Validity of a smartphone app using artificial intelligence for the real time measurement of barbell velocity in the bench press exercise.

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The validity of a smartphone app using artificial intelligence for the real time measurement of barbell velocity in the bench press exercise

ABSTRACT

The purpose of the present study was to explore the validity and within-session reliability of the newly developed My Jump Lab application (app), which uses artificial intelligence techniques to monitor barbell velocity in real time. Twenty-seven sport science students performed 5 repetitions at 50% and 75% of their self-reported bench press one repetition maximum (1-RM) during a single testing session, while barbell velocity was concurrently measured using the app (installed on an iPhone 12 Pro) and the GymAware linear position transducer (LPT). A very high correlation was observed between devices at each loading condition (50%1-RM: r = 0.90 [0.82, 0.97]; 75%1-RM: r = 0.92 [0.86, 0.98]). Results showed trivial differences between the app and LPT at both 50%1-RM (g = -0.06) and 75%1-RM (g = -0.12). Bland-Altman analysis showed a bias estimate of -0.010 $m.s^{-1}$ and -0.026 $m.s^{-1}$ for the 50% and 75%1-RM, respectively. Finally, similar levels of reliability, as revealed by the coefficient of variation (CV) were observed for both devices (50%1-RM: LPT = 6.52%, app = 8.17%; 75%1-RM: LPT = 12.10%, app = 13.55%). Collectively, the findings of this study support the use of My Jump Lab for the measurement of real time barbell velocity in the bench press exercise.

Keywords: computer vision; technology; resistance training; monitoring.

INTRODUCTION

Measuring mean concentric velocity (MCV) during resistance exercises has been proposed as a non-invasive way to objectively quantify an athlete's response to training stressors such as load and volume, and indicate the level of effort produced during strength training (22). A practically perfect relationship ($r \geq 0.94$) has been established between MCV and % 1-RM in the bench press, back squat, and deadlift among other exercises, enabling practitioners to accurately estimate 1-RM and its percentages by measuring lifting velocity (5,7,9,20,21). By doing so, practitioners can utilize velocity to inform training prescriptions, test athletes, provide feedback, autoregulate, and control volume (6,11,17,22). In addition, subjective (i.e., the rate of perceived exertion or the number of repetitions in reserve) parameters have been shown to correlate strongly with with MCV, demonstrating the versatility of velocity-based training (12). The predictive capabilities of load-velocity profiling can help practitioners to prescribe training loads based on velocity metrics rather than doing direct 1-RM assessments, which can be time consuming, interrupt training phases through increased neuromuscular fatigue, and potentially inappropriate for certain populations (e.g., youth or novice). Thus, the measurement of MCV during resistance exercises has been rapidly adopted in the strength and conditioning community to monitor training load and optimize training prescription (11,22).

Several technologies have been validated for the measurement of MCV, with linear position transducers (LPTs) often being considered as the gold standard (19,23). The main drawback of LPTs, however, is often their price point, sometimes restricting their use from practitioners with limited budgets. To address this limitation, more affordable technologies (e.g., inertial measurement units, lower-cost motion capture systems, or smartphone apps) have been developed to measure MCV, with smartphone apps and inertial measurement units being the most popular and validated options (1,19,23). Specifically, video-analysis apps such as My Lift or iLoad have been proposed as valid and reliable low-cost alternatives for the measurement of MCV (2,14). Nevertheless, these video-analysis apps have always been restricted by their calculation method which required post-set inspection of each repetition, preventing real-time feedback to the athlete. Real-time feedback is an important VBT application, and has been shown to facilitate a higher inter- and intra-set mechanical output, in addition to eliciting greater performance improvements (15,24,25). Implementing velocity loss thresholds, autoregulating load through load manipulation, and driving intent through extrinsic motivation also rely on valid and reliable real-time MCV feedback (6,16,25). Recent developments in computer vision and machine learning for mobile devices, however, have now made real-time tracking and feedback of MCV possible. Therefore, the purpose of this study was to explore the validity of a newly developed smartphone app (My Jump Lab) which uses artificial intelligence techniques for the measurement of MCV in real time.

METHODS

Experimental approach to the problem

For the present validation study, we aimed to compare mean concentric velocity in the bench-press exercise, measured by the gold standard instrument (i.e., a LPT) and a newly developed iOS app. To do this, two sets of five repetitions were performed by 27 resistance trained subjects in the bench press exercise at 50% and 75% of their self-reported 1-RM while MCV was simultaneously monitored by an LPT (Gym Aware, Technologies, Canberra, Australia) and My Jump Lab app installed on an iPhone 12 Pro running iOS 15.5 (Apple Inc., Cupertino, USA). A total of 270 repetitions were registered, and data between both devices were compared for validity and reliability purposes.

Subjects

Twenty-seven sport science students with a minimum of one year's experience in the bench press exercise were recruited (mean ± SD: age = 24.7 ± 4.5 years; mass = 77.2 ± 10.4 kg; Bench press 1-RM = 1.0 ± 0.3 kg.kg^{-1}). Subjects were instructed to avoid any strenuous exercise two days before the testing session, had no reported injuries during the time of testing, and were informed of the risks and benefits of the study before any data collection. The study protocol complied with the seventh Declaration of Helsinki for Human Experimentation and was approved by the Institutional Review Board at the Autonomous University of Madrid. Written informed consent was obtained from each participant before the beginning of data collection.

Procedures

Subjects performed a single testing session where MCV at 50% and 75% of their self-reported 1-RM was simultaneously registered by an LPT and the My Jump Lab app on the bench press exercise. The intention of the present study was not to test the 1-RM but to use a self-reported measure to register MCV across two different submaximal loads.. Subjects were instructed to report their closest 1-RM to the testing session, and they were required to have performed it no more than 3 months and no less than 3 days before the testing session. After a standardized 10-minute dynamic warm-up including body weight exercises (i.e., push-ups, lunges, squats, etc.) and 2 sets with an empty barbell on the bench press, subjects performed two sets of five repetitions at their self-reported 50% and 75% 1-RM. Intra-set repetitions were separated by 2 seconds of rest, while inter-set passive rest was set at 2 minutes. The bench press was performed in the usual manner, where subjects unracked the barbell and were asked to hold it above their chest for 2-seconds (allow the My Jump Lab app to detect the plate), and then initiated the eccentric portion of the movement under control, whilst being asked to perform the concentric phase of the exercise as explosively as possible.

Instruments

The validated GymAware LPT was used as the gold standard method in the present investigation (13). All data collected from the LPT was transmitted via a Bluetooth connection to the iPad Pro 12 (Apple Inc., USA) using GymAware Lite software (v2.10, Kinetic Performance Technology, Canberra, Australia). An updated version of the previously validated *My Lift* iOS app (2), rebranded under the name *My Jump Lab* was used to explore its validity and reliability. The updated My Jump Lab v. 3.0 for iOS was installed on an iPhone 12 Pro running iOS 15.5 (Apple Inc., Cupertino, USA). The appmeasured MCV in real time by performing an object recognition request using an ad-hoc machine learning model. Specifically, an object detection network based on YOLOv2 architecture was trained using the free CreateML software (Apple Inc., Cupertino, USA) and a set of 1000 images of weightlifting plates of different manufacturers and colors. Images included bumper plates, iron plates and standard weightlifting plates; however, only completely circular and standard size plates (i.e., 0.45 m of diameter) were used. The model was then integrated into the app by using Apple's open-source Swift 5 programming language and Xcode 13.4.1 for macOS (Apple Inc., Cupertino, USA). Live object recognition features were included using Apple's computer-vision framework "Vision" (Apple Inc., Cupertino, USA). Specific, technical details of this framework can be found following this link: https://developer.apple.com/documentation/vision. Finally, MCV of each repetition was calculated by the object recognition algorithm.

To register MCV from the app, the iPhone was mounted to a camera tripod to record the sagittal plane of the participants, at a height such that the focal center of the video screen passed approximately 1.2 m above the floor with the barbell centered horizontally on the screen. The positioning of the tripod from the participant was determined from pilot testing and was chosen such that the full bench movement could be recorded, without the plate going of the screen while the tripod was as close to the participant as possible. Data from the app was collected at 60Hz.

Statistical analyses

All values were initially recorded as means ± SD in Microsoft Excel. Normality of the data was confirmed using the Kolmogorov Smirnov test ($p > 0.05$). Within-session reliability was computed for both measurement methods using the coefficient of variation (CV) with 95% confidence intervals (CI), calculated as: (SD/average)*100 and a two-way random intraclass correlation coefficient (ICC 2,1) with absolute agreement and 95% CI. CV values less than 10% were deemed acceptable (4) and guidelines from (10) were used to interpret ICC values, where: > 0.90 = excellent, 0.75-0.90 = good, 0.50-0.74 = moderate, and < 0.50 = poor. Limits of agreement (LOA) and 95% CI between the LPT and the My Jump Lab app were determined from Bland-Altman plots (3). In order to determine concurrent validity between measurement methods, Pearson's correlation coefficients (r) were calculated. Systematic bias between methods was determined by paired samples t-tests for each load, with statistical significance set at $p < 0.05$. Finally, practical significance between the LPT and My Jump Lab app was also determined using Cohen's d with a Hedges g correction effect sizes with 95% CI. These were interpreted in line with suggestions by Rhea (2004) relative to the "recreationally trained" sample in the present study: < 0.35 = trivial, 0.35-0.79 = small, 0.80-1.49 = moderate and > 1.50 = large. The statistical software Jamovi 2.3.21 for macOS was used.

RESULTS

All data were normally distributed ($p > 0.05$). Table 1 and Table 2 show reliability statistics and mean ± SD data for the LPT and the app, respectively. Both methods showed acceptable CV values for 50% load (LPT = 6.52%, app = 8.17%). However, both measurement methods exhibited greater variability for the 75% load (LPT = 12.10%, app = 13.55%), which consequently had impacted reliability of the pooled data when using the app (10.86%). The ICC values were excellent for 50% and 70% of maximum loads using LPT (0.96-0.98) and app (0.96-0.97). When assessing systematic bias between measurement methods, no significant differences were evident across either load (table 2). Specifically, differences between the LPT and app were *trivial* at 50% load (g = -0.06), *trivial* at 75% load (g = -0.12), and *trivial* when data was pooled (g = -0.14).

*** Insert Table 1-2 about here ***

Figures 1 and 2 show scatter plot graphs presenting all trials for 50% and 75% of maximum load, respectively, with correction equations and r^2 values. Pearson's r values were as follows: 50% load (0.90 [0.82, 0.97]) and 75% (0.92 [0.86, 0.98]). Figures 3 and 4 show Bland-Altman plots for 50% load and 75% load, respectively. Mean differences (bias estimate) for 50% load concentric velocity were -0.010 $m.s^{-1}$ (95%CI: -0.024, 0.003 $m.s^{-1}$), indicating perfect levels of agreement between two methods. Almost perfect levels of agreement were also evidence between LPT and the app when the bias estimate was applied to 75% load concentric velocity (-0.026 $m.s^{-1}$; 95%CI: -0.038, -0.014 $m.s^{-1}$). Coefficients of determination of the regression line in the Bland-Altman plots were R^2 = 0.01 and R^2 = 0.08 for 50% and 75% load, respectively.

*** Insert Figures 1-4 about here ***

Discussion

The aims of the present study were to: 1) determine the validity of the My Jump Lab smartphone app for measuring MCV in real time during the bench press exercise across 50% and 75% 1RM, and 2) determine the within-session reliability of the My Jump Lab app within these loads. From a validity standpoint, the My Jump Lab app showed a near perfect correlation with an LPT for the measurement of MCV across different loads (r > 0.920; r^2 = 0.803). The reliability were excellent for both loads across the LPT (ICC = 0.97-0.98) and app (ICC = 0.96), but with the slightly elevated CV values for the 75% loading condition in both the LPT (CV = 12.10%) and the app (CV = 13.55%).

My Jump Lab uses a machine learning model that has been 'trained' to detect the coordinates of a weight plate during live video feed. This information is then used to calibrate pixels and convert to distance travelled, as an initial form of analysis. The app then calculates the time taken for that distance to be travelled, which subsequently enables the calculation of mean velocity (i.e., distance/time). Figure 1 and 2 show the near perfect correlation between the two technologies, and practitioners can now confidently measure MCV during the bench press exercise using the My Jump Lab smartphone app, in real time. This is further supported by the Bland-Altman analysis (Figure 3 and 4), which shows mean bias estimates of -0.010 [lower -0.168 and upper 0.147 limits of agreement] at 50% self-reported loads and -0.026 [lower -0.166 and upper 0.114 limits of agreement] at 75%, indicating excellent levels of agreement between the two technologies. LPT's can cost a minimum of $400, often outpricing practitioners and limiting their use within practice (18). In contrast, the My Jump Lab app can be installed on any mobile device running iOS 13 or higher at a substantially more affordable cost ($4.99 per month or $84.99 for a lifetime license), which can be used as a valid alternative to the gold standard LPT. In addition, monitoring velocity is now considered an integral aspect of autoregulation, enabling practitioners to monitor acute fatigue and subsequently adapt training programs in real time, if required (8).

The My Jump Lab app, also exhibits excellent within-session reliability (ICC ⩾ 0.96) when measuring MCV across two different loads (50% and 75% 1RM, Table 1), while the CV values were very similar for both technologies across all measured loads (table 1).

Nevertheless, it should be acknowledged that when increasing to 75% of the maximum load, the measured MCV exhibits a larger amount of within-session variability, regardless of whether practitioners use an LPT (CV = 12.10%) or the My Jump Lab app (CV = 13.55%). Whilst this data suggests that reliability is worse at greater loads (i.e., CV > 10% threshold), it is our suggestion that participants showed greater trial-to-trial variation at 75%, because the load was 'heavy enough' to exhibit some level of acute fatigue by the fifth repetition, consequently impacting the consistency of MCV (as measured by the CV). In addition, we also quantified differences in MCV between technologies (Table 2). A notable trend in the data was the over-estimation of velocity for the My Jump Lab app, which is likely down to the conversion from pixels to distance travelled. Simply put, the app slightly under-estimates the diameter of the weight plate, which results in a slight over-estimation of the distance data that is reported. Furthermore, given how velocity is then calculated, this has a knock-on effect in reporting higher MCV values. When considering the effects of this across two devices, only trivial differences in MCV have been found under 50% (g = -0.06) and 75% (g = -0.12) loading conditions. Consequently, it appears that the My Jump Lab app is a valid and reliable tool to measure the MCV during the bench press. While previous research relating to the validity of existing technologies to monitor barbell velocity have used different loads and instruments (24), results in our study suggest that the coefficient of determination of My Jump Lab in comparison with the criterion are slightly smaller than those obtained with linear transducers, and slightly higher than those obtained with inertial measurement units.

A few limitations of the present study should be acknowledged. Firstly, the present study employed a single testing session for the purpose of validating the My Jump Lab app. Future studies may wish to consider a test-retest design, which will provide true day-to-day consistency and reliability data for My Jump Lab. Secondly, future research should also aim to quantify the validity and reliability of the My Jump Lab app in lower body exercises (e.g., back squat and deadlift). Given the prevalence of these exercises in athlete training programmes, this would be a useful addition to the research conducted using smartphone technologies. Thirdly, we recruited sport science students as subjects and future studies should also consider the use of elite athlete populations when using the My Jump Lab app, as their increased training age are likely to result in different raw MCV values, which in turn, may also impact the subsequent reliability data as well. Fourthly, the app was trained with images of circular, 0.45 m diameter plates, so it shouldn't be used with smaller plates or plates that are not circular in shape. However, future studies may wish to to explore the ability of the app to measure movement velocity with such non-standard equipment, enabling an even wider reach to practitioners. Finally, the data from this study only pertains to two loads out the LVP spectrum. We decided to use 50% and 75% loads in order to cover a wide enough range of velocities, enabling us to test the accuracy of the app with fast to slow repetitions. Velocities in our data ranged from 1.24 to 0.17 m/s, with an average velocity of 0.80 m/s and 0.55 m/s for 50% and 75% 1-RM, respectively. Thus, with those two selected loads, we were able to test a range of velocities. Better understanding how the reliability and validity changes across a full LVP could be useful information for S&C coaches to know.

In conclusion, the findings of this study indicate that the My Jump Lab app can provide the reliable and almost identical MCV data to that of the LPT when using 50% of the maximum load. Furthermore, the app may well be usable at heavier loads (i.e., 75%), seeing as reliability data was comparable with the LPT. However, as previously mentioned, further research is needed to more accurately determine the day-to-day variability of MCV using the My Jump Lab app, especially using heavier loads (i.e., ≥ 75%).

Practical Applications

Results in our study showed that a smartphone app using artificial intelligence is able to monitor barbell velocity in the bench press exercise with a range of velocities in a valid and reliable way, in comparison with a professional linear transducer. Moreover, no markers on the barbell are needed, and the app works without previous calibration other than placing the phone on a tripod and recording the athlete in the sagittal plane. Considering how valuable velocity-based training can be for the strength and conditioning community, results in our study could be of interest to athletes, sport scientists, or coaches who wish to monitor barbell velocity during the bench press exercise without the need for expensive equipment.

Conflicts of Interest Statement

The first author of the present investigation is the developer of the app mentioned. To guarantee data independency, data were collected and analyzed by independent researchers not related with the app's development (specifically, the second, third and last authors of the present manuscript). Raw data is available at shorturl.at/clwMV.

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FIGURE LEGENDS

Figure 1. Linear regression for mean velocity between the two measurement methods during 50% of maximum load, inclusive of correction factor equation and R^2.

Figure 2. Linear regression for mean velocity between the two measurement methods during 75% of maximum load, inclusive of correction factor equation and R^2.

Figure 3. Bland-Altman plot showing levels of agreement between measurement methods for mean velocity during 50% of maximum load, including mean bias estimate (-0.010) and both lower (-0.168) and upper (0.147) limits of agreement.

Figure 4. Bland-Altman plot showing levels of agreement between measurement methods for mean velocity during 75% of maximum load, including mean bias estimate (-0.026) and both lower (-0.166) and upper (0.114) limits of agreement.