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Longitudinal concordance of body composition and anthropometric assessment by a novel smartphone application across a 12-week self-managed weight loss intervention

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Abstract

Smartphone applications (SPA) now offer the ability to provide accessible in-home monitoring of relevant individual health biomarkers. Previous cross-sectional validations of similar technologies have reported acceptable accuracy with high-grade body composition assessments; this research assessed longitudinal agreement of a novel SPA across a self-managed weight loss intervention of thirty-eight participants (twenty-one males, seventeen females). Estimations of body mass (BM), body fat percentage (BF%), fat-free mass (FFM) and waist circumference (WC) from the SPA were compared with ground truth (GT) measures from a dual-energy X-ray absorptiometry scanner and expert technician measurement. Small mean differences (MD) and standard error of estimate (SEE) were observed between method deltas (ΔBM: MD = 0·12 kg, SEE = 2·82 kg; ΔBF%: MD = 0·06 %, SEE = 1·65 %; ΔFFM: MD = 0·17 kg, SEE = 1·65 kg; ΔWC: MD = 1·16 cm, SEE = 2·52 cm). Concordance correlation coefficient (CCC) assessed longitudinal agreement between the SPA and GT methods, with moderate concordance (CCC: 0·55–0·73) observed for all measures. The novel SPA may not be interchangeable with high-accuracy medical scanning methods yet offers significant benefits in cost, accessibility and user comfort, in conjunction with the ability to monitor body shape and composition estimates over time.

Key words: Two-dimensional images: Dual-energy X-ray absorptiometry: Digital anthropometry: Weight-loss monitoring

The assessment of body composition is vital for monitoring health, chronic disease risk, as well as athletic performance, with measures of body mass (BM), fat mass (FM), body fat percentage (BF%), fat-free mass (FFM) and waist circumference (WC) often reported[1,2]. Whether direct assessments or indirect surrogate measurements of body composition are used typically relies on the context for which the measurement is required. Methods such as MRI, computed tomography and dual-energy X-ray absorptiometry (DXA) provide accurate body composition assessment yet are expensive and time-costly with potential participant burden[1]. Though others may provide improved accessibility, such as bioelectrical impedance analysis (BIA), three-dimensional (3D) optical body scanning and anthropometrics, they do not deliver the accuracy of computed tomography, MRI or DXA methods[4,5]. Nonetheless, many of these accessible surrogate methods can still provide an individual or clinician with the potential to estimate body composition levels to infer disease risk, track health improvements or set performance outcomes[5].

Accessible assessments of body shape and composition have been validated cross-sectionally, and to a lesser extent, longitudinally[6,7]. Longitudinal research has primarily utilised BIA for body composition assessment, comparing changes over time with methods[8–12]. The findings have varied in support for measuring changes in adiposity and muscle mass, with mean differences (MD) ranging between 2–6 kg for FFM and 2–3 percentage points for BF%. Novel methods of assessment are now available via smartphones, which offer the hardware

Abbreviations: BIA, bioelectrical impedance analysis; BM, body mass; BF%, body fat percentage; CCC, concordance correlation coefficient; DXA, dual-energy X-ray absorptiometry; FM, fat mass; FFM, fat-free mass; GT, ground truth; MD, mean differences; SEE, standard error of estimate; SPA, smartphone application; WC, waist circumference; 3D, three-dimensional.

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and processing capabilities to utilise high-grade digital imaging technologies and machine learning models for body shape and composition assessment[13].

Previously validated smartphone and digital imagery technologies have provided promising results compared with expert measurement and multi-camera digital 3D photogrammetry[14–17]. A two-dimensional smartphone application (SPA) 'BodyScan' (Body Composition Technologies, Advanced Human Imaging, CompleteScan, Version 21.1.2) utilises machine learning and computer vision trained on a large dataset of medical images to predict body shape and composition from two-dimensional smartphone images. Results of the BodyScan technology were clinically equivalent to DXA and technician circumferences, similar to those achieved by other technologies[15]. Other techniques have been reported by Farina *et al.* who found low cross-sectional standard errors in two-dimensional smartphone image predictions of body FM (standard error of estimate (SEE): 2·7–2·9 kg) for male and females across a wide range of body fat[14]. However, these previous validations have relied on back-end cloud processing (i.e. model processing did not run on the smartphone device) or have utilised cross-validation techniques of model outputs. These preliminary validations are also cross-sectional comparisons, rather than a longitudinal data series employed to monitor change over time. Ultimately, a body composition assessment tool must be able to accurately track change if it can be meaningfully used to improve health and reduce risk of chronic disease.

To provide further narrative to a rapidly evolving field, this research aims to analyse agreement between the commercially available SPA and ground truth (GT) methods of DXA and expert tape-measure circumference. Longitudinal agreement between the SPA estimations and GT measures of BM, BF%, FFM and WC will be compared across a 12-week weight loss intervention. In line with previous smartphone measurement validations, we hypothesise that there will be significant correlations in longitudinal concordance of the SPA and GT measures, MD of each measurement will trend in the same direction for monitoring change over time and that no significant differences ($P < 0·05$) in method and method by time changes will be observed between the methods.

Methods

Participants

Participants interested in self-managed weight loss, aged between 30–65 years, were invited to participate in this study. Participants with a physical disability that prevented an accurate measurement of their anthropometry or body composition were excluded from participation, as were those who were pregnant or weighed >160 kg (DXA table limitation). This study was conducted according to the guidelines laid down in the Declaration of Helsinki and all procedures were approved by The University of Western Australia's Human Ethics Research Committee (RA:2021/ET000254). The study procedure was explained to each participant, who provided their written consent. Participants agreed to self-manage their weight loss across the 12 weeks of measurement. As part of participation in this research, all participants were offered the option of a free consult with a metabolic specialist and exercise physiologist to help advise their own goals. The focus of this research was not the monitoring of an intervention; each participant's individual goal of change in their body composition was encouraged, with a variation in weight loss and body composition to be expected. Participants were requested to wear form-fitting clothing, be barefoot and void their bladder and bowel before assessment. Two sessions were analysed across a self-directed 12-week weight-loss intervention period; the same measures were taken at each session.

Anthropometric measurements

Firstly, GT measurements including height, BM and WC were measured by a single trained technician (International Society for the Advancement of Kinanthropometry (ISAK)) across all three sessions. Standing height was recorded with a wall-mounted stadiometer and BM was measured to the nearest 0·01 kg using a self-calibrating digital platform scale (MultiRange, Model ED 3300). WC was measured twice with an inelastic retractable anthropometric tape (Lufkin W606PM Executive Diameter Tape) following ISAK standard protocols[18]. Both measurements were averaged if they were taken within 2 % measurement error (~1·8 cm). WC was measured horizontally at the narrowest point between the iliac crest and the tenth rib. When the technician was unable to identify the narrowest point, WC was measured at the midpoint of these landmarks, with the specific assessment point kept consistent across the testing sessions for each participant.

Dual-energy X-ray absorptiometry

A DXA scanner with Encore Version 17 software (GE Lunar iDXA, GE Healthcare) was used to assess each participant's body composition. Daily quality assurance tests were performed as per the manufacturer's procedures. In a supine position, participants rested with their arms by their side and feet apart. Participants who did not fit inside the scan plane had their left arm cropped in the same position each session using the manufacturer's mirror analysis. Regions of interest were manually annotated and adjusted post-scan to standardise segmentation as per previously published methods[19]. Outputs were processed for whole-body BF% and FFM. Previous scan–rescan analysis using the same scanner indicated a SEE of 0·4 % points for BF% and 0·52 kg for FFM.

Smartphone application assessment

An iPhone 13 (Apple Inc. California) with the BodyScan SPA was placed upright on a tripod to capture the participant images. The SPA directs the capture process using automated on-screen guides to allow the participant to fit themselves within a standardised front and side pose. Participant height and BM are entered into the phone to generate a participant-specific contour shape for the participant to fit their body within. Six rounds of front and side images were taken of the participant in front of a chroma key screen, totalling twelve images.

The images were captured and processed through the BodyScan SPA which utilises the on-device GPU processing capabilities. After image capture, the application downloads the machine learning models onto the device which estimate shape and body composition outputs including BM, BF%, FFM and WC. Entered BM for the image capture process is not used by the technology to guide the smartphone estimations of BM. The BodyScan proprietary machine learning models were trained using a large dataset of front and side profile images and body shape and composition data from previously published heterogeneous populations[19,20]. All iPhone images were inspected for participant position quality and model processing errors. Outputs from all quality attempts were averaged to provide a single output for BM, BF%, FFM and WC for each testing session.

Statistical analysis

A power analysis was conducted on a previously collected cohort using a conservative power of 0·95 and determined that twenty-one participants would be necessary to observe significant associations at an $\alpha = 0{\cdot}05$ between the devices/methods in question and GT-derived values[19]. Statistical analyses were performed within JASP (JASP v0.16.2) and Excel (Microsoft). All data were assessed for normality with visualisation of distribution plots, analysis of skewness, kurtosis and Shapiro–Wilk tests. Repeated-measures ANOVA was undertaken using GT and SPA as comparison methods (within-subject factors) across the participant's first and last session measurements (time). Lin's concordance correlation coefficient (CCC) and 95 % CI were used to assess precision and accuracy correlation between GT and SPA deltas across the first and last testing sessions[21]. SEE and MD for measurement deltas are also presented.

Results

Forty-one participants completed their first and last sessions across the 12-week intervention. Three participants with measurement errors were not included within the analysis, leaving thirty-eight participants, twenty-one males (39·0 (SD 11·8) years, 94·1 (SD 16·8) kg, 1·79 (SD 0·05) m, 29·3 (SD 4·9) kg/m^2) and seventeen females (47·4 (SD 0·5) years, 75·1 (SD 11·7) kg, 1·67 (SD 0·07) m, 27·1 (SD 4·0) kg/m^2) for the final analysis. Mean decreases in BM, BF%, FFM and WC were observed across the cohort for both SPA and GT measures (Fig. 1). Differences between the GT measurements of the first and the last sessions exceeded the DXA scan–rescan error for BF% (MD = −1·93 % *v.* error of ± 0·4 %) and exceeded scale and technician error for BM (MD = −3·47 kg *v.* error of ± 0·001 kg) and WC (MD = −4·31 cm *v.* error of ±2 cm). The changes in FFM were similar to the reported scan–rescan error (MD = −0·48 kg *v.* error of ±0·52 kg). Repeated-measures ANOVA (Table 1) observed method main effects in male and female measures of WC, BF% and FFM ($P < 0{\cdot}05$), with larger SPA values for WC and BF% and larger GT values for FFM. Method by time interactions was observed for the combined cohort WC and male WC ($P \leq 0{\cdot}05$). Follow-up testing indicated that male WC significantly decreased in both GT and SPA measures ($P \leq 0{\cdot}001$); however, decreases in GT measures (MD = 4·64 cm) were larger when compared with SPA (3·37 cm). Time main effects indicated decreases in BM, WC and BF% for males and females. Time effects were not observed in male and female FFM. SEE values for all measurement deltas exceeded those reported for the same scanner, technician measurements for WC and BM scale accuracy. All SPA changes were significantly correlated with GT methods, with all CCC results greater than 0·55, except for female FFM (CCC = 0·25). CCC plots are presented in Fig. 2 for BM, WC, %BF and FFM.

Discussion

This research aimed to examine the longitudinal agreement of anthropometry and body composition measurements predicted from a novel smartphone technology across a 12-week self-managed weight loss intervention, compared with GT measurements from trained anthropometry technicians and DXA scans. The importance of body shape and composition tracking for clinical health risk and athletic performance has been explained by previous research, with a significant call for technological advancements to promote accessibility of assessment[5]. The most important finding from the current study is that the novel SPA provides value in the accessible tracking of body composition and anthropometry changes. Measurement tracking of changes showed a significant decrease in GT and SPA measures of BM, WC and BF%. Our hypothesis was partially supported with no significant differences observed between methods across the two testing time points for BM, BF% and FFM, although a method by time main effect was seen in significant differences in male and female changes in WC. SPA-derived BM, WC and BF% measurement changes were significantly correlated with changes in GT measurement across the 12-week intervention.

Changes in BF% and FFM were significantly correlated between GT DXA and SPA measures ($P \leq 0{\cdot}05$). Similar agreement has been observed in previous longitudinal research comparing accessible BIA and GT methods. Due to its ease of use, BIA is employed as a standard of accessible measurement, despite known limitations and reported errors[4]. Boykin *et al.* reported a longitudinal agreement for BIA estimated FFM of 0·49 CCC (95 % CI 0·17, 0·72) and 0·50 CCC (95 % CI 0·23, 0·70) for FM[9]. Recent findings by Schoenfeld *et al.* and Tinsley *et al.* also supported the use of accessible measurements via BIA for whole-body composition changes[8,12]. Contrary conclusions have previously been proposed with low correlations across ΔFM and ΔFFM estimations, suggesting the tracking of body composition is not interchangeable between methods and may not be applicable for longitudinal monitoring[10,11]. Although method differences were observed between SPA and GT measures of BF% and FFM in the current study, both methods observed the same decreasing trend across the first and final testing sessions. Similar to the current study, overestimation of FFM and underestimation of BF% by alternate accessible methods of BIA have been observed[9]. However, when these differences occur, longitudinal agreement can still be achieved between methods with a reliance on consistency of estimation over time[9]. Male and female MD between methods

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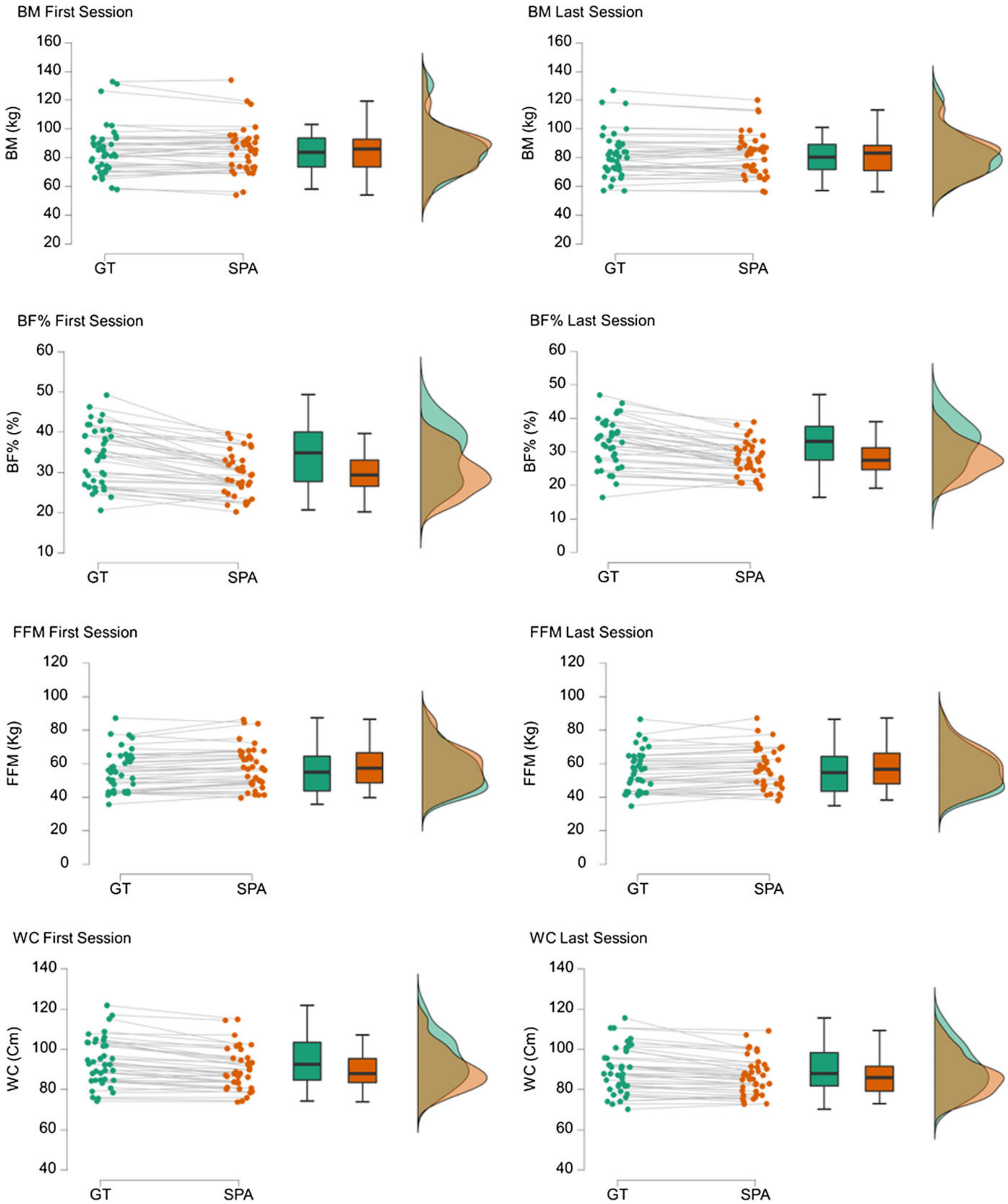

Fig. 1. Raw ground truth (GT) and smartphone application (SPA) measures of body mass (BM), waist circumference (WC), body fat percentage (BF%) and fat-free mass (FFM) displayed in raincloud, box and distribution plots for the first (left) and last sessions (right).

Table 1. Agreement between ground truth and the smartphone application measurement changes
(Mean values and standard deviations; standard error of estimates and 95 % confidence intervals)

		GT change		SPA change							Repeated-measures ANOVA (*P*)		
	Measure	Mean	SD	Mean	SD	MD	SD	SEE	CCC	95 % CI	Time	Method	Time * Method
All participants (*n* 38)	BM (kg)	−3·47	3·56	−3·35	3·66	0·12	2·89	2·82	0·68	0·46, 0·82	<0·001*	0·809	0·806
	WC (cm)	−4·31	3·77	−3·15	2·99	1·16	2·3	2·52	0·73	0·56, 0·84	<0·001*	<0·001*	0·004*
	BF% (%)	−1·93	1·77	−1·87	1·83	0·06	1·7	1·65	0·55	0·29, 0·74	<0·001*	<0·001*	0·836
	FFM (kg)	−0·48	1·3	−0·65	2·16	−0·17	1·68	1·65	0·55	0·34, 0·71	0·033*	<0·001*	0·542
Females (*n* 17)	BM (kg)	−2·98	2·7	−2·68	3·22	0·31	2·38	2·27	0·69	0·35, 0·87	<0·001*	0·878	0·618
	WC (cm)	−3·91	4·07	−2·88	2·96	1·02	2·96	2·96	0·65	0·31, 0·84	<0·001*	0·013*	0·172
	BF% (%)	−1·64	1·51	−2·02	1·92	−0·38	1·65	1·60	0·56	0·15, 0·80	<0·001*	<0·001*	0·34
	FFM (kg)	−0·57	0·87	−0·38	1·65	0·19	1·66	1·58	0·25	0·15, 0·58	0·086	0·027*	0·638
Males (*n* 21)	BM (kg)	−3·87	4·1	−3·9	3·91	−0·02	3·29	3·14	0·66	0·34, 0·85	<0·001*	0·617	0·969
	WC (cm)	−4·64	3·46	−3·37	3	1·27	1·67	2·01	0·8	0·61, 0·90	<0·001*	<0·001*	0·002*
	BF% (%)	−2·18	1·92	−1·76	1·74	0·42	1·69	1·66	0·56	0·20, 0·79	<0·001*	<0·001*	0·268
	FFM (kg)	−0·4	1·57	−0·86	2·49	−0·46	1·68	1·66	0·66	0·40, 0·82	0·143	0·003*	0·224

GT, ground truth; SPA, smartphone application; MD, mean difference; SEE, standard error of estimate; CCC, Lin's concordance correlation coefficient; BM, body mass; WC, waist circumference; BF%, body fat percentage; FFM, fat-free mass.
* Repeated-measures ANOVA was performed on raw data, significant *P* values (< 0·05).

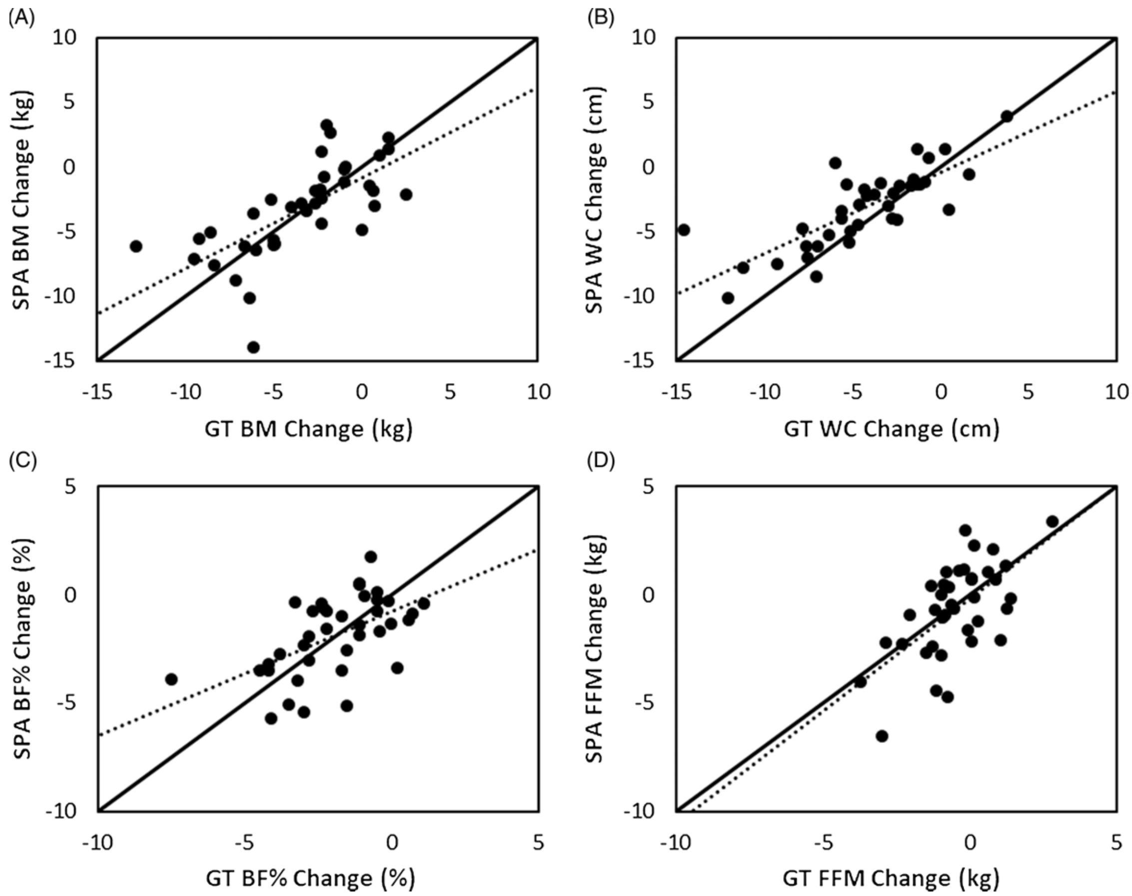

Fig. 2. Agreement of changes in body mass (A), waist circumference (B), body fat percentage (C) and fat-free mass (D). Smartphone application (SPA) prediction and ground truth (GT) change between first and last sessions are plotted and compared with the solid black line of perfect agreement. The dotted line shows the trend and correlation for comparison using Lin's concordance correlation coefficient.

were not larger than 0·42 percentage points for BF% and 0·46 kg for FFM. These observations suggest that while body composition estimates from DXA and the SPA may not be interchangeable, low differences between total FFM changes detected by each method provide a strong case for the utility of the novel SPA technology.

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The longitudinal agreement of the SPA in the current study also aligns with the high accuracy reported in cross-sectional research using two-dimensional digital and smartphone images to train machine learning and multiple regression models[14,15,17]. Our previous validation of 929 participants compared the same SPA technology used in the current study against DXA and BIA measures of BF% and FFM, with high accuracy across the heterogeneous cohort (SEE: BF% = 2·8–2·9 %, FFM = 1·7–2·3 kg)[15]. As expected, lower CCC were found in the current study when compared with the previous validation, due to the comparison of smaller longitudinal changes. Although these previously published results reported high accuracy, the outputs and model predictions were performed 'offline' on a desktop computer. This current research utilised a cloud-hosted model, downloaded onto the device to process the images using the smartphone's GPU for real-time outputs that a user could expect in their own home. With the continuously evolving development of inexpensive imaging devices, body composition assessment in clinical and home settings can be safe, practical and relatively inexpensive[5]. The novel SPA offers significant benefits in cost, accessibility and user comfort, in conjunction with comparable agreement of body composition estimates that are congruent with previously reported accessible methods such as BIA.

SPA anthropometry measures of BM and WC had strong and significant correlations with GT methods. Both GT and SPA measures significantly decreased across the weight loss intervention. However, despite a strong concordance (CCC = 0·80, 95 % CI 0·61, 0·90), male GT and SPA ΔWC were statistically different across method and time interactions (P = 0·002). Male and female ΔBM had a MD of less than 0·31 kg, with a larger SEE in males (3·14 kg). No significant differences were seen in BM between methods across the first and last sessions, with high agreement correlations. SEE of 2·5 cm for female and 2·0 cm for male ΔWC are comparable with those observed in the SPA technology's previous cross-sectional validation, with variations between the sexes due to significant differences in body shape[15]. A recent cross-sectional study compared tape measured WC with smartphone estimations and a commercial grade 3D optical scanner, with authors reporting an error of 6·1 cm for the smartphone technology, compared with 9·2 cm for the optical scanner[16]. As a generally accepted standard for digital anthropometry, lower errors of WC prediction (2·60–3·27 cm) have been reported for 3D optical scanners, with the systems sometimes requiring multiple calibrated cameras or depth sensors for accurate and repeatable measures[6,7]. These systems also require appropriate participant preparation, including swimming caps, and post-processing adjustment to improve the identification of difficult-to-scan areas such as the armpits and inner thighs. The SPA in the current study performed well when compared with these costly and widely considered robust systems, potentially paving way for a new standard of digital anthropometry – one that could be made widely available on any smartphone. Epidemiologists are becoming increasingly reliant on telehealth and 'mhealth' applications for large populations and the monitoring of at-risk cohorts in remote locations[13]. The accessibility and suitability of the measures from the novel SPA significantly increase the reach of disease and health risk monitoring.

Some limitations are present in the current study. First, while all participants aimed to reduce their FM and WC over the length of the research, not all participants achieved this goal. Mean FFM decrease was similar to the observed scan–rescan measurement error of the same DXA machine (–0·48 kg *v.* 0·52 kg). This is likely due to many participants losing FFM with weight loss, while some attempted to gain lean muscle mass across the intervention. Many participants had a goal of losing BF% and gaining FFM; thirteen participants were able to achieve this, with twenty-one participants losing both FFM and FM. Longitudinal changes in FM and FFM were explored by Tinsley *et al.* who split their cohort analysis by whether participants gained FFM but lost FM, or gained both FFM and FM, which the current study was not able to perform due to insufficient numbers[8]. However, a strength of the study was the ability to split the cohort by sex to assess the SPA's robustness, given typical differences in male and female body shape and composition.

Second, we did not monitor or control the nutritional intake of each participant, which may have provided further context to the results of the research. However, a clear reduction in BM, FM and WC was seen for both males and females, supporting the aim of the research which was to assess the SPA across longitudinal changes in body composition. Third, another limitation may be present in our choice of GT methods chosen for comparison. The GE DXA machine is considered by some to be a 'gold-standard' for whole body composition yet has its own limitations when compared with other methods, such as computed tomography, MRI or the four-component method[1]. Variations have also been reported between machines and laboratories. Technician circumference measures have also been shown to vary widely, with a variation of ~2 cm generally accepted as normal for intra-tester measurements[18]. These variations are also seen between digital technologies and manual methods due to differences in landmark location, especially for WC measurements[5]. Lastly, the SPA was utilised in a controlled laboratory to provide a 'best-case' comparison of the technology. Users may experience larger differences in uncontrolled environments; however, the application does provide examples and onboarding which explain the need for even lighting and an uncluttered background for the best estimation results. Future research will need to assess the efficacy of the SPA within settings closer to 'real-world'.

Conclusion

This research explored the longitudinal body composition and anthropometry assessment with a novel smartphone technology. The SPA was able to achieve comparable agreement of decreases in BM, BF%, FFM and WC measurement across a 12-week weight loss intervention. Similar to published reports of high-end accessible methods such as BIA and 3D body scanners, the SPA estimations offer longitudinal monitoring of body shape and composition. For the accessible measurement of anthropometry and body composition changes, it is necessary for researchers, clinicians and sports practitioners to be aware of the limitations of each method and the advantages of new technologies such as the SPA. With acknowledged measurement variation, the novel smartphone technology's ability to monitor

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trend can be utilised for performance and health risk monitoring over time.

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All authors were involved in the study design. M. K. S., A. E.-S., T. R. A. and J. R. E. organised the acquisition of the data. M. K. S. performed all statistical analysis. All authors provided interpretation of the data and revised written work for intellectual content.

M. K. S. is an employee at Body Composition Technologies, part-owned by Advance Human Imaging. A. E.-S. is employed by Advanced Human Imaging. J. M. D. S., T. R. A., J. R. E. report no conflicts.

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