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Accuracy and Precision of an Accelerometer-Based Smartphone App Designed to Monitor and Record Angular Movement over Time

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Abstract

Background: *Therapeutic exercise is a central component in the management of many common conditions. It is imperative, therefore, that clinicians monitor and correct patient performance to facilitate the use of proper form both in the clinic and during home exercise programs. Although clinicians are trained to prescribe exercise and analyze form, there are many subtleties that may be missed by relying on visual assessment. This study investigated the accuracy and precision of a novel, exercise-training smartphone application (app), running on an iPhone® (Apple, Cupertino, CA) 4 and using its LIS331DLH accelerometer to dynamically measure and record movement during exercise.* **Materials and Methods:** *The iPhone, running the app, was mounted to the movement arm of a Biodex™ isokinetic dynamometer System 4 (Biodex Corp., Shirley, NY). Angle and time measurements taken by the app were compared with the dynamometer (gold standard) while rotating at 30°/s, 60°/s, 90°/s, 120°/s, and 150°/s. Accuracy was assessed using limits of agreement and fast Fourier transform analyses. Precision was assessed using the coefficient of variation.* **Results:** *The mean difference between the app and the Biodex recordings was less than 1°/s for all test velocities. The coefficient of variation was less than 3% at velocities from 30°/s to 120°/s and less than 7% at 150°/s.* **Conclusions:** *The app was highly accurate and precise. The validation of apps designed for motion tracking is a vital prerequisite to clinical implementation. The app described in this article is clinically identical to the Biodex dynamometer in its ability to accurately and precisely read angular movement over time.*

Key words: *rehabilitation, telehealth, telemedicine, sensor technology*

Introduction

Rehabilitative exercise is a central component in the management of multiple orthopedic, cardiovascular, and neurological conditions and is often prescribed as part of a home treatment program. The effectiveness of an exercise program is contingent upon (1) performing exercises with the proper form and (2) using proper combinations of frequency, intensity, and time while training. In many cases, patients make performance errors, such as moving too quickly, moving too slowly, or not moving through the entire range of motion. These errors may occur because an individual is unfamiliar with the prescribed exercise, has functional limitations that make the exercise more challenging, or forgot the exercise parameters (reps, sets, movement velocity, etc.). They may also occur when an individual loses focus while training (a common occurrence in busy clinics) or becomes fatigued.[1–4] These performance errors may increase the patient's risk of injury and reduce the efficacy and efficiency of the exercise, while inhibiting the clinician's ability to determine the patient's physiological response—an integral component of exercise modification and optimization.

Given the limited time patients have in the clinic, it is imperative that healthcare clinicians monitor and correct patient performance in order to reinforce the use of proper form during their visit and during home exercise programs. However, this supervision may be difficult in busy clinics, and there are few devices capable of monitoring patient exercises while at home. Over the last several years there has been a growing effort to develop technologies designed to assist clinicians with the identification, diagnosis, and correction of performance errors during exercise or daily activities. These technologies include robotic devices, computer vision, computer gaming, virtual reality, and computational modeling.[5] Much effort has been recently placed on developing wearable sensors, which can be smaller, affordable, and less invasive. Examples include the DirectLife, Fitbit, Jawbone, Nike FuelBand, and Actigraph consumer-based physical activity monitors.[5] Wearable sensors may also offer unique opportunities to monitor various aspects of patient health in the clinic and at home through telehealth initiatives.[6]

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Currently, many of these wearable sensor systems are designed to monitor physiological functioning, including heart rate, blood pressure, respiratory rate, blood oxygen saturation, and caloric expenditure.[7–10] However, there are often several unique challenges to designing and implementing a system capable of monitoring physical activity without the use of large equipment.[10] As Corbishley and Rodriguez-Villegas[11] acknowledge, an ideal system must use small sensors, such that they do not interfere with the individual's movement pattern. The size of the device has important implications for its function, including how big the battery must be, the weight of the sensors selected, and the system's processing power. It is of central importance to design a device that reaches an appropriate compromise between its size and clinical utility. One device that has grown increasingly popular for its small size and tremendous processing power is the smartphone.

Smartphones, with their internal accelerometers and gyroscopes, have been used for several movement analysis applications (apps), including balance training, the early detection of falls, activity detection, and gait analysis.[12–17] Pan et al.,[18] for example, outlined an accelerometer-based system using smartphone software to integrate readings from multiple sensors in order to monitor patient adherence to upper extremity exercises for frozen shoulders.

Despite the growing popularity of smartphone technology in rehabilitation, the devices have had limited usage for strength training analysis—a central component of most rehabilitative interventions and home exercise programs. Currently, one of the only devices capable of monitoring resistance training is the isokinetic dynamometer. Although the analytical capabilities of this device make it valuable in academic research, its use in the clinical setting is often limited by its high cost and limited mobility. Indeed, today, most determinations regarding form adherence are made from the clinician's experience and familiarity with the exercise. Clinicians are trained to understand proper exercise prescription and form, but there are many performance errors that may be missed by relying simply on visual assessment. Furthermore, even in instances when clinicians can use isokinetic dynamometry, much interpretation is left to the therapist regarding the types of errors made, when they occurred, and how to correct them.

Clinicians need a device that will help monitor patient exercise performance and identify errors when exercising in the clinic or at home. This article describes a novel exercise-testing and training app running on a smartphone that uses its built-in accelerometer to record patient movement during exercise, analyze performance for errors, provide real-time feedback regarding error correction, and store movement and error information for electronic submission to the clinician. The purpose of this study is to determine the accuracy and precision of this app when recording angular movement over time—a prerequisite to its clinical implementation.

Materials and Methods

HARDWARE

For this study, an iPhone® (Apple, Cupertino, CA) 4 was used. The iPhone 4 contains an ultra-low-power triaxial LIS331DLH accelerometer, which consists of a silicon proof mass supported by a set of silicon leaf springs, as well as a capacitor structure. The proof masses become displaced in three cardinal axes (x, y, z) as the pitch, roll, and yaw of the accelerometer change during movement of the iPhone. The change in position is quantified as a change in the capacitance across interdigitated, parallel-plate capacitors. The iPhone uses a low-noise capacitive amplifier to convert the change in capacitance to an analog voltage, which is used by the analog-to-digital converter to pass signals from the sensor.[19]

The accelerometer's signal is dependent on its position relative to gravity. This signal can be used for assessing body segment angles and linear acceleration.[20] By design, when used to distinguish static or dynamic activities on the basis of minute angle differences of body segments, an accelerometer is most sensitive to changes in inclination when its sensitive axis is horizontal. Thus, during movement, there are predictable, and uneven, changes in its sensitivity. A smartphone's (including the iPhone's) triaxial accelerometer was chosen as the sensor for this device due to its capacity to avoid these nonlinearity issues. With the phone fixed and rotated about a single point, as the sensitivity of one axis increases, the sensitivity of the perpendicular axis decreases (*Fig. 1*).[21] Combining those readings yields an accurate, linear response that does not require special alignment to control sensitivity. A triaxial accelerometer returns values in three axes, which were combined to derive a new reading of linear sensitivity throughout its range of measurement.

SOFTWARE

The app used in this study was created using the smartphone programming framework AppMobi (https://www.appmobi.com/), which provided a development environment with a smartphone simulator for rapid prototyping and testing. The iPhone was chosen because it ran the application best, but the same code could run on other platforms as well.

To record movement, the core function of the app uses an event loop that samples the LIS331DLH accelerometer every 50 ms and displays the data values (in this case, time and angle). Each time the accelerometer is sampled, the raw values

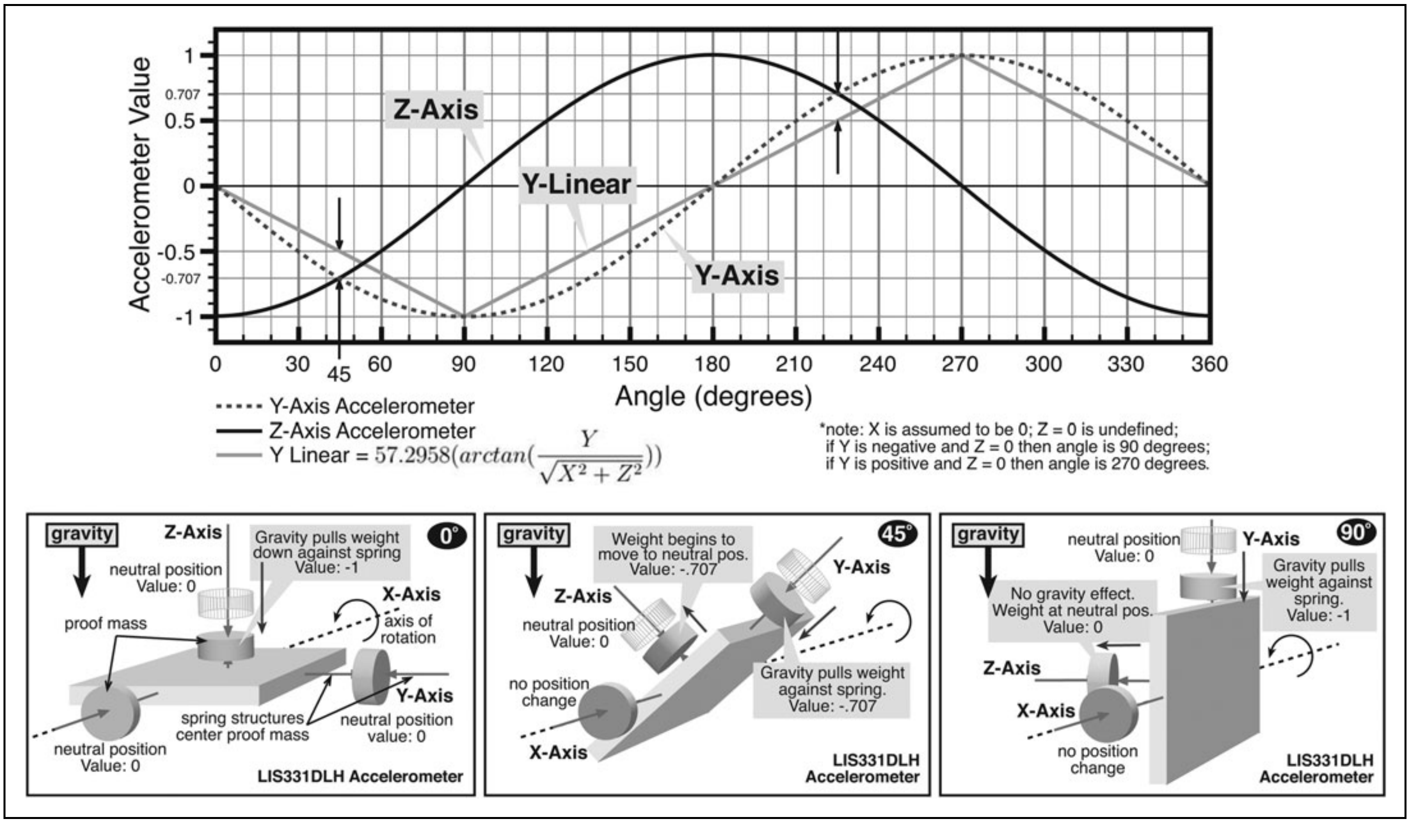

Fig. 1. Accelerometer function. **(Top panel)** LIS331DLH accelerometer output based on the angle of pitch: black line, accelerometer reading in *z*-axis; dotted black line, accelerometer reading in the *y*-axis; gray line, linear *y*-axis readings calculated using the equation given below the graph. **(Bottom panels)** Behavior of the accelerometer **(left, middle,** and **right)** when horizontal, at 45°, and at 90°, respectively.

are converted to degrees and saved along with the time the sample was taken. These data are analyzed in real time to look for performance errors (e.g., moving too quickly, too slowly, resting during movement). The saved data are also exported via e-mail to an external computer for saving, processing, and analysis, including the production of movement graphs and error pattern detection. *Figure 2* shows some of the user screens for the app described in this article.

ACCURACY AND PRECISION

To test the accuracy and precision of the smartphone accelerometer-based app, data retrieved from the phone's LIS331DLH accelerometer were assessed by comparing angular movement data recorded (angle and time) concurrently by the app and a dynamometer (Biodex™ isokinetic dynamometer System 4; Biodex Corp., Shirley, NY) during a uniplanar knee flexion and extension motion. The iPhone was activated and mounted 2 cm from the axis of rotation of the dynamometer's movement arm. The phone was positioned face up, such that the touch screen was facing away from the exercise seat, with the top of the phone (the side of the phone with the earpiece) placed proximally and the bottom of the phone sitting distally on the movement arm (*Fig. 3*).

The dynamometer was set to passive mode, which allowed the movement arm to rotate into knee extension and flexion (approximately 100° of total rotation), at 30°/s, 60°/s, 90°/s, 120°/s, and 150°/s) without externally applied force. Therefore, participants were not required for this study. Nine repetitions were performed at each velocity (except for 30°/s, for which only three repetitions were recorded), and all data from each repetition were used in the statistical analysis. Nine repetitions were analyzed to mimic the number of repetitions recommended per set by the American College of Sports Medicine.[22] Only three repetitions at 30°/s were recorded because each repetition was two to five times slower than the other test velocities. A spline interpolation was used to ensure an equivalent number of data points collected by the iPhone and Biodex system, which was necessary for the statistical analysis (see below). The angle and time measurements taken by each instrument were compared to determine the accuracy and precision of the smartphone app.

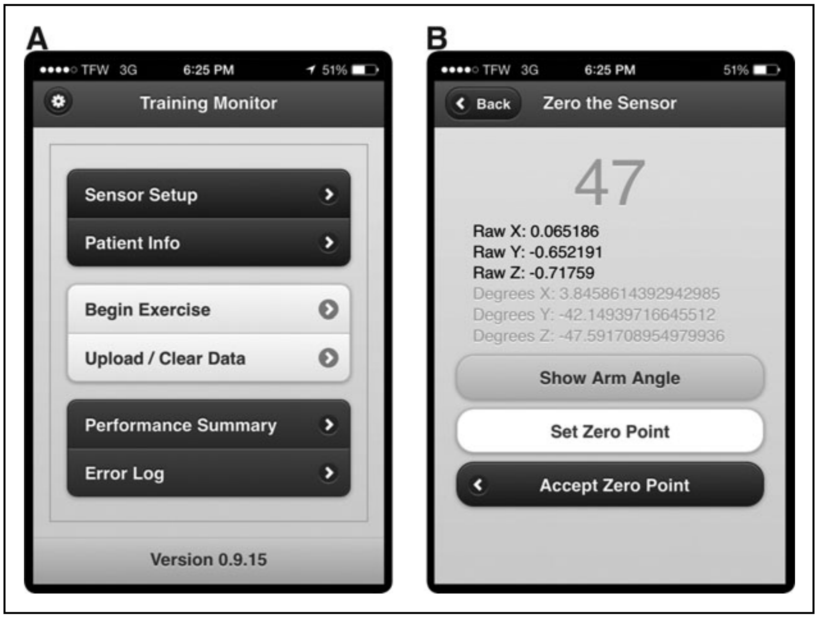

Fig. 2. User screens for the app validated in this study. **(A)** App home screen, with options to enter patient information, calibrate the accelerometer, and begin exercise/export exercise data. **(B)** Accelerometer calibration screen, with the raw accelerometer values in black, and the angle (in degrees) for each axis shown in gray. The large gray angle on the top shows the angle of the movement arm, calculated by combining measurements from all three axes.

STATISTICAL ANALYSIS

Accuracy analysis. Pearson product moment correlation coefficients were calculated to identify the degree of association and the strength of the linear relationship between the measurements recorded concurrently by the dynamometer and the app (evaluated at the alpha = 0.05 level). The limits of agreement between the angle measurements taken by each instrument were calculated at each test velocity as described by Bland and Altman.[23] Additionally, root mean square errors between each instrument were calculated at 15°, 30°, 45°, 60°, 75°, and 90° of knee extension for each test velocity. Finally, fast Fourier transforms were used to compare the spectrum of the waveforms produced when plotting the rotation of the dynamometer movement arm over time. Spectra were compared for the similarity of the dominant frequencies.

Precision analysis. From the app's angle and time readings, the slopes of the movement plots (angular velocity) were calculated during the extension and flexion phases of rotation. The mean velocity recorded by the app across the nine repetitions recorded at each test speed (except for 30°/s [see Accuracy and Precision section above]) and the standard deviation of those velocities were used to calculate the standard error of measure.

Results

ACCURACY

Figure 4 shows the concurrent readings taken by the app and the dynamometer. The Pearson correlation coefficients, quantifying the strength of the linear relationship between these two instruments, were significant and high: $r = 0.999$ at 30°/s, 90°/s, 120°/s, and 150°/s and $r = 0.994$ at 60°/s (all $p < 0.05$).

The limits of agreement between the smartphone app and the Biodex angle/time readings are listed in *Table 1*. The mean difference between the app and the Biodex was less than 1° for all test velocities. The limits of agreement for angle readings taken at each velocity are within 2° (except at 150°/s with a lower bound of –2.16°), and the velocity with the highest level of agreement was 30°/s. The root mean square errors for the selected angles of knee extension are shown in *Table 2*. The root mean square error never exceeded 1.5° for any angle across any test velocity.

The fast Fourier transforms (*Fig. 5*) compared the spectrum of the waveforms produced when plotting the rotation of the Biodex movement arm. At all speeds, the dominant frequencies in the waveforms recorded by each instrument were

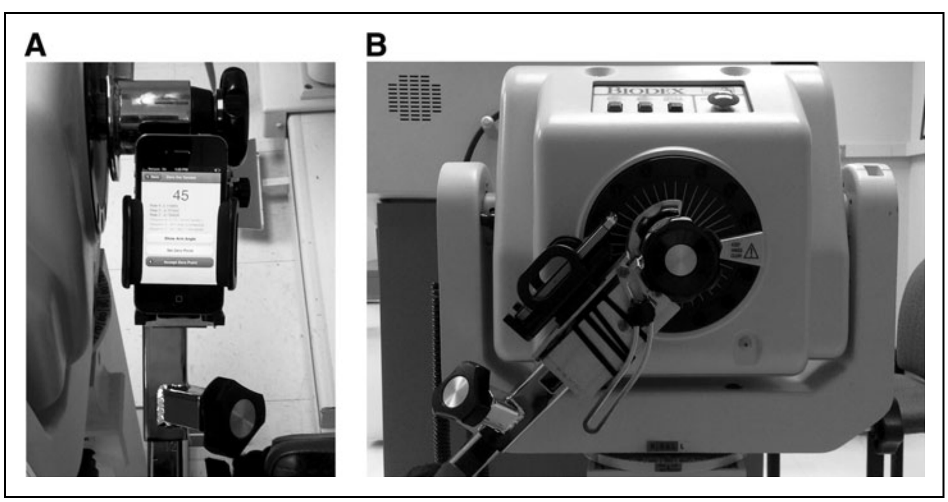

Fig. 3. Experimental setup: **(A)** anteroposterior and **(B)** lateral views of the experimental setup of the iPhone on the movement arm of the dynamometer set to 45° of knee flexion.

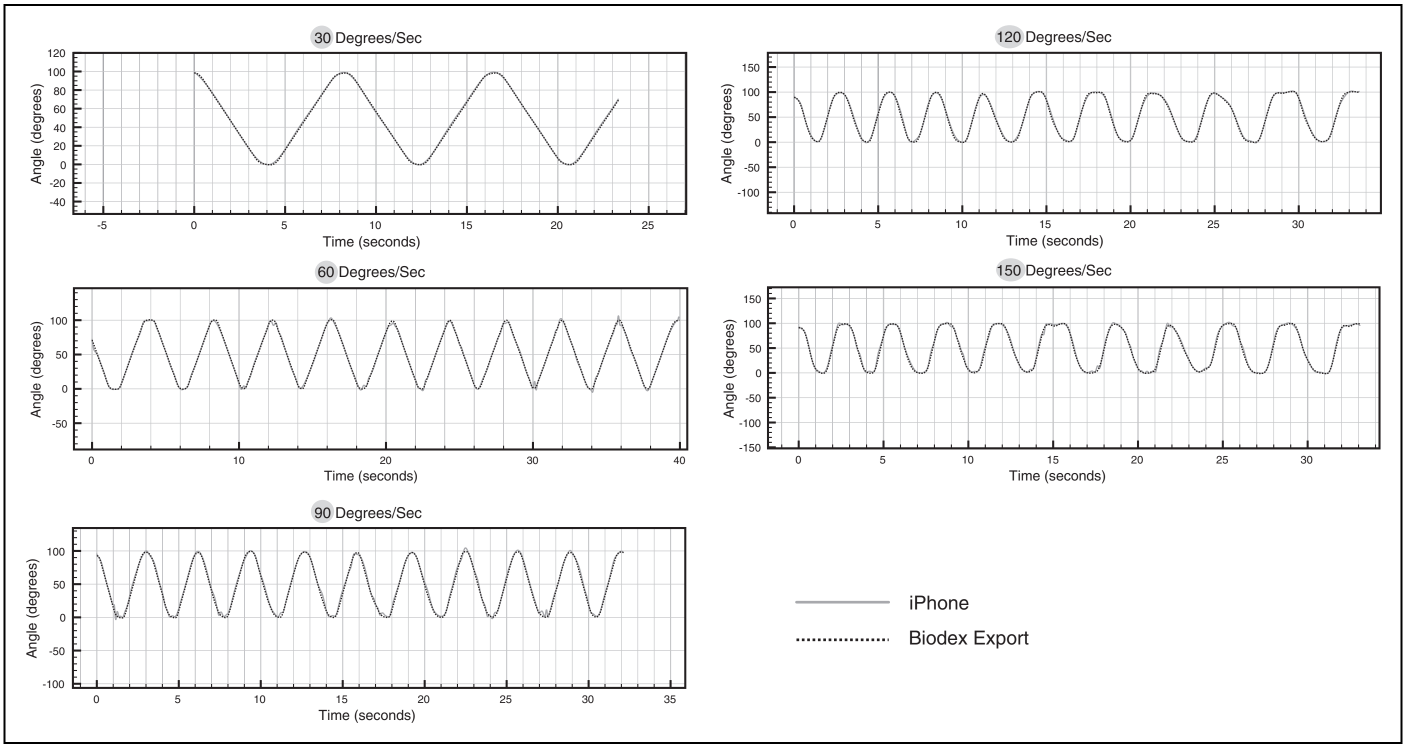

Fig. 4. Biodex dynamometer and iPhone recordings. Graphs show movement recordings (angle and time) taken concurrently by the iPhone app (straight line [——]) and the Biodex (dotted line [-----]). Nine repetitions were performed at each test speed except for 30°/s (three repetitions).

identical (the peaks in the graphs occur at the same location in the frequency domain), indicating strong similarity between instruments.

PRECISION

The results of the coefficient of variation analyses demonstrated that the app was highly precise when measuring angular movement over time (*Table 3*). The coefficient of variation was less than 3% at 30–120°/s, and less than 7% at 150°/s.

Table 1. Limits of Agreement

	SELECTED VELOCITY				
	30°/S	60°/S	90°/S	120°/S	150°/S
Mean difference (°)	0.12	0.19	−0.42	−0.41	−0.80
Limits of agreement (95% CI)	−0.65 to 0.62	−2 to 2	−1.5 to 0.65	−1.97 to 1.15	−2.16 to 0.58

Mean difference, and 95% CI between angle measurements taken by the iPhone app and Biodex isokinetic dynamometer for all test velocities.

CI, confidence interval.

Discussion

The purpose of this study was to determine the accuracy and precision of a novel accelerometer-based smartphone application when monitoring and recording angular movement over time. The results demonstrate that the app was highly accurate when compared with the gold standard in monitoring resistance training—the Biodex isokinetic dynamometer. At all test speeds, the Pearson correlation coefficient between the app and the dynamometer was 0.994 or greater. The mean difference between instruments was less than 1° across all test speeds, with the 95% confidence interval never exceeding 2.2°. This 2.2° error does not exceed the 5° mean error limit established by the American Medical Association for reliable evaluation of movement impairments in a clinical context and is therefore clinically insignificant.[24] Furthermore, the fast Fourier transform analysis revealed that the iPhone app and dynamometer recorded the same dominant frequencies during rotation of the dynamometer's movement arm. Finally, the iPhone app demonstrated a high level of precision, with the coefficients of variation measuring less than 3% for all speeds except 150°/s (6.8%).

The findings in this study coincide with the findings of work previously performed regarding the accuracy and precision of applications using smartphone hardware to monitor

Table 2. Root Mean Square Errors

TEST VELOCITY	SELECTED KNEE EXTENSION ANGLE					
	15°	30°	45°	60°	75°	90°
30°/s	0.42°	0.53°	0.56°	0.63°	0.41°	0.45°
60°/s	0.89°	0.49°	0.30°	0.36°	0.58°	0.61°
90°/s	0.69°	0.64°	0.62°	0.75°	0.70°	0.59°
120°/s	0.76°	0.79°	0.90°	1.1°	1.0°	0.54°
150°/s	1.3°	1.1°	1.4°	1.5°	1.3°	1.1°

Root mean square errors between the iPhone application and the Biodex isokinetic dynamometer at different angles of knee extension and test velocities.

uniplanar movement. Ockendon and Gilbert[25] reported a correlation coefficient of 0.947 between a smartphone accelerometer-based knee goniometer and a traditional goniometer. Their iPhone goniometer demonstrated superior intra- and inter-rater reliability to the traditional goniometer, reducing inter-rater discrepancy by more than 70%.[25] Smartphone accelerometers have also been shown to be valid and reliable when measuring combined movements. The apps used by Yamada et al.[26] and Nishiguchi et al.[13] demonstrated "remarkable consistency" during gait analysis (e.g., peak frequency and acceleration peak intervals) and correlated significantly ($r > 0.82$) with more traditional triaxial accelerometers. Likewise, the iPhone app used by Tousignant-Laflamme et al.[27] demonstrated good inter-rater reliability and validity when measuring cervical range of motion.

The use of these mobile devices has become a growing trend in the field of rehabilitation due to their small size, significant processing power, portability, prevalence in the general population, long battery life, and low cost. Additionally, smartphones use internal real-time clocks, allowing these devices to differentiate activity patterns over extended recording periods. For apps designed to recognize inappropriate exercise performance, validation of their ability to accurately and precisely track a user's movement is a vital prerequisite to their clinical implementation. However, in a recent systematic review, Milani et al.[28] determined that, to date, no movement tracking smartphone app has been properly validated in dynamic conditions (e.g., validating measurements during active rotations, rather than at static positions), as was done in this study. Additionally, the authors identified a paucity of validation

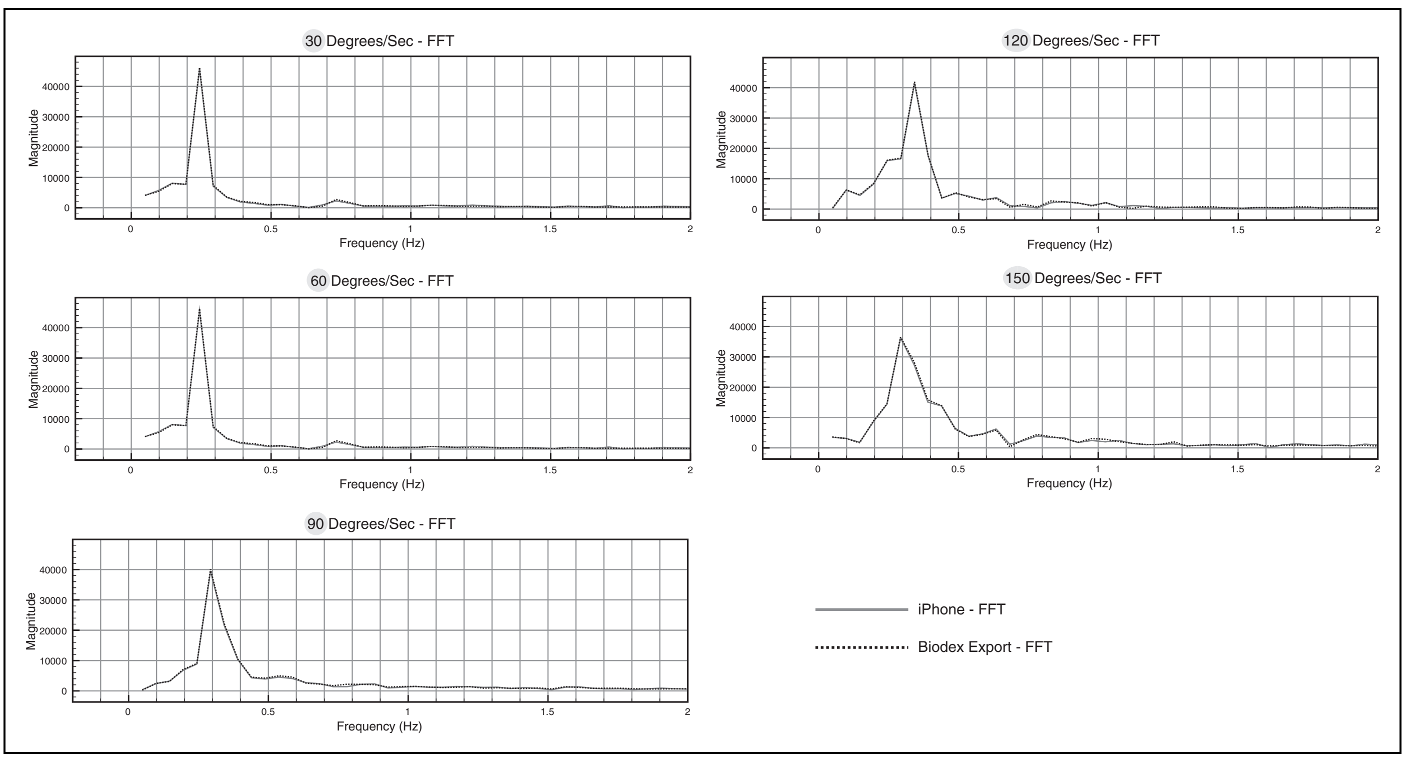

Fig. 5. Fast Fourier transform (FFT) plots. Graphs show FFT analyses of angle and time readings taken by the iPhone (straight line [——]) and dynamometer (dotted line [-----]) during each test speed. *x*-axis = frequency (Hz), *y*-axis = magnitude.

Table 3. Precision Analysis for the iPhone Application

APP	SELECTED REFERENCE DYNAMOMETER VELOCITY 30°/S	60°/S	90°/S	120°/S	150°/S
App average velocity (°/s)	29.78	59.96	89.75	121.13	137.48
SD (°/s)	0.87	0.45	1.56	3.38	9.39
Coefficient of variation (%)	2.9	0.7	1.7	2.8	6.8

For each selected velocity on the Biodex isokinetic dynamometer are given the average velocity recorded by the application (app), the standard deviation (SD) of the average velocities, and the coefficient of variation of the average velocities.

studies on apps measuring angular movement during therapeutic exercise.[28]

Pernek et al.[29] did investigate the reliability of smartphone hardware when measuring exercise data. Specifically, they found that after 3,598 repetitions, the repetition miscount rate was approximately 1%, with a temporal detection error of 11%—indicating that a smartphone could detect correct repetition start and end times based on their time-warping algorithm.[29] Spina et al.[30] also investigated an app using the Android™ (Google, Mountain View, CA) SDK on a smartphone to monitor rehabilitative exercise performance and to provide corrective audio voice prompts based on several different errors nested within their performance detection algorithm. Their validation process, however, was limited, and the app was not compared with a reliable external measure as was done in this study (Biodex isokinetic dynamometer System 4). As a result, the feedback prompts designed to correct performance were only 63% accurate.[30]

The app validated in our study is written to monitor patient exercise performance, to identify movement errors (e.g., deviations from the velocity, range of motion, or control instructions established by the therapist or physician), and to provide real-time feedback regarding the errors made and how to correct those errors on subsequent repetitions. After their exercise session, or following completion of their home exercise program, patients can export their performance data (time and angle data, as well as performance summary) directly to their therapist, physician, or physiatrist for analysis through e-mail. The time and angle data can be used to generate detailed graphs for movement pattern analysis. Also, the performance summary includes the number of errors, the type of error, and when the error occurred in the exercise (time and angle) in a neatly organized table. These features were used in a subsequent study in which 38 participants trained with the app to determine its ability to monitor participant movement and to identify and count errors. Participant movement and performance data were exported through email to determine the app's ability to improve exercise form and assess for common patterns of resistance training errors (e.g., use of improper range of motion, moving too quickly, not controlling the weight).

Data obtained through these built-in features can be used in progress reports and to help justify continuation or discontinuation of health services—providing objective, accurate evidence of patient progress during treatment. In the current clinical model, it is difficult to determine the level of adherence to home exercise programs, and even harder to determine if patients are following the prescription (reps, sets, movement speed, etc.) outlined by their doctor or therapist. This app can bridge this gap—allowing clinicians to closely monitor patient adherence, increase their access to the patient, and increase supervision outside the clinic. Although the app does not currently support live-streaming of data, a live-streaming feature could be developed and would facilitate the use of smartphone accelerometer data with other motion capture devices, such as video, infrared, or electromagnetic systems.

Given the accuracy and precision of this app, the next steps are (1) to determine its accuracy and precision during multiplanar movement and (2) to determine its ability to identify and correct movement errors and to improve exercise performance. The app uses LIS331DLH measurements in the x, y, and z directions to yield linear sensitivity, suggesting that angle/time data recorded in the other axes may be just as accurate as the single axis measurements taken in this study.

Apps designed to inform patients of the errors they are making during exercise, and how to correct them through real-time feedback, may improve the safety and efficacy of the exercise while promoting long-term motivation and adherence.[31] Thus, accurate and timely feedback is crucial. To establish a system of accurate feedback and prompting, validation of movement tracking against accurate devices is a necessity.

Conclusions

Based on the findings in this study, the smartphone app written by the authors of this study, designed to use the iPhone 4S's LIS331DLH accelerometer, is statistically and clinically identical to the Biodex isokinetic dynamometer in its ability to accurately and precisely record angular movement over time. Moreover, the app can use movement data to identify resistance-training errors and provide real-time feedback regarding the type of error made and how to correct the error during subsequent repetitions. Further investigation is needed to determine the ability of this app to identify and correct these movement errors, which would allow clinicians to monitor patient exercise performance at home or in the clinic.

Disclosure Statement

No competing financial interests exist.

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