

TITLE

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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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Preferred running head: Accuracy of velocities and 1-RM prediction

1 **Abstract**

2

3 **Purpose:** to examine the reliability of load-velocity profiles (LVPs) and validity of 1-
4 repetition maximum (1-RM) prediction methods in the back-squat using the novel Vitruve
5 linear position transducer (LPT). **Methods:** twenty-five men completed a back-squat 1-RM
6 assessment followed by 2 LVP trials using 5 incremental loads (20%-40%-60%-80%-90% 1-
7 RM). Mean propulsive velocity (MPV), mean velocity (MV), and peak velocity (PV) were
8 measured via a (LPT). Linear and polynomial regression models were applied to the data.
9 The reliability and validity criteria were defined *a-priori* as intraclass correlation coefficient
10 (ICC) or Pearson correlation coefficient (r) > 0.70 , coefficient of variation (CV) $\leq 10\%$, and
11 effect size (ES) < 0.60 . Bland-Altman analysis and heteroscedasticity of errors (r^2) were also
12 assessed. **Results:** the main findings indicated MPV, MV and PV were reliable across 20-
13 90% 1-RM (CV $< 8.8\%$). The secondary findings inferred all prediction models had
14 acceptable reliability (CV $< 8.0\%$). While the MPV linear and MV linear models
15 demonstrated the best estimation of 1-RM (CV $< 5.9\%$), all prediction models displayed
16 unacceptable validity and a tendency to overestimate or underestimate 1-RM. Mean
17 systematic bias (-7.29 to 2.83 kg) was detected for all prediction models, along with little to
18 no heteroscedasticity of errors for linear ($r^2 < 0.04$) and polynomial models ($r^2 < 0.08$).
19 Furthermore, all 1-RM estimations were significantly different from each other ($p < 0.03$).
20 **Conclusions:** MPV, MV, and PV can provide reliable LVPs and repeatable 1-RM
21 predictions. However, prediction methods may not be sensitive enough to replace direct
22 assessment of 1-RM. Polynomial regression is not suitable for 1-RM prediction.
23
24 **Key words:** Velocity-Based Training, Load-Velocity Relationship, Relative Load,
25 Regression, Linear Position Transducer

26 1.0 Introduction

27 The ongoing collaboration between coaches, engineers and scientists has brought about
28 a multitude of technology which helps athletes to train and prepare for the demands of
29 competition.¹ The ability to objectively quantify, monitor, and analyse resistance training
30 variables are an essential component for practitioners aiming to maximise adaptations.² One
31 of the most important variables for program design is training volume as it influences neural
32 and morphological adaptations.^{3,4} Velocity-based training (VBT) uses velocity to inform or
33 enhance training practice,⁵ and has received considerable interest in recent years for the
34 regulation of training volume.^{6,7} VBT utilises the well-established inverse linear relationship
35 between relative load and movement velocity to produce a load-velocity profile (LVP) which
36 provides insights into an individual's current physiological status.⁸⁻¹⁰ Applications of VBT
37 include the provision of feedback during resistance training,¹¹⁻¹⁴ autoregulatory prescriptive
38 methods,^{15,16} fatigue monitoring,¹⁷ and prediction of 1-repetition maximum (1-RM) from
39 submaximal loads.^{18,19} The successful implementation of VBT relies on instruments which
40 are reliable and valid.²⁰ While it is widely accepted that linear position transducers (LPTs)
41 outperform other technologies including accelerometers and optic laser devices,²¹⁻²⁹ the price
42 of an LPT presents a barrier of entry for practitioners.³⁰

43 Cost concerns may be alleviated by the Vitruve (previously Speed4Lifts) which is the
44 cheapest commercially available LPT. Real-time feedback is provided via a digital display on
45 the device and a smartphone application, the latter of which also generates a wider range of
46 features including load summary reports. When compared to 6 other devices, the Vitruve
47 displayed the highest validity ($r^2 = 0.95-0.96$) and the lowest levels of variability (coefficient
48 of variation [CV] = 2.61%) during Smith machine bench press exercise.³¹ Very high intra-
49 device reliability for the Vitruve has also been found during Smith machine back-squat
50 exercise.³² However, previous studies reliance on un-trained participants and Smith machine

51 modalities limits the transferability of findings to strength-trained populations.^{31,32} This is
52 because stronger participants exhibit different LVPs due to an increased capacity to
53 overcome the sticking region associated with heavy loads at a lower concentric velocity.³³

54 The Vitruve can also be distinguished from other LPTs for its ability to calculate all 3
55 commonly used variables: mean propulsive velocity (MPV), mean velocity (MV), and peak
56 velocity (PV). MPV is the average velocity from the start of the concentric phase until
57 acceleration is less than gravity ($-9.81 \text{ m}\cdot\text{s}^{-2}$).^{10,34} Whereas MV is the average velocity
58 across the entire concentric phase.³⁵ PV is the highest recorded velocity attained from the
59 concentric phase.³⁶ MPV accounts for the breaking phase of the movement, whereas MV
60 does not. Historically, MV has been the most commonly reported variable on a number of
61 devices,⁵ and has featured in considerably more research as a result.³⁷ Nonetheless, while
62 both MPV and MV have been used to generate LVPs of nonaerial movements, inconsistent
63 findings have made it unclear which measure is best for training prescription.^{38,39} This may
64 be associated with variations in research methodologies in relation to sample size and
65 strength ability, exercise type, and statistical approaches. Hence, a comprehensive
66 comparison of these velocity measures would help coaches to understand and monitor the
67 performance potential of their athletes.

68 No research has examined the test-retest reliability of velocity measures from the
69 Vitruve during free-weight exercise. The back-squat is a closed kinetic chain exercise often
70 used by practitioners to enable the transfer of strength adaptations into athletic performance.⁴⁰
71 Unlike Smith machine modalities, the back-squat can involve greater horizontal movement of
72 the barbell which is known to affect velocity measures calculated by LPTs.⁴¹ Therefore, the
73 findings from Smith machine investigations of the Vitruve should not be used to infer the
74 LPTs reliability during free-weight exercise. While a plethora of studies have investigated the
75 reliability of LPTs during lower body free-weight exercises,⁴²⁻⁴⁴ the reliability of the Vitruve

76 during back-squat exercise is not known. Given the Vitruve's substantially lower retail value,
77 this is worthy of further investigation.

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

87 To date, lower body Smith machine protocols have generated accurate predictions of 1-
88 RM ($R^2 = 0.94-0.96$) using submaximal loads during full-depth squat exercise.^{8,48} However,
89 Banyard et al³⁸ found back-squat 1-RM predictions were not only different to measured 1-
90 RM (effect size $[ES] = 0.71-1.04$), but all 1-RM prediction equations were different from
91 each other. This result was attributed to high between-session variability of the velocity used
92 to predict 1-RM. Subsequently, the authors suggested the validity of back-squat 1-RM
93 predictions could be improved using MPV or second order polynomial regression.
94 Interestingly, recent research reported no differences between back-squat LVPs derived from
95 linear or nonlinear regression using MPV, MV, and PV.^{49,50} Furthermore, Thompson et al⁵⁰
96 found individualised back-squat LVPs for MV ($r = 0.98-0.99$) and PV ($r = 0.98-0.99$) were
97 stable and displayed improved goodness of fit when using nonlinear regression. However,
98 neither Banyard et al⁴⁹ nor Thompson et al⁵⁰ published any data relating to 1-RM prediction.
99 This may be attributed to the added complexity of applying nonlinear regression fits outside
100 of dedicated software platforms.⁴⁹ Collectively, while the usefulness of different regression

101 models and velocity measures have previously been examined, their precision in estimating
102 back-squat 1-RM has not been compared within the same study. Further examination would
103 also be useful for engineers. For instance, in the event polynomial models are shown to be
104 more accurate than their linear counterparts, this could guide future innovations to software
105 development which may enhance the efficiency of training programs.

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

112

113 **2.0 Materials and methods**

114 **2.1 Subjects**

115 Twenty-five strength-trained males (mean \pm SD; age = 25.2 ± 2.8 y; body mass = 91.2
116 ± 14.0 kg; stature = 180.0 ± 9.7 cm; back-squat = 1-RM 178.0 ± 28.0 kg; relative 1-RM = 2.0
117 ± 0.4 x/body mass) were recruited for this study. All subjects had at least 4 years' experience
118 of resistance training and trained approximately 8.6 ± 2.5 hours per week. *A-priori* sample
119 size estimation was calculated using G*Power software (Version 3.1.9.3).⁵¹ Twenty-four
120 subjects were needed to identify differences between 2 dependant means using a Cohen d_z of
121 0.59 ,^{38,49} a 2-sided α level of 0.05, and $1-\beta$ of 0.80. Informed consent was provided prior to
122 data collection with ethical approval granted by the St Mary's University, Twickenham's
123 ethics committee in accordance with the seventh revision of the Declaration of Helsinki
124 (2013). All sessions were performed at a similar time of day (± 1 h) and were separated by

125 48-72 h. Subjects were instructed to refrain from strenuous exercise, and to avoid alcohol and
126 caffeine consumption within 24 h and 12 h of testing respectively.

127

128 **2.2 Design**

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

132

133 **2.3 Maximum strength assessment**

134 All sessions were initiated with a standardised warm-up protocol. The warm-up
135 consisted of 5 minutes cycling at 60 RPM and 60 W using an air-braked cycle ergometer
136 (Wattbike Pro, Wattbike Ltd, Nottingham, UK) followed by 5 mobility exercises and 10
137 repetitions with an unloaded barbell. All repetitions were performed using a squat stand,
138 calibrated 20 kg barbell, and bumper plates (Eleiko®, Halmstad, Sweden). Back-squat 1-RM
139 was assessed via an established protocol, as used previously.^{42,43} Participants completed 5
140 repetitions at 50% 1-RM, 3 repetitions at 70% and 80% 1-RM, and 1 repetition at 90% 1-RM.
141 A maximum of 5 1-RM attempts were allowed, with loads increasing by 1-10 kg between
142 attempts. Rest periods were 3 minutes between warm-up sets and up to 5 minutes between 1-
143 RM attempts. Adequate squat depth was confirmed by video capture and a strength and
144 conditioning coach with more than 5 years' experience. Participants were also familiarised
145 with the performance of light loads with maximal intent.⁵⁰

146

147 **2.4 Load-velocity profile assessment**

148 Sessions 2 and 3 assessed each participant's individual LVP. Participants performed 3
149 repetitions at 20%, 40%, 60% and 80% 1-RM and 2 repetitions at 90% 1-RM. These intensity

150 zones were chosen based on their high reliability to predict 1-RM using MPV.⁴⁹ Up to 3
151 minutes rest was provided between sets. All relative loads were rounded up to the nearest 1
152 kg. Participants were instructed to control the eccentric portion of the back-squat at a self-
153 selected pace until full knee flexion was achieved, followed by execution of the concentric
154 portion with maximal intent until full hip and knee extension was achieved.³⁸ Participants
155 were told to keep their feet in contact with the ground and to apply constant downward
156 pressure on the barbell onto the superior aspect of the trapezius muscle.^{30,49} Visual feedback
157 of velocity scores and verbal encouragement were provided throughout. Adequate squat
158 depth was retrospectively confirmed using validated motion-capture software (Coach's Eye,
159 TechSmith Corporation, USA, version 6.5.3.0)⁵² via a smartphone camera system (iPhone 11,
160 version iOS 14.4.2; Apple, Cupertino, CA) which captured video footage at 60 fps and
161 1080p. The smartphone was rigged onto a tripod set at a height of 62 cm (floor to camera)
162 and distance of 250 cm (camera to centre of lifting area) in the sagittal plane. The setup was
163 identical for all trials. Only repetitions with the highest mean concentric velocity outputs
164 were analysed.

165 Individualised LVPs were constructed for each participant using least squares
166 regression. Relative load was plotted as the independent variable, and velocity measures as
167 the dependent variable. Both linear and polynomial lines were fitted to the data. Post hoc
168 analysis was undertaken to predict 1-RM from these LVPs using the minimum velocity
169 threshold (MVT) method. The MVT for each individual was established using the velocity
170 from the final successful 1-RM attempt ($1RM_{MVT}$). This method was employed due to its
171 greater reliability of indicating general performance potential when compared to alternate 1-
172 RM prediction methods.⁵³

173

174 ***2.5 Data acquisition***

175 The Vitruve (Vitruve encoder; Madrid, Spain) was used to measure MPV, MV, and
176 PV. The unit was placed on the floor with a Velcro attachment strapped around the inside of
177 the barbell's right-hand collar. All data was captured at a sampling rate of 100 Hz through
178 Bluetooth connection to a third-generation iPad tablet (iPad; Apple Inc, Cupertino, CA) using
179 the Vitruve teams (version 1.11.2) application. The Vitruve recorded displacement-time-
180 curve data by determining changes in the barbell position. Barbell acceleration was then
181 obtained from double-differentiation of the displacement-time curve. MPV was calculated
182 using average velocity data during the concentric phase until acceleration was less than
183 gravity ($-9.82 \text{ m}\cdot\text{s}^{-2}$). Whereas MV was calculated using average velocity data from the
184 entire concentric phase. Finally, PV was determined as the maximum value in the same
185 concentric period.

186

187 ***2.6 Statistical analyses***

188 All measures were tested for normality using the Shapiro-Wilk test at an α level of
189 0.05. All data are presented as mean and SD unless stated otherwise. The confidence intervals
190 (CI) for all analyses were set at 95%. Test re-test reliability of outcome measures from the
191 LPT and 1-RM predictions were assessed at each relative intensity against the magnitude of
192 the intraclass correlation coefficient ($\text{ICC}_{3,1}$), CV, and *ES*. The strength of the correlations
193 were determined using the following criteria: trivial (0.00-0.09), small (0.10-0.29), moderate
194 (0.30-0.49), large (0.50-0.69), very large (0.70-0.89), or nearly perfect (0.90-1.0).⁵⁴ The
195 magnitude of the CV were categorised as poor ($> 10\%$), moderate (5-10%), or good ($< 5\%$).⁵⁴
196 The magnitude of the *ES* were considered trivial (< 0.19), small (0.2-0.59), moderate (0.60-
197 1.19), large (1.20-1.99), or very large (> 2.0).⁵⁴ This study considered the variables highly
198 reliable if they met the following 3 criteria: very large correlation (> 0.70), moderate CV (\leq

199 10%), and a small *ES* (< 0.60).^{38,49} The smallest detectable difference (SDD) was determined
200 using the formula⁵⁵:

$$201 \quad \text{SDD} = 1.96 \times \sqrt{2} \times \text{SEM}$$

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

203 The relationship between relative load and velocity were examined in GraphPad Prism
204 (GraphPad Software, San Diego, CA, USA, version 9.1.0). A 1-tailed runs test was
205 performed on all regression models to detect the presence of autocorrelation. The goodness of
206 fit of the load-velocity relationships were assessed using the coefficient of determination (r^2)
207 and the standard error of the estimate (SEE). The validity of the 1-RM prediction methods in
208 relation to measured 1-RM were assessed using Bland-Altman analysis (systematic bias and
209 95% limits of agreement [LOA]), heteroscedasticity of errors (r^2), the Pearson correlation
210 coefficient (r), CV, *ES*, and SEE. The threshold for acceptable validity required low
211 heteroscedasticity of errors ($r^2 < 0.10$),⁵⁶ a very large correlation (> 0.70), moderate CV (\leq
212 10%), and a small *ES* (< 0.60).^{30,38} Correlations between 1-RM predictions and measured 1-
213 RM were compared using the Fisher r to z -transformation and a 1-tailed Meng's z -test.⁵⁷
214 Finally, comparisons for reliability and validity were assessed for all measures using a 2-
215 tailed paired samples t test with Bonferroni corrections and type 1 error rate set at $\alpha < 0.05$.
216 The test re-test reliability and validity analysis were performed via a custom spreadsheet.⁵⁸
217 All other analyses were performed on SPSS (version 27.0: SPSS Inc, Chicago, IL).

218

219 **3.0 Results**

220 Results from the Shapiro-Wilk test confirmed all measures were normally distributed (p
221 > 0.05). Group mean peak knee flexion (20% = $131.0 \pm 7.3^\circ$; 40% = $131.2 \pm 8.4^\circ$; 60% =
222 $131.3 \pm 8.6^\circ$; 80% = $131.3 \pm 9.4^\circ$; 90% = $131.4 \pm 9.9^\circ$;) are as reported. The group mean 1-

223 RM_{MVT} 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 ± 0.13
224 $\text{m}\cdot\text{s}^{-1}$.

225

226 ***3.1 Reliability of outcome measures***

227 [Table 1 here]

228 [Figure 1 here]

229

230 Group means between trials of velocity measures are presented in table 1. Significant
231 differences were found for PV and MV at 60% 1-RM. The test re-test reliability results of
232 velocity measures are shown in figure 1. MPV and MV were highly reliable at all relative
233 intensities, while PV displayed poor reliability at 60% 1-RM. The low reliability observed at
234 60% 1-RM was informed by moderate *ES* and significant differences between trials (table 1).
235 The SDD of the outcome measures are shown in table 2.

236

237 [Table 2 here]

238

239 ***3.2 Maximum strength prediction***

240

241 [Figure 2 here]

242

243 All LVPs and their corresponding prediction equations can be seen in figure 2. The runs test
244 produced non-significant results for all linear (MPV: $p = 0.90$; MV: $p = 0.50$; PV: $p = 0.50$)
245 and polynomial (MPV: $p = 0.90$; MV: $p = 0.90$; PV: $p = 0.90$) regression models. All models
246 presented nearly perfect r^2 . Both linear and polynomial regression models for MPV and MV
247 displayed nearly perfect Pearson's correlations with relative load. Whilst PV models showed

248 a very large correlation with relative load (figure 2). Group mean 1-RM predictions are
249 shown in table 1. No significant differences were found between mean 1-RM predictions
250 between trial 1 and trial 2 from either prediction model. The test re-test reliability of the 1-
251 RM prediction models are displayed in figure 3. All models exhibited acceptable reliability.

252

253 [Figure 3 here]

254 [Figure 4 here]

255 [Figure 5 here]

256 [Figure 6 here]

257

258 The paired samples *t* test revealed that all PV derived 1-RM predictions were not
259 statistically different to measured 1-RM (PV linear: $t_{24} = -0.23$, $p = 0.82$; PV polynomial: t_{21}
260 $= 0.24$, $p = 0.81$). All other models were found to differ significantly from measured 1-RM
261 (MPV linear: $t_{24} = -3.23$, $p = 0.004$; MPV polynomial: $t_{24} = -4.09$, $p < 0.001$; MV linear: t_{24}
262 $= -4.87$, $p < 0.001$; MV polynomial: $t_{24} = -2.80$, $p = 0.01$). Figures 4 and 5 feature Bland-
263 Altman plots describing the agreement and heteroscedasticity of error present between
264 measured and predicted 1-RM using the respective models. Figure 6 contains further validity
265 findings of 1-RM prediction using data from both trials. The PV polynomial model was the
266 only regression method which satisfied the acceptable criteria of validity. All models
267 demonstrated significant ($p < 0.001$) correlations between measured 1-RM and predicted 1-
268 RM ranging from very large to nearly perfect. The Fisher *r* to *z*-transformation revealed all 1-
269 RM prediction models were significantly different from each other (linear models: $p < 0.001$;
270 polynomial models: $p = 0.001-0.03$). Poor CV and moderate *ES* were apparent in all other
271 models. Figure 7 expresses the absolute difference between measured 1-RM and predicted 1-

272 RM. All MPV and MV derived models consistently overestimated 1-RM. Whereas all PV
273 derived models were capable of overestimating and underestimating 1-RM.

274

275 [Figure 7 here]

276

277 **4.0 Discussion**

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

289

290 ***4.1 Reliability of outcome measures***

291 The reliability results from this study compare favourably to that of the GymAware,
292 which is widely regarded as the most accurate LPT.⁴³ Using the same intensities from this
293 study, Orange et al⁴² found the GymAware produced either the same or more SEM for PV
294 (range = 0.03-0.05 m·s⁻¹) and MV (range = 0.06-0.09 m·s⁻¹). Interestingly, the 95% CI for
295 ICC were markedly wider than reported in this study for MV (20%: ICC = 0.49-0.86; 60%:
296 ICC = 0.67-0.92; 80%: ICC = 0.66-0.92) and PV (20%: ICC = 0.57-0.89; 60%: ICC = 0.61-

297 0.90; 80%: ICC = 0.42-0.84; 90%: ICC = 0.37-0.82) across light to heavy intensities. Using
298 the correlation classification in this study,⁵⁴ the ICC at 20%, 80%, and 90% overlap into the
299 moderate category, which was not observed in our study. The tighter CI from the present
300 study could signify confidence in the Vitruve's reliability, although variations in ICC may
301 also imply the load-velocity relationship is participant-dependant.^{10,50} Nonetheless, across 20-
302 90% 1-RM the difference in SEM between the Vitruve and GymAware is marginal for MPV
303 and MV ($< 0.02 \text{ m}\cdot\text{s}^{-1}$).⁴⁹ The Vitruve also produced less SEM for MV and PV in comparison
304 to other free-weight squat investigations.^{43,44,53,59,60} Although the Vitruve's reduced reliability
305 at 90% 1-RM was consistent with other analyses.^{38,42,43,49,50} This has been attributed to
306 horizontal variations in the barbell path during the free-weight squat⁴¹ and the use of the
307 SSC.^{61,62} This is why previous investigations have used Smith machine modalities which
308 minimise error, but at the cost of ecological validity. For instance, Martinez-Cava et al³²
309 found superior results for PV (ICC = 0.99; CV = 0.86%; SEM = $0.01 \text{ m}\cdot\text{s}^{-1}$) and MPV (ICC =
310 0.99; CV = 1.24%; SEM = $0.01 \text{ m}\cdot\text{s}^{-1}$) from the Vitruve.

311 An unexpected finding was the detection of significant differences for MV and PV
312 between trials at 60% 1-RM. This unexplained variance could be attributed to the fast
313 execution of light to moderate loads which may result in a lower degree of limb coordination
314 and more varied muscle activation patterns.^{48,49} Collectively, this study recommends all 3
315 velocity measures can be used to predict 1-RM. Considering that small differences (< 0.1
316 $\text{m}\cdot\text{s}^{-1}$) in movement velocity could represent variations equating to approximately 5% in
317 training intensity¹⁰: changes in velocity greater than the SDD presented herein may be used to
318 monitor improvements in performance.

319

320 ***4.2 Maximum strength prediction***

321 A novel finding from this study was the repeatability of all back-squat 1-RM
322 estimations, regardless of the velocity measure or regression model used. To date, only 3
323 studies have investigated back-squat 1-RM prediction using linear regression, MV, and
324 strength trained males.^{38,53,63} Neither Banyard et al³⁸ nor Hughes et al⁵³ detected significant
325 differences between predictions using loads 20-90% 1-RM, which coincides with this study.
326 Almost identical variation was observed by Hughes et al⁵³ (ICC = 0.92; CV = 5.0%), and
327 Banyard et al³⁸ (CV = 5.7%; SEM = 8.6 kg; ES = -0.02). In spite of each study utilising a
328 different LPT, the similar findings may be explained by methodological parallels in relation
329 to the sample's relative strength (> 1.5 squat body ratio) and squat depth (knee flexion: 121.0
330 \pm 10.9°).³⁸

331 Contrariwise, this study adds to the reports of significant overestimations of 1-RM in
332 the free-weight back-squat.^{38,53} Large absolute errors and systematic biases were observed,
333 notwithstanding very large to nearly perfect correlations between load and velocity and little
334 to no heteroscedasticity of error. This finding reflects other studies,^{64,65} and demonstrates the
335 interindividual variability associated with 1-RM predictions in lower body multi joint
336 exercises.^{38,53,66-68} Alternatively, 1 study reports lower SEE and systematic biases in tandem
337 with a tendency for linear models to underestimate back squat 1-RM.⁶³ Although this may be
338 attributable to the study's reliance on a different extrapolation method using data up to 80%
339 1-RM. Other studies found linear models using MV are known to overestimate back-squat 1-
340 RM between 2.2-20.0 kg.^{38,53} The larger absolute differences found by Banyard et al³⁸ may
341 be attributed to the researchers 4 trial assessment of 1-RM. Considering the variability of
342 $1RM_{MVT}$ (CV = 25%), multiple assessments of 1-RM may have amplified the variation
343 observed in that study in comparison to our study. This supports previous findings that daily
344 predictions of maximal strength are not sensitive enough to detect fatigue or modify training
345 load,⁶⁹ as originally propositioned.^{10,19} Intriguingly, a recent study found bench press 1-RM

346 can be estimated more accurately with machine learning methods than the MVT method,⁷⁰
347 but it is unknown if this can be translated into free-weight examinations. This should be a
348 consideration for future research.

349 It was not anticipated the data would suggest both PV models possessed the most valid
350 estimation of back-squat 1-RM in relation to measured 1-RM. Under closer inspection, the
351 range of estimated 1-RMs from the PV polynomial and PV linear models were considerably
352 wider in comparison to the MPV and MV models (figure 7). This study does not recommend
353 the use of PV for back-squat 1-RM prediction. This is informed by both PV models
354 presenting higher SEE and CV than the other models, which is consistent with other
355 investigations.⁴⁸ Though PV may be used to monitor ballistic exercises, this is beyond the
356 scope of this study. Altogether, this study found the MV linear model displayed the highest
357 validity.

358 The higher precision of linear 1-RM estimations in this study weighs in on the assertion
359 that polynomial regression adds an unnecessary complexity.^{36,38,49,53,71} Predicting 1-RM
360 beyond the known data of a polynomial curve is known to yield implausible results.⁶⁵ In this
361 study 2 participants (n = 2) exhibited a hyperbolic curve for PV which resulted in no
362 estimation of 1-RM at all. Moreover, some studies advocating polynomial regression have
363 breached the assumption of independence by pooling data.^{10,48} This practice has been
364 critiqued within the literature.^{5,22} When data from multiple LVP sessions are combined for a
365 given participant, the data observations are no longer independent. This causes
366 autocorrelation which overinflates regression statistics.⁷² Consequently, overestimations of
367 relative load may occur. A runs test can be used to detect both autocorrelation and whether a
368 data set differs from its desired model.⁷³ It is important to note the runs test found none of the
369 linear models in this study departed from linearity. Furthermore, all of the variance between
370 load and velocity was accounted for by the linear models. This objectively infers polynomial

371 curve fitting in this instance is not only an unnecessary complexity, but also a statistical
372 misdemeanour. The inclusion of a runs test is a distinguishing feature between this study and
373 the extensive work of Thompson et al⁶³, whose findings conflict with ours in recommending
374 quadratic modelling for the prediction of back squat 1-RM. Altogether, the acceptance of a
375 linear load-velocity relationship would be consistent with the growing consensus concerning
376 the linearity of the force velocity relationship during multi-joint movements.⁷⁴

377 The present study shows that all 3 velocity measures produced by the Vitruve can
378 generate stable individualised LVPs. Although practitioners should be consistent with their
379 use of velocity measure. Lamentably, this study was unable to distinguish the variability
380 associated with the Vitruve LPT from the variability associated with the subjects. Although
381 the Vitruve is known to display very high inter-device reliability during Smith machine back-
382 squat exercise (MPV: SEM = 0.03 m·s⁻¹; SDC = 0.08 m·s⁻¹; CV = 3.09%; PV: SEM = 0.02
383 m·s⁻¹; SDC = 0.07 m·s⁻¹; CV = 1.60%),³² future research must consider the influence of
384 biological variation when assessing the reliability of the Vitruve during free weight
385 exercise.²⁷ Otherwise researchers risk misreporting the true precision of a given device.³⁷

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

391

392 **4.3 Conclusions**

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

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

397

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402

403 **Disclosure statement**

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405

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

Table 2. Smallest Detectable Difference of Velocity Measures at 20%, 40%, 60%, 80% and 90% 1-RM.

Figure 1. Forest plot displaying the test re-rest 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. D, SEM. Gray-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.

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.

Figure 3. Forest plot displaying the test re-rest reliability of 1-RM prediction methods using linear and polynomial regression with relative loads between 20% to 90% of 1-RM. A, ICC. B, CV. C, *ES*. D, SEM. Gray-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.

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.

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.

Figure 6. Forest plot displaying the validity of 1-RM prediction methods using linear and polynomial regression with relative loads between 20% to 90% of 1-RM. A, r . B, CV. C, *ES*. D, SEE. Gray-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.

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% to 90% of 1-RM. Error bars indicate SD. 1-RM indicates 1-repetition maximum; MPV, mean propulsive velocity; MV, mean velocity; PV, peak velocity.

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

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

^aAnalyses were performed after the removal of outliers.

^bThe *df* = 24.

^cThe *df* = 23.

^eThe *df* = 20.

^fThe *df* = 22.

^gThe *df* = 16.

**p* values are significant at < 0.05.

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

Abbreviation: 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.

^aDid not meet reliability criteria (ICC > 0.70, CV ≤ 10% and *ES* < 0.60).

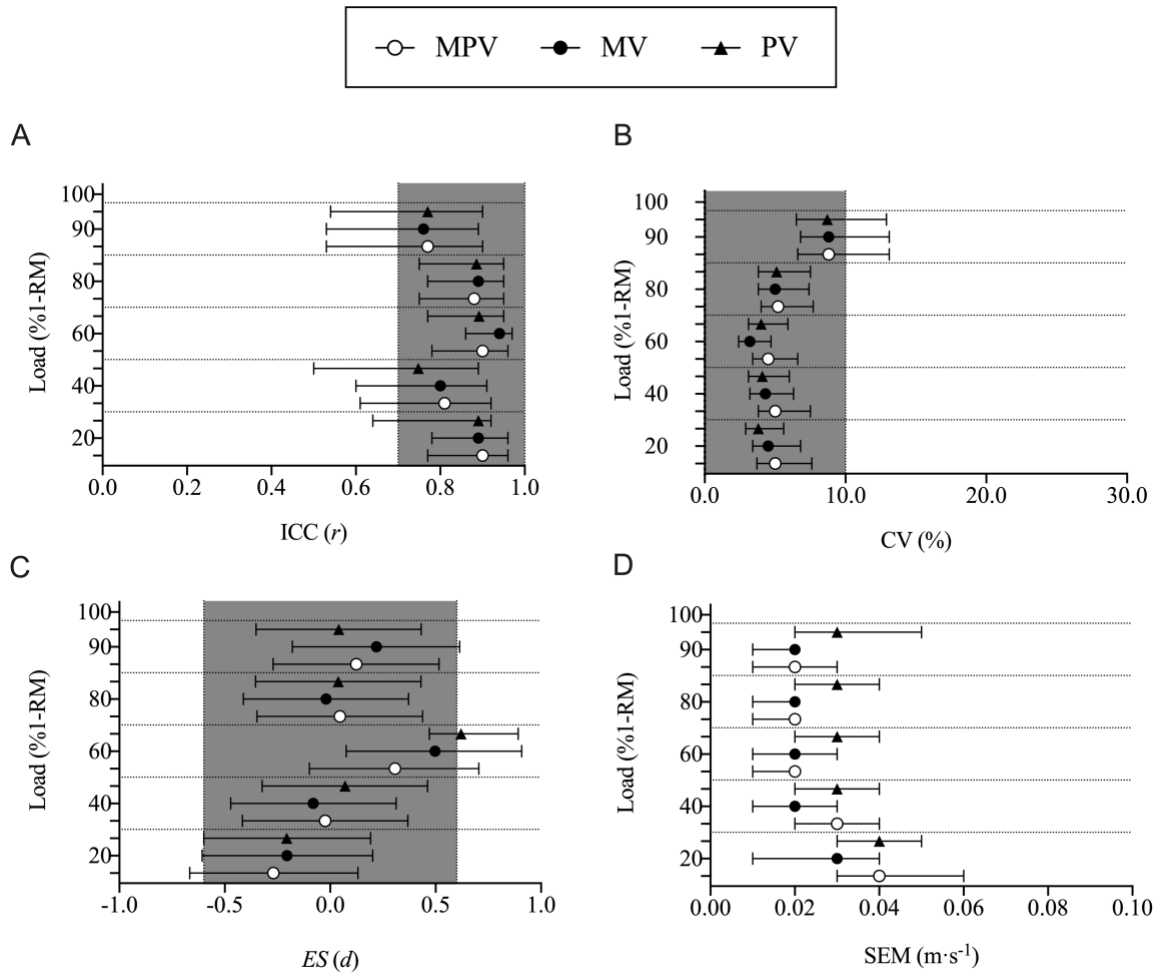


Figure 1. Forest plot displaying the test re-rest reliability of MPV, MV, and PV in the back squat at 20%, 40%, 60%, 80%, and 90% 1-RM load. A, ICC. B, CV. C, ES. D, SEM. Gray-shaded area indicates the zone of acceptable reliability. Error bars indicate 95% confidence limits. MPV indicates mean propulsive 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.

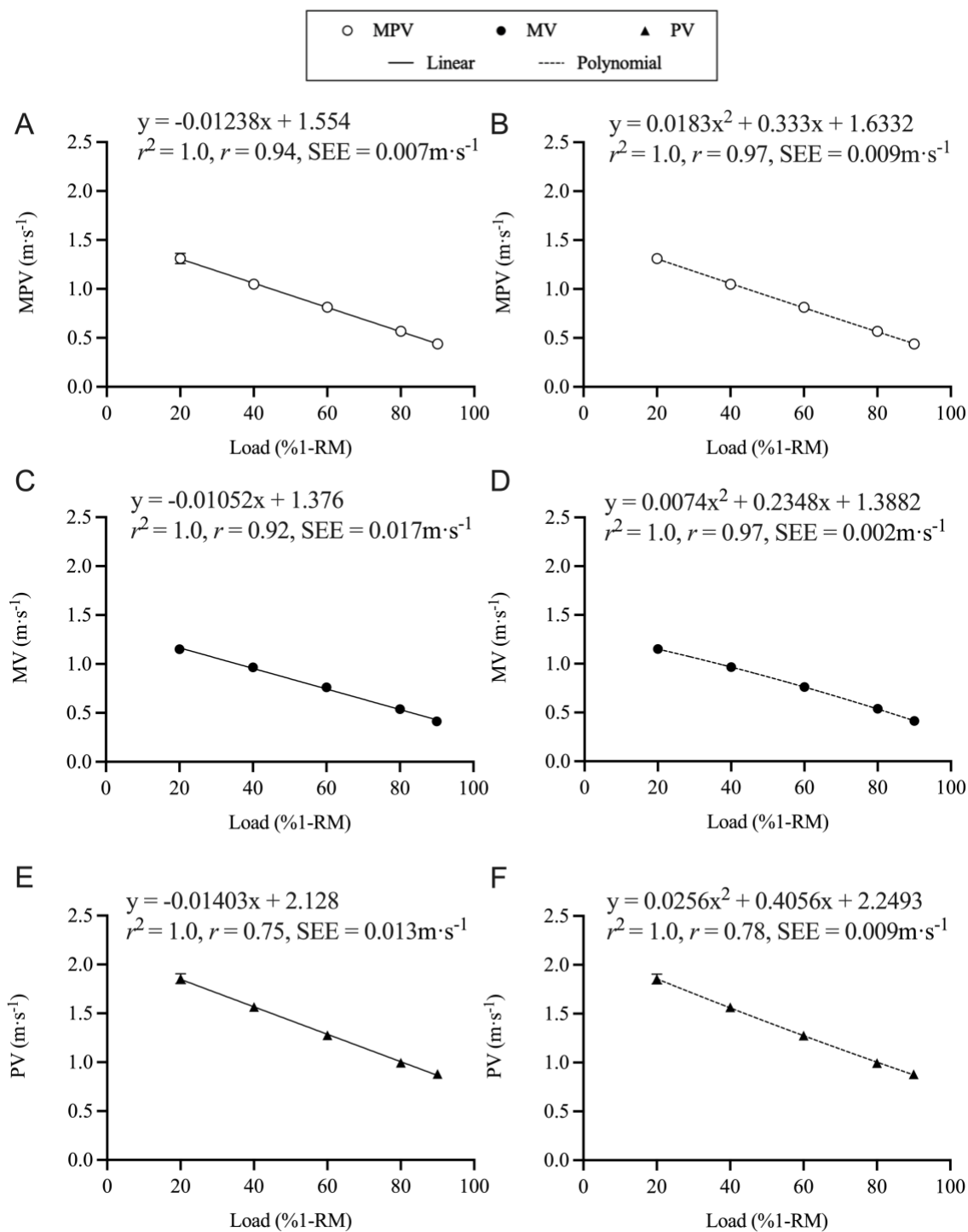


Figure 2. Relationship between relative load (%1-RM) and MPV, MV, and PV using linear and polynomial regression. A, MPV linear fit from 20% to 90% 1-RM. B, MPV polynomial fit from 20% to 90% 1-RM. C, MV linear fit from 20% to 90% 1-RM. D, MV polynomial fit from 20% to 90% 1-RM. E, PV linear fit from 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.

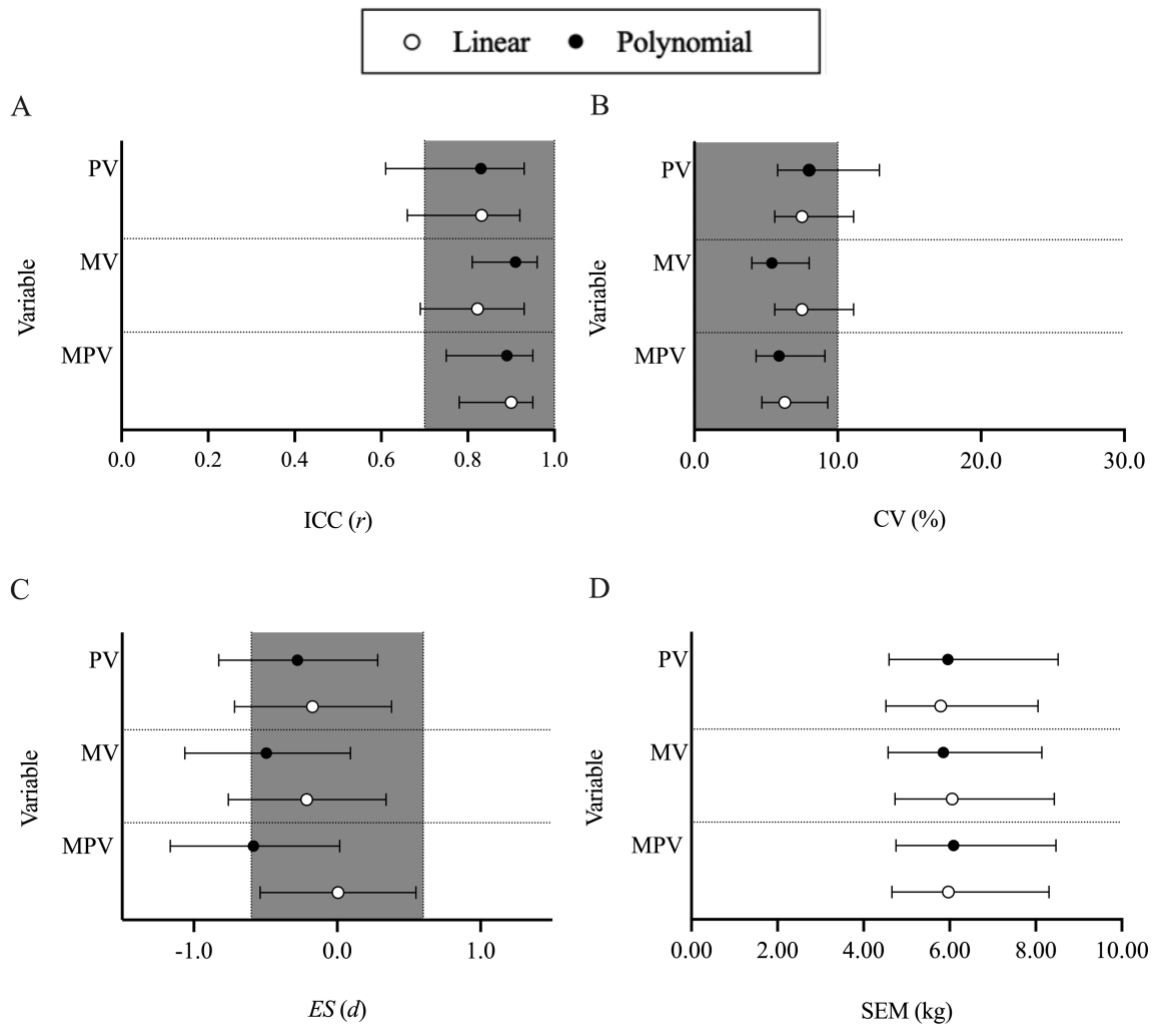


Figure 3. Forest plot displaying the test re-rest reliability of 1-RM prediction methods using linear and polynomial regression with relative loads between 20% to 90% of 1-RM. A, ICC. B, CV. C, *ES*. D, SEM. Gray-shaded area indicates the zone of acceptable reliability. Error bars indicate 95% confidence 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.

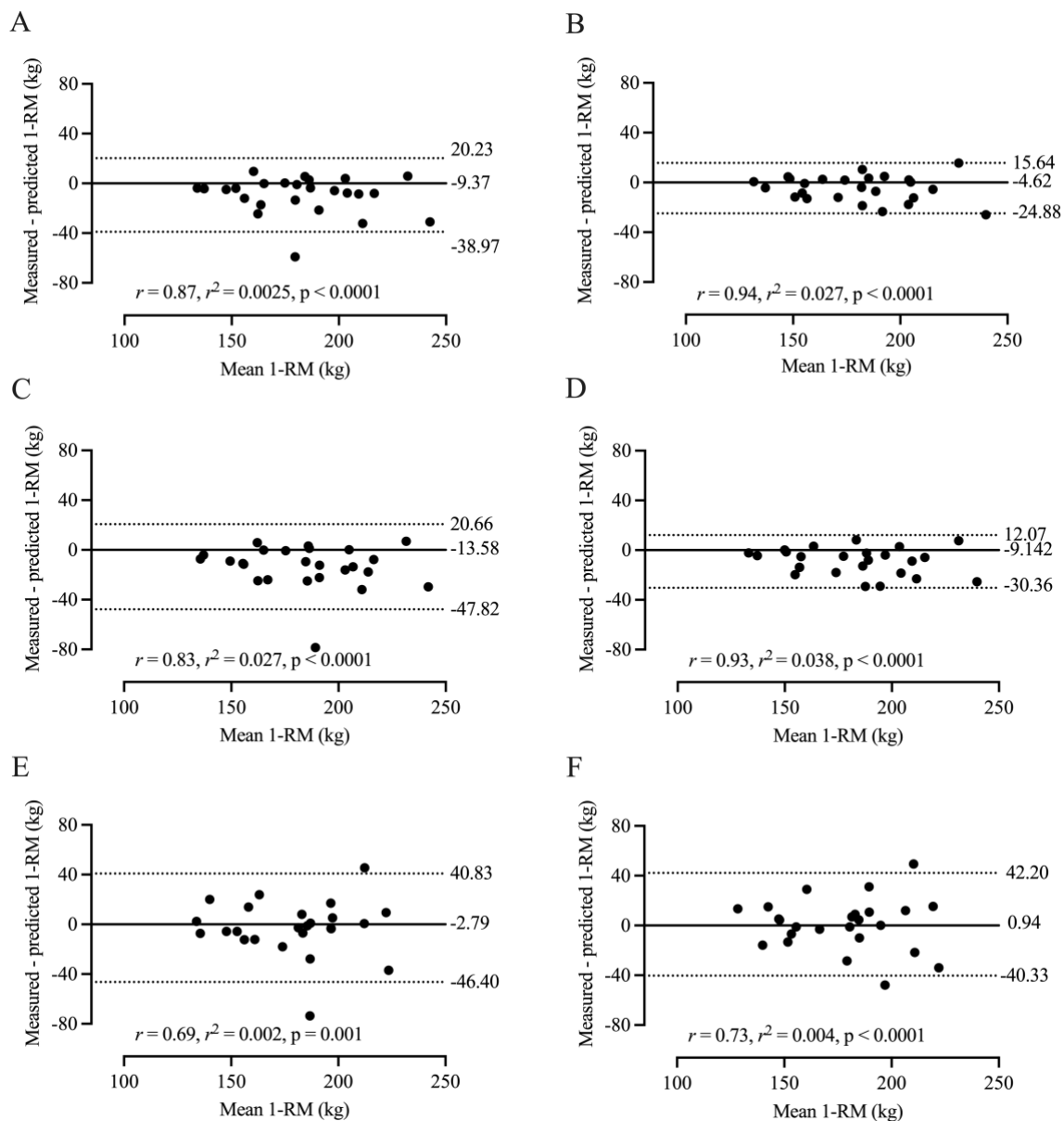


Figure 4. Bland-Altman plots illustrating the variation in measured 1-RM against predicted 1-RM using linear regression and loads 20-90% 1-RM for trials 1 and 2. A, MPV (kg) trial 1; B MPV (kg) trial 2; C, MV (kg) trial 1; D, MV (kg) trial 2; E, PV (kg) trial 1; F, PV (kg) trial 2. — represents mean 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.

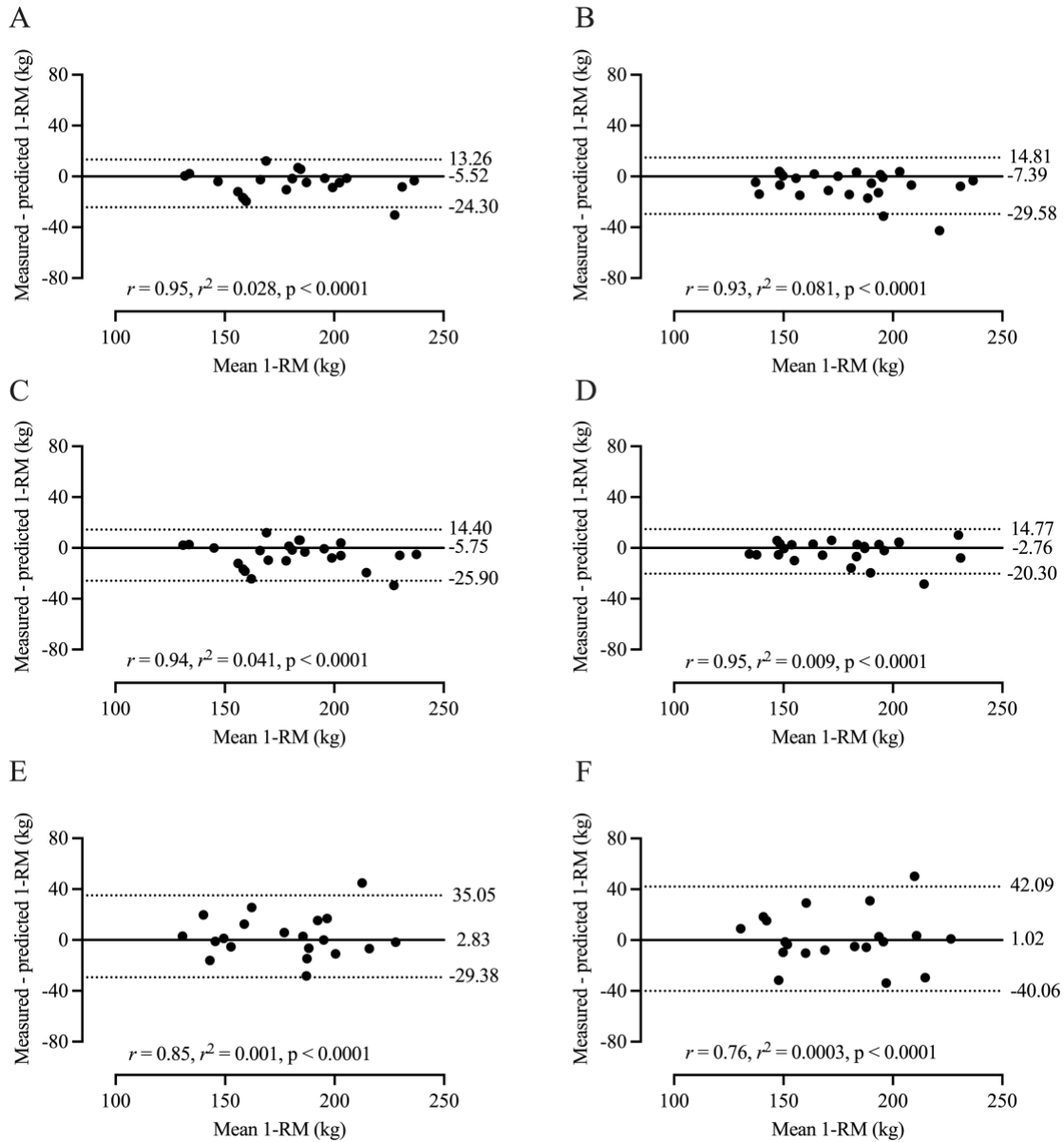


Figure 5. Bland-Altman plots illustrating the variation in measured 1-RM against predicted 1-RM using second order polynomial regression and loads 20-90% 1-RM for trials 1 and 2. A, MPV (kg) trial 1; B MPV (kg) trial 2; C, MV (kg) trial 1; D, MV (kg) trial 2; E, PV (kg) trial 1; F, PV (kg) trial 2. — 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.

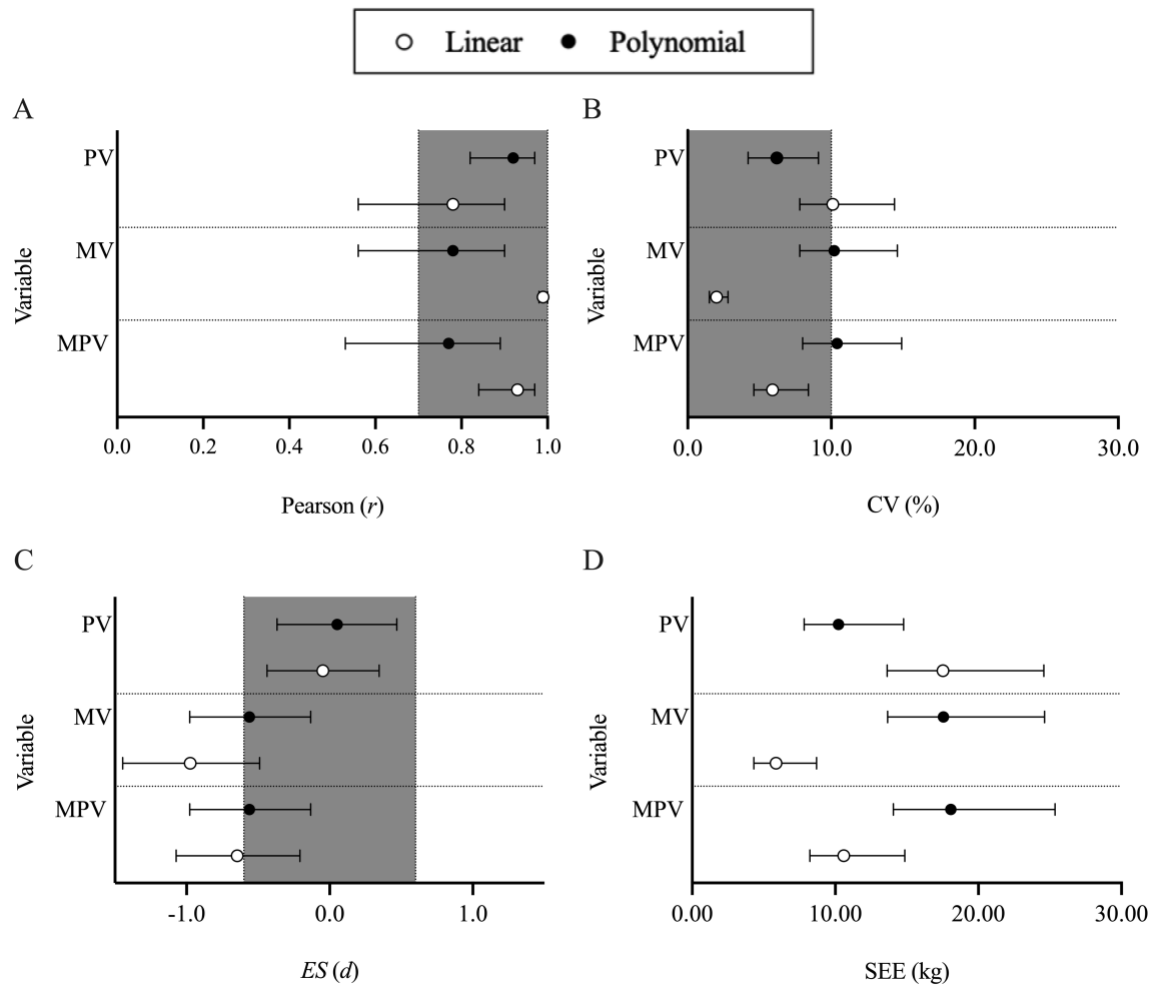


Figure 6. Forest plot displaying the validity of 1-RM prediction methods using linear and polynomial regression with relative loads between 20% to 90% of 1-RM. A, r . B, CV. C, ES . D, SEE. Gray-shaded area indicates the zone of acceptable validity. Error bars indicate 95% confidence limits. PV indicates 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.

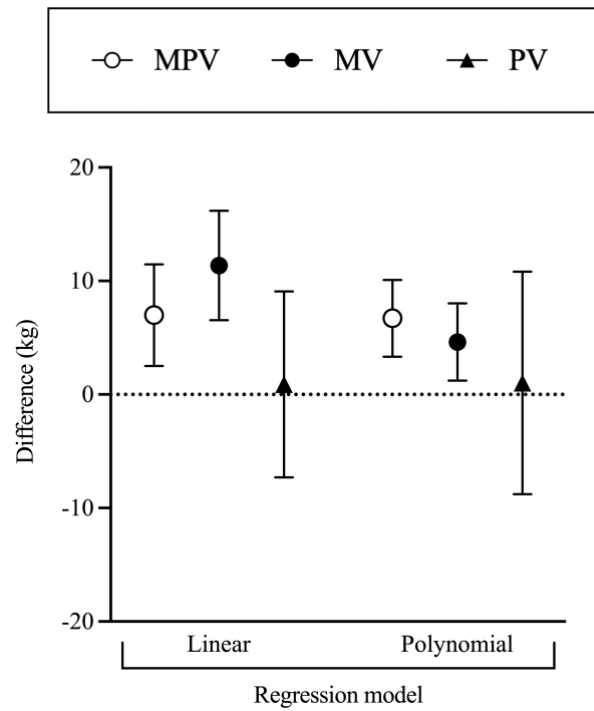


Figure 7. Point graph demonstrating the mean absolute difference between measured 1-RM and predicted 1-RM using linear and polynomial regression with relative loads between 20% to 90% of 1-RM. Error bars indicate SD. 1-RM indicates 1-repetition maximum; MPV, mean propulsive velocity; MV, mean velocity;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