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Effectiveness of digital health interventions to increase cardiorespiratory fitness: A systematic review and meta-analysis

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Abstract

Background: Interventions using commercial digital health tools do favorably affect health outcomes. However, the effect of digital tools on cardiorespiratory fitness, a more novel indicator cardiovascular risk, is unclear.

Purpose: Synthesize the digital health intervention literature and answer the following question: What is the effect of interventions using mobile health apps, wearable activity trackers, and/or text messaging on cardiorespiratory fitness?

Methods: A systematic review and a meta-analysis (PROSPERO CRD42023423925) were conducted to evaluate the immediate digital health intervention effect on adult cardiorespiratory fitness. In March 2023, a search of databases Embase, MEDLINE, CINHAL, and Cochrane Library was completed. Studies were included if the intervention used a mobile health app, text messaging, and/or activity tracker. Studies were excluded if an objective measure of fitness was not used; the sample included children; the setting was hospital-based; and the digital health technology was only used for data collection or described as virtual reality. Using a random-effects model, two separate meta-analyses were completed: one for single-group studies and one for multi-group studies. Standardized mean difference effect sizes (Cohen's *d*) were calculated. Study quality was evaluated with the Cochrane Risk of Bias tool and ROBINS-I tool.

Results: Fifty-three studies (3657 individuals) with pre-post designs (12 single-group, 41 multi-group) were included. Most studies targeted participants with a specific chronic health condition. Digital health interventions in the single-group studies had a moderate-to-large effect size ($d = 0.62$, 95% confidence interval (*CI*) [0.41–0.84], $p < 0.001$), and multi-group studies had small-to-moderate effect size ($d = 0.38$, 95% *CI* 0.21–0.55, $p < 0.001$). Significant heterogeneity of effects was observed in both the single-group and multi-group studies.

Conclusions: Interventions using text messaging, a mobile app, or activity tracker alone or in combination are effective in improving cardiorespiratory fitness in adults, particularly for those with a chronic health condition.

Keywords

Cardiorespiratory fitness, digital health, digital tools, meta-analysis, physical activity

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Introduction

Digital health tools, including wearable physical activity monitors, smartphone health apps, and text messaging, are effective intervention components to improve health behaviors and health outcomes.[1–7] For example, meta-analytic evidence indicates that weight loss intervention participants lost seven times more weight when text messaging was included as an intervention component.[8]

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Likewise, among participants with type II diabetes, brief text messaging interventions had a significant favorable effect on hemoglobin A1C (3-month average blood glucose) compared to usual care conditions.[9] Other effective digital health strategies include mobile app use for informational support and as a tool to self-monitor weight and/or physical activity behavior.[1,10] Digital health interventions commonly evaluate physical activity behaviors (i.e., steps, duration, intensity) and cardiovascular outcomes, including body mass index, blood pressure, cholesterol, and glycosylated hemoglobin (A1C). Cardiorespiratory fitness, a powerful predictor of cardiovascular risk, is a relatively novel outcome of interest in health behavior research. High-level evidence of the effect of digital health tools on fitness in adults is limited. Emberson et al. (2021) conducted a systematic review evaluating the effects of smartphone-based physical activity interventions; only one of the 20 studies included in the review evaluated fitness as an outcome.[11] In that one randomized design study with low-activity adults in New Zealand (N = 51), there was no significant difference in fitness evaluated with a 1 mile walk/run test compared to control.[11] In another recent systematic review with meta-analysis, the effect of smartphone-based interventions on fitness in adults with coronary artery disease included eight studies (1120 participants).[12] Here, where the fitness measure (6 min walk test) was the same across all eight studies reviewed, fitness was significantly better among those receiving the smartphone app intervention versus those who received standard cardiac rehab.

Cardiorespiratory fitness is the efficiency of the heart and lungs working together to supply oxygen to muscles in the body during exertional physical activity. Common measures of fitness include volume of oxygen consumed during activity (VO_2) and metabolic equivalents (METs), which are the metabolic cost of an activity compared to resting metabolism. In adults, optimal health is associated with performing activities at a MET level of 8 to 10; increased risk of cardiovascular disease and all-cause mortality are associated with only performing activities with a MET level less than 5.[13] The gold standard method of fitness evaluation is a graded exercise test (on treadmill or bicycle) that progresses until maximum effort or exhaustion is achieved while the individual wears a mask to measure oxygen and carbon dioxide exchange.[14] Reliable and valid submaximal fitness evaluation, which is more amenable to clinical and community settings, has been developed and include walk, step, and cycle tests.[15,16] As a biomarker, submaximal fitness tests are sensitive to intervention and therefore useful for serial evaluation of efforts to change physical activity behavior.[17] Since 2016, the American Heart Association has called for fitness assessment in adults at least annually during routine clinical visits to improve cardiovascular risk prediction and risk management by objectively evaluating the cardiorespiratory efficiency.[13] Given the surge in digital health research and the increasing focus on cardiorespiratory fitness, description of the effect of digital health interventions on fitness outcomes is needed to support evidence-based practice. The purpose of this systematic review and meta-analysis was to synthesize the current digital health intervention literature and answer the following question: what is the effect of interventions using mobile health apps, wearable activity trackers, and/or text messaging on cardiorespiratory fitness?

Methods

The PRISMA guidelines[18] guided the protocol development for this systematic review and meta-analysis, and the protocol is registered with PROSPERO (CRD42023423925).

Information sources

Search strategy. The literature was searched using search strategies developed by a health sciences librarian (DW) on the topics of mobile or digital health behavior interventions, physical activity, and cardiorespiratory fitness in adults. These strategies were developed using a combination of standardized index terms and keywords and were performed in Embase (Elsevier), MEDLINE (EBSCO), CINHAL (EBSCO), and Cochrane Library (Wiley). Search limits applied were published in English, published between January 2000 and December 2023, adult sample, and all study types, except for reviews, letters, notes, and editorials. The publication timeframe was set according to two key digital health milestones; mobile phone data interaction functionality (email and text) began in 2000, and Fitbit, the first commercial wearable activity tracker, became available in 2009.[19] The databases were searched, and articles were retrieved on 31 March 2023. The search strategies used are available to view in Supplemental file 1.

Eligibility criteria. Studies were included if they reported on interventions that used a mobile health app, text messaging, and/or a wearable activity tracker and an objective measure of cardiorespiratory fitness. Studies were excluded if an objective measure of fitness was not used; the sample included children; the setting was hospital based; and the digital health technology was only used for data collection or was described as virtual reality.

Selection process. Using Covidence software,[20] two doctorally prepared researchers (SR and CB) independently reviewed titles and abstracts to confirm eligibility, then together, the researchers reconciled all discrepancies. Figure 1 details the study selection process.

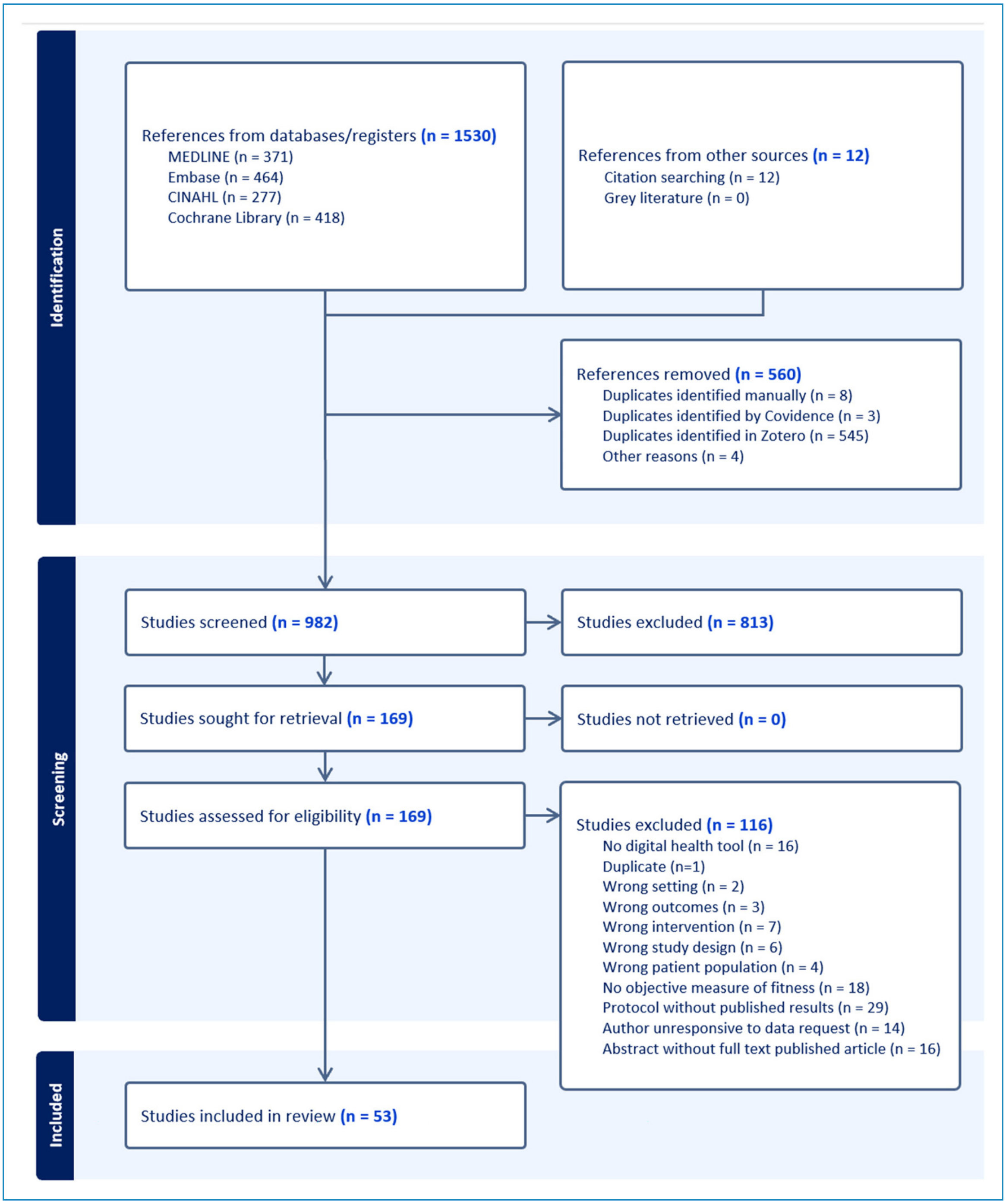

Figure 1. PRISMA flowchart.

Data collection

Coding. An a priori codebook was developed from prior physical activity studies performed by the first author, including a meta-analysis on interventions targeting sedentary behavior in older adults.[21–23] To evaluate the codebook performance with data extraction, the codebook was piloted independently by SR and CB with 10 studies, and then revised following consensus. All eligible studies were independently coded by SR and CB using Covidence software, and all discrepancies reconciled through discussion and re-review of the associated study.

Data items. Descriptive data on each study (Supplemental Table 2) were collected, including study location, setting, funding status, study design, sample demographics (i.e., age, gender, ethnicity), and intervention characteristics (i.e., duration, digital health components, behavior change components). Select taxonomy-defined behavior change components collected included self-monitoring, goal-setting, feedback, problem solving, and role modeling,[24] as well as shared and supervised physical activities. Data needed to calculate effect sizes were also collected, including sample size, outcome mean (most proximal to end of intervention), and measures of variability. If a study did not report data needed to calculate effect sizes, a request for the missing data was made to the corresponding author. A total of 21 corresponding authors were contacted for missing data; 28.5% (n = 6) responded with the data needed to include their study in our meta-analysis.

Bias assessment. The Cochrane Risk of Bias tool was used to evaluate the quality of studies using a randomized control trial (RCT) design.[25] The Cochrane tool evaluates bias as high, low, or unclear across five domains, namely, selection, allocation concealment, reporting, and other sources. The ROBINS-I tool was used to evaluate the quality of non-randomized design studies.[26] The ROBINS-I tool evaluates bias as low, moderate, critical, or no information across seven domains, including confounding, participant selection, intervention classification, intervention deviation, missing data, and measurements. Both tools have an overall bias rating. Researchers (SR and CB) evaluated the quality of each study independently, then discrepancies were reconciled through discussion. Publication bias was also evaluated with the trim and fill test,[27] Egger's regression intercept,[28] and funnel plots[29] using Comprehensive Meta-Analysis software (CMA). Multiple publication bias tests are done in order to provide greater confidence in the results.[30]

Data analysis

Data analysis was accomplished with CMA software.[31] A random effects-model was chosen due to the expected heterogeneity among the studies.[30] Two separate meta-analyses were completed: one for single-group studies and one for multi-group studies using either randomized or non-randomized designs.[30] Only objective measures of cardiorespiratory fitness were used. Standardized mean difference effect sizes were calculated in CMA, with the majority done by subtracting the mean of the control group from the mean of the treatment group and dividing by the pooled standard deviation. In the multi-group meta-analysis, two studies required the use of difference in means and p values;[32,33] one study required sample size and p value;[34] and one study required means and t value.[35] In the single-group meta-analysis, the study involved three intervention groups who all used pedometers and were combined into one group. As per our inclusion criteria, every group had a wearable device.[36] Where studies had more than one outcome measure, they were combined in CMA by taking the average of the means.[30] The type of fitness outcome measure can be seen in the forest plots for each meta-analysis (Figures 2 and 3), including subjective, objective, or combined.

Cohen's d was chosen to quantify the effect sizes as recent research has questioned the bias of Hedge's g.[37] A positive effect size was set to indicate improvement in cardiorespiratory outcomes in the intervention group compared to the control group or to themselves pre-intervention. A negative effect size indicates worse cardiorespiratory outcomes in the intervention group compared to the controls or compared to themselves pre-intervention.

Study Name	Statistics for each study			
	Std diff in means	Lower limit	Upper limit	p-Value
Browne 2021	0.855	0.243	1.467	0.006
Buchholz 2016	0.545	0.179	0.911	0.003
Cheong 2018	0.490	0.250	0.730	0.000
Child 2023	0.167	-0.361	0.694	0.536
Linke 2019	0.596	-0.045	1.238	0.068
Maltais 2019	0.736	0.518	0.955	0.000
Nabutovsky 2020	3.400	2.259	4.541	0.000
Orleans-Pobee 2022	0.152	-0.357	0.661	0.558
Pfirrmann 2019	0.457	0.143	0.771	0.004
Pope 2019	0.000	-0.693	0.693	1.000
Wilbur 2016	0.446	0.308	0.584	0.000
Wilczynska 2021	1.196	0.622	1.770	0.000
Pooled	0.596	0.386	0.806	0.000
Prediction Interval	0.596	-0.087	1.279	

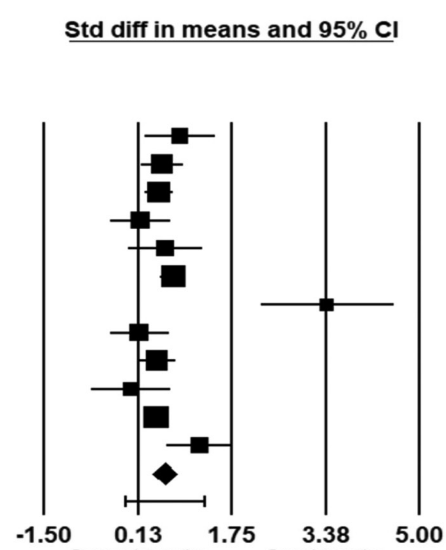

Figure 2. Forest plot of single-group, posttest cardiorespiratory fitness outcomes among adults. A random-effects model was used to calculate effect sizes. Square areas are proportional to the study weight.

Study name	Std diff in means	Lower limit	Upper limit	p-Value
Alibhai 2022	0.099	-0.623	0.821	0.788
Aschbrenner 2022	-0.873	-1.275	-0.471	0.000
Avila 2018	0.210	-0.325	0.745	0.442
Berglind 2020	0.023	-0.398	0.443	0.915
Bonato 2020	0.462	-0.220	1.145	0.184
Brooker 2023	0.453	0.015	0.891	0.042
Browne 2023	0.899	-0.025	1.823	0.057
Chang 2021	0.669	0.196	1.141	0.006
Chen 2020	0.309	-0.884	1.503	0.611
Chiang 2022	0.559	0.074	1.045	0.024
Christensen 2019	0.115	-0.559	0.789	0.739
Coombes 2021	0.355	-0.436	1.146	0.379
Dunning 2018	0.040	-0.841	0.921	0.928
Duscha 2018	0.413	-0.411	1.238	0.326
Gehring 2018	0.014	-0.779	0.807	0.972
Gordon 2017	1.537	0.454	2.621	0.005
Heron 2017	0.702	-0.575	1.980	0.281
Höchsmann 2019	0.480	-0.192	1.152	0.162
Howie 2021	0.033	-0.699	0.765	0.929
Jakicic 2016	-0.362	-0.544	-0.180	0.000
Joseph 2023	0.383	-0.172	0.938	0.176
Keytsman 2019	0.095	-0.550	0.740	0.773
Lahtio 2023	0.075	-0.464	0.614	0.785
Ma 2021	0.821	0.573	1.070	0.000
Ma 2022	0.929	0.245	1.613	0.008
McNeil 2019	0.606	-0.058	1.269	0.074
Mora-Gonzalez 2020	2.048	1.600	2.495	0.000
Muntaner-Mas 2017	0.303	-0.690	1.296	0.550
Ochi 2022	0.488	-0.112	1.089	0.111
Pandey 2015	0.536	-0.028	1.101	0.062
Park 2021	0.200	-0.123	0.523	0.225
Plotnikoff 2017	0.394	-0.038	0.826	0.074
Plotnikoff 2023	-0.086	-0.394	0.221	0.582
Pope 2018	0.249	-0.649	1.147	0.587
Rowland 2022	0.200	-0.368	0.768	0.490
Stork 2021	0.224	-0.343	0.792	0.439
Thorsen 2022	0.326	-0.107	0.759	0.140
Tulasiram 2021	0.931	0.119	1.742	0.025
vanBlarigan 2022	0.134	-0.761	1.030	0.769
Varnfield 2014	0.080	-0.397	0.557	0.743
Wood 2020	0.176	-0.838	1.190	0.734
Pooled	0.352	0.169	0.534	0.000
Prediction Interval	0.352	-0.669	1.372	

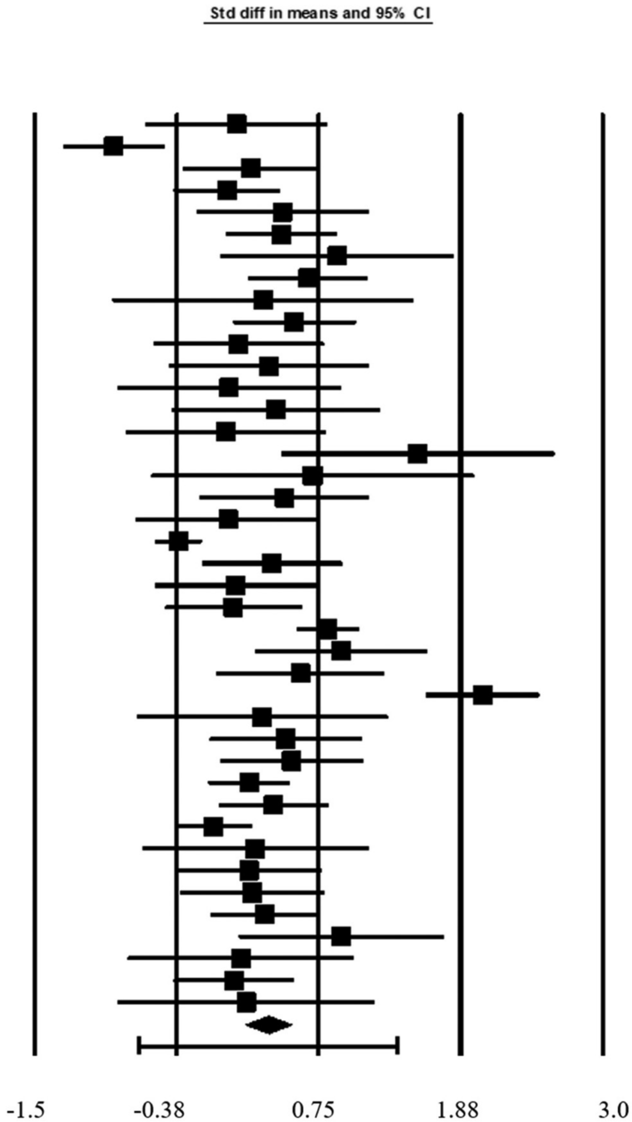

Figure 3. Forest plot of multi-group, posttest cardiorespiratory fitness outcomes among adults. A random-effects model was used to calculate effect sizes. Square areas are proportional to the study weight.

Effect sizes are classified as small (≤0.20), medium (=0.50), or large (≥0.80).[38] Heterogeneity of effects was assessed using prediction intervals (PI), T, and I^2. Q is no longer recommended as an accurate measure of heterogeneity.[39] A one-study-removed sensitivity analysis was also done for each meta-analysis to identify outliers.

Results

Study characteristics

A total of 53 distinct studies published between 2014 and 2023 were included in the narrative synthesis. All studies collected pre-post measures; 12 used a single-group design, and 41 used a multi-group design. Of those testing more than one group, 85% (n = 35) randomized participants to groups. Studies were conducted in North America (n = 23), Europe (n = 15), Asia (n = 8), Australia (n = 6), Africa (n = 1), and the Middle East (n = 1).

Sample characteristics. The single-group studies (12 studies with a total of 699 individuals) were more diverse with race compared to the multi-group studies (41 studies with a total of 2958 individuals); participants were 47.4% non-White in the single-group studies and 10.4% non-White in the multi-group studies. The mean age of participants in the single-group studies was 48.0 (SD 7.4) years and 49.5 (SD 15.3) years in the multi-group studies. Females comprised

64.1% of the sample in the single-group studies and 55.5% of the samples in the multi-group studies. Most of the studies (n = 44; 78.5%) targeted participants with a specific chronic health condition or problem, including cancer, diabetes, obesity, cardiovascular disease, liver disease, kidney disease, substance use disorder, or psychological disorder. The sample size range was 10–288 in the single-group studies and 11–335 in the multi-group studies.

Intervention characteristics. Across studies, intervention duration was between 4 and 168 weeks (3.2 years), with most delivering a 12-week intervention. Most studies delivered the intervention in the home setting (n = 42; 76%) or a combination of home and elsewhere (i.e., clinic, community center). Interventions were also delivered in clinical settings (n = 3),[40–42] workplaces (n = 3),[43–45] community settings (n = 9),[33,36,46–51] and, all or in part, at an academic setting (n = 3).[52–54] Most studies used a combination of digital health intervention strategies; four studies used text messaging and an activity tracker;[32,44,53,55] four studies used text messaging and an app;[23,46,56,57] 14 studies used an app and a wearable activity tracker;[42,47,48,52,58–68] and nine studies used text messaging, an app, and activity tracker.[35,51,69–75] Only two studies used text messaging alone.[45,76] A number of studies used only an app[33,46,48–50,54,68,77–82] or only an activity tracker.[36,83–90] Supplemental Table 2 details the behavior change strategies used along with the digital health tools, including goal setting, feedback, barrier problem solving, shared physical activity, supervised physical activity, and motivational interviewing.

Study quality of the 35 randomized design studies were evaluated with the Cochrane Risk of Bias Tool. While there were no studies evaluated as "high risk" on overall risk of bias, 45.7% (n = 16) were evaluated as "low risk," and 54.2% (n = 19) did not report enough information to render an overall bias judgement. Evaluation of the 18 non-randomized studies using the ROBINS-I risk of bias tool found a range related to the overall risk of bias, including low risk (n = 2), moderate risk (n = 2), serious risk (n = 6), and not enough information (n = 8).

Outcome measures

All included studies used an objective measure of cardiorespiratory fitness (inclusion criteria); however, a total of 19 studies (35%) also used a subjective measure of physical activity behavior. The International Physical Activity Questionnaire (IPAQ), a measure of physical activity level, was the most common subjective measure of physical activity behavior used. Objective measures used to evaluate cardiorespiratory fitness included maximal exertion walking or cycling tests and submaximal exertion walking or stepping tests.

Effect of digital health interventions on cardiorespiratory fitness

A summary of effect sizes for both the single group and multi-group meta-analyses is presented in Figures 2 and 3, respectively. Digital health interventions in the single-group studies ($k = 12$, $n = 12$) had a statistically significant, moderate-to-large effect size ($d = 0.60$, 95% CI [0.39–0.81], $p < 0.001$) on cardiorespiratory fitness (Figure 2). Effect sizes ranged from 0 to 3.40, with no negative effect sizes. As expected, there was a statistically significant heterogeneity of effects across the studies 0.09–1.28, $I^2 = 73.77\%$, $T = 0.29$, $p < 0.001$). Digital health interventions in the multi-group studies ($k = 41$, $n = 41$) had a small-to-moderate effect size ($d = 0.35$, 95% CI 0.17–0.53, $p < 0.001$) (Figure 3). Effect sizes ranged from −0.36 to 2.05, with a positive effect size indicative of the intervention group having better cardiorespiratory fitness outcomes compared to the control group. Heterogeneity was again at statistically significant levels, as expected (95% PI −0.67–1.37, $I^2 = 78.72\%$, $T = 0.50$, $p < 0.001$).

The one-study-removed sensitivity analysis demonstrated that no studies had a significant influence on the magnitude of the summary effect sizes in either meta-analysis. Despite sensitivity analysis not identifying any outliers, we also completed the single-group meta-analysis without Nabutovsky et al. (2020), the largest effect size in the study. This reduced the summary effect size by approximately to 0.52, a minimal change. Pre-post correlations of 0.5 were used for all studies after sensitivity analysis was done by setting correlations to 0.01, and then 0.09 with no change observed in the effect sizes.

The funnel plots for the single-group meta-analysis (Figure 4) and multi-group meta-analysis (Figure 5) are generally symmetrical, though we note few studies in the lower left corner of the plots representing studies with smaller effect sizes, which would hypothetically demonstrate less publication bias. Egger's regression test in the single-group meta-analysis was not significant ($t = 1.16$, $p = 0.27$, intercept 1.21), but was significant in the multi-group meta-analysis ($t = 2.01$, $p = 0.05$, intercept 1.49). This suggests that the single-group data set was unlikely to be influenced by small sample bias, but the multi-group data may have been.[91] Both of the trim and fill tests returned no studies trimmed, and, therefore, the point estimates and funnel plots remained exactly the same, indicating less likelihood of publication bias.[27]

Moderator analyses

Moderator analyses were completed to investigate heterogeneity (Table 1). Subgroup analyses included United States versus international location, sample mean age greater or less than 45.0, randomized design, if the study

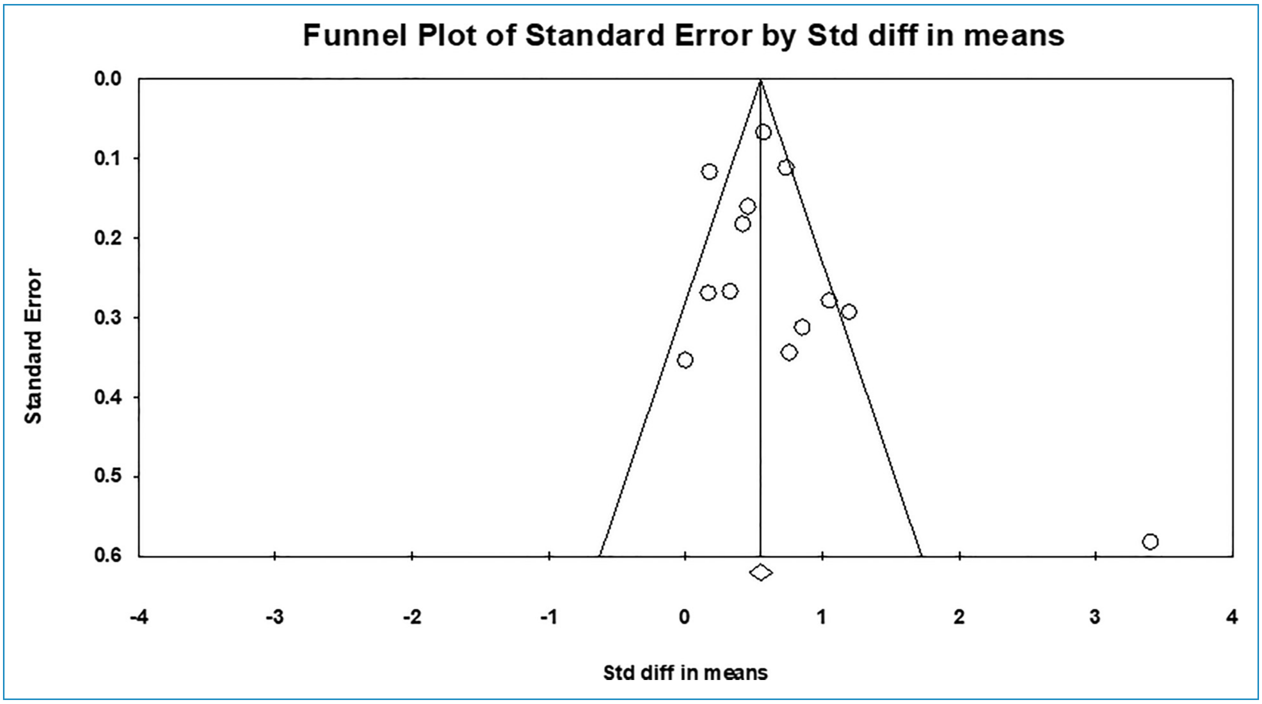

Figure 4. Forest plot of single-group, posttest cardiorespiratory fitness outcomes among adults. A random-effects model was used to calculate effect sizes. Square areas are proportional to the study weight.

included individuals with chronic conditions or not, and multiple intervention characteristics, including inclusion of physical activity education, self-tracking of physical activity, encouragement, goal-setting, feedback on progress or technique, addressing barriers to physical activity, peer role modeling, shared peer physical activity, supervised physical activity, motivational interviewing, text messaging, wearable device, and use of an app. Meta-regression was done to determine if the duration of the intervention or age of participants affected its efficacy.

In the single-group studies, there was one significant moderator finding when examining subgroups. Studies that included addressing participants' barriers to physical activity ($k = 4$, $n = 4$) had a statistically significant higher effect size ($d = 1.39$, 95% CI 0.52–2.26, $p = 0.002$) compared to studies, which did not ($d = 0.43$, $k = 7$, $n = 7$, 95% CI 0.33–0.53, $p < 0.001$, $Q = 10.26$, p of $Q < 0.01$). There were no statistically significant differences between interventions with shared physical activity, those inclusive of a mobile app versus not, or supervised versus unsupervised peer activity, location of study, and there were no differences based on the average participant age (Table 1). Participants with chronic conditions, peer modeling, education, self-tracking of activity, encouragement, feedback, goal setting, motivational interviewing, text messaging, and use of a wearable device (if reported) did not have enough studies in each subgroup (minimum $k = 4$) to perform a reliable analysis.

In the multi-group studies, there were two significant moderator findings. Studies that included individuals with chronic conditions (e.g. diabetes) had a significantly higher effect size ($d = 0.30$, $k = 33$, $n = 33$, 95% CI 0.12–0.47, $p = 0.001$) than studies, which did not ($d = 0.27$, $k = 7$, $n = 7$, 95% CI −0.04–0.57, $p = 0.09$, $Q = 53.21$, p of $Q < 0.001$). Studies conducted in the US had a significantly lower effect size ($d = 0.05$, $k = 11$, $n = 11$, 95% CI −0.28–0.37, $p = 0.78$) than those conducted elsewhere ($d = 0.35$, $k = 30$, $n = 30$, 95% CI 0.19–0.51, $p < 0.001$, $Q = 4.43$, p of $Q = 0.04$). Studies with and without individuals with chronic conditions, randomization, mean age, goal setting, feedback, addressing barriers, shared peer activity, supervised physical activity, text messaging, a wearable device, and use of an app were not statistically significant compared to their absence. Passive versus active control groups and use of education, self-tracking, peer modeling, subjective outcome alone, and motivational interviewing did not have enough studies in each subgroup (minimum $k = 4$) to perform reliable analyses.

In each meta-analysis, a meta-regression with the Knapp–Hartung correction was completed to determine if the duration of the intervention or mean age was correlated with effect size. Neither of the analyses had statistical significance (Table 1). With removal of duration outliers (Maltais et al. (2019) in the single-group studies and Ma et al. (2019) in the multi-group studies), the statistical significance did not change.

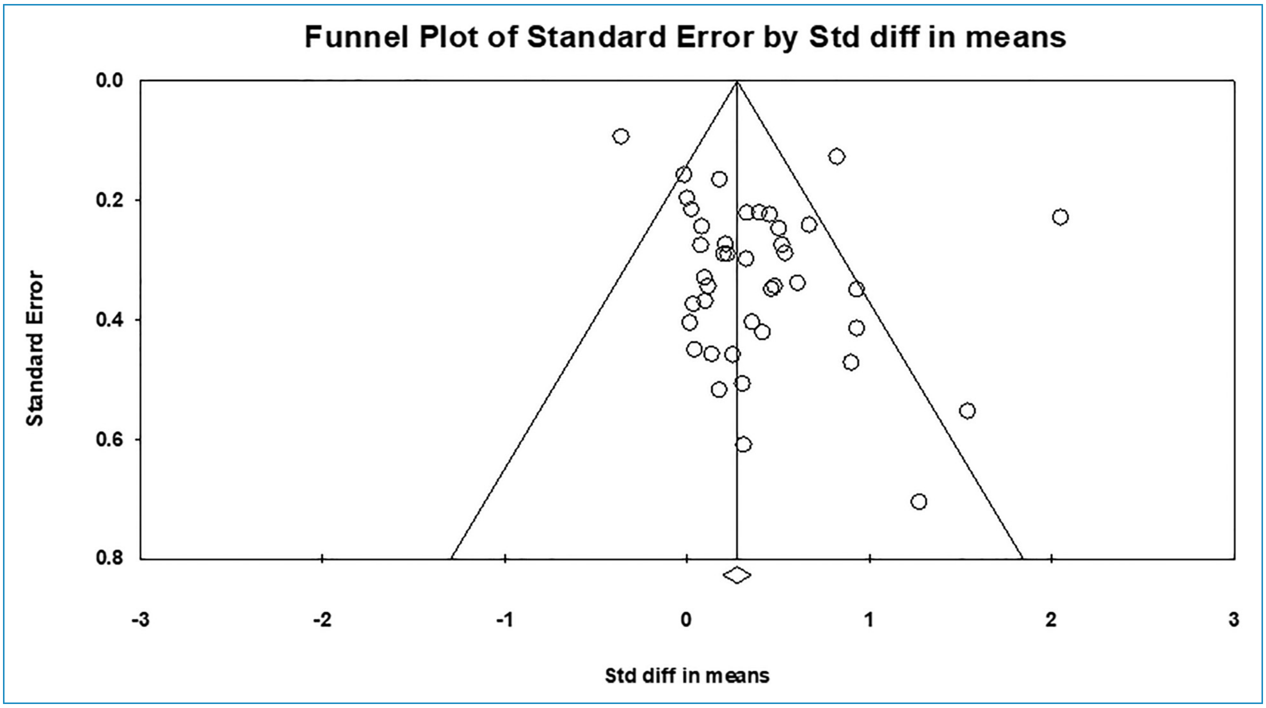

Figure 5. Forest plot of multi-group, posttest cardiorespiratory fitness outcomes among adults. A random-effects model was used to calculate effect sizes. Square areas are proportional to the study weight.

Discussion

This systematic review and meta-analysis advance our understanding of digital health interventions by examining their effect on cardiorespiratory fitness, a novel and increasingly recognized important health outcome. Cardiorespiratory fitness (heart–lung efficiency) is one of the most important correlates of general health status and a powerful predictor of all-cause mortality independent of age, ethnicity, body mass index, cholesterol, type II diabetes, and smoking.[13,92] The American Heart Association now recommends routine measurement of fitness to both evaluate and modify cardiovascular risk. In our study, digital health interventions using text messaging, a wearable activity tracker, and/or a smartphone app had a significant favorable effect on fitness with a moderate to large effect in single-group studies and small to moderate effect in multi-group studies. These findings are good news as even small changes in fitness are clinically significant. A 1-MET increase in fitness (corresponding to $V0_2$ of 3.5 ml/kg/min during exercise) is associated with a 10–30% reduction in cardiovascular mortality.[13]

Few included studies tested the effect of text messaging alone, so it remains unclear whether text messaging alone can favorably affect cardiorespiratory fitness. It is important to note, cardiorespiratory fitness did significantly improve with the use of only an app or use of only an activity tracker. While the combination of the two strategies did appear helpful, the improvement in fitness was not significant. Health behavior researchers and health care providers can be reassured that digital health interventions need not be overly complex or multi-component to have a favorable effect on cardiorespiratory fitness, particularly for those with a chronic health condition. It may be that complex, intensive, multi-component health behavior strategies are needed for primary prevention and not as needed for secondary or tertiary prevention. In other words, a chronic health condition may be a strong motivator to overcome barriers to increasing physical activity. Our moderator analysis findings among the single-group studies suggest two key non-digital components to consider as part of a digital health intervention: shared physical activity and addressing participant barriers to physical activity.

Studies included in this review had samples with a wide range of chronic health conditions, including cardiovascular disease, cancer, and severe psychological conditions, and, notably, there were only two negative effect sizes. There was, however, considerable heterogeneity of effects in both the single-group and multi-group studies. This is likely due to the wide variation in study design, interventions, and patient populations. While the study samples were diverse with respect to sex and health conditions, they were not diverse with respect to race or ethnicity, particularly when a multi-group design was used. There is a clear gap in high-level evidence (i.e., randomized controlled trials) for the use of digital health interventions to affect fitness among non-White samples. Given cardiovascular morbidity and mortality outcomes are worse for the

Table 1. Moderator analyses.

Subgroup analysis						
Single-group Studies	Cohen's *d*	*k*	*p* value	95% CI	$Q_{between}$	*p* of *Q*
Mean age ≤45.0 versus	0.48***	4	<0.001	0.27–0.69	1.10	0.29
>45.0 years old	0.68***	8	<0.001	0.41–1.01		
Barriers to PA addressed versus	1.39**	4	0.002	0.52–2.61	10.26**	<0.01
not addressed	0.43***	7	<0.001	0.33–0.53		
Shared peer activity versus	1.12**	5	0.004	0.35–1.89	2.47	0.12
None	0.50***	7	<0.001	0.37–0.62		
Use of app versus	0.72**	8	0.001	0.28–1.16	0.57	0.45
no app	0.58***	4	<0.001	0.39–0.70		
US-based versus	0.59**	8	0.001	0.24–0.94	0.08	0.78
international	0.65***	4	<0.001	0.42–0.88		
Multi-group studies						
US versus	0.05	11	0.78	−0.28–0.37	4.43*	0.04
international	0.44***	30	<0.001	0.26–0.62		
Randomized versus	0.34**	34	0.002	0.13–0.55	0.25	0.62
non-randomized	0.38***	7	<0.001	0.23–0.53		
Mean age ≤45.0 versus	0.43	24	0.06	−0.01–0.87	1.90	0.39
>45.0 years old	0.35***	30	<0.001	0.21–0.50		
Chronic conditions versus	0.30**	33	0.001	0.12–0.47	53.21***	<0.001
no chronic conditions	0.27	7	0.09	−0.04–0.57		
Goal setting versus	0.32*	33	0.003	0.11–0.54	0.82	0.37
none	0.46***	8	<0.001	0.25–0.67		
Feedback versus	0.25*	33	0.004	0.08–0.41	4.40	0.11
none	0.91*	7	0.004	0.29–1.54		
Barriers to PA addressed	0.25	10	0.19	−0.12–0.61	1.61	0.45
versus not addressed	0.40***	30	<0.001	0.18–0.62		
Shared peer activity versus	0.38***	6	<0.001	0.17–0.59	0.04	0.84
none	0.38**	35	0.001	0.14–0.56		

(continued)

Table 1. Continued.

Subgroup analysis						
Single-group Studies	Cohen's *d*	*k*	*p* value	95% CI	$Q_{between}$	*p* of *Q*
Supervised PA versus	0.39***	10	<0.001	0.23–0.56	0.13	0.72
unsupervised	0.38*	31	0.005	0.10–0.57		
Text messaging versus	0.28	16	0.13	−0.06–0.46	1.96	0.16
none	0.44***	25	<0.001	0.23–0.67		
Wearable device versus	0.31*	26	0.008	0.08–0.55	0.24	0.63
none	0.41*	15	0.007	0.11–0.70		
Use of app versus	0.36**	30	0.001	0.16–0.56	0.01	0.92
no app	0.33	11	0.09	−0.05–0.71		

Meta-regression				
Single-group studies	**Coeff.**	***n***	***p* value**	**95% CI**
Duration	0.56	9	0.84	−0.02–0.03
Mean age	−0.43	9	0.40	−0.03–0.08
Multi-group studies				
Duration	0.41	19	0.99	−0.04–0.86
Mean age	0.40	19	0.98	−0.02–0.02

PA: physical activity; Coeff: coefficient.
$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Black and Hispanic/Latino adults, digital health research with ethnically and racially diverse samples is greatly needed.[93–95]

Limitations

We were unable to ascertain the study quality for approximately half of the single-group studies and half of the multi-group studies. No studies reported on baseline outcome blinding of participants. The effect of knowing your fitness level prior to a digital health intervention could not be explored. Small sample bias was likely in the multi-group meta-analysis. Small sample sizes also prevented a comprehensive analysis of moderators of intervention effects. The lack of ethnic and racial diversity among samples limits the generalizability of the findings to populations under-represented in digital health research. This study also evaluated the most proximal intervention effect. Future research on the long-term effect of digital health interventions on cardiorespiratory fitness is needed. Nonetheless, our findings provide a rigorous comprehensive analysis of a diverse range of studies using digital health strategies to affect cardiorespiratory fitness. Most multi-group studies used some form of control group and randomized participants. The findings also appear to be robust given the minimal impact on the summary of effect sizes with removal of outlier studies.

Conclusion

Digital health interventions using text messaging, a smartphone app, or activity tracker alone or in combination are effective at improving cardiorespiratory fitness in adults, particularly those with a chronic health condition. Future research is needed to determine the moderating effects of non-digital strategies commonly used along with digital health interventions (i.e., goal setting, feedback, shared physical activity). Research evaluating the long-term effect of digital health interventions as well as the effect among non-White populations is also needed. Lastly, digital health researchers are called to report on common quality metrics, such as participant and personnel blinding.

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