{24} = -4.09, p < 0.001$ ; MV linear:  $t_{24} = -4.87, p < 0.001$ ; MV polynomial:  $t_{24} = -2.80, p = 0.01$ ). Figures 4 and 5 feature Bland–Altman plots describing the agreement and heteroscedasticity of error present between measured and predicted 1-RM using the respective models. Figure 6 contains further validity findings of 1-RM prediction using data from both trials. The PV polynomial model was the only regression method which satisfied the acceptable criteria of

validity. All models demonstrated significant ( $p < 0.001$ ) correlations between measured 1-RM and predicted 1-RM ranging from very large to nearly perfect. The Fisher *r* to *z*-transformation revealed all 1-RM prediction models were significantly different from each other (linear models:  $p < 0.001$ ; polynomial models:  $p = 0.001–0.03$ ). Poor CV and moderate ES were apparent in all other models. Figure 7 expresses the absolute difference between measured 1-RM and predicted 1-RM. All MPV and MV derived models consistently overestimated 1-RM. Whereas all PV derived



**Figure 1.** Forest plot displaying the test re-test reliability of MPV, MV and PV in the back squat at 20%, 40%, 60%, 80% and 90% 1-RM load: (a) ICC, (b) CV, (c) ES, and (d) SEM. Grey-shaded area indicates the zone of acceptable reliability. Error bars indicate 95% confidence limits. MPV indicates mean propulsive velocity; MV: mean velocity; PV: peak velocity; 1-RM: 1-repetition maximum; ICC: intraclass correlation coefficient; CV: coefficient of variation; ES: effect size; SEM: standard error of the measurement.

models were capable of overestimating and underestimating 1-RM.

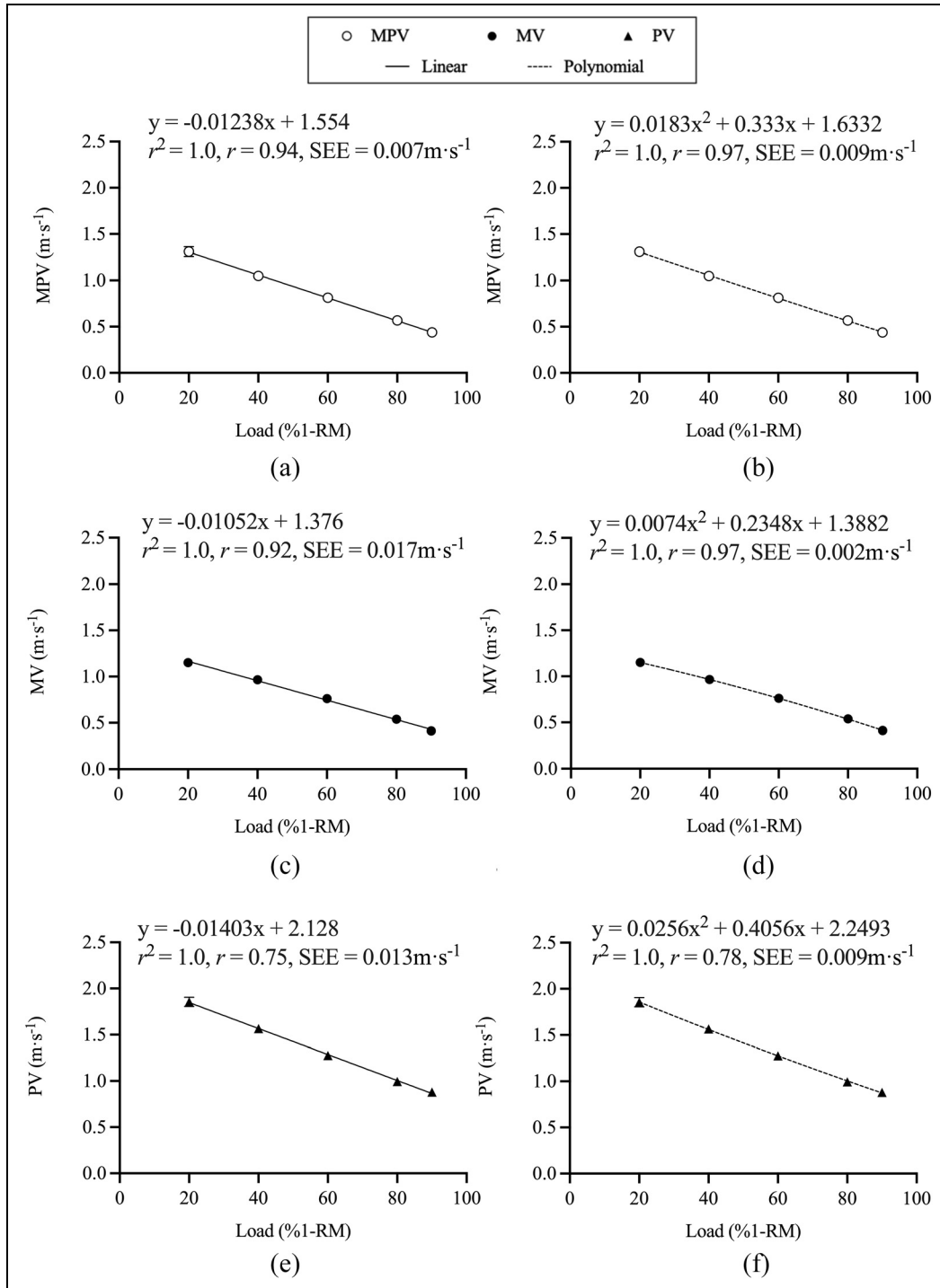
## Discussion

This is the first study to assess the reliability of MPV, MV and PV to develop LVPs using the Vitruve LPT during back-squat exercise. The findings deduce MPV and MV are highly reliable across 20%–90% 1-RM. Similarly, PV was highly reliable at all intensities apart from 60% 1-RM. The secondary aim examined the reliability and validity of 1-RM back-squat predictions derived from MPV, MV and PV using linear and polynomial regression models. Notably, this is the first study to compare all velocity measures and regression methods within the same study. All 1-RM predictions were highly reliable but displayed poor validity. While both the MPV and MV linear models demonstrated acceptable predictive ability, the MV model was marginally better, whereas both PV models showed the worst predictive ability. However, all prediction models overestimated or underestimated 1-RM. Further, all

estimations of 1-RM were significantly different from each other.

## Reliability of outcome measures

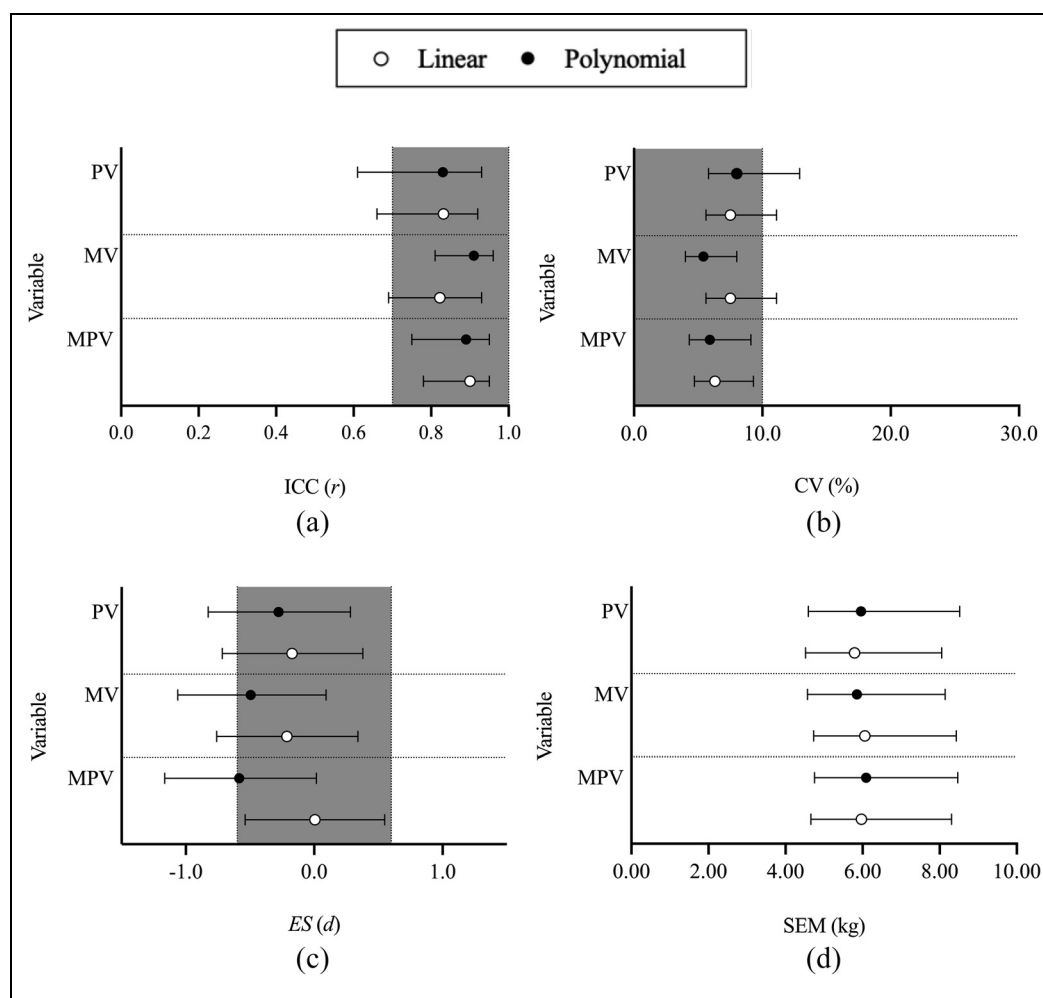
The reliability results from this study compare favourably to that of the GymAware, which is widely regarded as the most accurate LPT.<sup>43</sup> Using the same intensities from this study, Orange et al.<sup>42</sup> found the GymAware produced either the same or more SEM for PV (range = 0.03–0.05 m·s<sup>-1</sup>) and MV (range = 0.06–0.09 m·s<sup>-1</sup>). Interestingly, the 95% CI for ICC were markedly wider than reported in this study for MV (20%: ICC = 0.49–0.86; 60%: ICC = 0.67–0.92; 80%: ICC = 0.66–0.92) and PV (20%: ICC = 0.57–0.89; 60%: ICC = 0.61–0.90; 80%: ICC = 0.42–0.84; 90%: ICC = 0.37–0.82) across light to heavy intensities. Using the correlation classification in this study,<sup>55</sup> the ICC at 20%, 80% and 90% overlap into the moderate category, which was not observed in our study. The tighter CI from the present study could signify confidence in the Vitruve's reliability, although variations in



**Figure 2.** Relationship between relative load (%1-RM) and MPV, MV and PV using linear and polynomial regression: (a) MPV linear fit from 20% to 90% 1-RM, (b) MPV polynomial fit from 20% to 90% 1-RM, (c) MV linear fit from 20% to 90% 1-RM, (d) MV polynomial fit from 20% to 90% 1-RM, (e) PV linear fit from 20% to 90% 1-RM, (f) PV polynomial fit from 20% to 90% 1-RM. Error bars indicate SD. 1-RM indicates 1-repetition maximum; MPV: mean propulsive velocity; MV: mean velocity; PV: peak velocity;  $r^2$ : bivariate coefficient of determination;  $r$ : Pearson correlation coefficient; SEE: standard error of the estimate.

ICC may also imply the load-velocity relationship is participant-dependant.<sup>10,50</sup> Nonetheless, across 20%–90% 1-RM the difference in SEM between the Vitruve and GymAware is marginal for MPV and MV (< 0.02 m·s<sup>-1</sup>).<sup>49</sup> The Vitruve also produced less SEM for MV and PV in comparison to other free-weight squat

investigations.<sup>43,44,54,60,61</sup> Although the Vitruve’s reduced reliability at 90% 1-RM was consistent with other analyses.<sup>38,42,43,49,50</sup> This has been attributed to horizontal variations in the barbell path during the free-weight squat<sup>41</sup> and the use of the SSC.<sup>62,63</sup> This is why previous investigations have used Smith machine



**Figure 3.** Forest plot displaying the test re-test reliability of 1-RM prediction methods using linear and polynomial regression with relative loads between 20% and 90% of 1-RM: (a) ICC, (b) CV, (c) ES and (d) SEM. Grey-shaded area indicates the zone of acceptable reliability. Error bars indicate 95% confidence limits. PV indicates peak velocity; MV: mean velocity; MPV: mean propulsive velocity; 1-RM: 1-repetition maximum; ICC: intraclass correlation coefficient; CV, coefficient of variation; ES, effect size; SEM, standard error of the measurement.

modalities which minimise error, but at the cost of ecological validity. For instance, Martinez-Cava et al.<sup>32</sup> found superior results for PV (ICC = 0.99; CV = 0.86%; SEM = 0.01 m·s<sup>-1</sup>) and MPV (ICC = 0.99; CV = 1.24%; SEM = 0.01 m·s<sup>-1</sup>) from the Vitruve.

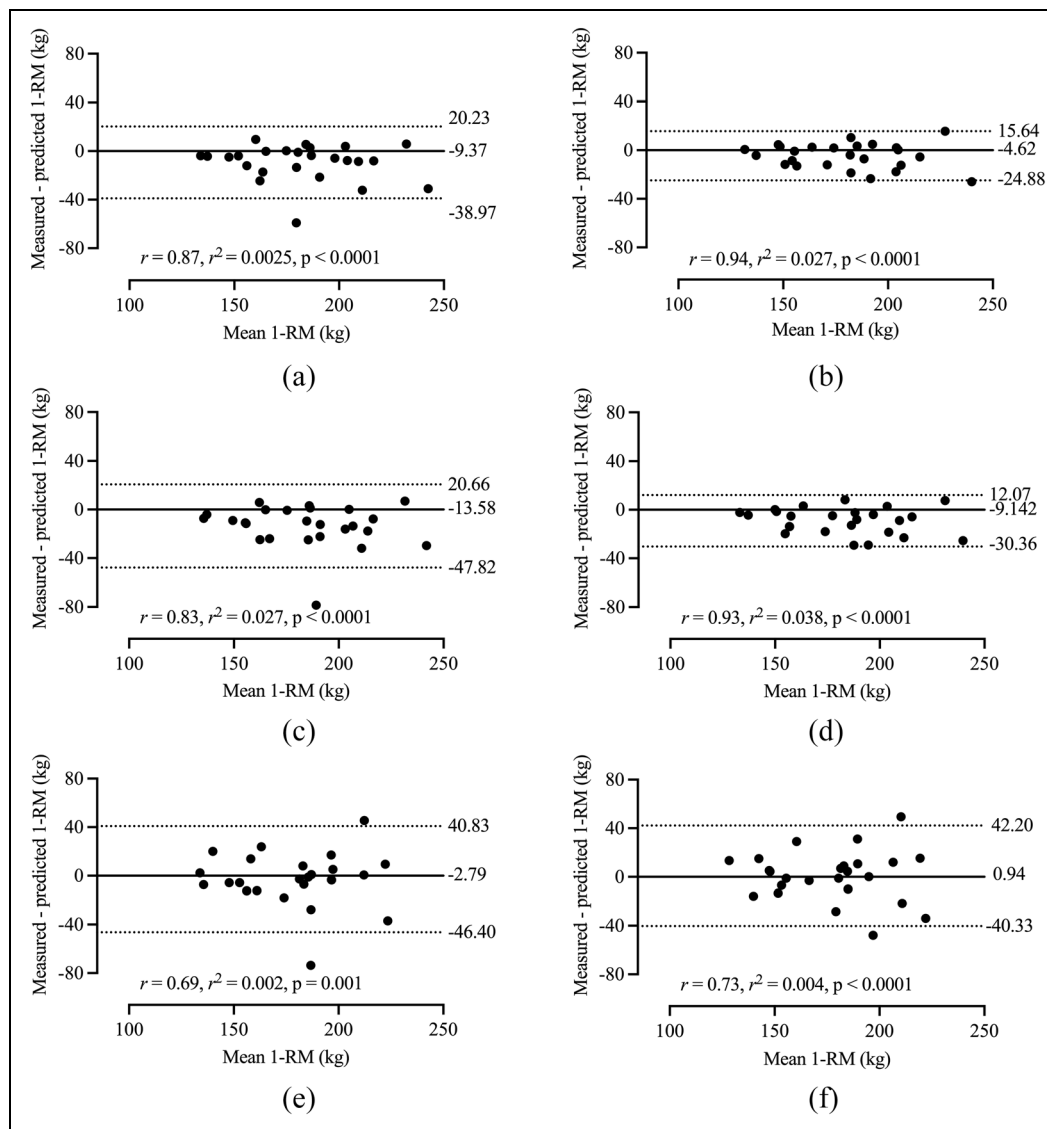
An unexpected finding was the detection of significant differences for MV and PV between trials at 60% 1-RM. This unexplained variance could be attributed to the fast execution of light to moderate loads which may result in a lower degree of limb coordination and more varied muscle activation patterns.<sup>48,49</sup> Collectively, this study recommends all three velocity measures can be used to predict 1-RM. Considering that small differences (< 0.1 m·s<sup>-1</sup>) in movement velocity could represent variations equating to approximately 5% in training intensity<sup>10</sup>: changes in velocity greater than the SDD presented herein may be used to monitor improvements in performance.

### Maximum strength prediction

A novel finding from this study was the repeatability of all back-squat 1-RM estimations, regardless of the velocity measure or regression model used. To date, only 3 studies have investigated back-squat 1-RM prediction using linear regression, MV, and strength trained males.<sup>38,54,64</sup> Neither Banyard et al.<sup>38</sup> nor Hughes et al.<sup>54</sup> detected significant differences between predictions using loads 20%–90% 1-RM, which coincides with this study. Almost identical variation was observed by Hughes et al.<sup>54</sup> (ICC = 0.92; CV = 5.0%), and Banyard et al.<sup>38</sup> (CV = 5.7%; SEM = 8.6 kg; ES = -0.02). Despite each study utilising a different LPT, the similar findings may be explained by methodological parallels in relation to the sample's relative strength (> 1.5 squat body ratio) and squat depth (knee flexion: 121.0° ± 10.9°).<sup>38</sup>

Contrariwise, this study adds to the reports of significant overestimations of 1-RM in the free-weight back-



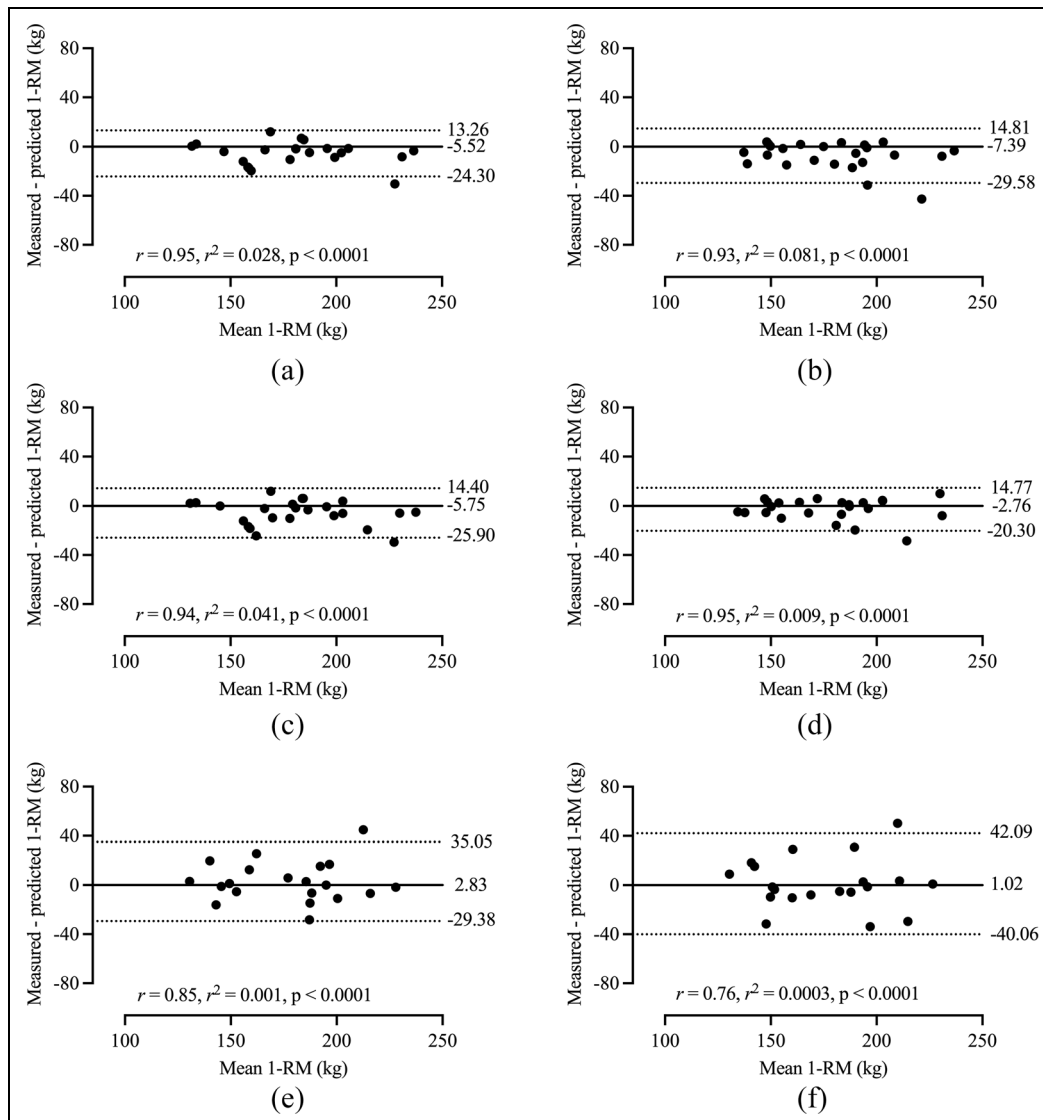


**Figure 4.** Bland-Altman plots illustrating the variation in measured 1-RM against predicted 1-RM using linear regression and loads 20%–90% 1-RM for trials 1 and 2. (a) MPV (kg) trial 1; (b) MPV (kg) trial 2; (c) MV (kg) trial 1; (d) MV (kg) trial 2; (e) PV (kg) trial 1; (f) PV (kg) trial 2. — represents mean systemic bias and - - - represents 95% LOA. 1-RM indicates: 1-repetition maximum; MPV: mean propulsive velocity; MV: mean velocity; PV: peak velocity; LOA: limits of agreement;  $r$ : Pearson product moment correlation;  $r^2$ : coefficient of determination.

squat.<sup>38,54</sup> Large absolute errors and systematic biases were observed, notwithstanding very large to nearly perfect correlations between load and velocity and little to no heteroscedasticity of error. This finding reflects other studies,<sup>65,66</sup> and demonstrates the interindividual variability associated with 1-RM predictions in lower body multi joint exercises.<sup>38,54,67–69</sup> Alternatively, one study reports lower SEE and systematic biases in tandem with a tendency for linear models to underestimate back squat 1-RM.<sup>64</sup> Although this may be attributable to the study's reliance on a different extrapolation method using data up to 80% 1-RM. Other studies found linear models using MV are known to overestimate back-squat 1-RM between 2.2 and 20.0 kg.<sup>38,54</sup> The larger absolute differences found by Banyard et al.<sup>38</sup> may be attributed to the researchers four trial

assessment of 1-RM. Considering the variability of  $1RM_{MVT}$  ( $CV = 25\%$ ), multiple assessments of 1-RM may have amplified the variation observed in that study in comparison to our study. This supports previous findings that daily predictions of maximal strength are not sensitive enough to detect fatigue or modify training load,<sup>70</sup> as originally propositioned.<sup>10,19</sup> Intriguingly, a recent study found bench press 1-RM can be estimated more accurately with machine learning methods than the MVT method,<sup>71</sup> but it is unknown if this can be translated into free-weight examinations. This should be a consideration for future research.

It was not anticipated the data would suggest both PV models possessed the most valid estimation of back-squat 1-RM in relation to measured 1-RM. Under closer inspection, the range of estimated 1-RMs

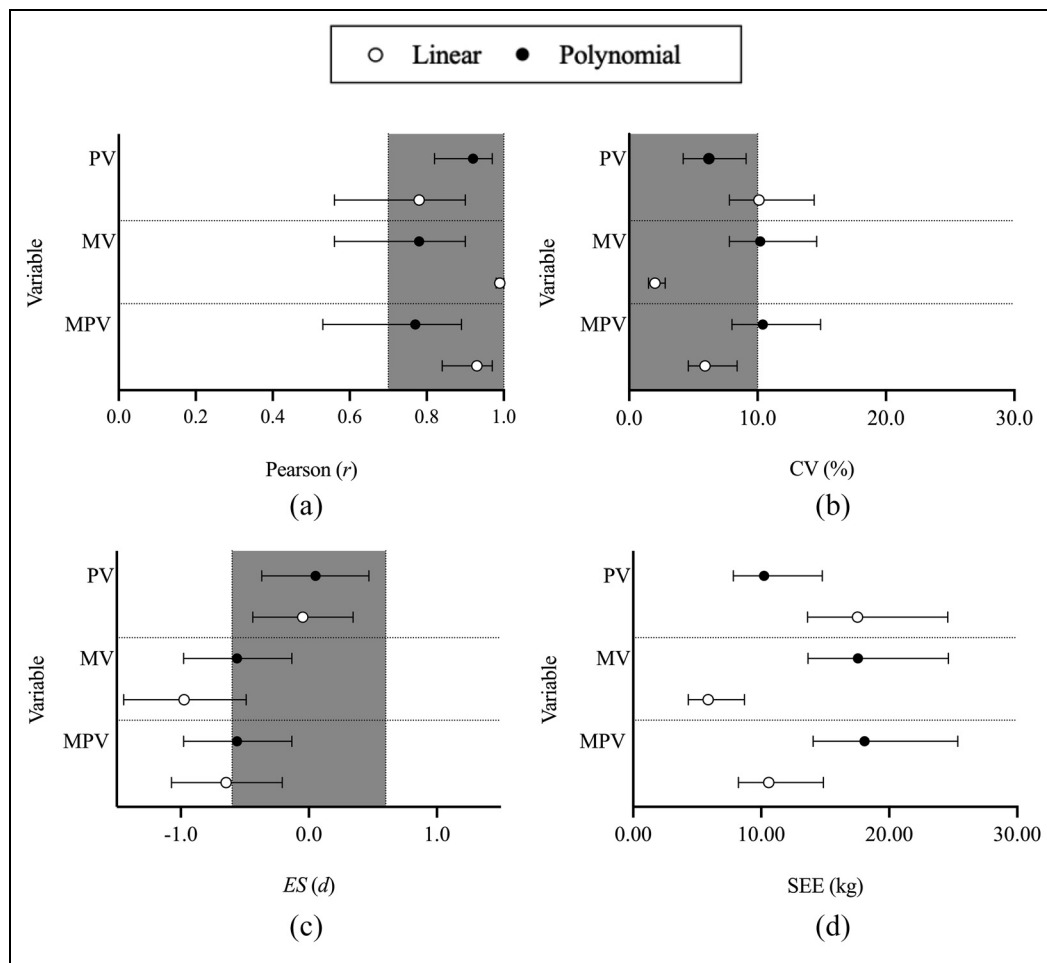


**Figure 5.** Bland-Altman plots illustrating the variation in measured 1-RM against predicted 1-RM using second order polynomial regression and loads 20%–90% 1-RM for trials 1 and 2: (a) MPV (kg) trial 1; (b) MPV (kg) trial 2; (c) MV (kg) trial 1; (d) MV (kg) trial 2; (e) PV (kg) trial 1; (f) PV (kg) trial 2. — represents mean systemic bias and - - - represents 95% LOA. 1-RM indicates: 1-repetition maximum; MPV: mean propulsive velocity; MV: mean velocity; PV: peak velocity; LOA: limits of agreement;  $r$ : Pearson product moment correlation;  $r^2$ : coefficient of determination.

from the PV polynomial and PV linear models were considerably wider in comparison to the MPV and MV models (Figure 7). This study does not recommend the use of PV for back-squat 1-RM prediction. This is informed by both PV models presenting higher SEE and CV than the other models, which is consistent with other investigations.<sup>48</sup> Though PV may be used to monitor ballistic exercises, this is beyond the scope of this study. Altogether, this study found the MV linear model displayed the highest validity.

The higher precision of linear 1-RM estimations in this study weighs in on the assertion that polynomial regression adds an unnecessary complexity.<sup>36,38,49,54,72</sup> Predicting 1-RM beyond the known data of a polynomial curve is known to yield implausible results.<sup>66</sup> In this study two participants ( $n = 2$ ) exhibited a

hyperbolic curve for PV which resulted in no estimation of 1-RM at all. Moreover, some studies advocating polynomial regression have breached the assumption of independence by pooling data.<sup>10,48</sup> This practice has been critiqued within the literature.<sup>5,22</sup> When data from multiple LVP sessions are combined for a given participant, the data observations are no longer independent. This causes autocorrelation which overinflates regression statistics.<sup>73</sup> Consequently, overestimations of relative load may occur. A runs test can be used to detect both autocorrelation and whether a data set differs from its desired model.<sup>74</sup> It is important to note the runs test found none of the linear models in this study departed from linearity. Furthermore, all of the variance between load and velocity was accounted for by the linear models. This objectively infers polynomial



**Figure 6.** Forest plot displaying the validity of 1-RM prediction methods using linear and polynomial regression with relative loads between 20% and 90% of 1-RM. (a)  $r$ . (b) CV. (c) ES. (d) SEE. Grey-shaded area indicates the zone of acceptable validity. Error bars indicate 95% confidence limits. PV indicates peak velocity; MV, mean velocity; MPV, mean propulsive velocity;  $r$ , Pearson correlation coefficient; CV, coefficient of variation; ES, effect size; SEE, standard error of the estimate.

curve fitting in this instance is not only an unnecessary complexity, but also a statistical misdemeanour. The inclusion of a runs test is a distinguishing feature between this study and the extensive work of Thompson et al.,<sup>64</sup> whose findings conflict with ours in recommending quadratic modelling for the prediction of back squat 1-RM. Altogether, the acceptance of a linear load-velocity relationship would be consistent with the growing consensus concerning the linearity of the force velocity relationship during multi-joint movements.<sup>75</sup>

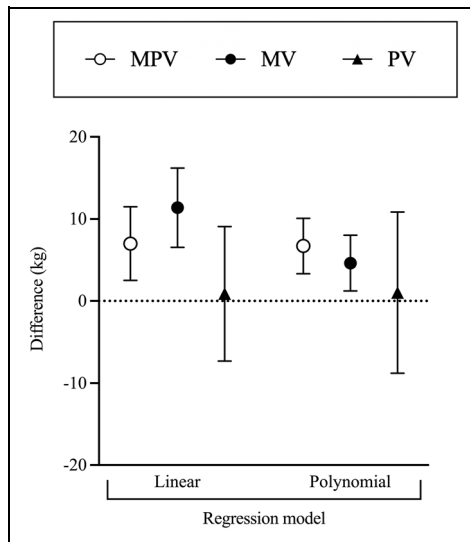
The present study shows that all 3 velocity measures produced by the Vitruve can generate stable individualised LVPs. Although practitioners should be consistent with their use of velocity measure. Lamentably, this study was unable to distinguish the variability associated with the Vitruve LPT from the variability associated with the subjects. Although the Vitruve is known to display very high inter-device reliability during Smith machine back-squat exercise (MPV: SEM = 0.03 m·s<sup>-1</sup>;

SDC = 0.08 m·s<sup>-1</sup>; CV = 3.09%; PV: SEM = 0.02 m·s<sup>-1</sup>; SDC = 0.07 m·s<sup>-1</sup>; CV = 1.60%),<sup>32</sup> future research must consider the influence of biological variation when assessing the reliability of the Vitruve during free weight exercise.<sup>27</sup> Otherwise researchers risk misreporting the true precision of a given device.<sup>37</sup>

Prediction methods may not be sensitive enough to replace direct assessment of 1-RM. However, LVPs using linear regression and MPV or MV may still provide practical information regarding an individual's performance potential. Future research should consider whether a combination of lighter loads, smaller range of velocities, or machine learning can improve the efficiency of 1-RM prediction in free-weight exercise.

### Conclusions

The Vitruve provides reliable LVPs for MPV, MV and PV in the back-squat using strength-trained males. Linear regression is superior for 1-RM prediction. Any



**Figure 7.** Point graph demonstrating the mean absolute difference between measured 1-RM and predicted 1-RM using linear and polynomial regression with relative loads between 20% and 90% of 1-RM. Error bars indicate SD. 1-RM indicates: 1-repetition maximum; MPV: mean propulsive velocity; MV: mean velocity; PV: peak velocity.

further investigations using polynomial regression should publish statistics which confirm the assumptions of regression are met.

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### ORCID iD

Jonathan Kilgallon  <https://orcid.org/0000-0003-2404-1950>

### Supplementary materials

All data generated or analysed during this study are included in this published article [and its supplementary information files].

### References

- McNitt-Gray JL, Sand K, Ramos C, et al. Using technology and engineering to facilitate skill acquisition and improvements in performance. *Proc IMechE, Part P: J Sports Engineering and Technology* 2015; 229(2): 103–115.
- Zatsiorsky VM, Kraemer WJ and Fry AC. *Science and practice of strength training*. 3rd ed. Champaign, IL: Human Kinetics, 2021.
- Bird SP, Tarpenning KM and Marino FE. Designing resistance training programmes to enhance muscular fitness: a review of the acute programme variables. *Sports Med* 2005; 35(10): 841–851.
- Kraemer WJ and Ratamess NA. Fundamentals of resistance training: progression and exercise prescription. *Med Sci Sports Exerc* 2004; 36(4): 674–688.
- Weakley J, Mann B, Banyard H, et al. Velocity-based training: from theory to application. *Strength Cond J* 2021; 43(2): 31–49.
- Nevin J. Autoregulated resistance training: does velocity-based training represent the future? *Strength Cond J* 2019; 41(4): 34–39.
- Pérez-Castilla A, Jerez-Mayorga D, Martínez-García D, et al. Influence of grip width and anthropometric characteristics on the bench-press load-velocity relationship. *Int J Sports Physiol Perform* 2020; 15(7): 1–9.
- Conceição F, Fernandes J, Lewis M, et al. Movement velocity as a measure of exercise intensity in three lower limb exercises. *J Sports Sci* 2016; 34(12): 1099–1106.
- González-Badillo JJ, Pareja-Blanco F, Rodríguez-Rosell D, et al. Effects of velocity-based resistance training on young soccer players of different ages. *J Strength Cond Res* 2015; 29(5): 1329–1338.
- González-Badillo JJ and Sánchez-Medina L. Movement velocity as a measure of loading intensity in resistance training. *Int J Sports Med* 2010; 31(5): 347–352.
- Argus CK, Gill ND, Keogh JW, et al. Acute effects of verbal feedback on upper-body performance in elite athletes. *J Strength Cond Res* 2011; 25(12): 3282–3287.
- Weakley J, Wilson K, Till K, et al. Show me, tell me, encourage me: the effect of different forms of feedback on resistance training performance. *J Strength Cond Res* 2020; 34(11): 3157–3163.
- Weakley JJS, Wilson KM, Till K, et al. Visual feedback attenuates mean concentric barbell velocity loss and improves motivation, competitiveness, and perceived workload in male adolescent athletes. *J Strength Cond Res* 2019; 33(9): 2420–2425.
- Weakley J, Till K, Sampson J, et al. The effects of augmented feedback on sprint, jump, and strength adaptations in rugby union players after a 4-week training program. *Int J Sports Physiol Perform* 2019; 2019:1205–1211.
- Banyard HG, Tufano JJ, Delgado J, et al. Comparison of the effects of velocity-based training methods and traditional 1RM-percent-based training prescription on acute kinetic and kinematic variables. *Int J Sports Physiol Perform* 2019; 14(2): 246–255.
- Dorrell HF, Smith MF and Gee TI. Comparison of velocity-based and traditional percentage-based loading methods on maximal strength and power adaptations. *J Strength Cond Res* 2020; 34(1): 46–53.

17. Callaghan DE, Guy JH, Kean CO, et al. Back squat velocity to assess neuromuscular status of rugby league players following a match. *J Sci Med Sport* 2021; 24(1): 36–40.
18. Jidovtseff B, Harris NK, Crielaard JM, et al. Using the load-velocity relationship for 1RM prediction. *J Strength Cond Res* 2011; 25(1): 267–270.
19. Jovanovic M and Flanagan E. Researched applications of velocity-based strength training. *J Aust Strength Cond* 2014; 22(2): 58–69.
20. Rodriguez-Perea Jerez-Mayorga D, García-Ramos A, et al. Reliability and concurrent validity of a functional electromechanical dynamometer device for the assessment of movement velocity. *Proc IMechE, Part P: J Sports Engineering and Technology* 2021; 235(3): 176–181.
21. Hughes LJ, Peiffer JJ and Scott BR. Reliability and validity of using the push band v2.0 to measure repetition velocity in free-weight and smith machine exercises. *J Strength Cond Res* 2022; 36:e81. DOI: 10.1519/JSC.0000000000004266
22. Orange ST, Metcalfe JW, Liefieith A, et al. Validity and reliability of a wearable inertial sensor to measure velocity and power in the back squat and bench press. *J Strength Cond Res* 2019; 33(9): 2398–2408.
23. Lake J, Augustus S, Austin K, et al. The reliability and validity of the bar-mounted PUSH Band™ 2.0 during bench press with moderate and heavy loads. *J Sports Sci* 2019; 37(23): 2685–2690.
24. Sato K, Beckham G, Carroll K, et al. Validity of wireless device measuring velocity of resistance exercises. *J Trainology* 2015; 4(1): 15–18.
25. Balsalobre-Fernández C, Marchante D, Baz-Valle E, et al. Analysis of wearable and smartphone-based technologies for the measurement of barbell velocity in different resistance training exercises. *Front Physiol* 2017; 8:649.
26. Jovanovic M and Jukic I. Within-unit reliability and between-units agreement of the commercially available linear position transducer and barbell-mounted inertial sensor to measure movement velocity. *J Strength Cond Res*. Epub ahead of print 9 October 2020. DOI: 10.1519/JSC.0000000000003776
27. Weakley J, Chalkley D, Johnston R, et al. Criterion validity, and interunit and between-day reliability of the FLEX for measuring barbell velocity during commonly used resistance training exercises. *J Strength Cond Res* 2020; 34(6): 1519–1524.
28. Pueo B, Lopez JJ, Mossi JM, et al. Video-based system for automatic measurement of barbell velocity in back squat. *Sensors* 2021; 21(3): 925.
29. Muñoz JM, Granero-Gil P and Pino-Ortega J. Reliability and validity of a new accelerometer (wimu®) system for measuring velocity during resistance exercises. *Proc IMechE, Part P: J Sports Engineering and Technology* 2018; 232(3): 218–224.
30. Banyard HG, Nosaka K, Sato K, et al. Validity of various methods for determining velocity, force, and power in the back squat. *Int J Sports Physiol Perform* 2017; 12(9): 1170–1176.
31. Pérez-Castilla A, Piepoli A, Delgado-García G, et al. Reliability and concurrent validity of seven commercially available devices for the assessment of movement velocity at different intensities during the bench press. *J Strength Cond Res* 2019; 33(5): 1258–1265.
32. Martínez-Cava A, Hernández-Belmonte A, Courel-Ibáñez J, et al. Correction: Reliability of technologies to measure the barbell velocity: implications for monitoring resistance training. *PLoS One* 2020; 15(7): e0236073.
33. Zourdos MC, Klemp A, Dolan C, et al. Novel resistance training-specific rating of perceived exertion scale measuring repetitions in reserve. *J Strength Cond Res* 2016; 30(1): 267–275.
34. Sánchez-medina L and González-badillo JJ. Velocity loss as an indicator of neuromuscular fatigue during resistance training. *Med Sci Sports Exerc* 2011; 43(9): 1725–1734.
35. García-Ramos A, Pestaña-Melero FL, Pérez-Castilla A, et al. Mean velocity vs. Mean propulsive velocity vs. Peak velocity: which variable determines bench press relative load with higher reliability? *J Strength Cond Res* 2018; 32(5): 1273–1279.
36. McBurnie AJ, Allen KP, Garry M, et al. The benefits and limitations of predicting one repetition maximum using the load-velocity relationship. *Strength Cond J* 2019; 41(6): 28–40.
37. Weakley J, Morrison M, García-Ramos A, et al. The validity and reliability of commercially available resistance training monitoring devices: a systematic review. *Sports Med* 2021; 51(3): 443–502.
38. Banyard HG, Nosaka K and Haff GG. Reliability and validity of the load-velocity relationship to predict the 1RM back squat. *J Strength Cond Res* 2017; 31(7): 1897–1904.
39. Abbott JC, Wagle JP, Sato K, et al. Validation of inertial sensor to measure barbell kinematics across a spectrum of loading conditions. *Sports* 2020; 8(7): 93.
40. Wirth K, Hartmann H, Sander A, et al. The impact of back squat and leg-press exercises on maximal strength and speed-strength parameters. *J Strength Cond Res* 2016; 30(5): 1205–1212.
41. Cotterman ML, Darby LA and Skelly WA. Comparison of muscle force production using the smith machine and free weights for bench press and squat exercises. *J Strength Cond Res* 2005; 19(1): 169–176.
42. Orange ST, Metcalfe JW, Marshall P, et al. Test-retest reliability of a commercial linear position transducer (GymAware PowerTool) to measure velocity and power in the back squat and bench press. *J Strength Cond Res* 2020; 34(3): 728–737.
43. Thompson SW, Rogerson D, Dorrell HF, et al. The reliability and validity of current technologies for measuring barbell velocity in the free-weight back squat and power clean. *Sports* 2020; 8:7.
44. Janicijevic D, García-Ramos A, Lamas-Cepero JL, et al. Comparison of the two most commonly used gold-standard velocity monitoring devices (GymAware and T-force) to assess lifting velocity during the free-weight barbell back squat exercise. *Proc IMechE, Part P: J Sports Engineering and Technology* 2021; 2021:1–8.
45. Padulo J, Mignogna P, Mignardi S, et al. Effect of different pushing speeds on bench press. *Int J Sports Med* 2012; 33(5): 376–380.
46. McLaughlin TM, Dillman CJ and Gardner TJ. A kinematic model of performance in the parallel squat by champion powerlifters. *Med Sci Sports* 1977; 9(2): 128–133.
47. McIntosh AS. Biomechanical considerations in the design of equipment to prevent sports injury. *Proc IMechE, Part P: J Sports Engineering and Technology* 2012; 226(3–4): 193–199.

48. Sánchez-Medina L, Pallarés JG, Pérez CE, et al. Estimation of relative load from bar velocity in the full back squat exercise. *Sports Med Int Open* 2017; 1(2): E80–E88.
49. Banyard HG, Nosaka K, Vernon AD, et al. The reliability of individualized load-velocity profiles. *Int J Sports Physiol Perform* 2018; 13(6): 763–769.
50. Thompson SW, Rogerson D, Ruddock A, et al. Pooled versus individualized load-velocity profiling in the free-weight back squat and power clean. *Int J Sports Physiol Perform* 2021; 16:825–833.
51. Faul F, Erdfelder E, Lang AG, et al. G\*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav Res Methods* 2007; 39(2): 175–191.
52. Krause DA, Boyd MS, Hager AN, et al. Reliability and accuracy of a goniometer mobile device application for video measurement of the functional movement screen deep squat test. *Int J Sports Phys Ther* 2015; 10(1): 37–44.
53. Kilgallon J, Cave J, Cushion E, et al. Reliability of the coach's eye goniometer application during squat exercise. *Cent Eur J Sport Sci Med* 2022. Epub ahead of print. DOI: 10.18276/cej
54. Hughes LJ, Banyard HG, Dempsey AR, et al. Using a load-velocity relationship to predict one repetition maximum in free-weight exercise: a comparison of the different methods. *J Strength Cond Res* 2019; 33(9): 2409–2419.
55. Hopkins WG, Marshall SW, Batterham AM, et al. Progressive statistics for studies in sports medicine and exercise science. *Med Sci Sports Exerc* 2009; 41(1): 3–13.
56. Beckerman H, Roebroeck ME, Lankhorst GJ, et al. Smallest real difference, a link between reproducibility and responsiveness. *Qual Life Res* 2001; 10(7): 571–578.
57. Atkinson G and Nevill AM. Statistical methods for assessing measurement error (reliability) in variables relevant to sports medicine. *Sports Med* 1998; 26(4): 217–238.
58. Meng XL, Rosenthal R and Rubin DB. Comparing correlated correlation coefficients. *Psychol Bull* 1992; 111(1): 172–175.
59. Hopkins W. Spreadsheets for analysis of validity and reliability by linear regression. *Sports* 2015; 19:36–42.
60. Dorrell HF, Moore JM, Smith MF, et al. Validity and reliability of a linear positional transducer across commonly practised resistance training exercises. *J Sports Sci* 2019; 37(1): 67–73.
61. Lorenzetti S, Lamparter T and Lüthy F. Validity and reliability of simple measurement device to assess the velocity of the barbell during squats. *BMC Res Notes* 2017; 10(1): 707.
62. Reilly T, Morris T and Whyte G. The specificity of training prescription and physiological assessment: A review. *J Sports Sci* 2009; 27(6): 575–589.
63. Garnacho-Castaño MV, Muñoz-González A, Garnacho-Castaño MA, et al. Power– and velocity–load relationships to improve resistance exercise performance. *Proc IMechE, Part P: J Sports Engineering and Technology* 2018; 232(4): 349–359.
64. Thompson SW, Rogerson D, Ruddock A, et al. A novel approach to 1RM prediction using the load-velocity profile: a comparison of models. *Sports* 2021; 9(7): 1–12.
65. Caven EJG, Bryan TJE, Dingley AF, et al. Group versus individualised minimum velocity thresholds in the prediction of maximal strength in trained female athletes. *Int J Environ Res Public Health* 2020; 17:21.
66. Fernandes JFT, Dingley AF, Garcia-Ramos A, et al. Prediction of one repetition maximum using reference minimum velocity threshold values in young and middle-aged resistance-trained males. *Behav Sci* 2021; 11(5): 71.
67. Ruf L, Chéry C and Taylor KL. Validity and reliability of the load-velocity relationship to predict the one-repetition maximum in deadlift. *J Strength Cond Res* 2018; 32(3): 681–689.
68. Jukic I, Garcia-Ramos A, Malecek J, et al. Validity of load-velocity relationship to predict 1 repetition maximum during deadlifts performed with and without lifting straps: the accuracy of six prediction models. *J Strength Cond Res* 2022; 36:902–910. DOI: 10.1519/JSC.0000000000003596
69. Haff GG, Garcia-Ramos A and James LP. Using velocity to predict the maximum dynamic strength in the power clean. *Sports* 2020; 8:9.
70. Hughes LJ, Banyard HG, Dempsey AR, et al. Using load-velocity relationships to quantify training-induced fatigue. *J Strength Cond Res* 2019; 33(3): 762–773.
71. Balsalobre-Fernández C and Kipp K. Use of machine-learning and load-velocity profiling to estimate 1-repetition maximums for two variations of the bench-press exercise. *Sports* 2021; 9(3): 39.
72. Janicijevic D, Jukic I, Weakley J, et al. Bench press 1-repetition maximum estimation through the individualized load-velocity relationship: comparison of different regression models and minimal velocity thresholds. *Int J Sports Physiol Perform* 2021; 2020:1–8.
73. Persaud R, Bland JM and Altman DG. Correlation, regression, and repeated data. *BMJ* 1994; 308(6942): 1510–1510.
74. Motulsky H and Christopoulos A. *Fitting models to biological data using linear and nonlinear regression: A practical guide to curve fitting*. New York: Oxford University Press, 2004. pp.35–47.
75. Iglesias-Soler E, Mayo X, Rial-Vázquez J, et al. Reliability of force-velocity parameters obtained from linear and curvilinear regressions for the bench press and squat exercises. *J Sports Sci* 2019; 37(22): 2596–2603.