HHS Public Access

Author manuscript

Br J Sports Med. Author manuscript; available in PMC 2023 April 20.

Published in final edited form as:

Br J Sports Med. 2021 August ; 55(16): 917–925. doi:10.1136/bjsports-2020-103594.

Health wearable devices for weight and BMI reduction in individuals with overweight/obesity and chronic comorbidities: systematic review and network meta-analysis

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Abstract

Objective—To analyse the comparative effectiveness of different health wearable-based physical activity (PA) promotion intervention strategies against each other and control for reducing body weight and body mass index (BMI) in individuals with overweight/obesity and chronic comorbidities.

Design—Systematic review and network meta-analysis (PROSPERO identifier: CRD42020158191).

Data sources—We performed two independent searches from December 2019 to September 2020 in PubMed, MEDLINE, Scopus, Web of Science, Central Register of Controlled Trials, EMBASE and PsycINFO databases for articles published in English between 2007 and 2020.

Eligibility criteria for selecting studies—Inclusion criteria were based on the PICOS framework. We included randomised controlled trials of health wearable-based interventions using two or more PA intervention arms/strategies and compared their effects on participants' body weight (kg) and BMI (kg/m^2) with a control group. Data were analysed using a Bayesian network meta-analysis to directly and indirectly compare the effects of the six different intervention strategies (comparators). The six comparators were: (1) control group (ie, usual care, waitlist); (2) comparison group (ie, traditional, non-health wearable PA interventions); (3) commercial health wearable-only intervention (eg, Fitbit, Polar M400); (4) research grade health wearable-only

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Contributors DM played a role in data collection, data extraction, data analysis and writing the article. XS played a role in data collection, data extraction and data analysis. ZG conceptualised the review, oversaw data collection and analysis and revised the article. All authors approved the final manuscript.

Competing interests None declared.

Patient consent for publication Not required.

Provenance and peer review Not commissioned; externally peer reviewed.

intervention (ie, accelerometers or pedometers); (5) multicomponent commercial health wearable intervention (eg, Fitbit + nutrition counselling); and (6) multicomponent research grade health wearable intervention. The results were reported as standardised mean differences (SMDs) with associated 95% credible intervals (CrIs).

Results—From 641 screened records, 31 studies were included. For body weight reduction in individuals with overweight/obesity and chronic comorbidities, accelerometer/pedometer-only (SMD −4.44, 95% CrI −8.94 to 0.07) and commercial health wearable-only (SMD −2.76, 95% CrI −4.80 to −0.81) intervention strategies were the most effective compared with the three other treatments and control. For BMI reduction, multicomponent accelerometer/pedometer (SMD −3.43, 95% CrI −4.94 to −2.09) and commercial health wearable-only (SMD −1.99, 95% CrI −4.95 to 0.96) intervention strategies were the most effective compared with the other four conditions.

Conclusion—Health wearable devices are effective intervention tools/strategies for reducing body weight and BMI in individuals with overweight/obesity and chronic comorbidities.

INTRODUCTION

Globally, there are over 1.9 billion adults who are overweight (body mass index (BMI) ≥25 kg/m^2) and 600 million with obesity (BMI ≥30 kg/m^2).[1] This has become a major public health concern, given that overweight and obesity are strongly associated with the incidence of chronic diseases (eg, heart disease, type 2 diabetes). In particular, weight-associated chronic diseases are responsible for approximately 70% of deaths and 85% of healthcare costs in the USA annually.[2 3] Accordingly, the WHO has declared overweight and obesity as “one of the greatest public health challenges of the 21st century”.[4] Physical inactivity is a major contributor to this issue and is now among the leading risk factors for mortality in the USA,[5] as only about 5% of US adults meet recommended physical activity (PA) levels and individuals with overweight/obesity and chronic comorbidities are even less likely to meet these recommendations due to fatigue and other factors.[6–8] As such, PA promotion in these populations is crucial, especially considering that the modest reductions in body weight (5–10%)[9] and BMI[10] reduce health risks associated with chronic diseases.[11] Indeed, PA promotion interventions are effective for body weight and BMI reduction[12] and are cost-effective in primary care,[13 14] and therefore should be considered as the first line of treatment for weight loss in patients with at least one weight-associated comorbidity rather than pharmacological treatments (eg, orlistat, lorcaserin, naltrexone-bupropion, liraglutide, phentermine-topiramate) which are costly[15] and often discontinued due to adverse events.[16–19] Thus, identifying innovative and engaging PA intervention strategies to promote body weight and BMI reduction in individuals with overweight/obesity and chronic comorbidities is of paramount importance.

Given the ubiquitous nature of technology in the modern world, recent public health efforts have aimed to incorporate novel technologies into PA interventions.[20] Because of their cost-effectiveness and accessibility, among the most commonly integrated technologies are commercial health fitness wearables[21] (eg, Fitbit, Apple Watch)—devices which use sensors to automatically set and track PA-related goals (eg, kcalories burned, step counts), sleep patterns, diet and other health-related behaviours.[22] In detail, health wearable devices have

the capability to upload health statistics to internet- and mobile-based applications which promote self-evaluation, self-monitoring, self-reinforcement, goal-setting and self-regulation via the tracking of health metrics.[23–25] Moreover, health fitness wearables facilitate social support among a network of connected users of these applications, further facilitating the achievement of PA- and health-related goals.[26] Thus, it stands to reason that these inherently motivating features may make health wearables effective for improving PA behaviours among individuals with overweight/obesity and chronic comorbidities who are often unmotivated to engage in PA given their increased levels of fatigue, pain and/or psychological distress.[6–8] Indeed, recent systematic reviews and meta-analyses have observed that health wearable-based PA interventions are effective for increasing PA in patients with various cancers[27] and cardiometabolic diseases,[28] and for decreasing body weight and BMI in healthy populations.[29] However, it remains unclear whether health wearable interventions are effective for decreasing body weight and BMI in individuals with overweight/obesity and chronic comorbidities.

Several randomised controlled trials (RCTs) have demonstrated the effectiveness of health wearable devices for reducing body weight and BMI in individuals with overweight/obesity and chronic comorbidities. However, challenges persist regarding the translation and dissemination of these results into widespread improved patient care, as there is no empirical evidence demonstrating the overall superiority of one intervention strategy over the others due to the absence of direct and indirect comparisons. Therefore, we performed a systematic review of the literature to identify RCTs which investigated the effects of health wearable-based PA interventions of individuals with overweight/obesity and chronic comorbidities, followed by a network meta-analysis (NMA) to allow for direct and indirect comparisons and simultaneously synthesise the effectiveness of each intervention strategy compared with other and control conditions. The findings may inform clinicians of safe, innovative and effective PA promotion intervention strategies for reducing body weight and BMI in their patients before pursuing pharmacological alternatives. Further, the US Preventive Services Task Force recommends that pharmacological treatments should only be used as part of a programme that also includes behavioural/lifestyle modification interventions,[30] and therefore the findings may help inform clinicians of optimal health wearable-based PA promotion intervention strategies to use in multicomponent treatments (ie, behavioural/lifestyle modification intervention + pharmacological therapy).

METHODS

We followed the PRISMA extension statement for NMAs[31] and registered the study with PROSPERO (CRD42020158191). Given individual patient data were not included and all data were previously published, institutional review board approval was not required.

Search strategy and selection criteria

The initial search was performed in December 2019 and a secondary search was conducted in September 2020 to ensure we included the most recent literature. The screening and selection processes were conducted independently by two investigators (DM and XS) who searched the following databases for peer-reviewed articles in consultation with a

search methodologist: PubMed, MEDLINE, Scopus, Web of Science, Central Register of Controlled Trials, EMBASE and PsycINFO. Within these databases, the following search terms and phrases were searched: (health wearable OR consumer wearable OR activity tracker OR fitness tracker OR [consumer-brand fitness tracker names] OR accelerometer OR pedometer) AND (weight OR body mass index OR BMI) AND (random* OR control* OR clinic*). An example of our full search strategy is available (see online supplemental file 1). Relevant studies were further identified by cross-referencing bibliographies of selected articles.

Eligibility criteria were defined based on the PICOS framework.[31] In detail, we included studies in which: (1) participants were adults with overweight/obesity and/or had at least one chronic comorbidity; (2) investigated a research grade or commercially available health wearable-based PA intervention against a control group; (3) the outcomes of interest were weight (kg) or BMI (kg/m^2); and (4) employed a RCT. To allow for sensitivity analyses to identify the impact of intervention length on the assessed outcomes, we applied no intervention length restrictions. Additionally, for logistical purposes and given that language restriction does not consistently bias the results of quantitative syntheses,[32] we only included studies published in English. Last, to our knowledge, the first commercially available health wearable device (Fitbit) was introduced to the market in 2009 and, therefore, giving a 2-year buffer in case earlier technologies were available, we only included articles published between 2007 and 2020 given our aim was to focus on novel health wearable technologies.

Comparators

We included accelerometer and pedometer (ie, research grade)-based interventions to compare their effectiveness against commercial health wearable technologies (eg, Fitbit, Polar M400). To help distinguish the most effective intervention strategies, we avoided lumping of nodes and included RCTs with two or more treatment arms and coded the six comparators as: (1) control group (ie, usual care, waitlist); (2) comparison group (ie, traditional, non-health wearable-based PA interventions); (3) commercial health wearable-only intervention; (4) research grade health wearable-only intervention (ie, accelerometers or pedometers); (5) multicomponent commercial health wearable intervention (eg, Fitbit + nutrition counselling); and (6) multicomponent research grade health wearable intervention.

Data extraction and processing

Initially, the titles of potentially relevant articles were screened independently by two investigators (DM and XS). If there was disagreement regarding study relevance, the study abstracts were reviewed and, if necessary, discrepancies were adjudicated by ZG. Study-level data were extracted by two investigators (DM and XS) and checked for accuracy by the third investigator (ZG). To ensure all relevant articles were included in our review, full texts of all potentially relevant articles were downloaded and stored in a shared online Google folder where all three investigators (DM, XS and ZG) independently reviewed each article. We then created a complete list of all relevant articles using an online spreadsheet. Mean differences and their associated standard deviations (SDs) were used to conduct the NMAs. Therefore, if mean differences were not directly reported in a given study, we extracted relevant arm-specific pre-/post-intervention point estimates (ie, means and

SDs) and calculated these quantities.[33] Specific equations for calculating pooled SDs have been previously described elsewhere.[34] Likewise, if 95% CIs were reported rather than SDs, we calculated the SDs from these values.[33] Notably, since not all of the included studies conducted mid-point and/or post-intervention follow-up testing, we only extracted data from week 0 (ie, baseline) and post-intervention (ie, the end of the final week of the predetermined intervention length). Additionally, to characterise the included studies, we extracted study location, publication year, study sample and design, intervention details (eg, instructions given, feedback provided, other intervention components added, etc), outcome measure, exposure and dose, and key findings regarding the effectiveness of health wearable interventions on body weight or BMI. Notably, we were not blinded to the study authors or journals and, given there was no missing relevant information, we did not contact authors or correspondents of the original articles.

Network geometry

We summarised the geometry of each evidence network using network plots for each outcome (body weight and BMI).[31] The nodes and edges were weighted relative to the number of available treatment structures and comparisons. Specifically, edges represented head-to-head comparisons between treatments and their thickness was proportional to the number of direct treatment comparisons. Nodes represented specific comparators and their size was proportional to the number of direct comparisons which contained that treatment node. Treatment nodes which were not connected by edges indicated no study directly compared those treatments. We established all nodes (comparators) a priori.

Statistical analysis

We first checked the assumption of transitivity—the major underlying assumption of NMA.[35] Since transitivity cannot be statistically evaluated, epidemiological judgement is required to assess whether the distribution of effect modifiers across studies allows for reliable indirect comparisons.[35 36] We a priori selected sex, age and clinical condition as potentially important effect modifiers. Network transitivity was discussed among the three investigators (DM, XS, ZG) and we determined that the included patients could, in principle, be randomised to any of the included treatments within either network given that all participants were physically able to participate in PA regardless of age or sex, and we therefore determined that the assumption of transitivity held.[36]

In PA promotion research with multiple intervention strategies, NMA allows for pooling of outputs resulting from direct and indirect evidence while upholding the benefits of randomised within-trial comparisons.[37] In accordance with the NICE-DSU Technical Support Document-2 recommendations,[33] we applied Bayesian random-effects evidence synthesis models with vague $\mathcal{N}(0, 1000)$ priors, which accounted for between-trial heterogeneity by adjusting for reference arm response.[38] To further assess heterogeneity, we visually examined the contrast plots for body weight and BMI for homogeneity of effects across comparators. Specifically, an arm-based NMA was conducted using the ‘pcnetmeta’ package in R statistical software (Version 1.2.5042, R Foundation), which used Bayesian hierarchical modelling derived from Markov Chain Monte-Carlo methods.[39] We avoided dichotomisation of results (ie, statistically significant or not) and, rather, presented

results with credible intervals (CrIs) to allow clinicians and health professionals to interpret the range of the likelihood of effects.[40 41] Specifically, comparative standardised mean differences (SMDs) were reported with their associated 95% CrIs with 2.5% and 97.5% quantiles as the lower and upper bounds.

Consistency is a statistical manifestation of transitivity and could not be assessed due to a lack of closed loops within the BMI network.[35] However, given our arm-based Bayesian NMA model accounted for heterogeneity—another form of inconsistency assessment[42]—and given the assumption of transitivity held, the three investigators collaborated and we agreed that global and local analyses for network consistency would not yield concerning levels of inconsistency within our NMA networks. Further, we used the Cochrane Risk of Bias Assessment Tool for RCTs[43] (table 1) to assess risk of bias within and across individual studies using the GRADE classification approach (high, medium/uncertain or low).

Lastly, we conducted two sensitivity analyses—one for intervention length and one for risk of bias. In detail, the first sensitivity analysis was performed to identify if shorter or longer intervention lengths were superior for promoting reductions in body weight and BMI. Specifically, we stratified study intervention lengths into two categories—short-term (<12 weeks in duration) and longer-term (≥12 weeks in duration)—and re-ran our NMAs for body weight and BMI for each category. The second sensitivity analysis was performed by re-running the NMA including only the studies identified as low risk of bias from the preceding risk of bias assessment (ie, removing studies with high or unclear risk of bias) to see if study bias materially affected the results of our primary analysis.

RESULTS

Search results and study characteristics

Of 641 citations retrieved, 31 (5%) studies met the inclusion criteria (figure 1) with an overall sample of 2268 patients (54% intervention treated; 46% control treated). Fifteen (48%) studies examined body weight as the outcome[23 44–57] and 16 (52%) examined BMI as the outcome.[58–73] Commercial health wearable devices used were the Fitbit,[23 45 56 58–60 72 73] SenseWear Armband,[47 48 50 53] Jawbone,[44 54] Polar smartwatches,[52 71] Samsung Charm,[46] FitMeter[49] and Withings Pulse.[57] The remaining studies used accelerometers[55 61 64–67 70] or pedometers.[62 63 68 69] Notably, 98% of the commercial health wearable-based interventions were conducted after 2017 and 97% of the accelerometer/pedometer-based interventions were conducted before 2015, indicating the emerging use of commercial health wearables in this field of inquiry. All studies had patients with chronic overweight or obesity and weight-related commodities included cancers,[45 52 56 57 59 71 72] type 2 diabetes mellitus,[61–63 67–69 73] coronary artery disease,[64] metabolic syndrome,[66] hypercholesterolaemia[65] and chronic sleep apnoea.[46]

Intervention duration ranged from 4 to 52 weeks. Seven (23%) studies employed interventions that were grounded in behaviour change theories—five of which used Social Cognitive Theory,[45 48 52 58 60] one used a combination of Social Cognitive Theory and Self-Determination Theory[54] and one used Self-Regulation Theory.[57] The interventions used in two other studies were based on other frameworks (CALO-RE Framework[23]

and Cognitive Behavioural Therapy[63]). Regarding diet-related intervention components, 18 (58%) studies had no dietary component in their intervention. Of the studies that did have a dietary component, three instructed participants to adhere to strict daily kcaloric restrictions (ie, 1200–1500 kcalories/day),[48 49 55] two studies instructed participants to adhere to a specific diet (Mediterranean diet,[69] Magdeburg Dual Diet[66]) and the remaining studies provided counselling with research personnel to educate participants about healthy dietary behaviours, set dietary intake goals (eg, increase intake of fruits and dietary fibres, reduce the consumption of sugar-sweetened beverages) and/or instructed the participants to maintain daily food logs in a health wearable-associated mobile application (eg, MyFitnessPal) to increase dietrelated self-awareness.[45 46 49–51 53 54 56 57 60 68] Nine (29%) studies used counselling throughout their respective interventions to provide PA-related feedback from the health wearable devices by telephone[23 44 45 47 55 65 66 70 72] or in-person meetings.[48 54 69] All studies employed interventions in which participants were instructed to set and meet goals based on steps per day and/or to reach the recommended weekly minimum of 150 min per week of moderate-to-vigorous intensity PA (namely, with brisk walking). Feedback based on these PA goals was provided by the health wearable devices and/or an associated mobile phone application in 13 (42%) studies,[23 46–49 52 53 56 63 68–70 73] in which these technologies reminded participants to increase their daily PA levels if they were not meeting their set PA goal(s), or by study researchers in the remaining studies where they interpreted the PA data for the participants based on their set goals and tailored the intervention accordingly. Notably, all studies using human feedback used trained and qualified personnel in the field of sports science and/or medicine. Also noteworthy is that all the studies only included physically inactive participants (determined by self-report questionnaires at baseline) and excluded participants who were on medication that would affect body weight, and two (6%) studies excluded participants who were users of health wearables at the start of the intervention.[44 49] Further, 21 (68%) studies included detailed descriptions of intervention fidelity/compliance assessments and the results of these assessments. Interestingly, only one (3%) study[44] used the social interaction feature of the commercial health wearable device used in the intervention and encouraged participants to engage and interact with other users of the device regarding their daily PA levels and achievements. A comprehensive description of the characteristics of each individual study and their respective interventions is available in online supplemental file 2.

The overall risk of bias was rated as high for 8 (25%) studies. Specifically, the percentage of studies with high, unclear and low risk of bias, respectively, for the individual items was: 26%, 9% and 65% for random sequence generation; 26%, 22% and 52% for allocation concealment; 26%, 32% and 42% for blinding of participants and personnel and blinding of outcome assessment; and 0%, 0% and 100% for incomplete data addressed and selective reporting.

Network geometry

The network plot for change in body weight is shown in figure 2A. Within this network, six different comparators were examined. In detail, the architecture of the network demonstrated a well-connected network such that all but two comparators (accelerometer/pedometer interventions and multi-component accelerometer/pedometer interventions) formed close

loops. Node sizes of control, commercial health wearable interventions, multicomponent commercial health wearable interventions and comparison conditions were all similar in size and large relative to accelerometer/pedometer interventions and multicomponent accelerometer/pedometer interventions, indicating novel health wearable technologies (eg, Fitbit) are more common in this line of research. Lastly, direct comparisons between control and commercial health wearable interventions, control and multicomponent commercial health wearable interventions and commercial health wearable interventions and comparison demonstrated the thickest edges, indicating these comparisons were most often examined.

The network plot for change in BMI is shown in figure 2B. Within this network, six different comparators were examined. The architecture of this network was poorly connected such that no closed loops were present. All but one comparator (traditional PA comparison) was directly compared with the control condition. Node sizes were largest for control, accelerometer/pedometer and multicomponent accelerometer/pedometer interventions, respectively, suggesting accelerometers and pedometers were more common when examining BMI as the outcome. Edge thickness was greatest for direct comparisons between control and accelerometer/pedometer, control and multicomponent accelerometer/pedometer and multicomponent commercial health wearable interventions, respectively.

Network meta-analysis

For change in body weight, 15 studies compared five different PA intervention strategies (554 patients) against control (471 patients). Compared with control, body weight greatly decreased with commercial health wearable interventions, accelerometer/pedometer interventions and multicomponent accelerometer/pedometer interventions (figure 3A). The SMDs for change in body weight ranged from −0.40 (95% CrI −5.11 to 4.34) for multicomponent accelerometer/pedometer interventions to −4.44 (95% CrI −8.94 to 0.07) for accelerometer/pedometeronly interventions. Notably, commercial health wearable interventions were the only PA intervention strategy not to include 0 in the 95% CrI and the CrI was most precise. Ranking based on the degree of weight loss identified accelerometer/pedometeronly and commercial health wearable-only as the best and control and traditional PA comparison as the worst PA intervention strategies (figure 4A). Visual inspection of the contrast plot associated with change in body weight suggested heterogeneity to be low because, for most treatment comparisons, the overall effects led to homogenous conclusions. Our sensitivity analysis for intervention length (ie, interventions <12 weeks in duration compared with interventions ≥12 weeks in duration) showed that health wearable-based PA interventions ≥12 weeks in duration were more effective than interventions <12 weeks in duration for body weight reduction and the CrIs were more precise. Interestingly, traditional PA comparison interventions (ie, non-health wearable-based PA promotion interventions) were more effective for body weight reduction during interventions <12 weeks in duration than for interventions ≥12 weeks and compared with our primary analysis, suggesting that PA behaviour change from health wearable-based PA interventions may need to be at least 12 weeks to promote the greatest loss in body weight. The results of the sensitivity analysis for body weight by intervention length are shown in online supplemental file 3 for clinicians and other health practitioners to make their own judgements against the primary analysis.

For change in BMI, 16 studies compared five different PA intervention strategies (681 patients) against control (562 patients). Compared with control, BMI greatly decreased in commercial health wearable interventions, and multicomponent accelerometer/pedometer interventions (figure 3B). The SMDs for change in BMI ranged from 0.08 (95% CrI −2.23 to 2.38) for traditional PA comparison interventions to −3.43 (95% CrI −4.94 to −2.09) for multicomponent accelerometer/pedometer interventions. Notably, accelerometer/pedometer interventions and multicomponent accelerometer/pedometer interventions were the only intervention strategies not to include 0 in the 95% CrI and, despite less precision of the CrI, commercial health wearable interventions produced similar positive effects. Ranking based on the degree of weight loss identified multicomponent accelerometer/pedometer and commercial health wearable-only as the best and control and traditional PA comparison as the worst PA intervention strategies (figure 4B). Visual inspection of the contrast plot associated with BMI change confirmed heterogeneity to be low because, for most treatment comparisons, the overall effects led to homogenous conclusions. Our sensitivity analysis for interventions ≥12 weeks in duration for the BMI outcome did not materially affect the relative treatment effects. However, given only two studies examined BMI as an outcome in interventions <12 weeks in duration, we were unable to generate a network for comparison and, therefore, we were unable to directly compare the effect of shorter and longer intervention lengths on BMI reduction across the included studies. For clinicians and other health practitioners to make their own judgements against the primary analysis, we have provided the results of the sensitivity analysis for interventions >12 weeks in duration in online supplemental file 4.

Lastly, our sensitivity analysis which only included studies identified as low risk of bias showed that the results did not materially differ from our primary analysis, indicating that individual study bias did not affect the relative treatment effects for body weight or BMI outcomes (online supplemental file 5).

DISCUSSION

Our NMAs compared commercial health wearable-only interventions, research grade health wearable-only interventions, multicomponent commercial health wearable interventions and multicomponent research grade health wearable interventions against traditional PA comparison and control conditions to allow for direct and indirect comparisons regarding their effectiveness on body weight and BMI reduction in individuals with overweight/obesity and chronic comorbidities. For reduction in body weight, we found commercial health wearable-only and accelerometer/pedometer-only PA interventions to be most effective compared with control. Specifically, interventions which were ≥12 weeks in duration were most effective for achieving this outcome. Notably, although accelerometer/pedometer-only interventions produced the greatest overall effect, commercial health wearable-only interventions were the only intervention strategy to not include 0 in the CrI (ie, no effect) and the CrI was more precise. For BMI reduction, we found commercial health wearable-only and multicomponent accelerometer/pedometer intervention strategies to be most effective and both strategies had the most precise CrIs, both of which did not include 0. Given the lack of available studies examining BMI as the outcome in interventions <12 weeks in duration, we were unable to determine if longer interventions were more effective

than shorter interventions for achieving this outcome. Commercial health wearable-only interventions were also highly effective for BMI reduction, but the CrI was less precise.

We postulate that increased PA participation mediated the effect of health wearable-based PA interventions on body weight and BMI reduction in individuals with overweight/obesity and chronic comorbidities. Indeed, modern commercially-available health wearable technologies like the Fitbit are motivating PA tools in that they allow users to set and track PA- and health-related goals and provide constant reminders to get up and move to achieve these goals which promotes self-monitoring and self-regulation, among other PA determinants.[22–26] Based on compiling evidence showing health wearable-based PA interventions are effective for increasing daily PA output in individuals with overweight/obesity and chronic comorbidities (ie, average steps per day and time in daily moderate-to-vigorous intensity PA),[27 28] we expected that health wearable-based PA interventions would be more effective than control and traditional non-health wearable-based PA interventions (comparison) for reducing body weight and BMI in individuals with overweight/obesity and chronic comorbidities. Indeed, those with higher weight status and chronic comorbidities are often burdened by fatigue, pain and/or psychological disorders,[6–8] which results in predominantly sedentary lifestyles—consistent with the samples included in the studies in our analysis. Thus, increases in PA from a primarily sedentary state, especially that of moderate-to-vigorous intensity, should contribute to a negative kcaloric balance and, therefore, weight loss and reductions in BMI, assuming dietary behaviours do not change drastically. Given that only three interventions included strict daily kcaloric restrictions in their interventions,[48 49 55] and given all studies instructed their participants to achieve moderate-to-vigorous intensity PA goals and/or step count goals consistent with meeting these recommendations, we believe that the resultant loss in body weight across trials was most favourably attributed to increases in PA from the health wearable-based PA promotion interventions.

Surprisingly, multicomponent commercial health wearable-based interventions were less effective than commercial health wearable-only interventions. Although the underlying mechanism is yet to be empirically determined, we purport that the added components of the multicomponent interventions (eg, journaling, telemonitoring, PA counselling) may have overwhelmed the participants who were highly physically inactive before the trials, thereby diluting the effectiveness of the commercial health wearables which inherently contain motivating PA features like tracking of PA metrics and daily PA goal reminders and feedback. Surprisingly, only one study included in our analysis[44] used the social feature of the commercial health wearables and encouraged participants to engage with other participants and interact with them regarding their shared PA data. Indeed, commercial health wearables facilitate social support—a well-documented PA determinant—among a network of connected users of these applications and may therefore enhance these interventions by further increasing participants' PA output and body weight-related outcomes.[26] Likewise, only seven interventions were grounded in theory,[45 48 52 54 57 58 60] which is a missed opportunity given theories like Social Cognitive Theory and Self-Determination Theory naturally integrate social support into behaviour change interventions which could easily be applied using the various features of commercial health wearables. Contrarily, multicomponent accelerometer/pedometer interventions were most effective for

BMI reduction compared with accelerometer/pedometer-only interventions. This makes sense given accelerometers and even pedometers provide limited, if any,[61] PA-related feedback and are therefore more likely to be enhanced by other intervention components like health education and/or PA counselling where trained staff can provide the feedback and motivation necessary for participants to increase their daily and weekly PA and, ultimately, lose weight and reduce their BMI. That said, we expected multicomponent accelerometer/pedometer interventions to yield greater effects on participants' body weight than accelerometer/pedometeronly interventions, but the latter intervention strategy actually yielded the greatest overall effect on this outcome. Thus, there are likely other factors which have a greater impact on the effectiveness of health wearables on patients' body weight and BMI, such as intervention dose (ie, duration, frequency).

Indeed, we believe intervention dose likely had the greatest impact on intervention effectiveness. Previous literature indicates a positive dose-response relationship between PA and weight loss[74] and, given that health wearables increase moderate-to-vigorous intensity PA output in individuals with overweight/obesity and chronic comorbidities,[27 28] increased PA over longer intervention periods should, in principle, lead to greater weight loss in these populations. In this review, interventions ranged from 4 to 52 weeks and studies which observed non-significant results tended to be of shorter duration (average 11 weeks) than those which observed statistically significant changes in body weight or BMI (average 20 weeks). Indeed, our sensitivity analyses showed that interventions that were ≥12 weeks in duration were more effective for achieving weight loss than those that were <12 weeks in duration. This is in line with literature observing increased PA to be associated with decreased health risks associated with various chronic diseases (breast cancer, colon cancer, diabetes, ischaemic heart disease).[75] Likewise, the longer an intervention is, the more important employing intervention fidelity/compliance procedures becomes (eg, encouraging/reminding participants to follow through on a daily and weekly basis). The majority (68%) of studies included in our analysis employed intervention fidelity/compliance process measures (most of which were the trials >12 weeks in duration) and adequately reported the results of these procedures which may have contributed to the increased PA output over longer periods of time and, thus, increased weight loss. This likely explains why multicomponent interventions with text or email reminders were most effective for research grade devices with limited feedback, whereas commercial health wearables automatically provided this feedback and relied less on human-based process measures and feedback.

Strengths and limitations

This was the first NMA to examine the effect of commercial and research grade health wearable-based PA interventions on body weight and BMI in individuals with overweight/obesity and chronic comorbidities. We obtained a homogenous sample by applying strict inclusion criteria and only including RCTs to control for potential biases and to provide the best possible estimates of health wearable-specific effects. Despite these strengths, our analysis had some notable limitations. First, in spite of the well-connected loop for the body weight outcome, the architecture of our network plot for BMI had no closed loops, indicating that not enough direct comparisons are currently available to draw strong conclusions on the effects of health wearable interventions on BMI in individuals

with overweight/obesity and chronic comorbidities, and that network inconsistency may have biased these results. Therefore, we warrant caution while interpreting these results. Nevertheless, our body weight network was well connected and produced reliable estimates and, given that BMI is a product of body weight, the similar findings between the two networks support the findings for BMI reduction, especially when the interventions are at least 12 weeks in duration. Second, because our arm-based Bayesian NMA models accounted for possible heterogeneity of included studies, we did not employ pairwise meta-analyses to directly check for heterogeneity. Nevertheless, we visually inspected the absolute and contrast plots and observed consistent effects across treatment groups and agreed that heterogeneity likely had minimal influence on our results. Third, because we were unable to statistically test for inconsistency given the lack of closed loops within the BMI network, we did not test for local or global inconsistency for either outcome. As previously discussed, however, all investigators collaborated and agreed that, because heterogeneity was not concerning and given the assumption of transitivity held, inconsistency of our networks on local and global levels would not materially influence our results. Fourth, although NMA uses all available data, evidence from indirect comparisons are not based directly on RCTs. Fifth, inherent among health wearable-based interventions is the potential for the performance bias such that participants may alter their behaviour as a result of being observed (wearing the monitors in this case). Sixth, given the heterogeneity of specific intervention strategies employed in the included multicomponent health wearable-based PA interventions within our NMA (eg, instructions given to participants, feedback received, etc), we were unable to identify the best instruction or feedback types to achieve optimal body weight or BMI reduction and, thus, rule out bias induced by different instructions or feedback provided in individual studies. Therefore, we recommend future health wearable-based PA interventions employ RCTs with multiple arms to assess which specific intervention instructions and feedback types are most effective for promoting weight and BMI reduction in individuals with overweight/obesity and chronic comorbidities.

CONCLUSIONS

Our study suggests that commercial health wearable devices are effective PA intervention components for body weight and BMI reduction in individuals with overweight/obesity and chronic comorbidities without other intervention components and that interventions at least 12 weeks in duration are more effective than interventions less than 12 weeks in duration for achieving this outcome. Further, research-oriented health wearables are effective PA promotion intervention strategies for reducing body weight and BMI in individuals with overweight/obesity and chronic comorbidities, especially when combined with other intervention components. Notably, based on the SMDs, this loss of body weight is clinically meaningful in that only modest reductions in body weight (5–10%)[9] and BMI[10] have been shown to attenuate adverse health effects associated with overweight/obesity and related comorbidities. Therefore, clinicians and health professionals with patients with overweight/obesity and chronic comorbidities should work with them to set daily PA goals and should consider using commercially available health wearable devices to track and remind them of these goals to increase their daily PA output and, ultimately, to promote modest body weight and BMI reduction to help attenuate health risks associated with their conditions.

Based on our analysis, we recommend clinicians and other health practitioners who seek to increase PA in their patients with overweight/obesity and chronic comorbidities with the goal of achieving modest body weight and/or BMI reductions apply the following strategies to optimise their commercial health wearable-based PA interventions: (1) educate participants at baseline of the importance of increasing daily and weekly PA for improving their health and for reducing their body weight and/or BMI; (2) work with participants to set short- and long-term step count- or intensity-based PA goals and instruct participants to engage in moderate-to-vigorous intensity PAs (eg, brisk walking) and to use the health wearables to track their daily and weekly progress towards these goals and help motivate them when they fall short on these goals; (3) ground the interventions in well-established behaviour change theory and use the various motivating features of commercial health wearables (eg, PA-related social connection) to help fulfil the various components of these theories; (4) design interventions that are at least 12 weeks in duration to allow for adequate behaviour change and gradual PA increases that optimise kcaloric deficits and, thus, weight loss; (5) employ adequate process measures to ensure intervention fidelity/compliance and track this weekly; (6) allow the health wearables to provide daily PA feedback and, if process measures indicate poor intervention adherence, consider adding in weekly or bi-weekly human-based PA feedback (eg, using telemonitoring) to ensure participants are on track to meet their short- and long-term PA and/or weight loss goals; and (7) despite our findings suggesting commercial health wearable-only interventions to be more effective than multicomponent commercial health wearable-based interventions, research has indicated that health behaviour change interventions targeting improved PA and dietary behaviours concurrently are more effective than interventions targeting either of these behaviours exclusively,[76] especially in the context of weight loss, and thus we recommend setting dietary goals and using the commercial health wearable-associated web application to track dietary behaviours and daily kcaloric intake to assess energy balance and allow for qualified research personnel to provide tailored feedback based on these data. However, we recommend gradual kcaloric restrictions[66] rather than immediate extreme restrictions[48 49 55] which may facilitate weight loss early on but may not be sustainable and favourable for long-term behaviour change—especially in individuals with overweight/obesity and chronic comorbidities.[76] If research grade health wearables are used, we recommend employing a multicomponent intervention with other intervention components (eg, weekly PA and dietary counselling, telemonitoring, etc) to make up for the minimal feedback provided by these devices.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgements

We would like to acknowledge and thank our expert search methodologist, Scott E Marsalis, for his contribution to this study in helping to locate the included studies within our analysis.

Funding

ZG was supported by a research grant on health wearables from University of Minnesota Twin Cities.

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What is already known

- Modest reductions in body weight (5–10%) and/or BMI reduces health risks associated with overweight/obesity and associated chronic diseases.
- Increased PA participation in patients with overweight/obesity and associated comorbidities can help contribute to body weight and BMI reduction. However, due to pain, discomfort and other factors, PA levels in individuals with overweight/obesity and chronic comorbidities are often inadequate. Health wearable technology-based PA interventions are effective for increasing PA behaviours in these populations, given their accessibility, cost-effectiveness and motivating features. However, due to a lack of direct and indirect comparisons, there is no empirical evidence demonstrating the overall superiority of one intervention strategy over the others.

What are the new findings

- Commercial health wearable devices are effective PA intervention strategies for body weight and BMI reduction in individuals with overweight/obesity and chronic comorbidities without other intervention components.
- Research-oriented health wearable devices are effective PA promotion intervention strategies for reducing body weight and BMI in individuals with overweight/obesity and chronic comorbidities, especially when combined with other intervention components.

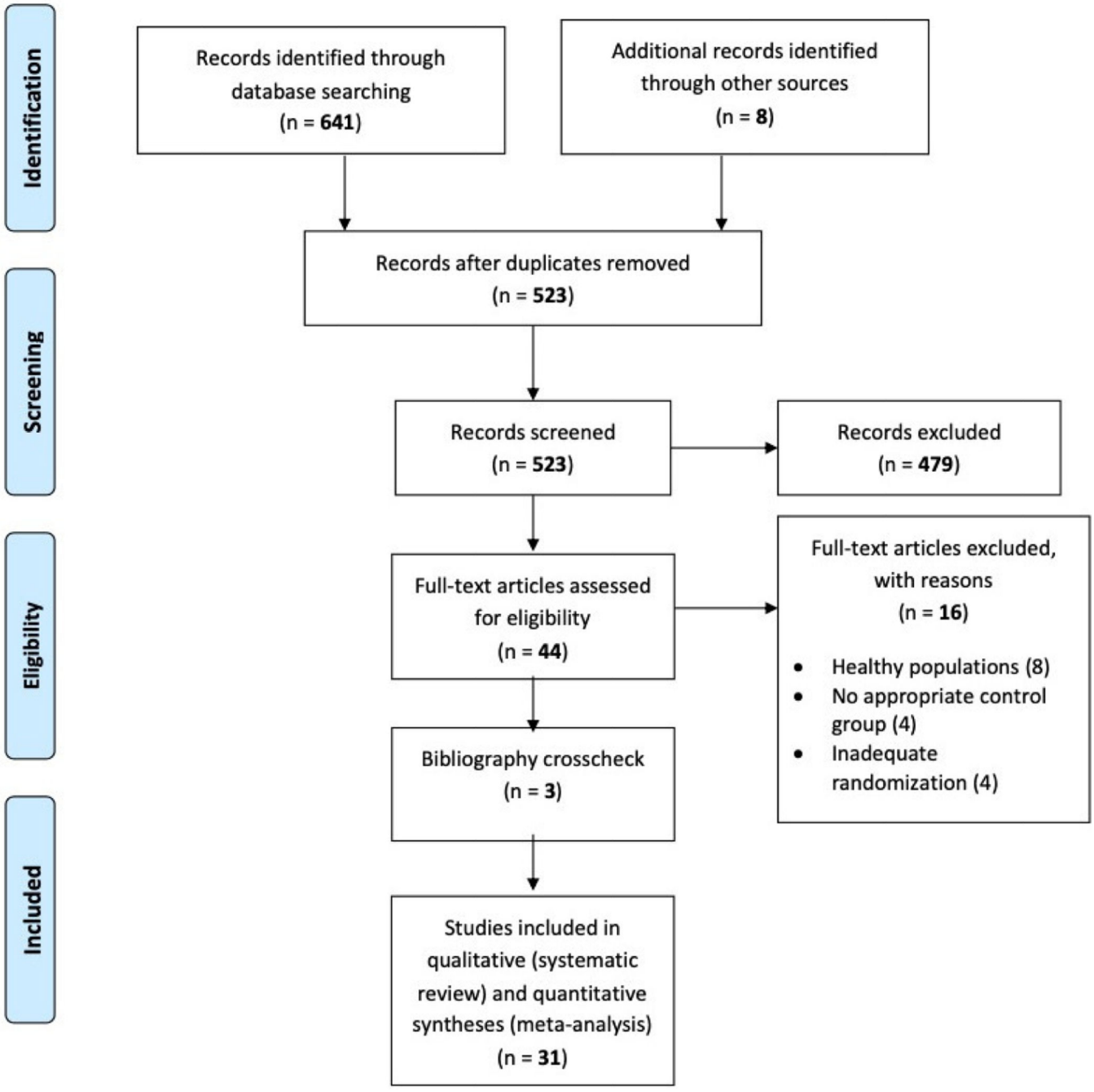

Figure 1.
PRISMA flow chart for systematic reviews.

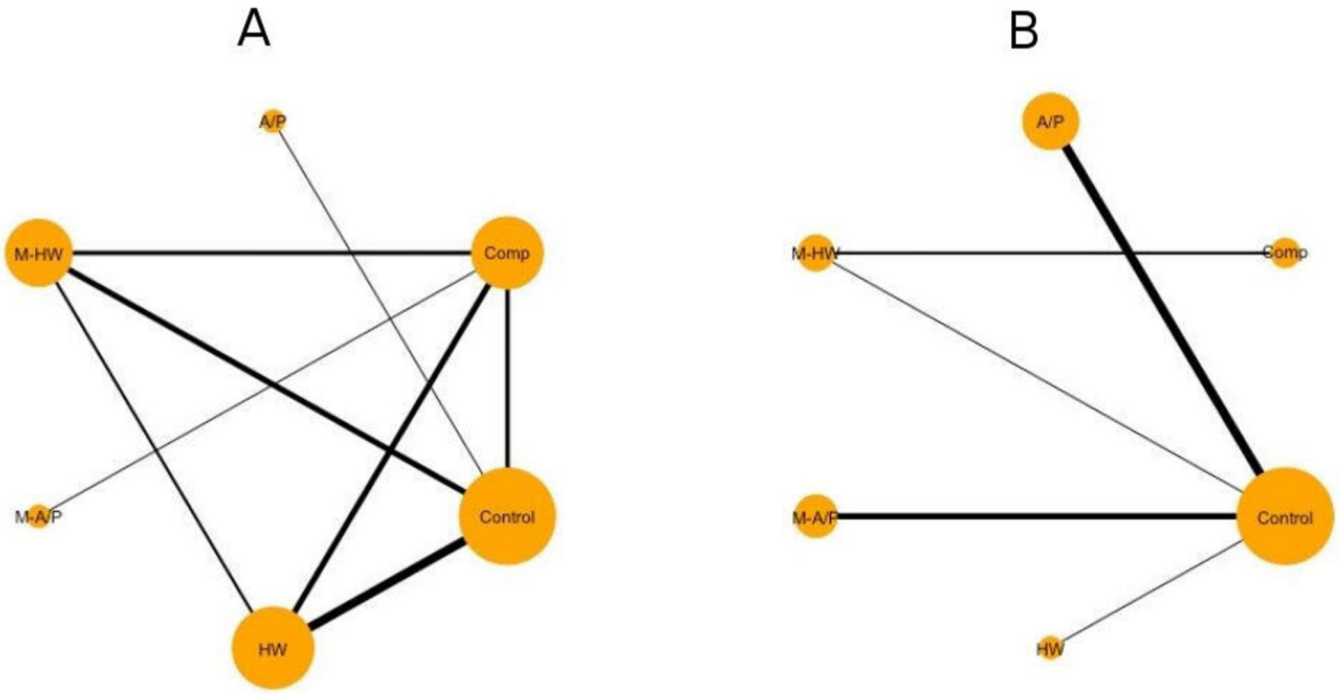

Figure 2.

Network plots of network meta-analyses for body weight (A) and body mass index (B). HW, health wearable intervention; A/P, accelerometer/pedometer intervention; M-HW, multicomponent health wearable intervention; M-A/P, multicomponent accelerometer/pedometer intervention; COMP, comparison (traditional, non-health wearable).

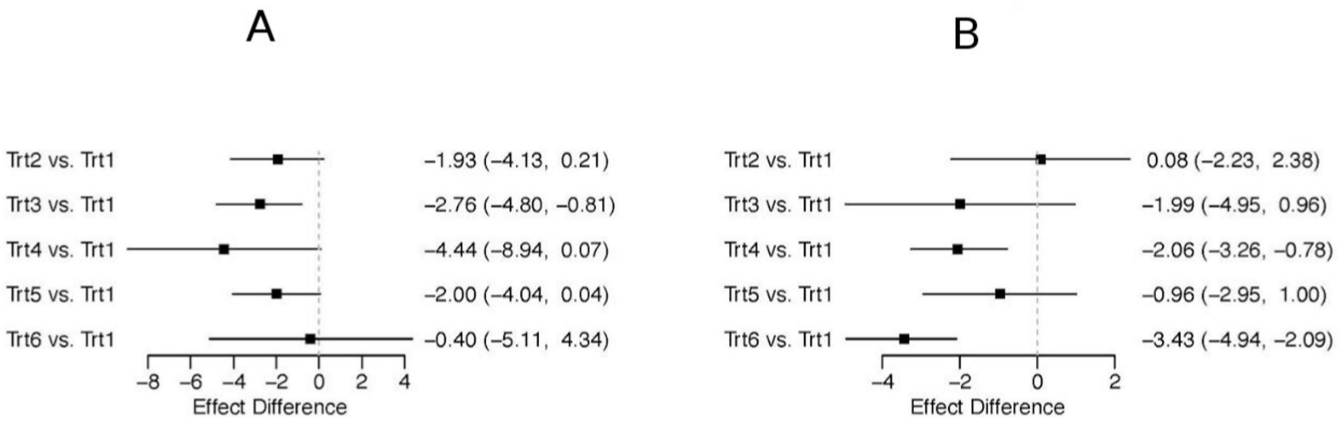

Figure 3.

Contrast plots for comparative effectiveness against control reference for body weight outcome (A) and body mass index outcome (B). Trt1, reference intervention arm (control); Trt2, comparison (traditional non-health wearable physical activity intervention); Trt3, commercial health wearable intervention; Trt4, accelerometer/pedometer intervention; Trt5, multicomponent health wearable intervention; Trt6, multicomponent accelerometer/pedometer intervention. squares represent comparative standardised mean differences and their associated lines are 95% credible intervals with 2.5% and 97.5% quantiles as the lower and upper bounds.

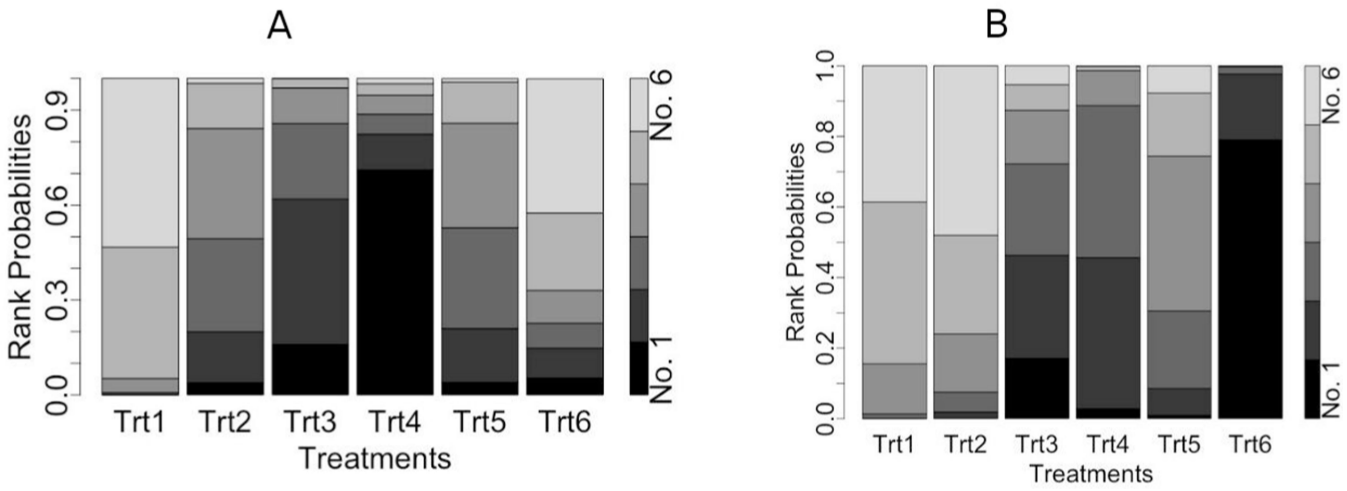

Figure 4.

Plots of treatment rank probabilities for body weight (A) and body mass index (B). Trt1, reference intervention arm (control); Trt2, comparison (traditional non-health wearable physical activity intervention); Trt3, commercial health wearable intervention; Trt4, accelerometer/pedometer intervention; Trt5, multicomponent health wearable intervention; Trt6, multicomponent accelerometer/pedometer intervention. A darker area indicates the probability of being a higher rank.

Br J Sports Med. Author manuscript; available in PMC 2023 April 20.

Table 1

Cochrane Risk of Bias Assessment for Randomised Controlled Trials (low, high, unclear)

Study	Random sequence generation	Allocation concealment	Blinding of participants and personnel	Blinding of outcome assessment	Incomplete outcome data addressed	Selective reporting
Lyons *et al*[44]	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**
Hartman *et al*[45]	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**
Zhang *et al*[58]	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**
Kim *et al*[46]	**Unclear risk**	**Unclear risk**	**Unclear risk**	**Unclear risk**	**Low risk**	**Low risk**
Shuger *et al*[47]	**Low risk**	**Unclear risk**	**Unclear risk**	**Unclear risk**	**Low risk**	**Low risk**
Cadmus-Bertram *et al*[23]	**High risk**	**High risk**	**High risk**	**High risk**	**Low risk**	**Low risk**
Hartman *et al*[59]	**Low risk**	**Unclear risk**	**Unclear risk**	**Unclear risk**	**Low risk**	**Low risk**
Polzien *et al*[48]	**High risk**	**High risk**	**High risk**	**High risk**	**Low risk**	**Low risk**
Shin *et al*[49]	**High risk**	**High risk**	**High risk**	**High risk**	**Low risk**	**Low risk**
Chen *et al*[50]	**High risk**	**High risk**	**High risk**	**High risk**	**Low risk**	**Low risk**
Ryu *et al*[51]	**High risk**	**High risk**	**High risk**	**High risk**	**Low risk**	**Low risk**
Pope *et al*[52]	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**
Peyer *et al*[53]	**Unclear risk**	**Unclear risk**	**Unclear risk**	**Unclear risk**	**Low risk**	**Low risk**
Chen *et al*[60]	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**
Ashton *et al*[54]	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**
Herzig *et al*[61]	**Low risk**	**Unclear risk**	**Unclear risk**	**Unclear risk**	**Low risk**	**Low risk**
Shenoy *et al*[62]	**Low risk**	**Unclear risk**	**Unclear risk**	**Unclear risk**	**Low risk**	**Low risk**
De Greef *et al*[63]	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**
Frederix *et al*[64]	**Unclear risk**	**Low risk**	**Unclear risk**	**Unclear risk**	**Low risk**	**Low risk**
Coghill *et al*[65]	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**
Luley *et al*[66]	**High risk**	**High risk**	**High risk**	**High risk**	**Low risk**	**Low risk**
Karstoft *et al*[67]	**High risk**	**High risk**	**High risk**	**High risk**	**Low risk**	**Low risk**
Fukuoka *et al*[68]	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**
Alonso-Dominguez *et al*[69]	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**
Spring *et al*[55]	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**
Hurling *et al*[70]	**Low risk**	**Low risk**	**Unclear risk**	**Unclear risk**	**Low risk**	**Low risk**

Study	Random sequence generation	Allocation concealment	Blinding of participants and personnel	Blinding of outcome assessment	Incomplete outcome data addressed	Selective reporting
McNeil *et al*[71]	**High risk**	**High risk**	**High risk**	**High risk**	**Low risk**	**Low risk**
Maxwell-Smith *et al*[72]	**Low risk**	**Low risk**	**Unclear risk**	**Unclear risk**	**Low risk**	**Low risk**
Polgreen *et al*[73]	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**
Kooiman *et al*[56]	**Low risk**	**Unclear risk**	**Unclear risk**	**Unclear risk**	**Low risk**	**Low risk**
Valle *et al*[57]	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**	**Low risk**

Within studies: Low risk=described adequately within the study; Unclear risk=described somewhat adequately within the study; High risk=was poorly described or not described within the study. Across studies: White highlighted rows indicate the study as a whole was at low risk of bias (ie, most information is from trials at low risk of bias); light grey highlighted rows indicate the study as a whole had an unclear risk of bias (ie, most information is from trials at low or unclear risk of bias); dark grey highlighted rows indicate the study was judged to be a high risk of bias (ie, the proportion of information from trials at high risk of bias is sufficient to affect the interpretation of results).