Effectiveness of mHealth App-Based Interventions for Increasing Physical Activity and Improving Physical Fitness in Children and Adolescents: Systematic Review and Meta-analysis

Jun-Wei Wang, Zhi-Cheng Zhu, Shu-Ling Zhang, Jia Fan, Yu Jin, Zhan-Le Gao, Wan-Di Chen, Xue Li

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Effectiveness of mHealth App-Based Interventions for Increasing Physical Activity and Improving Physical Fitness in Children and Adolescents: Systematic Review and Meta-analysis

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Abstract

Background: The COVID-19 pandemic has significantly reduced physical activity (PA) levels and increased sedentary behavior (SB), which can lead to worsening physical fitness (PF). Children and adolescents may benefit from mobile health apps (mHealth apps) to increase PA and improve PF. However, the effectiveness of mHealth app-based interventions and potential moderators in this population are not yet fully understood.

Objective: Objectives: This study aims to review and analyze the effectiveness of mHealth app-based interventions in promoting PA and improving PF, and identify potential moderators of efficacy of mHealth app-based interventions in children and adolescents. Methods: Methods: We searched for articles published in the PubMed, Web of Science, EBSCO, and Cochrane Library databases until October 25, 2022 to conduct this meta-analysis. Subgroup analysis was performed to identify potential influences that impact effect sizes. Results: Results: We included 15 randomized controlled trials with a total of 2476 participants. Our findings showed that mHealth app-based interventions significantly increased total PA (TPA) (standardized mean difference [SMD] 0.24, 95% confidence interval [CI] 0.01–0.48, P=0.04), reduced body mass index (BMI) (weighted mean difference [WMD] ?0.39, 95% CI ?0.67 to ?0.10, P=0.0009), and improved muscle strength (WMD 2.86, 95% CI 1.57 to 4.16, P=0.0001) in children and adolescents. However, mHealth app-based interventions insignificantly affected SB (SMD ?0.18, 95% CI ?0.38 to 0.02, P=0.09), moderate-to-vigorous PA (MVPA) (WMD 0.11, 95% CI ?0.69 to 0.90, P=0.79), waist circumference (WMD ?0.16, 95% CI ?2.66 to 2.99, P=0.91), and cardiorespiratory fitness (WMD ?0.14, 95% CI ?0.50 to 0.23, P=0.46). Subgroup analyses indicated that mHealth app interventions based on social cognitive theory (SCT) with 7 behavior change technique (BCT) clusters could produce higher effect sizes for TPA; mHealth app interventions based on age 13?18 years old, research apps, a combination of SCT and self-determination theory, 7 BCT clusters, and intervention duration of 20?24 weeks revealed higher effect sizes for SB; and mHealth app interventions based on age 3?6 years old, research apps, SCT, 7 BCT clusters, and intervention duration of 12 weeks revealed higher effect sizes for BMI. Conclusions: Conclusions: Our meta-analysis suggests that mHealth app-based interventions may have beneficial effects on TPA, BMI, and muscle strength but not on SB, MVPA, waist circumference, and cardiorespiratory fitness in children and adolescents. Moderating effects, including theoretical paradigm and BCT clusters, were significantly related to higher effectiveness of mHealth app-based interventions on TPA. Similarly, moderating effects, including age, theoretical paradigm, BCT clusters, types of apps, and intervention duration, were significantly related to higher effectiveness of mHealth app-based interventions on SB and BMI but not on MVPA. However, the small sample size and high heterogeneity of the included literature still necessitate further studies to validate our findings. Clinical Trial: Trial Registration: PROSPERO CRD42023426532

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Conclusions: Our meta-analysis suggests that mHealth app-based interventions may have beneficial effects on TPA, BMI, and muscle strength but not on SB, MVPA, waist circumference, and cardiorespiratory fitness in children and adolescents. Moderating effects, including theoretical paradigm and BCT clusters, were significantly related to higher effectiveness of mHealth app-based interventions on TPA. Similarly, moderating effects, including age, theoretical paradigm, BCT clusters, types of apps, and intervention duration, were significantly related to higher effectiveness of mHealth app-based interventions on SB and BMI but not on MVPA. However, the small sample size and high heterogeneity of the included literature still necessitate further studies to validate our findings. Clinical Trial: Trial Registration: PROSPERO CRD42023426532

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Review

Effectiveness of mHealth App-Based Interventions for Increasing Physical Activity and Improving Physical Fitness in Children and Adolescents: Systematic Review and Meta-analysis

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Abstract

Background: The COVID-19 pandemic has significantly reduced physical activity (PA) levels and increased sedentary behavior (SB), which can lead to worsening physical fitness (PF). Children and adolescents may benefit from mobile health apps (mHealth apps) to increase PA and improve PF. However, the effectiveness of mHealth app-based interventions and potential moderators in this population are not yet fully understood.

Objectives: This study aims to review and analyze the effectiveness of mHealth app-based interventions in promoting PA and improving PF, and identify potential moderators of efficacy of mHealth app-based interventions in children and adolescents.

Methods: We searched for articles published in the PubMed, Web of Science, EBSCO, and Cochrane Library databases until December 25, 2023 to conduct this meta-analysis. The inclusion criteria were as follows: population age 3 to 18 years; interventions involving smartphone and/or tablet-based mHealth apps; study design encompassing randomized controlled trials (RCTs); outcomes including PA, SB, PF, and others. Due to high heterogeneity, a meta-analysis was conducted using a random-effects model. The Cochrane Risk of Bias Assessment Tool was utilized to evaluate the risk of bias in the included studies. Subgroup analysis and meta-regression analyses were performed to identify potential influences impacting effect sizes.

Results: We included 28 randomized controlled trials with a total of 5643 participants. In general, the risk of bias of included studies was low. Our findings showed that mHealth app-based interventions significantly increased total PA (TPA) (standardized mean difference [SMD] 0.29, 95% confidence interval [CI] 0.13 to 0.45, P=0.0004), reduced SB (SMD -0.97, 95% CI -1.67 to -0.28, P=0.006), body mass index (BMI) (weighted mean difference [WMD] -0.31, 95% CI -0.60 to -0.01 kg/m^2, P=0.12), and improved muscle strength (SMD 1.97, 95% CI 0.09 to 3.86, P=0.04), agility (SMD -0.35, 95% CI -0.61 to -0.10, P=0.006) in children and adolescents. However, mHealth app-based interventions insignificantly affected moderate-to-vigorous PA (MVPA) (SMD 0.11, 95% CI -0.04 to 0.25, P=0.0002), waist circumference (WMD 0.38, 95% CI -1.28 to 2.04 cm, P=0.65), muscular power (SMD 0.01, 95% CI −0.08 to 0.10, *P*=0.81), cardiorespiratory fitness (SMD -0.20,

95% CI -0.45 to 0.05, P=0.11), muscular endurance (SMD 0.47, 95% CI -0.08 to 1.02, P=0.10), and flexibility (SMD 0.09, 95% CI -0.23 to 0.41, P=0.58). Subgroup analyses indicated that mHealth app interventions targeting individuals aged 13–18 years, utilizing commercial apps, and 2–4 weeks were associated with a significant increase in TPA; interventions based on age 7–12 years, research apps, concerted intervention, social cognitive theory (SCT) , 4 BCT clusters, and 20–48 weeks were associated with a significant reduce in SB; interventions based on aged 13–18 years, Self-determination theory (SDT), and 2–4 weeks were associated with a significant increase in MVPA; interventions based on aged 7–12 years, concerted intervention, and 20–48 weeks with a significant reduce in BMI. Meta-regression showed that intervention duration was associated with TPA (*P*=0.0026) and MVPA (*P*=0.045), and age (*P*=0.04) and types of intervention (*P*=0.016) was associated with BMI, while other potential factors did not contribute significantly to explaining high heterogeneity.
Conclusions: Our meta-analysis suggests that mHealth app-based interventions may yield small-to-large beneficial effects on TPA, SB, BMI, agility, and muscle strength in children and adolescents. Furthermore, age and intervention duration may correlate with the higher effectiveness of mHealth app-based interventions. However, due to the limited number and quality of included studies, the aforementioned conclusions require validation through additional high-quality research.
Trial Registration: PROSPERO CRD42023426532
KEYWORDS: mHealth apps; children and adolescents; physical activity; physical fitness; systematic review; meta-analysis

Introduction

The global pandemic caused by COVID-19 has negatively impacted the physical fitness (PF) and mental health of children and adolescents[1]. Prior to the COVID-19 outbreak, only approximately 30% of children and adolescents worldwide could meet the recommended levels of physical activity (PA) [2, 3]. However, the COVID-19 pandemic has exacerbated this issue by decreasing their levels of PA, increasing sedentary behavior (SB), and leading to a decline in their PF[4]. A recent study in the UK discovered that children exhibited lower performance scores on the Seated Forward Bend and Twenty-Meter Shuttle Run Test and higher body mass index (BMI) values in 2020 than in 2019[5]. PF is a crucial determinant of children's and adolescents' health status[6], which can be influenced by various factors, including genetic, environmental, and PA-related factors[7]. Epidemiological studies have established a "dose–response" relationship between PA and PF, which showed that increased PA levels and reduced SB were positively associated with improved PF in adolescents[8]. Therefore, the way to increase PA and improve PF is still one of the most important social problems to be solved for children and adolescents.
The rapid advancement of intelligent technology has increased the use of smartphones among young generation and the wide utilization of mobile health (mHealth) technologies[9, 10]. At present, mHealth technologies, including wearable devices, smartphones, tablets, mHealth apps, smartwatches, and pedometers, are commonly used in the health field[11]. Recently, two systematic reviews have investigated the impact of mHealth-based interventions on behavioral changes, including PA and SB, in children and adolescents[12, 13]. However, these reviews primarily concentrated on specific mHealth technology interventions, including text messages with Short Message Service (SMS), wearable devices, web-based interventions, and others. Moreover, these systematic reviews exclusively focus on one or more behavioral changes, encompassing physical inactivity and SB, and the overall quality of the evidence is deemed low[13]. Current research indicates that apps-based interventions on smartphones may represent the most effective strategy[13]. mHealth app-based interventions are among the most commonly employed methods within the realm of mHealth technologies. Among these technologies, mHealth apps have been extensively used in the fitness and medical fields due to their affordability, personalization, and

diverse features[14]. mHealth apps can provide quantitative visual feedback of the health behaviors for users, such as PA; meanwhile, users upload their personal information to app databases, and apps facilitate interactive, personalized, long-distance, and low-contact training to improve the healthy development of users[15]. In recent years, mHealth app-based interventions have shown significant promise in promoting healthy behaviors, including increased PA and reduced SB, among children and adolescents. Nevertheless, there is a lack of systematic reviews comprehensively summarizing the impacts of standalone mHealth apps or concerted interventions utilizing apps as one of multiple components (e.g., behavioral counseling combined with app interventions) on various health behaviors, including PF. Additionally, studies in this domain have predominantly centered on adults, with a noticeable dearth of pertinent research within populations like children and adolescents[16].

Studies have demonstrated that mHealth app-based interventions can lead to effective outcomes in improving the PA behavior of users[17]. However, another study found that such intervention has indicated only small effects on PA and is likely related to potential influencing factors[18]. Furthermore, the efficacy of mHealth app-based interventions on PF is inconsistent. One study linked lower BMI and higher motor competence to the frequency and type of mHealth app use[19], while another study indicated that mHealth app-based interventions were ineffective in improving PF among adolescents, which is possibly due to the characteristics of the intervention[20]. The use of theory-based mHealth app interventions may also be more advantageous in increasing PA and enhancing PF in children and adolescents[21]. Several theoretical paradigms, including self-determination theory (SDT), the transtheoretical model, the health belief model (HBM), the theory of planned behavior (TPB), and social cognitive theory (SCT), have been employed in mHealth app-based interventions[22]. The number and type of behavior change technique (BCT) clusters may also play a significant role in the effectiveness of mHealth app interventions. Michie et al. provided a standardized taxonomy of BCT that categorizes them into 16 clusters, such as feedback and monitoring, reward and threat, goals and planning, shaping knowledge, social support, and comparison of outcomes[23]. This taxonomy aids in identifying which BCT clusters are more effectively applied to apps, thereby enhancing PA promotion and PF improvement. In conclusion, various factors, including the type of mHealth app, intervention characteristics, theoretical paradigms, and BCT clusters, are important considerations in the effectiveness of mHealth app interventions. Despite the increasing number of articles summarizing interventions based on m-health apps, a noteworthy research gap persists. The majority of these articles concentrate on interventions utilizing commercially available m-health apps that lack evidence-based behavior change strategies. Nevertheless, a significant proportion of users and patients rely on commercially available app-based m-health interventions that lack empirical evaluation and rarely incorporate evidence-based behavior change strategies. Furthermore, current research predominantly highlights the intervention effects of m-health apps on health-related outcome measures. However, there is a notable deficiency in evidence-based m-health apps intervention programs and studies that integrate various target behaviors.

Therefore, this systematic review aims to evaluate the effectiveness of mHealth app-based interventions in promoting PA and improving PF among children and adolescents. The second objective is to specifically assess moderating effects (e.g., age, types of apps, theoretical paradigm, BCT clusters, and intervention duration) on the effectiveness of mHealth app-based interventions in subgroups within these studies. Unlike previous studies, our review contributes evidence-based, high-quality content for potential m-health app interventions addressing PA and PF. This contribution results from a meticulous evaluation and meta-analysis of relevant RCTs. Additionally, we conducted an extensive analysis of key moderating variables using subgroups and meta-regression, encompassing theoretical paradigms, BCT clusters, intervention duration, and more. This comprehensive approach enhances our understanding of factors influencing intervention effects and facilitates the precise quantification of the intervention program. Our endeavors significantly expand the research scope beyond previous reviews.

Method

Registration and Approval

The systematic reviews were registered on the PROSPERO (NO. CRD42023426532). The literature search, reporting guidance, and implementation process of the study followed the guidelines of Preferred Reporting Items for Systematic Reviews and Meta-analyses[24].

Search Strategy

Several databases were searched, including PubMed, Web of Science, EBSCO, and Cochrane Library, to identify relevant RCTs published until December 25, 2023. The search strategy involved a Boolean search using a combination of subject and free words. Search terms was used (Child OR Preschool OR Adolescent), (“Mobile health application*” OR “mHealth app*” OR “Portable Software Application*” OR “Mobile Application*” OR App*), and (“Physical Activity” OR PA OR MVPA OR “sedentary behavior” OR SB OR “Physical Fitness”). A detailed search strategy for Web of Science is presented in Multimedia Appendix 1. We opted to update the searches in the same databases used for the initial search to refine the results for this study. Additionally, we examined the references cited in previous reviews to identify additional relevant literature. Concurrently, we reached out to authors of potentially eligible studies to obtain complete data. If more than two attempts were made to contact authors without receiving a response, the study was excluded. The literature search was not restricted by language.

Inclusion and Exclusion Criteria

Inclusion Criteria

The following criteria were included for inclusion in the literature review: (1) The study comprised children and adolescents, aged 3 to 18 years, with the majority falling within this range. Participants did not exhibit physical dysfunction, and overweight or obesity, among other factors, were not exclusionary criteria. Children and adolescents were categorized into three groups: preschoolers aged 3–6 years, children aged 7–12 years, and adolescents aged 13–18 years. (2) Interventions utilizing smartphone and/or tablet-based mHealth apps may involve either stand-alone apps (solely apps) or concerted intervention (apps combined with another intervention). The control group comprised genuine controls, such as no interventions, wait-list conditions, and usual clinical care. Additionally, active controls, including interventions via apps, were considered. Studies employing placebo and sham apps also met the inclusion criteria. (3) RCTs as the study design. (4) Primary outcome measures included PA, SB, performance-related PF (e.g., coordination and balance), health-related PF (e.g., cardiorespiratory endurance, muscle strength, and body composition), and physiological function (e.g., body shape and metabolism).

Exclusion Criteria

Among the exclusion criteria were the following: (1) Articles written in languages other than English and Chinese. (2) Repeated published studies, basic studies, observational studies, reviews, and case series articles. (3) Studies for which full text was unavailable or data were incomplete. (4) mHealth apps that only used SMS interventions or were incompatible with smartphones or tablets.

Study Selection

After the literature search, the initial search results were imported into EndNote 20 to remove duplicate articles. Predefined inclusion and exclusion criteria were applied to the literature. Two authors (Z-CZ and S-LZ) initially screened the titles and abstracts. Literature meeting the criteria was downloaded, and one author (Z-CZ) thoroughly evaluated the full text based on the inclusion and exclusion criteria, while the other author (S-LZ) conducted a randomized assessment. A third party (JF) was involved in resolving discrepancies between two independent reviewers to determine if a study met the inclusion criteria.

Data Extraction

The included literature was independently extracted by two researchers (YJ and Z-LG). The extracted information included basic details (e.g., authors, publication year, country, and study type), characteristics of the study population (e.g., age, gender, and sample size), characteristics of mHealth apps (e.g., name, type, theoretical paradigm, and number or type of BCT clusters), intervention characteristics, outcome measures, and indicators related to risk of bias assessment. Two authors (YJ and Z-LG) assessed the utilization of BCT in apps using Michie's taxonomy[23]. Relevant information was primarily extracted from the study descriptions; in cases of incomplete data, the original apps were consulted. Disputes were resolved through third-party consultation (W-DC).

Risk of Bias Assessment

Two independent (YJ and Z-LG) investigators assessed the risk of bias using the Cochrane Working Group's tool[25]. Any disagreements were resolved by a third independent researcher (W-DC) through consultation. Each study underwent evaluation in seven domains, and the risk of bias was categorized as unclear, low, or high.

Statistical Analysis

If the number of included papers was fewer than 3, then a systematic review was conducted. When a sufficient number of included studies were available for a meta-analysis, we utilized Revman 5.4 and Stata 16.0 to estimate effect sizes, conduct subgroup analysis, and sensitivity analysis. Weighted mean difference (WMD) and 95% confidence interval (CI) were used as effect measures when the same measurement method was employed. When measurement methods were consistent, the standardized mean difference (SMD) and 95% CI were used. The magnitude of SMD was interpreted as follows: SMD < 0.2, negligible; 0.2 ≤ SMD < 0.5, small; 0.5 ≤ SMD < 0.8, medium; SMD ≥ 0.8, large[26].

The study indirectly mentioned the mean and standard deviation, and the MD and SMD were calculated as the postintervention mean and standard deviation based on the Cochrane Handbook[27]. The study examined the magnitude of heterogeneity using I^2 and P values. If $I^2 \leq 50\%$ and/or $P \geq 0.1$, a fixed-effect model was used for data analysis. On the contrary, if $I^2 > 50\%$ and/or $P < 0.1$, a random-effect model was utilized for meta-analysis[27]. The sources of heterogeneity were identified by subgroup analyses and meta-regression analysis based on type of apps, theoretical paradigm, age, and BCT clusters. The robustness of each study was evaluated using sensitivity analysis, and publication bias was assessed with funnel plots and Egger’s test.

Results

Study Selection

A total of 12,025 relevant articles were retrieved from PubMed (n=69), Web of Science (n=11,033), EBSCO (n=217), and Cochrane Library (n=706). Duplicate references were removed, which resulted in 6867 studies. Following an initial screening by abstracts, 136 articles were identified, which were then assessed by reading the full text. Finally, 28 articles were chosen for inclusion (Figure 1).

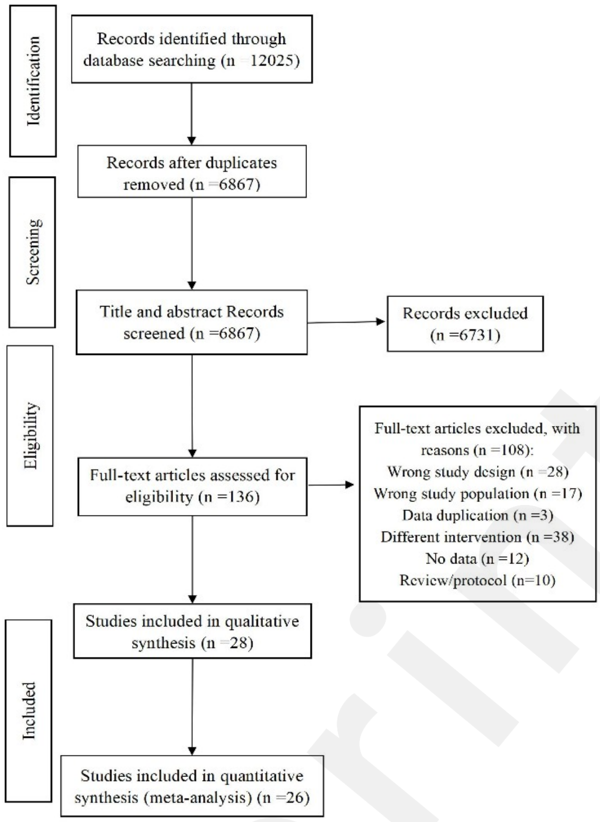

Figure 1. Flowchart of study selection.

Characteristics of Included Studies

The study included 28 publications, all of which were RCTs published between 2014 and 2023[20, 26, 28-49]. The sample size included a total of 5,643 subjects, ranging from 12 to 1392 participants per study. As shown in Table 1, the included studies have the following basic characteristics. The age of the participants varied from 3 to 18 years, with 5 studies involving preschool children[26, 44, 46, 48, 50], 8 studies involving children[28-31, 33, 36, 37, 51], and 15 studies involving adolescents[20, 32, 34, 35, 38-43, 45, 47, 49, 52, 53]. The objectives of the studies differed, and the selection criteria for the target population varied inconsistently. Most studies focused on healthy children and adolescents, while nine studies included overweight and obese participants[29-31, 35, 36, 39, 43, 45, 52], two studies involved children with cancer[34, 53], and one study enrolled youth with congenital heart disease[40]. Eight study was conducted in Asia[31, 36, 37, 39-41, 44, 45], while the remaining studies were performed in Oceania[29, 30, 35, 38, 46, 50, 53], North America[28, 33, 34, 43, 51], and Europe[20, 26, 32, 42, 47-49, 52].

This review encompassed 28 studies that utilized 14 different mHealth apps. These included 9 commercial apps[20, 31-33, 35, 38, 41, 47, 49] and 14 research apps[28-30, 39, 40, 42-46, 48, 51-53] , and 5 mHealth apps did not provide corresponding information[26, 34, 36, 37, 50]. The type of intervention in 15 studies was stand-alone apps[20, 26, 28, 32, 33, 40, 41, 43-47, 49-51], and 13 studies used concerted intervention[29-31, 34-39, 42, 48, 52, 53]. Participant engagement with the intervention was mentioned in 28 studies, 8 studies focused on parent-centered[26, 31, 36, 37, 44, 46, 48, 50], the remaining studies were child-centered. The mHealth apps were based on various theoretical paradigms, including self-regulation theory (SRT), SDT, and SCT. Different numbers or types of BCT clusters were identified, and they ranged from 1 to 7 clusters. Examples of BCT clusters used included goal setting and planning, feedback and monitoring, and behavioral comparison. Interventions duration lasted 2 to 48 weeks (Table 1). The primary and secondary outcome measures included total PA (TPA), moderate-to-vigorous PA (MVPA), SB, cardiorespiratory fitness (CRF), BMI, waist circumference (WC), muscle strength, agility, flexibility, muscular power and endurance.

Risk of Bias Assessment

Overall, 11 studies were classified as having a low risk of bias[20, 26, 28, 29, 34, 35, 37, 39, 51-53] and a high risk of bias in 17 studies[30-33, 36, 38, 40-50]. The methods for random sequence generation were adequately reported in 28 studies, and 14 studies described allocation concealment protocols[20, 26, 29, 31, 35, 37, 39, 43, 46, 48, 50-53]. Blinding of participants and personnel was unclear in 17 studies[20, 28-33, 38-41, 43-45, 47, 49, 51], high risk of bias in 7 studies[26, 34, 35, 37, 50, 52, 53]; blinding of outcome assessment was unclear in 18 studies[18, 28-34, 38, 40, 41, 44, 45, 47-51, 53]. Four studies had information on subjects lost to follow-up[30-32, 34], unclear in 1 study[51]. None of the 28 studies were found to have selective outcome reporting, and other aspects of bias were evaluated mainly in terms of baseline data and conflicts of interest (Figure 2).

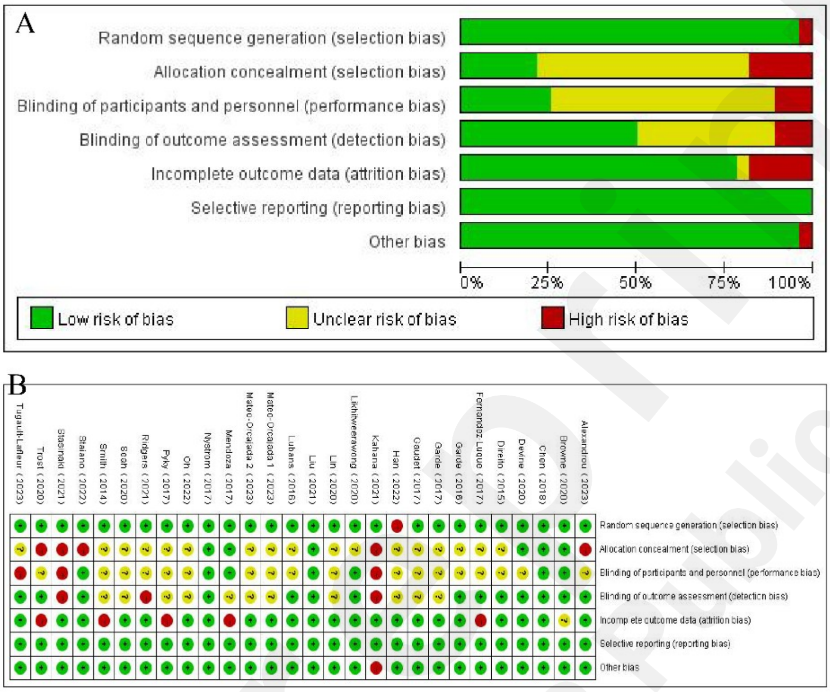

Figure 2. Risk bias assessment of the included studies.

Table 1. Summary of intervention characteristics of included studies.

Author, year	Participants/ Population	Age (years)	Sample size （[a]T / [b]C）	Interventions	Comparator	Type of mHealth apps	Theoretical paradigm	BCT clusters	Duration（weeks）	Outcomes
Direito, 2015[20]	Insufficiently active healthy young people	15.7 ± 1.2	32/17	Group 1: immersive app *Zombies Run* Group 2: nonimmersive app *Get Running*	No interventions	Commercial apps	[g]SRT	Feedback and monitoring	8	[l]CRF, [h]TPA, [i]SB, [j]MVPA
Garde, 2016[28]	Healthy students	11.3 ± 1.2	26/16	MKMM game app	Wait list (crossed over after 3weeks)	Research apps	[d]SDT, Theory of Motivation	Reward and Threat、feedback and monitoring	4	[h]TPA
Lubans, 2016[29]	Adolescent boys'at risk' of obesity	12.7 ± 0.5	181/180	Face-to-face PA sessions + pedometers for PA self-monitoring + purpose-built web-based smartphone apps + other	Regular curriculum	Research apps	[e]SCT、[d]SDT	Goals and planning, Shaping knowledge, Social support, Feedback and monitoring	32	[i]SB, [j]MVPA, [k]BMI, WC[m], muscle strength,muscular endurance
Smith, 2014[30]	Adolescent boys'at risk' of obesity	12.7 ± 0.5	181/180	Face to face PA sessions + pedometers for PA self-monitoring + purpose-built web-based smartphone apps + other	Regular curriculum	Research apps	[e]SCT、[d]SDT	Goals and planning, Shaping knowledge, Social support, Feedback and monitoring	20	[h]TPA , [i]SB, [j]MVPA, [k]BMI, WC[m], muscle strength
Fernandez-Luque, 2017[31]	Overweight and obese children	9～12	108/119	wearable sensors + mobile and social media (WhatsApp and Instagram)	No intervention	Commercial apps	[c]NA	Goals and planning, Social support, Feedback and monitoring	12	[k]BMI

Pyky, 2017[32]	Young adolescent men	17.8 ± 0.6	250/246	*MOPOrtal* app	No intervention	Commercial apps	[f]TTM	Goals and planning, Shaping knowledge, Feedback and monitoring, Comparison of outcomes	24	[i]SB , [k]BMI
Gaudet, 2017[33]	Young adolescents	13 ± 0.35	23/23	An individualized goal was set by *Fitbit app*	No intervention	Commercial apps	[g]SRT, Self-monitoring theory	Goals and planning, Feedback and monitoring, Regulation	7	[j]MVPA
Mendoza, 2017[34]	Adolescent and young adult childhood cancer survivors	16.6 ± 1.5	29/20	Fitbit Flex wearable wristband and mHealth app + peer-based virtual support group	Usual care	[c]NA	[d]SDT	Goals and planning, Feedback and monitoring	10	[i]SB, [j]MVPA
Nystrom, 2017[26]	Healthy Swedish children	4.5 ± 0.1	156/159	MINISTOP app	Information/ advice about a healthy diet + PA via a four-page pamphlet	Research apps	[e]SCT	Shaping knowledge, Feedback, and monitoring	24	[i]SB, [j]MVPA
Chen, 2018[35]	Adolescents who are overweight or obese adolescents	14.9 ± 1.67	23/17	Fitbit Flex app + iStart Smart for Teens online educational program + biweekly text messages	Omron HJ-105 pedometer + a blank food-and-activity diary	Commercial apps	[e]SCT	Goals and planning, Feedback and monitoring, Shaping knowledge, Social support, Regulation, Natural consequences, Covert learning	12–24	[h]TPA, [i]SB, [k]BMI
Browne,	Children with	9–16	8/12	Usual clinical care +	Usual clinical	Commercial	[c]NA	Goals and planning,	4	[k]BMI

2020[52]	obesity			Mandolean training (*myBigO app*)	care	apps		Feedback and monitoring, Comparison of outcomes, Shaping knowledge, Social support, Repetition and substitution, Antecedents		
Garde, 2017[51]	Elementary school students	10.6 ± 0.51	19/18	*MKMM* game app	No intervention	Research apps	[d]SDT, Theory of Motivation	Goals and planning, Feedback and monitoring, Comparison of outcomes, Social support	2	[h]TPA
Trost, 2021[50]	Children	3–6	17/17	*Moovosity*™ app	No intervention	[c]NA	[c]NA	[c]NA	8	[h]TPA
Devine, 2020[53]	Adolescent and young adult survivors of childhood cancer	13–25	25/24	In-person group sessions + mobile app + fitness tracker use alone	Wait list	Research apps	[e]SCT	Goals and planning, Feedback and monitoring, Shaping knowledge, Social support	12	[l]CRF, [i]SB, [j]MVPA, [k]BMI, WC[m], muscle strength, coordination
Kahana, （2021）[36]	Children with Overweight and Obesity	median age 10 years	32/47	structured PA sessions, nutritional, and behavioral counseling + *"Just Dance Now"* and *"Motion Sports" app*	Structured PA sessions, nutritional, and behavioral counseling	[c]NA	[c]NA	[c]NA	20	[k]BMI, muscle strength, muscular power, muscular endurance, agility
Liu,（2021）[37]	Primary school children	9.6 ± 0.4	705/687	Health Education，Reinforcement of PA and BMI	Health education lessons and physical	[c]NA	[c]NA	[c]NA Feedback and monitoring,	36	[l]CRF, [h]TPA, [j]MVPA, [k]BMI, WC[m], muscular

				Monitoring and Feedback (*Eat Wisely and Move Happily* app) et al	education sessions					power, muscular endurance
Likhitweera wong, (2020)[39]	Children and adolescents with obesity	10～15	35/35	OBEST app+standard care	Standard care	Research apps	Theory of Motivation	Goals and planning, Feedback and monitoring, Shaping knowledge	24	[k]BMI, waist circumference,
Lin, (2020) [40]	Youth with congenital heart disease	15～24	100/50	Group 1: *COOL Passport* app Group 2: *COOL Passport app* + Health Promotion Cloud	Standard-care	Research apps	[g]SRT	Goals and planning, Feedback and monitoring, Shaping knowledge, Reward and threat	24～48	[h]TPA
Seah, （2020）[41]	Adolescent girls	14.9 ± 0.3	13/23	*MapMyFitness* app	No intervention	Commercial apps	[d]SDT	Goals and planning, Feedback and monitoring, social support	2～3	[h]TPA, [j]MVPA
Stasinaki, （2021）[42]	Adolescents with obesity	10～18	18/13	Nutritional education and PA + *PathMate2 (PM)* app	Nutritional education and PA	Research apps	Theory of Motivation	Goals and planning, Feedback and monitoring, Reward and threat, Comparison of behavior	22	[l]CRF, WC[m], muscular power, muscular endurance, agility, flexibility, balance
Tugault-Lafleur, （2023）[43]	Children With Overweight or Obesity	10～17	107/107	*Aim2Be* app	No intervention	Research apps	[e]SCT, [g]SRT	Goals and planning, Feedback and monitoring, Identity, social support	12	[h]TPA, [i]SB
Han, （2022）[44]	Preschool children	3～6	66/44	*“YOUXUE UP”*app	No intervention	Research apps	Socioecological Model	Goals and planning, social support, Reward and threat	8	[i]SB, [j]MVPA, muscle strength, muscular power, agility, flexibility,

										coordination, balance
Oh, 2022[45]	Adolescents with Obesity	13.2 ± 3.6	12/12	*SUKIA* app	Nintendo Switch	Research apps	[c]NA	Feedback and monitoring, Shaping knowledge	3	[l]CRF, [k]BMI
Staiano, 2022[46]	Preschoolers	4.0 ± 0.8	32/37	Motor Skills app	Free Play app	Research apps	[e]SCT	Goals and planning, social support, Shaping knowledge, Feedback and monitoring	12	[h]TPA, [i]SB, [j]MVPA
Mateo-Orcajada, 2023[47]	Adolescents	13.96 ± 1.21	240/160	*Poksammon Go* app or *Pacer* app or *Strava* app or *MapMyWalk* app	No intervention	Commercial apps	[c]NA	810 change techniques per application	10	[l]CRF, [h]TPA, [k]BMI, WC[m], muscle strength, muscular power, muscular endurance, flexibility
Ridger, 2021[38]	Inactive adolescents	13.7 ± 0.4	144/131	Wrist-worn Fitbit® Flex and accompanying *Fitbit® app*, digital behaviour change resources et al	No intervention	Commercial apps	[e]SCT, behavioural choice theory	Goals and planning, Feedback and monitoring, Self-belief	12	[h]TPA, [j]MVPA
Alexandrou, 2023[48]	Preschool-aged children	2.53	270/271	Standard care + *MINISTOP 2.0 app*	Standard care	Research apps	[e]SCT	Identity, Goals and planning, shaping knowledge, Feedback and monitoring	24	[i]SB, [j]MVPA

Mateo-Orcajada, （2023）[49]	Adolescents	13.66 ± 1.17	92/46	Group 1: *Pokémon Go Playing* app continuously Group 2: *Pokémon Go Playing* app intermittently	No intervention	Commercial apps	[c]NA	[c]NA	10	[h]TPA, [k]BMI, WC[m],

[a]T: intervention group; [b]C: control group; [c]NA: Not reported; [d]SDT: self-determination theory; [e]SCT: social cognitive theory; [f]TTM: Transtheoretical model; [g]SRT: Self-regulation theory; [h]TPA: total physical activity；[i]SB: sedentary behavior ；[j]MVPA: moderate-to-vigorous physical activity；[k]BMI: body mass index; [l]CRF: cardiorespiratory fitness; WC[m]: waist circumference

Results of the Meta-analysis

Effects of mHealth app-based interventions on PA

Twenty-one studies were examined to assess the impact of mHealth app-based interventions on TPA. The heterogeneity test indicated a substantial level of heterogeneity among the studies (I^2=75%, P<0.00001), which led to the adoption of a random effects model for the analysis. The meta-analysis results indicated that the intervention group exhibited higher TPA (SMD 0.29, 95% CI 0.13 to 0.45, P=0.0004) (Figure 3), but the effect size was small.

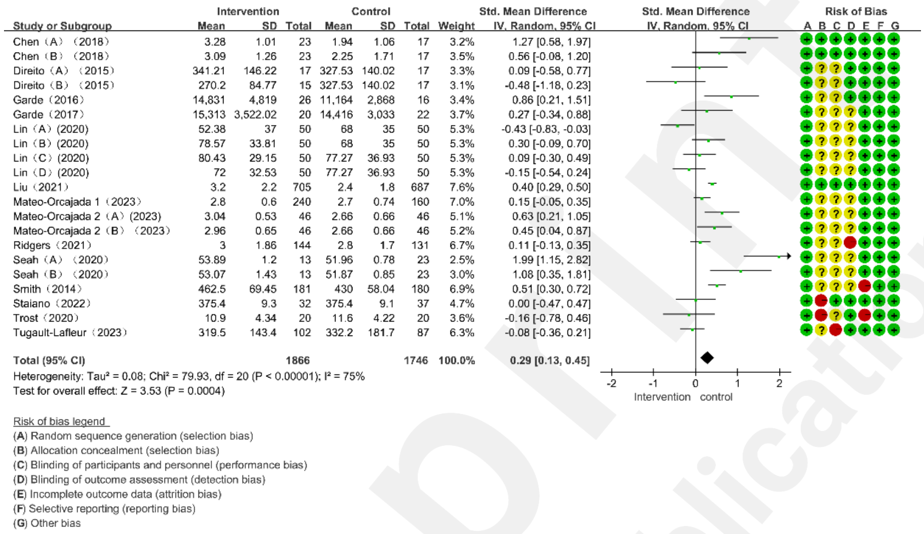

Figure 3. Forest plot for the effect of mHealth apps-based interventions on increasing TPA.

A total of 14 studies reported the impact of mHealth app-based interventions on SB levels. Heterogeneity tests revealed homogeneity between the studies (I^2=98%, P<0.00001), which required analysis using a random effect model. Meta-analysis found that mHealth app-based interventions significantly reduced SB (SMD −0.97, 95% CI −1.67 to -0.28, P=0.006) (Figure 4).

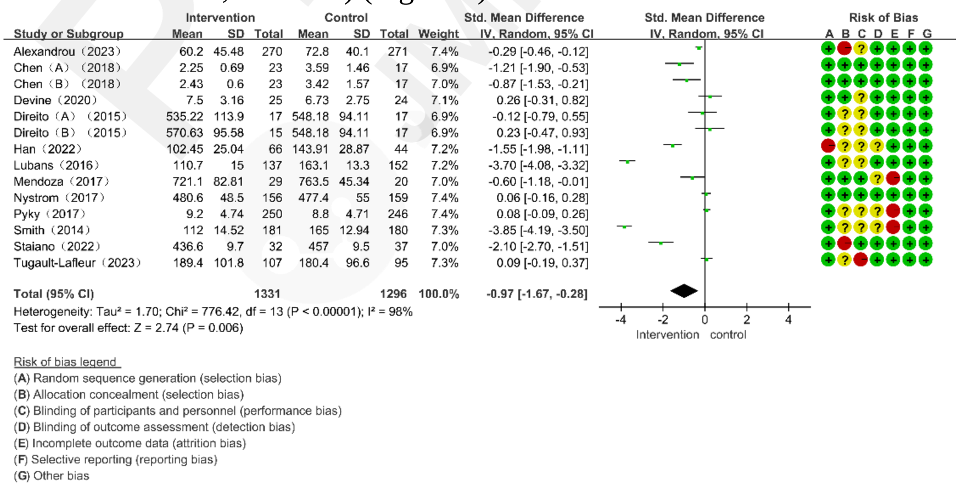

Figure 4. Forest plot for the effect of mHealth apps-based interventions on decreasing SB.

A total of 14 studies investigated the impact of mHealth app-based interventions on MVPA levels. The heterogeneity test indicated homogeneity among the studies

(I^2=67%, *P*=0.0002), which allowed for analysis using a random effect model. There were no significant differences between the control and intervention groups (SMD 0.11, 95% CI −0.04 to 0.25, *P*=0.0002) (Figure 5).

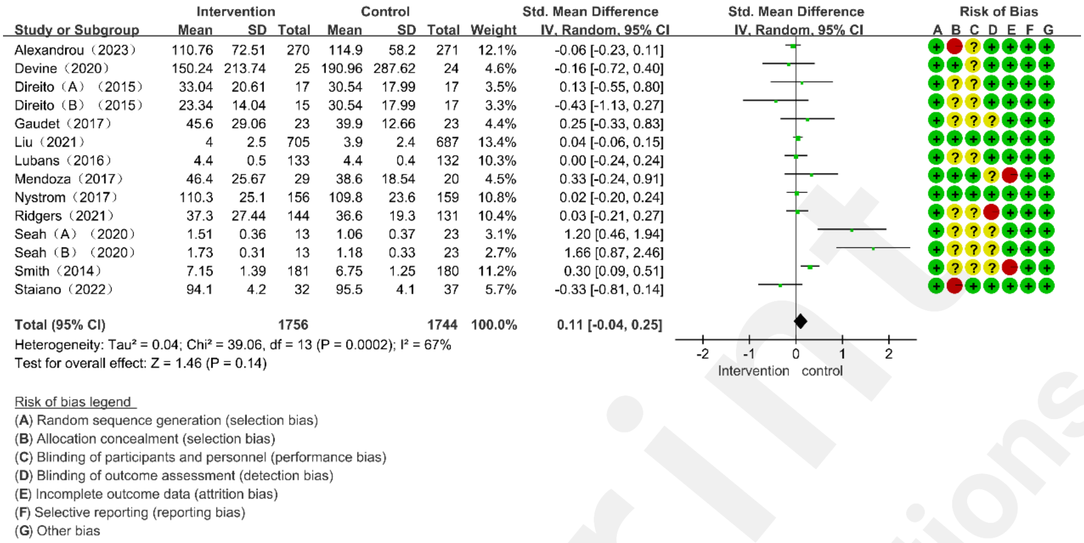

Figure 5. Forest plot for the effect of mHealth app-based interventions on increasing MVPA.

Effects of mHealth app-based interventions on BMI and waist circumference

A total of 13 studies investigated the effects of mHealth app-based interventions on BMI, of which 2 did not directly conduct changes in outcome indicators before and after interventions[31, 52] and were only included in systematic reviews. The heterogeneity test demonstrated homogeneity among the studies (I^2=32%, *P*=0.12), which enabled analysis using a fixed effect model. Meta-analysis found that mHealth app-based interventions significantly reduced BMI (WMD −0.31, 95% CI −0.60 to −0.01, *P*=0.12) (Figure 6). The two other studies on BMI reported a significant reduction in BMI among obese children with mHealth app-based interventions[31, 52], which is consistent with the meta-analysis results.

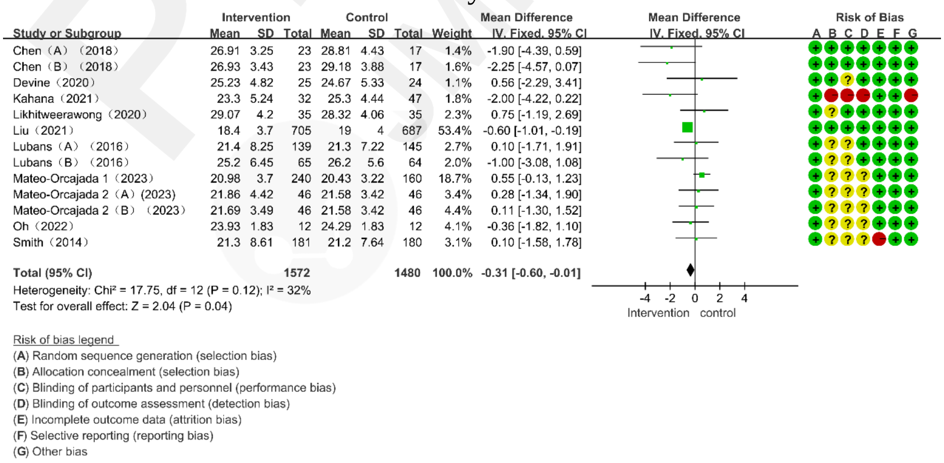

Figure 6. Forest plot of the effect of mHealth apps-based interventions on BMI.

Nine studies reported the effect of mHealth app-based interventions on WC. The heterogeneity tests showed homogeneity among the studies (I^2=54%, *P*=0.02), which allowed for analysis using a random effect model. There were no significant differences in WC between the intervention and control groups (WMD 0.38, 95% CI −1.28 to 2.04 kg/m^2, P=0.65) (Figure 7).

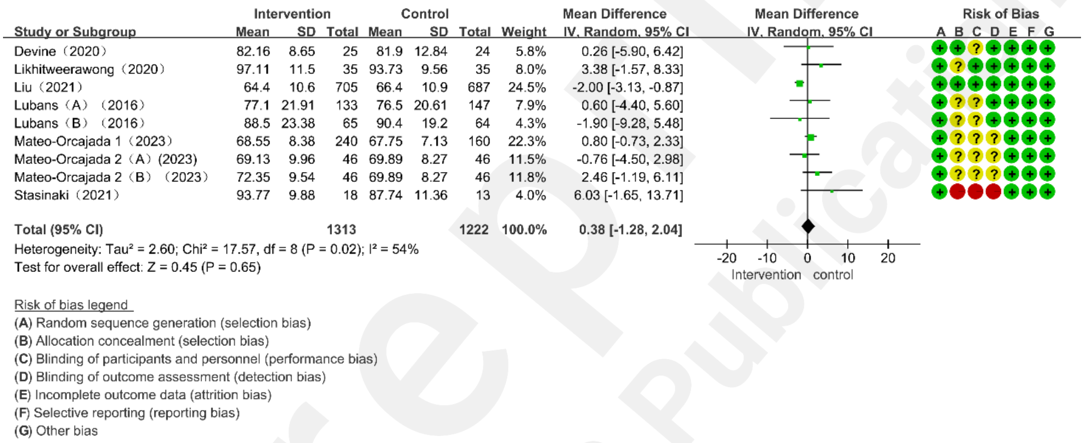

Figure 7. Forest plot of the effect of mHealth app-based interventions on waist circumference.

Effects of mHealth app-based interventions on PF

Seven studies investigated the impact of mHealth app-based interventions on CRF. Heterogeneity tests showed homogeneity among the studies (I^2=66%, *P*=0.007), and were conducted using a random effect model. No significant differences were found between intervention and control groups in CRF (SMD −0.20, 95% CI −0.45 to 0.05 cm, *P*=0.11) (Figure 8).

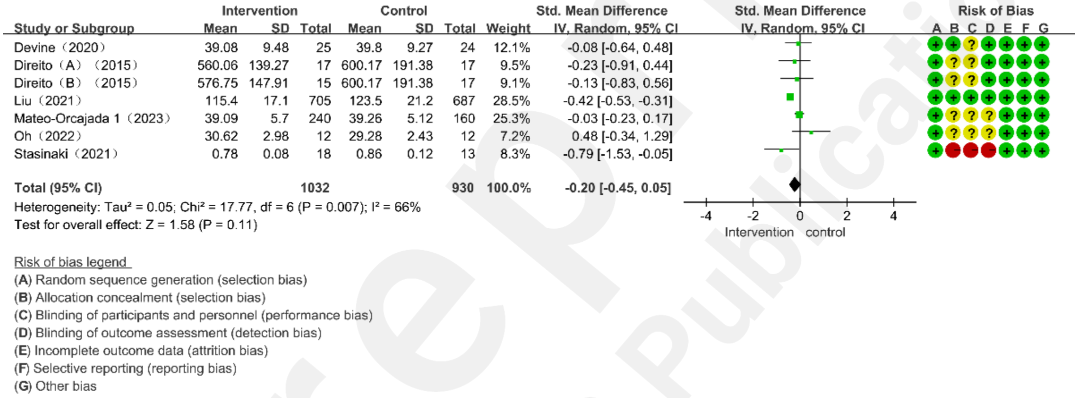

Figure 8. Forest plot of the effect of mHealth app-based interventions on CRF.

Six studies reported the impact of mHealth app-based interventions on muscle strength. Heterogeneity tests revealed homogeneity in the studies (I^2=99%, *P*<0.00001) and were conducted using a random effect model. Meta-analysis found that mHealth app-based interventions significantly increased muscle strength (SMD 1.97, 95% CI 0.09 to 3.86, *P*=0.04) (Figure 9).

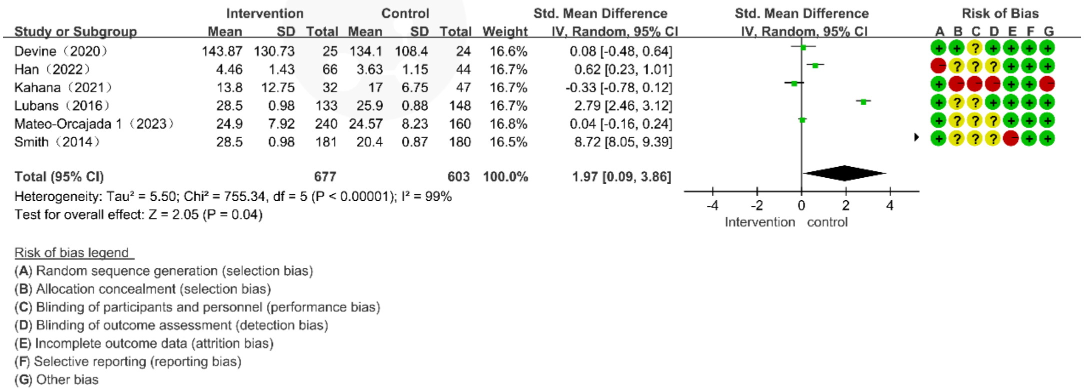

Figure 9. Forest plot of the effect of mHealth app-based interventions on muscular strength.

A total of 5 studies investigated the impact of mHealth app-based interventions on muscular power. The heterogeneity test indicated homogeneity among the studies (I^2=45%, *P*=0.12), which allowed for analysis using a fixed effect model. There were no significant differences between the control and intervention groups (SMD 0.01, 95% CI −0.08 to 0.10, *P*=0.81) (Figure 10).

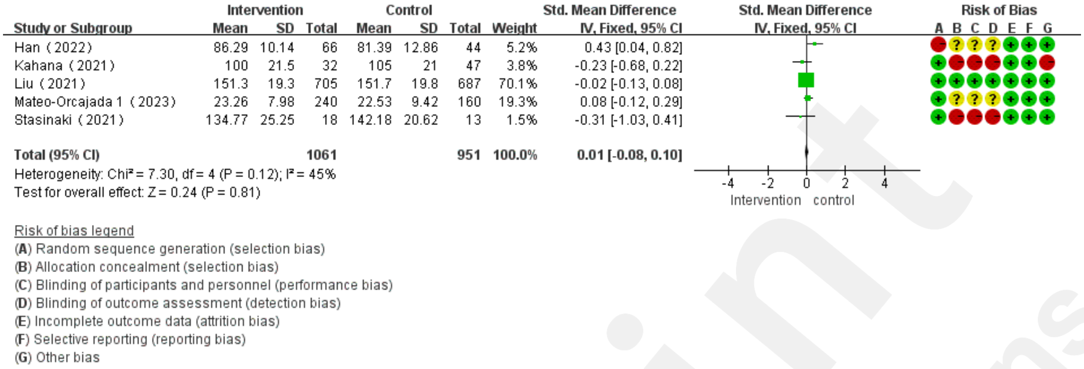

Figure 10. Forest plot of the effect of mHealth app-based interventions on muscular power .

Eight studies were examined to assess the impact of mHealth app-based interventions on muscular endurance. The heterogeneity test indicated a substantial level of heterogeneity among the studies (I^2=98%, *P*<0.00001), which led to the adoption of a random effects model for the analysis. The meta-analysis results indicated that no significant difference in muscle endurance between the intervention and control groups (SMD 0.47, 95% CI -0.08 to 1.02, *P*=0.10) (Figure 11).

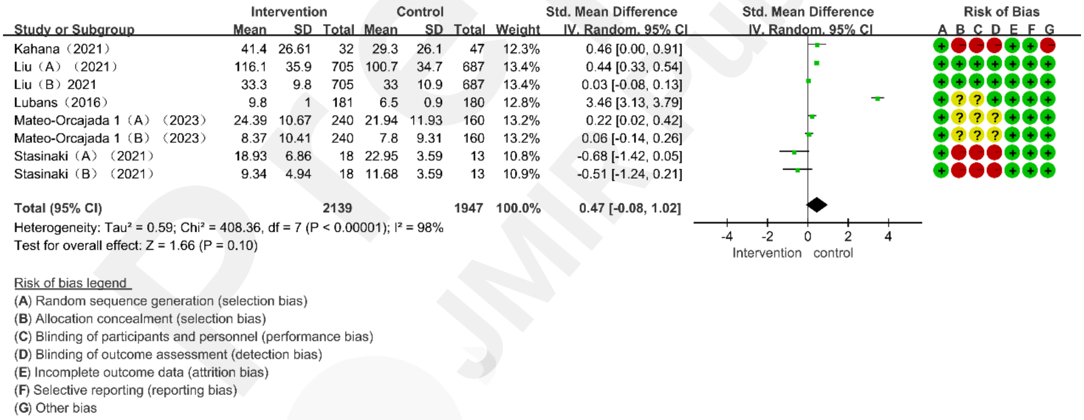

Figure 11. Forest plot of the effect of mHealth app-based interventions on muscular endurance.

A total of 4 studies investigated the impact of mHealth app-based interventions on agility. The heterogeneity test indicated homogeneity among the studies (I^2=0%, P=0.87), which allowed for analysis using a fixed effect model. Meta-analysis found that mHealth app-based interventions significantly improved agility (SMD −0.35, 95% CI −0.61 to -0.10, *P*=0.006) (Figure 12).

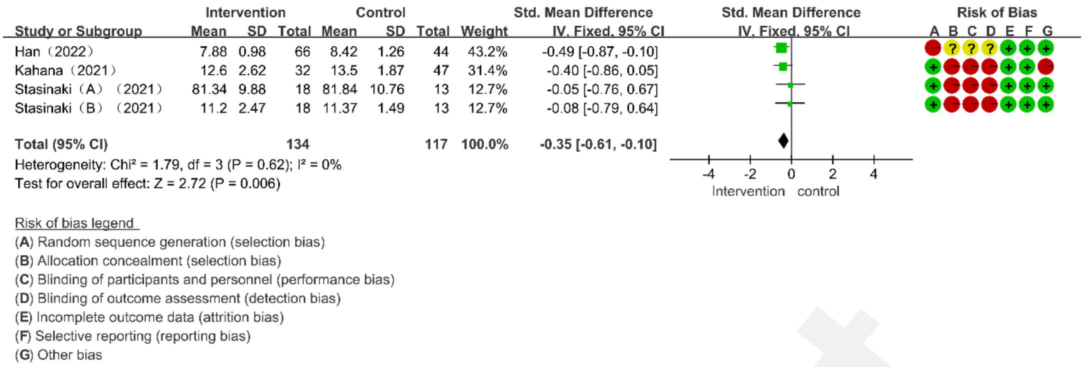

Figure 12. Forest plot of the effect of mHealth app-based interventions on agility.

Three studies reported the impact of mHealth app-based interventions on flexib-ility. Heterogeneity tests revealed homogeneity in the studies (I^2=52%, *P*=0.12) and were conducted using a random effect model. There were no significant differences in flexibility between the control and intervention groups (SMD 0.09, 95% CI −0.23 to 0.41, *P*=0.58) (Figure 13).

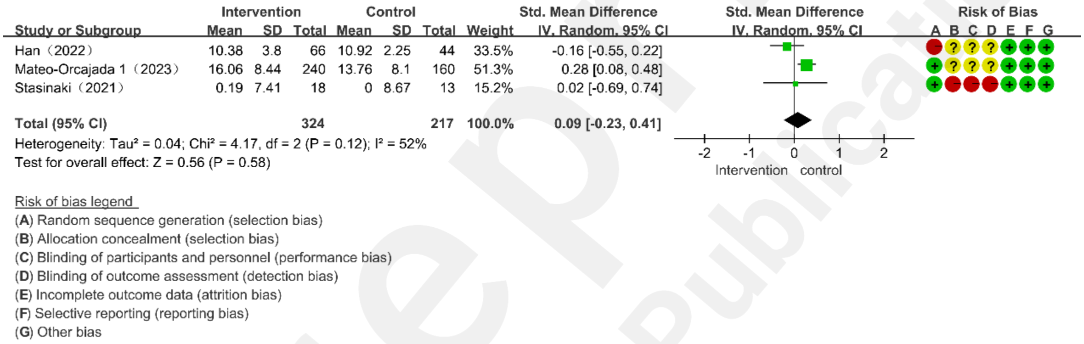

Figure 13. Forest plot of the effect of mHealth app-based interventions on flexibility.

Sensitivity analysis

In this study, Stata 16.0 was used to conduct sensitivity analyses on TPA, SB, MVPA, and BMI for evaluating the robustness and reliability of the results. The sensitivity analysis results demonstrated that excluding any single study did not impact the effect size of the mHealth app-based intervention in outcomes such as TPA, SB, and MVPA (Multimedia Appendix 2 and 4), which indicates the robustness and reliability of the study results. In terms of BMI, sensitivity analyses identified one study as an outlier[37] (Multimedia Appendix 5). Removing this study altered the overall effect size, indicating that the study results were not sufficiently robust (SMD 0.03, 95% CI −0.41 to 0.46 cm, *P*=0.90) and should be interpreted with caution.

Subgroup analyses

Subgroup analyses were conducted to investigate the potential sources of heterogeneity and moderating effects, which considered factors such as age, types of apps, theoretical paradigm, number or type of BCT clusters, and intervention duration. The primary outcome indicators included TPA, BMI, SB and MVPA. Sensitivity analysis, subgroup analysis, and assessment of publication bias were not conducted for the remaining outcome indicators due to the limited number of included studies.

Subgroup analyses on the effect of mHealth app-based interventions on TPA

The results of subgroup analyses investigating the impact of mHealth app-based interventions on TPA are presented in Table 2 (Multimedia Appendix 6 and 12). Subgroup analyses indicated no significant difference in types of Intervention, theoretical paradigm, and the number of BCT clusters concerning the improvement in TPA in children and adolescents.

Age-based subgroup analysis revealed a significant positive effects for interventions towards children aged 7–12 years group (SMD 0.42) and adolescents aged 13–18 years group (SMD 0.29), but negligible effect for the preschool children aged 3–6 years group (SMD -0.06).

Subgroup analysis based on types of apps revealed a significantly greater effect size for the commercial apps (SMD 0.51) compared to the research apps intervention (SMD 0.13). Substantial heterogeneity existed between these two groups (I^2=75%, *P*<0.00001), but the 95% confidence interval for the effect size between the two groups overlapped.

Subgroup analysis based on intervention duration revealed a significant increase in TPA for the 2–4 weeks intervention (SMD 1.01), 8–12 weeks intervention (SMD 0.23). Heterogeneity was observed between the two groups (I^2=75%, *P*<0.00001), but the 95% confidence interval for the effect size between the two groups overlapped.

Subgroup analyses on the effect of mHealth app-based interventions on SB

The results of subgroup analyses on SB are presented in Table 3 (Multimedia Appendix 13 and 19). Subgroup analyses showed no significant difference in intervention duration regarding the reduction of SB in children and adolescents.

Age-based subgroup analysis unveiled a notably larger effect size for interventions directed at children aged 7–12 years (SMD −3.78) compared to the group of preschool children aged 3–6 years (SMD -0.92). Heterogeneity was evident among the two groups (I^2=99%, *P*<0.00001), and the 95% confidence interval for the effect size between the two groups did not overlap.

Subgroup analysis based on types of apps demonstrated a significantly stronger effect size for research app interventions (SMD −1.38) than for commercial app interventions (SMD −0.35). Heterogeneity was observed between the two groups (I^2=98%, *P*<0.00001), but the 95% confidence interval for the effect size between the two groups overlapped.

Subgroup analysis based on types of intervention revealed a significantly greater effect size for the concerted intervention (SMD −1.47) compared to the stand-alone apps intervention (SMD −0.45). Substantial heterogeneity existed between these two groups (I^2=98%, *P*<0.00001), but the 95% confidence interval for the effect size between the two groups overlapped.

Subgroup analyses based on the theoretical paradigm showed a greater effect size for interventions based on the SCT (SMD −0.64) than for intervention based on combination of SCT and other theories (SMD −2.18) and solely on SRT (SMD 0.05). Substantial heterogeneity existed between these two groups (I^2=98%, *P*<0.00001), but the 95% confidence interval for the effect size between the two groups overlapped.

Subgroup analysis based on the number of BCT clusters demonstrated a significant reduction in SB for interventions based on 7□10 BCT clusters (SMD −1.03) and interventions based on 4 BCT clusters (SMD -1.36), and the 95% confidence interval for the effect size between the two groups overlapped.

Subgroup analysis based on intervention duration revealed a significant reduction in SB for the 20□48 weeks intervention (SMD −1.42), but had a negligible effect at 8□12 weeks intervention (SMD -0.63).

Subgroup analyses on the effect of mHealth app-based interventions on MVPA

The results of subgroup analyses on MVPA are shown in Table 4 (Multimedia Appendix 20 and 26). Subgroup analyses revealed no significant difference in type of apps, types of intervention and the number of BCT clusters in improving MVPA in children and adolescents, which were not moderators of the effect of mHealth app interventions.

Age-based subgroup analysis unveiled a notably larger effect size for interventions directed at adolescents aged 13□18 years (SMD 0.42) compared to the group of preschool children aged 3□6 years (SMD -0.05) and children aged 7□12 years (SMD 0.11). Heterogeneity was evident among the two groups (I^2=68%, *P*=0.0002), but the 95% confidence interval for the effect size between the two groups overlapped.

Subgroup analyses based on theoretical paradigm demonstrated a significant increase in MVPA for SDT-based intervention (SMD 1.03), while no significant effect was observed for SCT (SMD -0.06), combination of SCT and other theories (SMD 0.12), SRT (SMD -0.14).

Subgroup analysis based on intervention duration revealed a significant increase in MVPA for the 2□4 weeks intervention (SMD 1.42), but negligible effect for the 8□12 weeks intervention(SMD -0.01) and 20□48 weeks intervention (SMD 0.05).

Subgroup analyses on the effect of mHealth app-based interventions on BMI

The results of subgroup analyses on BMI are shown in Table 5 (Multimedia Appendix 27 and 33). Subgroup analyses revealed no significant difference in type of apps, theoretical paradigm and the number of BCT clusters in decreasing BMI in children and adolescents.

Age-based subgroup analysis revealed a significant decrease in BMI for interventions targeting children aged 7□12 years (WMD -0.59), but no significant difference was observed for adolescents ages 13□18 years (WMD 0.03).

Subgroup analysis based on types of intervention revealed a significantly greater effect size for the concerted intervention (WMD −0.59) compared to the stand-alone apps intervention (WMD 0.34), but the 95% confidence interval for the effect size between the two groups overlapped.

Subgroup analysis based on intervention duration revealed a significant reduction in BMI for the 20□48 weeks intervention (WMD −0.57) and the 8□12 weeks intervention (WMD 0.33), and the former showed a clearly superior effect.

Meta-regression

We conducted meta-regressions for TPA, BMI, SB, and MVPA, focusing on statistically significant moderators identified in the subgroup analyses. The results of the meta-regression for TPA (*P*=0.026, 95% CI −1.127 to -0.082) and MVPA (*P*=0.045, 95% CI −2.052 to -0.033) revealed that intervention duration had a potential moderating effect on high heterogeneity, no statistical differences were found for other variables acting as moderators. In the case of BMI, meta-regression results indicated that age (*P*=0.04, 95% CI 0.041 to 1.473) and types of intervention (*P*=0.016, 95% CI −1.648 to -0.205) could be potential moderators for high heterogeneity, whereas other factors did not significantly contribute to explaining high heterogeneity.

Reporting Biases

Funnel plots were utilized to assess publication bias in the effects of mHealth app-based interventions on TPA, SB, BMI and MVPA in children and adolescents. The funnel plots exhibited mostly symmetrical patterns in the four studies (Multimedia Appendix 34 and 37). In addition, Egger's test was performed for TPA, SB, MVPA, and BMI, and the results suggested no significant publication bias (t=0.01, *P*=0.991; t=-0.1.35, *P*=0.0.202; t=1.22, *P*=0.245; t=-0.07, *P*=0.947) (Multimedia Appendix 38 and 41).

Discussion

Principal Findings

This study conducts a systematic review and meta-analysis to assess the effectiveness of mHealth app-based interventions in promoting PA and enhancing PF in children and adolescents. It also examines potential moderators that may influence the efficacy of these interventions. The findings of this study suggest that mHealth app-based interventions may yield positive effects on TPA, SB, BMI, agility, and muscle strength in children and adolescents. However, no significant effects were observed for MVPA, WC, CRF, muscular power and endurance, and flexibility. Age, theoretical paradigm, BCT clusters, types of intervention, types of apps, and intervention duration were identified as significant moderating factors associated with the increased effectiveness of mHealth app interventions on PA and PF, but the impact on effect size is not entirely consistent.

Overall Effect

PA Levels

The study findings indicated that mHealth app-based interventions increased TPA and reduced SB among children and adolescents but had no significant effect on MVPA. Our research findings represent a valuable expansion of recently published systematic reviews; however, they do not entirely align with the results of previous studies. A prior systematic review reported that mHealth-based interventions increased TPA levels and addressed physical inactivity in children and adolescents but did not lead to reduced SB and improved MVPA[12, 13]. The inconsistency in findings may be attributed to the co-intervention effect of technologies such as SMS, wearable devices, web-based interventions, and smartphone apps[13]. Among these, smartphone apps-based interventions might be the most effective strategy. The use of apps may contribute to increased SB time. Nevertheless, this study's results indicate that mHealth apps-based interventions can effectively reduce SB in children and adolescents. Distinguishing whether the effect is from stand-alone app interventions or other strategies within concerted interventions is challenging. Subgroup analyses in this study demonstrated the superiority of concerted interventions over stand-alone app interventions. In conclusion, mHealth apps-based interventions serve as a valuable adjunct in reducing SB in children and adolescents. Further concerted interventions, such as combining educational policies with mHealth apps intervention-ns, are recommended.

The effectiveness of mHealth app-based interventions was influenced by age and intervention format. Notably, these interventions were more effective in improving PA levels among adolescents than among children, and greater effects were observed when using mHealth apps than when using only SMS interventions[35, 50]. These findings support the conclusions of the present study, but some researchers hold differing views. Trost et al. [50] indicated that an 8 weeks intervention with Moovosity™ apps improved proficiency in fundamental movement skills (FMS) but did not increase PA levels. The phenomenon may be associated with the types of design and goal setting of the apps. The apps in the study were primarily used to increase the FMS of children, which may have resulted in the activity of FMS replacing the original PA. As a result, the TPA of children was unchanged. Another study identified that targeted app interventions would be effective in reducing SB in adolescents, which must be based on certain theoretical paradigms and BCT clusters[35]. Gamification-based app interventions are also more favorable for increasing TPA and reducing SB levels in children and adolescents and must be combined with the theoretical paradigm, intervention duration, and features of apps[54]. In conclusion, the reasons for inconsistent intervention results may be related to population characteristics, types of apps, theoretical paradigm, BCT clusters, and intervention duration. Moreover, further research is needed in the future.

PF

Another significant finding of the meta-analysis was that mHealth app-based interventions decreased BMI, improved muscle strength and agility among children and adolescents. However, no significant effects were observed for WC, CRF, muscular power and endurance, and flexibility. These findings are not entirely aligned with the results of previous studies. For example, a previous study reported an increase in PA levels among adolescents and significant reductions in sugary drink consumption and BMI following a 3-month intervention using Fitbit Flex apps[35]. Meanwhile, a different study indicated that an 18-month app intervention did not lead to significant reductions in BMI and WC, but it improved exercise capacity and reduced screen time[29]. Several potential factors may contribute to the inconsistent results. First, the choice of outcome measure could be a contributing factor. BMI and WC may indicate distinct aspects of obesity; while BMI primarily assesses body size and shape, WC is a measure of abdominal obesity, leading to a weak correlation between the two[55, 56]. Moreover, BMI tends to underestimate overweight prevalence when abdominal obesity is considered[56]. Hence, although mHealth app-based interventions show minor effects on BMI in children and adolescents, they might not induce significant changes in WC. Nonetheless, such interventions can still yield favorable outcomes. Another possible reason for the inconsistency in interventions could be related to the age of the population under study. Some studies have shown that mHealth app-based interventions are effective in reducing body weight and BMI in individuals above the age of 45, but they are less effective in children and adolescents[57]. Additionally, our meta-regression analysis revealed that age significantly influences the effectiveness of app-based interventions. This result could be attributed to the fact that children and adolescents are in a period of rapid growth and development, and the effects of the interventions may be masked by the significant changes in height and weight during this stage.

In terms of muscular strength, power and endurance, previous studies have shown that a 6-month intervention utilizing mHealth apps and trackers resulted in increased muscle strength among children and adolescents but did not have a significant effect on CRF[53]; Stasinak et al. discovered that a daily conversational agent intervention, utilizing a mobile app for adolescents with obesity, enhanced subjects' muscular fitness, with no discernible difference between the intervention and control groups[42]. Conversely, other studies have indicated that interventions utilizing AIMFIT apps can positively impact maximal oxygen uptake[20]; Mateo-Orcajada et al. found that a 10-week after-school intervention for adolescents utilizing mobile step-tracking applications significantly enhanced subjects' upper limb strength, hamstring and lower back flexibility, explosive power of the lower limbs, as well as abdominal muscular strength and endurance[47]. Various factors can influence the effectiveness of interventions, including subject characteristics, intervention dosage, engagement levels, and willingness to use apps. Some of the studies included in this work involved participants who were cancer patients[53], Children with overweight and Obesity[42], and this factor may have influenced the outcomes of the intervention. Furthermore, low user willingness to engage with apps may reduce PA engagement, which consequently impacts the effectiveness of the intervention. Finally, insufficient dosage of mHealth app-based interventions has been associated with a small effect size on TPA in children and adolescents and has shown no increase in MVPA levels. This insufficiency in dosage may explain the lack of intervention effects observed in children.

Moderating Variables on the Effects of mHealth App-Based Interventions for PA and PF

Age

The study results revealed that age moderates the effects of mHealth app interventions on TPA, MVPA, SB and BMI. Subgroup analysis indicated that mHealth app-based interventions significantly increased TPA, MVPA and reduced SB in children and adolescents aged 7～18 years; increased TPA and MVPA adolescents aged 7～18 years; only reduced SB for children aged 3～6 years. It is noteworthy that previous studies have indicated that mHealth app-based interventions did not effectively decrease SB in children and adolescents. This observation may stem from the fact that the use of apps may result in increased SB time, consequently reallocating the time resources of children and adolescents[12]. However, the findings of the present study do not support this conclusion. A separate study reported that the intervention using Fit

Survivor apps on SB in adolescents was ineffective, which is possibly due to the characteristics of the population; notably, the majority of participants in these studies had cancer, which may require a longer period of SB to observe significant changes[53]. The findings regarding BMI indicate that parent-focused mHealth app-based interventions have not been successful in reducing BMI among children and adolescents[29], somewhat not entirely consistent with the findings of this study. Our meta-regression analysis revealed that age significantly influences the effectiveness of app-based interventions.

This phenomenon may be closely associated with willingness of users and their behavioral intention to use apps. Individual differences, such as age and gender, play a crucial role in moderating willingness and intention of users. In general, behavioral habits and expected performance serve as predictors of willingness and intention of users[58], and age can increase the frequency of use by moderating behavioral habit and performance[59], which in turn have an influence on SB. In addition, most of the app intervention is parenting-focused intervention among preschoolers[60]. The successful implementation of interventions relies on parental involvement, thus parental attitudes significantly influence the participation of preschoolers aged 3～6 years, potentially impacting the efficacy of mHealth app interventions[13]. In the case of children and adolescents aged 7～18 years, increasing age correlates with improved expected performance[61]. In adolescents, this performance expectation is closely linked to user intention, bolstering their willingness to engage with apps. However, older adolescents, who prioritize academic achievement, may exhibit reduced effectiveness in app interventions[62]. In conclusion, the effects of mHealth app-based interventions may vary across different age groups. However, only four studies included subjects aged 3～6 years, potentially affecting the generalizability of the findings. Therefore, further validation through a larger number of high-quality studies is warranted to strengthen the conclusions.

Types of intervention

Concerning types of interventions, there is a lack of systematic reviews analyzing the impacts of stand-alone apps and/or concerted interventions on PA and PF, including their distinctions. Subgroup analysis revealed that concerted interventions significantly increased TPA and reduced SB and BMI in children and adolescents, whereas stand-alone app interventions had only a modest positive effect on TPA with a small effect size. The findings diverge somewhat from prior research. Some studies indicate that interventions employing COOL Passport apps or a combination of COOL Passport apps and game-based interactive platforms do not enhance PA in youth with congenital heart disease[40]. Conversely, other studies suggest that mobile applications can increase TPA while decreasing SB and BMI in youth[46, 47]. This phenomenon may be associated with behavior change interventions. Effective behavior change interventions can enhance health status and reduce healthcare spending, with theory-based interventions often yielding superior results[63]. Hence, interventions based on the high-scoring theoretical paradigm, or in combination with other specific high-scoring strategies, are more likely to yield positive outcomes[64]. In summary, interventions integrating apps with high-scoring strategies are probably more effective than stand-alone apps, although the optimal number and type of strategies remain undetermined.

Theoretical paradigm

Effective behavior change interventions can improve health status and reduce healthcare spending, and theory-based interventions generally yielded superior results[63]. Currently, mHealth app interventions employ multiple types of BCT that have been shown to be effective in influencing intervention outcomes[21]. Eight out of the 28 included studies did not employ theoretical frameworks in their mHealth app interventions[31, 36, 37, 45, 47, 49, 50, 52], while the remaining 20 studies were grounded in theoretical paradigms such as SCT, SDT, and SRT.

The most commonly utilized theoretical paradigms in the research are SCT and SDT, and interventions based on these frameworks have demonstrated positive effects on TPA, MVPA, and SB in children and adolescents. Subgroup analysis revealed that interventions based on SDT significantly increased TPA and MVPA in children and adolescents, while interventions based on SCT significantly reduced SB in this population. Previous studies have consistently shown that interventions based on SCT effectively improve PA among adolescents, which aligns with the findings of the present study[65]. SCT is commonly used to elucidate the mechanisms underlying the improvement in PA through behavior change interventions. SCT posits that PA is influenced by personal, social, and environmental factors. Personal factors, including self-efficacy, self-management, and expected performance, play a crucial role in enhancing PA and reducing SB. mHealth apps can effectively promote the increase in PA and the reduction in SB by modifying these factors[66].

SDT is frequently utilized to account for variations in individual behavior resulting from differences in intrinsic and extrinsic motivation. Intrinsic motivation, which is a crucial predictor of PA levels, is lacking in approximately 40% of Europeans; this situation leads to failure to meet the recommended PA levels[67]. In contrast to extrinsic motivation, intrinsic motivation drives the initiation and sustained engagement in individual behaviors. Thus, interventions grounded in SDT can effectively enhance leisure-time PA and PA in physical education classes and reduce SB among adolescents by fostering intrinsic motivation[68]. Furthermore, interventions utilizing mHealth apps based on the HBM and TPB may yield positive effects on increasing PA in children and adolescents. However, which theory yields optimal intervention effects requires further investigation. In conclusion, interventions based on SCT or SDT within mHealth apps may likely yield more effective results. However, due to the limited number of included studies, further validation through a larger volume of high-quality research is necessary to bolster these conclusions.

BCT clusters

BCT clusters represent specific implementation strategies in behavior change interventions. Previous studies have demonstrated that interventions incorporating a specific number of BCT clusters are more effective in promoting the PA of users. However, further investigation is needed to determine the optimal combination of the number and type of BCT clusters to achieve optimal intervention effects[69].

The BCT clusters that emerged frequently in this study were feedback and monitoring (n=22), goals and planning (n=19), shaping knowledge (n=12), and social support (n=11) et al. A previous study focusing on app interventions targeting PA and SB in adults also identified feedback and monitoring, as well as goals and planning, as the most commonly used BCT clusters[70]. Another study also highlighted the positive effects of mHealth app-based interventions on PA and SB, particularly when specific BCT clusters such as goals and planning, feedback and monitoring, and social support were implemented[16]. Consequently, specific BCT clusters, including goals and planning, feedback, and monitoring, play a crucial role in influencing the effectiveness of mHealth app-based interventions, ensuring increased TPA, decreased SB, and reduced BMI by enhancing the willingness and engagement of users[71].

Limited research exists on the impact of varying numbers of BCT clusters implemented on PA and PF in children and adolescents. In the current study, we discovered that mHealth app-based interventions incorporating 4 and 7□10 BCT clusters resulted in a significant reduction in SB among child adolescents, and the latter showed a greater effect size than the former. Conroy et al reported a mean of 4.2 for the use of BCT in app[72]. The number of studies included in the analysis varies, and the majority of studies used 4 BCT clusters, which is slightly lower than the number of BCT used in previous studies. This discrepancy may be attributed to the characteristics of the subjects[73]. Moreover, more BCT clusters in mHealth apps do not necessarily lead to better outcomes. Excessive use of BCT can decrease willingness of users and their frequency of app usage[74]. Thus, further research is needed to determine the optimal number of BCT clusters.

This phenomenon appears to be strongly associated with the willingness of users and their engagement in using apps. Feedback and monitoring, which involves design patterns enabling users to track their performance or status, play a crucial role in enhancing the trust, motivation, and engagement with the app of users. Consequently, this situation leads to the effective promotion of PA levels and reduction in BMI[75]. Similarly, goals and planning, which involve planned behaviors and the conversion of the intentions of users into actionable steps through self-regulation and self-efficacy, have been shown to improve PA and reduce BMI[76].

Types of apps and intervention duration

The available evidence suggests that commercial apps did not yield improvements in PA or reductions in SB among children and adolescents[20, 31-33, 35]. However, Jasmine et al. [77] found that integrating commercial apps with web-based social networking platforms was effective in improving PA. However, a certain usage frequency was needed, and a significant correlation between frequency of use and PA was observed. Our study discovered that research apps significantly reduced SB, while commercial apps increased TPA in children and adolescents, but the effect size is small. However, the effect size was small for commercial apps, which contrasts with our expectations. This discrepancy may be attributed to the design and characteristics of the apps. Commercial app developers often prioritize user interface simplification and the inclusion of complex features to enhance app engagement. However, they may overlook incorporating theoretical frameworks and BCT clusters that are closely associated with intervention effectiveness[78].

An intriguing finding emerged regarding the duration of the interventions. The 2～4 week and 8～12 week interventions significantly increased TPA, but the former demonstrated superior effectiveness to the latter; 8～12 week interventions significantly increased MVPA. Furthermore, the 20～48 week intervention significantly reduced SB and BMI in children and adolescents. This finding aligns with the results of previous studies that short-term mHealth app interventions effectively increased the PA of children, while longer interventions yielded diminished outcomes[40, 51]. The results of the present study support the notion that intervention effects are closely linked to the willingness of participants to engage. The reason is that shortly after engaging in an mHealth app-based intervention, children and adolescents will experience a sensitive attraction period[79]; prolonged interventions may lead to diminished interest and compliance, thereby weakening the impact. Another plausible explanation is that behavior change interventions rooted in theoretical frameworks yield better outcomes, but they require sufficient time for users to develop habitual behaviors conducive to lasting positive changes, and interventions targeting sedentary behavior (SB) and body mass index (BMI) take even longer. Additionally, our meta-regression analysis revealed that intervention duration significantly influences the effectiveness of app-based interventions.

Limitations

This study has several limitations. The search was restricted to English literature, which may introduce language bias and affect the reliability of the findings. Only a limited number of published studies were included, which potentially omit unpublished manuscripts and other sources (e.g., conference papers and dissertations) that could contribute to publication bias. The outcome measures used in this study had inconsistent units, and the interpretation of results using SMD as effect indicators requires caution. PF encompasses multiple dimensions, and different studies focus on various subdimensions.

Most studies encompassed multiple metrics, and some were not primarily designed to enhance PA and PF. These factors could have biased the results, potentially limiting the effect sizes and hindering a full reflection of the true effects in this study. Despite our extensive meta-regression and subgroup analyses, only age and intervention period demonstrated significant associations. Heterogeneity for some outcome metrics remained high, and the 95% CIs for the effect size overlapped between groups. Consequently, caution is advised when interpreting partial conclusions from subgroups. Our findings indicate heterogeneity in some studies, and the source of this heterogeneity remains unclear. The effectiveness of mHealth app-based interventions may vary among children and adolescents based on demographics (e.g., ethnic backgrounds, regions, genders, body mass index), economic levels, intervention models (parent-centered vs. child-centered), and the degree of app individualization. These factors could contribute to the observed heterogeneity. However, due to limitations stemming from the number and characteristics of included studies, these factors were not analyzed in this study. In conclusion, the findings of this systematic review and meta-analysis should be interpreted cautiously.

Conclusion

The findings from a systematic review and meta-analysis indicate that mHealth app-based interventions hold significant potential as a therapeutic strategy for increasing TPA levels, reducing BMI and SB, improving agility and muscle strength among children and adolescents. However, these interventions insignificantly affected MVPA, WC, CRF, muscular power and endurance, and flexibility, which are crucial for promoting PA and enhancing PF. Age, app types, types of intervention, theoretical paradigms, BCT clusters, and intervention duration emerged as important moderating variables that influence the effectiveness of mHealth app-based interventions. These moderating effects should be considered during the design, preparation, and promotion of interventions.

Considering the potential benefits of using mHealth apps, future research should explore the combination of different types and quantities of mHealth app-based interventions to determine the optimal approach for increasing PA levels and improving PF in children and adolescents. Furthermore, future studies could investigate the impact of additional influences on the intervention effectiveness of m-health APPs interventions, such as demographics characteristics, economic levels, intervention models et al.

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Authors' Contributions

J-WW designed the study protocol, drafted the report; Z-CZ, S-LZ, JF searched for literature, analyzed the data, and interpreted the results; YJ, Z-LG, W-DC contributed to the study protocol and reviewed the report; XL reviewed and revised the report.

Conflicts of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Abbreviations
PA: physical activity
PF: physical fitness
mHealth apps: mobile health apps
TPA: total PA
SMD: standardized mean difference
CI: confidence interval
WMD: weighted mean difference
BMI: body mass index
MVPA: moderate-to-vigorous PA
SCT: social cognitive theory
BCT: behavior change technique
SDT: self-determination theory
HBM: health belief model
TPB: theory of planned behavior
SCT: social cognitive theory
RCTs: randomized controlled trials
SB: sedentary behavior
CRF: cardiorespiratory fitness
TTM: Transtheoretical model
SRT: Self-regulation theory
SMS: Short Message Service

Supplementary Files

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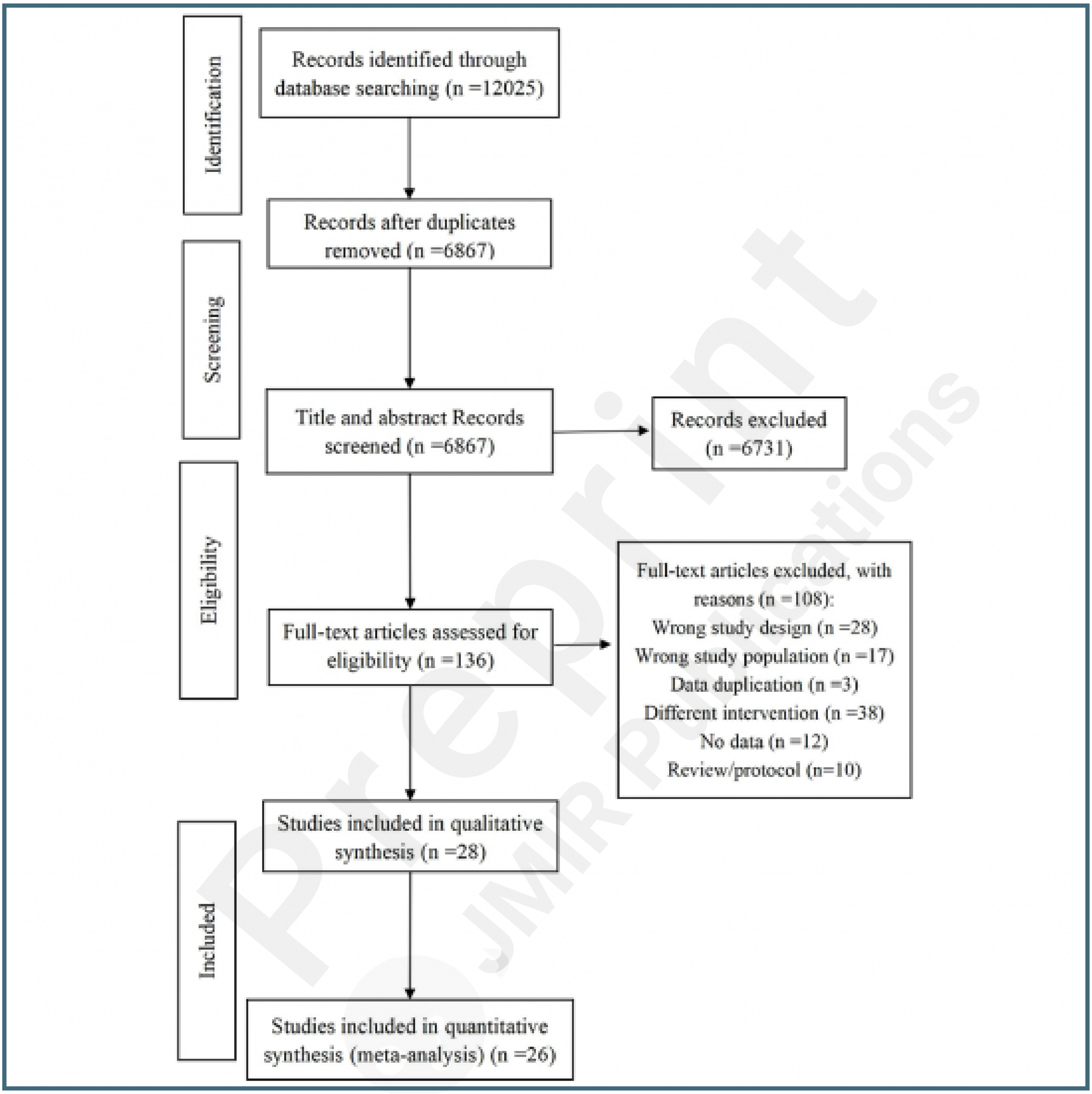
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Screening
Records after duplicates removed (n =6867)
Title and abstract Records screened (n =6867)
Records excluded (n =6731)
Eligibility
Full-text articles assessed for eligibility (n =136)
Full-text articles excluded, with reasons (n =108):
Wrong study design (n =28)
Wrong study population (n =17)
Data duplication (n =3)
Different intervention (n =38)
No data (n =12)
Review/protocol (n=10)
Included
Studies included in qualitative synthesis (n =28)
Studies included in quantitative synthesis (meta-analysis) (n =26)

Figures

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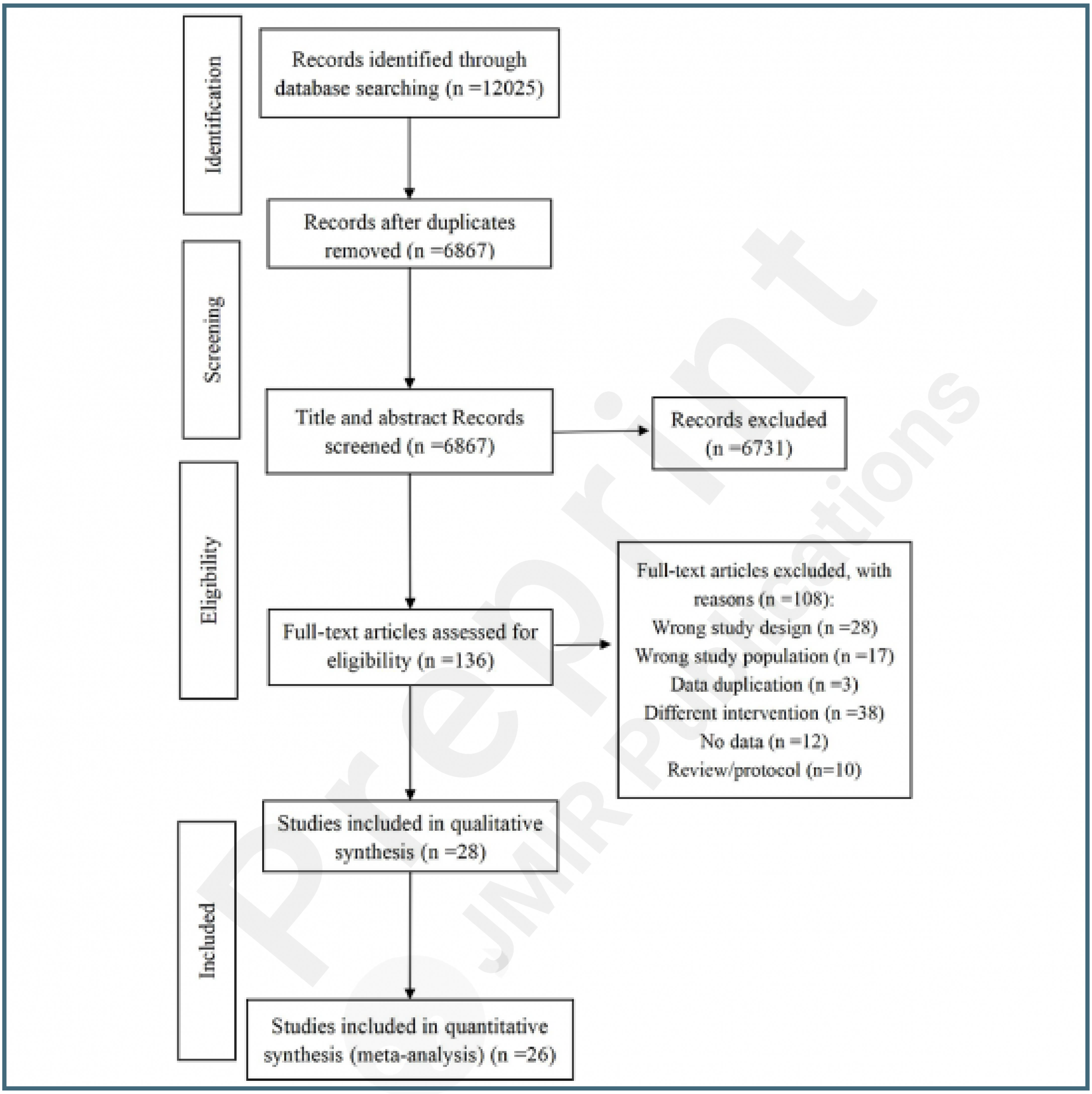
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A
Random sequence generation (selection bias)
Allocation concealment (selection bias)
Blinding of participants and personnel (performance bias)
Blinding of outcome assessment (detection bias)
Incomplete outcome data (attrition bias)
Selective reporting (reporting bias)
Other bias
0%
25%
50%
75%
100%
Low risk of bias
Unclear risk of bias
High risk of bias
B
Random sequence generation (selection bias)
Allocation concealment (selection bias)
Blinding of participants and personnel (performance bias)
Blinding of outcome assessment (detection bias)
Incomplete outcome data (attrition bias)
Selective reporting (reporting bias)
Other bias

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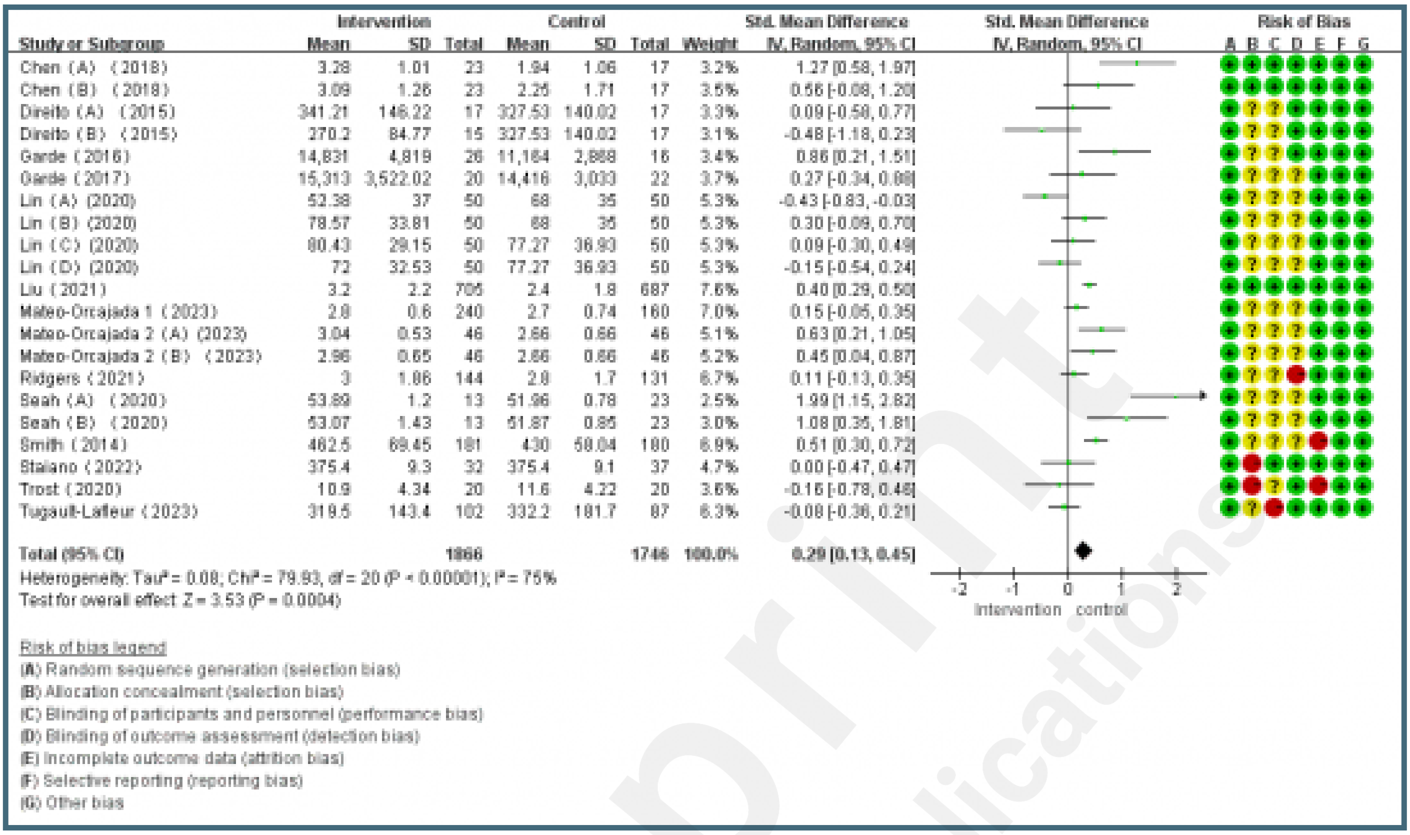

Study or Subgroup	Intervention Mean	Intervention SD	Intervention Total	Control Mean	Control SD	Control Total	Weight	Std. Mean Difference IV, Random, 95% CI
Chen (A) (2018)	3.28	1.01	23	1.94	1.06	17	3.2%	1.27 [0.58, 1.97]
Chen (B) (2018)	3.09	1.26	23	2.25	1.71	17	3.5%	0.56 [-0.08, 1.20]
Direito (A) (2015)	341.21	146.22	17	327.53	140.02	17	3.3%	0.09 [-0.58, 0.77]
Direito (B) (2015)	270.2	84.77	15	327.53	140.02	17	3.1%	-0.48 [-1.18, 0.23]
Garde (2016)	14,831	4,819	26	11,164	2,888	16	3.4%	0.86 [0.21, 1.51]
Garde (2017)	15,313	3,522.02	20	14,416	3,033	22	3.7%	0.27 [-0.34, 0.88]
Lin (A) (2020)	52.38	37	50	68	35	50	5.3%	-0.43 [-0.83, -0.03]
Lin (B) (2020)	78.57	33.81	50	68	35	50	5.3%	0.30 [-0.09, 0.70]
Lin (C) (2020)	80.43	29.15	50	77.27	36.93	50	5.3%	0.09 [-0.30, 0.49]
Lin (D) (2020)	72	32.53	50	77.27	36.93	50	5.3%	-0.15 [-0.54, 0.24]
Liu (2021)	3.2	2.2	706	2.4	1.8	687	7.6%	0.40 [0.29, 0.50]
Mateo-Orcajada 1 (2023)	2.8	0.6	240	2.7	0.74	160	7.0%	0.15 [-0.05, 0.35]
Mateo-Orcajada 2 (A) (2023)	3.04	0.53	46	2.66	0.66	46	5.1%	0.63 [0.21, 1.05]
Mateo-Orcajada 2 (B) (2023)	2.96	0.65	46	2.66	0.66	46	5.2%	0.45 [0.04, 0.87]
Ridgers (2021)	3	1.86	144	2.8	1.7	131	6.7%	0.11 [-0.13, 0.35]
Seah (A) (2020)	53.89	1.2	13	51.96	0.78	23	2.5%	1.99 [1.15, 2.82]
Seah (B) (2020)	53.07	1.43	13	51.87	0.85	23	3.0%	1.08 [0.35, 1.81]
Smith (2014)	462.5	69.45	181	430	58.04	180	6.9%	0.51 [0.30, 0.72]
Staiano (2022)	375.4	9.3	32	375.4	9.1	37	4.7%	0.00 [-0.47, 0.47]
Trost (2020)	10.9	4.34	20	11.6	4.22	20	3.6%	-0.16 [-0.78, 0.46]
Tugault-Lafleur (2023)	319.5	143.4	102	332.2	181.7	87	6.3%	-0.08 [-0.36, 0.21]
Total (95% CI)			**1866**			**1746**	**100.0%**	**0.29 [0.13, 0.45]**

Heterogeneity: $Tau^2 = 0.08$; $Chi^2 = 79.93$, $df = 20$ ($P < 0.00001$); $I^2 = 75\%$

Test for overall effect: $Z = 3.53$ ($P = 0.0004$)

Risk of bias legend
(A) Random sequence generation (selection bias)
(B) Allocation concealment (selection bias)
(C) Blinding of participants and personnel (performance bias)
(D) Blinding of outcome assessment (detection bias)
(E) Incomplete outcome data (attrition bias)
(F) Selective reporting (reporting bias)
(G) Other bias

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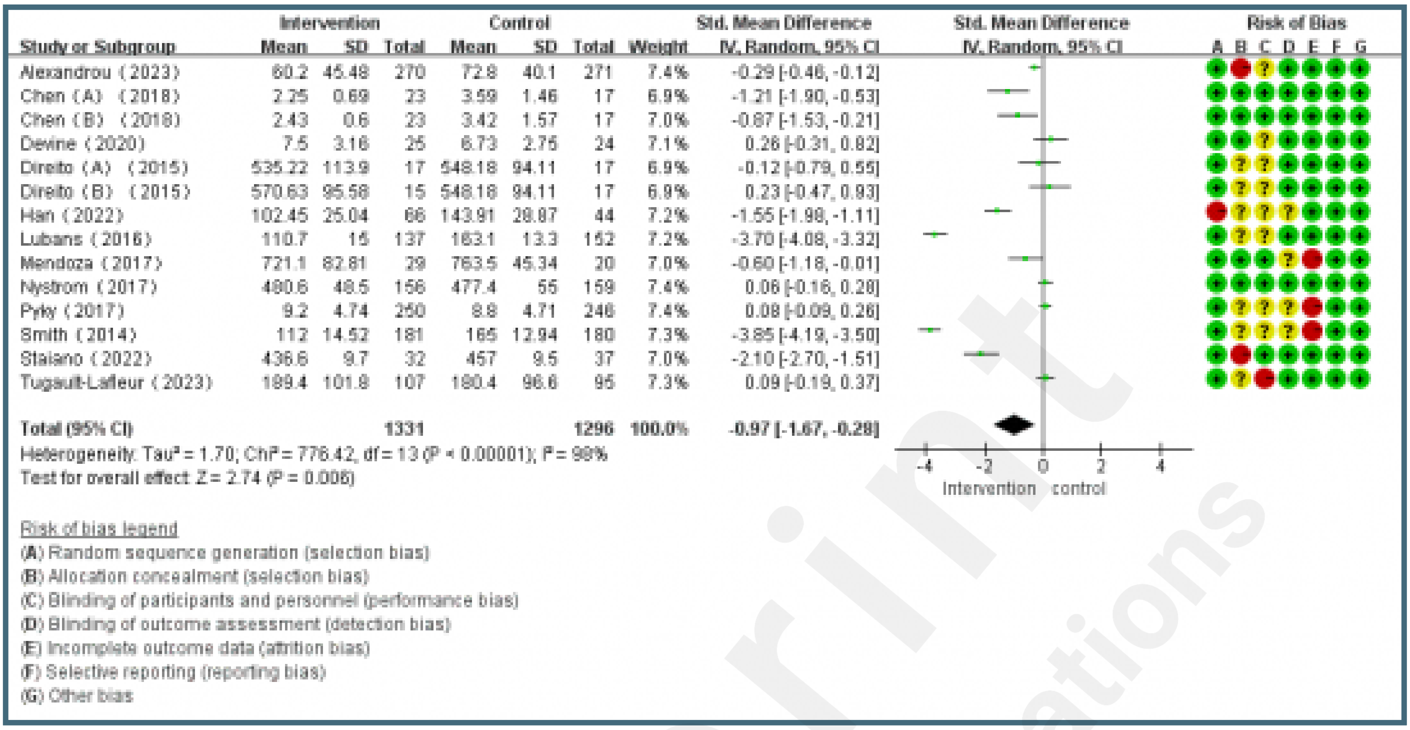
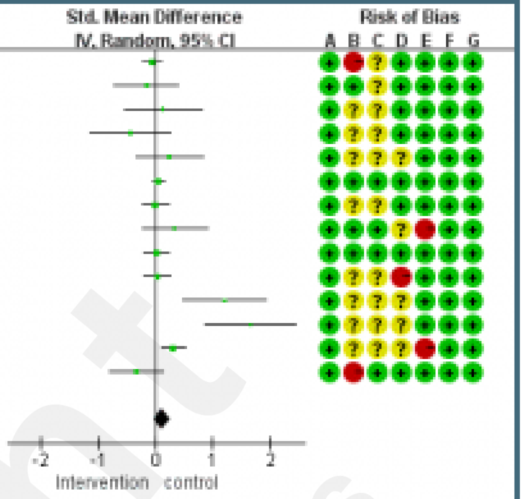

Intervention
Control
Std. Mean Difference
Std. Mean Difference
Risk of Bias
Study or Subgroup Mean SD Total Mean SD Total Weight IV, Random, 95% CI
IV, Random, 95% CI
A B C D E F G
Alexandrou (2023) 60.2 45.48 270 72.8 40.1 271 7.4% -0.29 [-0.46, -0.12]
Chen (A) (2018) 2.25 0.69 23 3.59 1.46 17 6.9% -1.21 [-1.90, -0.53]
Chen (B) (2018) 2.43 0.6 23 3.42 1.57 17 7.0% -0.87 [-1.53, -0.21]
Devine (2020) 7.5 3.16 25 6.73 2.75 24 7.1% 0.26 [-0.31, 0.82]
Direito (A) (2015) 535.22 113.9 17 548.18 94.11 17 6.9% -0.12 [-0.79, 0.55]
Direito (B) (2015) 570.63 95.58 15 548.18 94.11 17 6.9% 0.23 [-0.47, 0.93]
Han (2022) 102.45 25.04 66 143.91 28.87 44 7.2% -1.55 [-1.98, -1.11]
Lubans (2016) 110.7 15 137 163.1 13.3 152 7.2% -3.70 [-4.08, -3.32]
Mendoza (2017) 721.1 82.81 29 763.5 45.34 20 7.0% -0.60 [-1.18, -0.01]
Nystrom (2017) 480.6 48.5 156 477.4 55 159 7.4% 0.06 [-0.16, 0.28]
Pyky (2017) 9.2 4.74 250 8.8 4.71 246 7.4% 0.08 [-0.09, 0.26]
Smith (2014) 112 14.52 181 165 12.94 180 7.3% -3.85 [-4.19, -3.50]
Staiano (2022) 436.6 9.7 32 457 9.5 37 7.0% -2.10 [-2.70, -1.51]
Tugault-Lafleur (2023) 189.4 101.8 107 180.4 96.6 95 7.3% 0.09 [-0.19, 0.37]
Total (95% CI) 1331 1296 100.0% -0.97 [-1.67, -0.28]
Heterogeneity: Tau² = 1.70; Chi² = 776.42, df = 13 (P < 0.00001); I² = 98%
Test for overall effect: Z = 2.74 (P = 0.006)
-4 -2 0 2 4
Intervention control
Risk of bias legend
(A) Random sequence generation (selection bias)
(B) Allocation concealment (selection bias)
(C) Blinding of participants and personnel (performance bias)
(D) Blinding of outcome assessment (detection bias)
(E) Incomplete outcome data (attrition bias)
(F) Selective reporting (reporting bias)
(G) Other bias

Untitled.

	Intervention			Control				Std. Mean Difference
Study or Subgroup	Mean	SD	Total	Mean	SD	Total	Weight	IV, Random, 95% CI
Alexandrou (2023)	110.76	72.51	270	114.9	58.2	271	12.1%	-0.06 [-0.23, 0.11]
Devine (2020)	150.24	213.74	25	190.96	287.62	24	4.6%	-0.16 [-0.72, 0.40]
Direito (A) (2015)	33.04	20.61	17	30.54	17.99	17	3.5%	0.13 [-0.55, 0.80]
Direito (B) (2015)	23.34	14.04	15	30.54	17.99	17	3.3%	-0.43 [-1.13, 0.27]
Gaudet (2017)	45.6	29.06	23	39.9	12.66	23	4.4%	0.25 [-0.33, 0.83]
Liu (2021)	4	2.5	705	3.9	2.4	687	13.4%	0.04 [-0.06, 0.15]
Lubans (2016)	4.4	0.5	133	4.4	0.4	132	10.3%	0.00 [-0.24, 0.24]
Mendoza (2017)	46.4	25.67	29	38.6	18.54	20	4.5%	0.33 [-0.24, 0.91]
Nystrom (2017)	110.3	25.1	156	109.8	23.6	159	10.8%	0.02 [-0.20, 0.24]
Ridgers (2021)	37.3	27.44	144	36.6	19.3	131	10.4%	0.03 [-0.21, 0.27]
Seah (A) (2020)	1.51	0.36	13	1.06	0.37	23	3.1%	1.20 [0.46, 1.94]
Seah (B) (2020)	1.73	0.31	13	1.18	0.33	23	2.7%	1.66 [0.87, 2.46]
Smith (2014)	7.15	1.39	181	6.75	1.25	180	11.2%	0.30 [0.09, 0.51]
Staiano (2022)	94.1	4.2	32	95.5	4.1	37	5.7%	-0.33 [-0.81, 0.14]
Total (95% CI)			**1756**			**1744**	**100.0%**	**0.11 [-0.04, 0.25]**

Heterogeneity: $Tau^2 = 0.04$; $Chi^2 = 39.06$, df = 13 (P = 0.0002); $I^2 = 67\%$

Test for overall effect: Z = 1.46 (P = 0.14)



Risk of bias legend

(A) Random sequence generation (selection bias)

(B) Allocation concealment (selection bias)

(C) Blinding of participants and personnel (performance bias)

(D) Blinding of outcome assessment (detection bias)

(E) Incomplete outcome data (attrition bias)

(F) Selective reporting (reporting bias)

(G) Other bias

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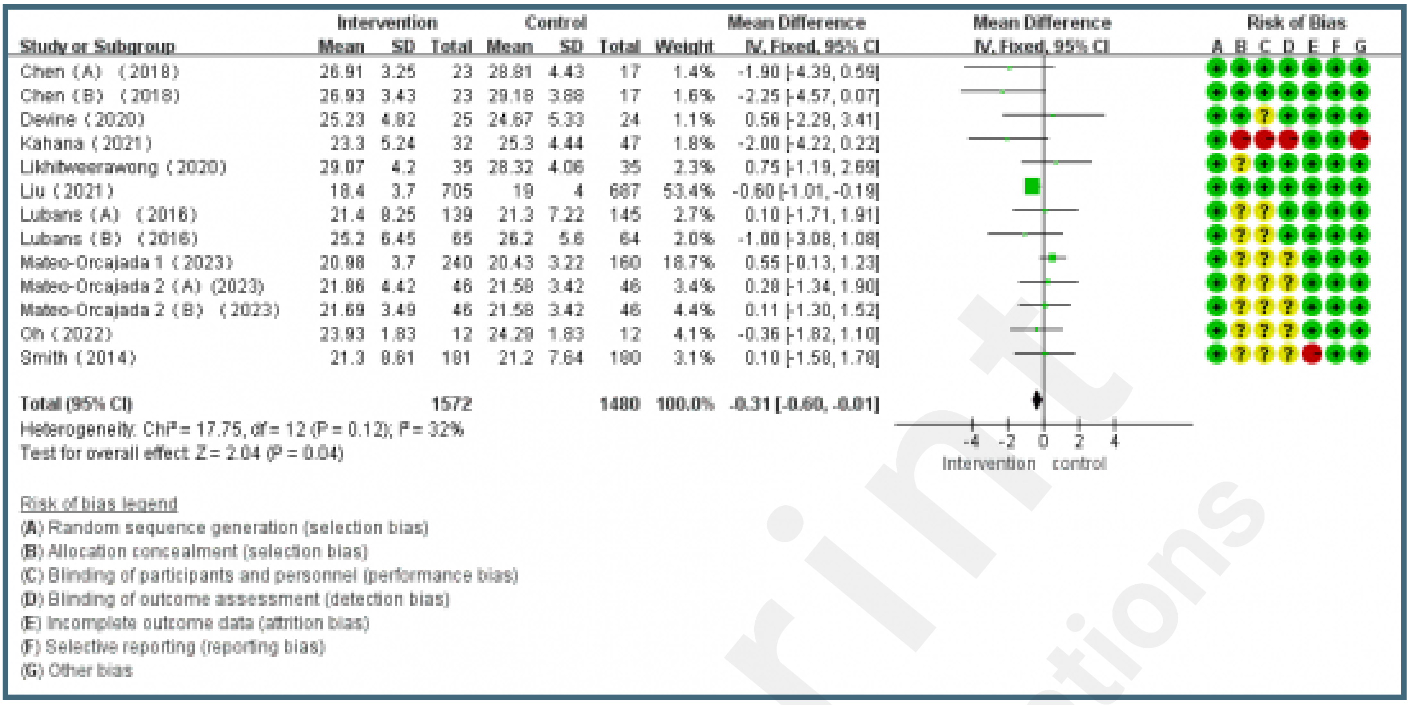

Study or Subgroup	Intervention Mean	Intervention SD	Intervention Total	Control Mean	Control SD	Control Total	Weight	Mean Difference IV, Fixed, 95% CI
Chen (A) (2018)	26.91	3.25	23	28.81	4.43	17	1.4%	-1.90 [-4.39, 0.59]
Chen (B) (2018)	26.93	3.43	23	29.18	3.88	17	1.6%	-2.25 [-4.57, 0.07]
Devine (2020)	25.23	4.82	25	24.67	5.33	24	1.1%	0.56 [-2.29, 3.41]
Kahana (2021)	23.3	5.24	32	25.3	4.44	47	1.8%	-2.00 [-4.22, 0.22]
Likhitweerawong (2020)	29.07	4.2	35	28.32	4.06	35	2.3%	0.75 [-1.19, 2.69]
Liu (2021)	18.4	3.7	705	19	4	687	53.4%	-0.60 [-1.01, -0.19]
Lubans (A) (2016)	21.4	8.25	139	21.3	7.22	145	2.7%	0.10 [-1.71, 1.91]
Lubans (B) (2016)	25.2	6.45	65	26.2	5.6	64	2.0%	-1.00 [-3.08, 1.08]
Mateo-Orcajada 1 (2023)	20.98	3.7	240	20.43	3.22	160	18.7%	0.55 [-0.13, 1.23]
Mateo-Orcajada 2 (A) (2023)	21.86	4.42	46	21.58	3.42	46	3.4%	0.28 [-1.34, 1.90]
Mateo-Orcajada 2 (B) (2023)	21.69	3.49	46	21.58	3.42	46	4.4%	0.11 [-1.30, 1.52]
Oh (2022)	23.93	1.83	12	24.29	1.83	12	4.1%	-0.36 [-1.82, 1.10]
Smith (2014)	21.3	8.61	181	21.2	7.64	180	3.1%	0.10 [-1.58, 1.78]
Total (95% CI)			**1572**			**1480**	**100.0%**	**-0.31 [-0.60, -0.01]**

Heterogeneity: $Chi^2 = 17.75$, df = 12 (P = 0.12); $I^2 = 32\%$
Test for overall effect: Z = 2.04 (P = 0.04)

Risk of bias legend
(A) Random sequence generation (selection bias)
(B) Allocation concealment (selection bias)
(C) Blinding of participants and personnel (performance bias)
(D) Blinding of outcome assessment (detection bias)
(E) Incomplete outcome data (attrition bias)
(F) Selective reporting (reporting bias)
(G) Other bias

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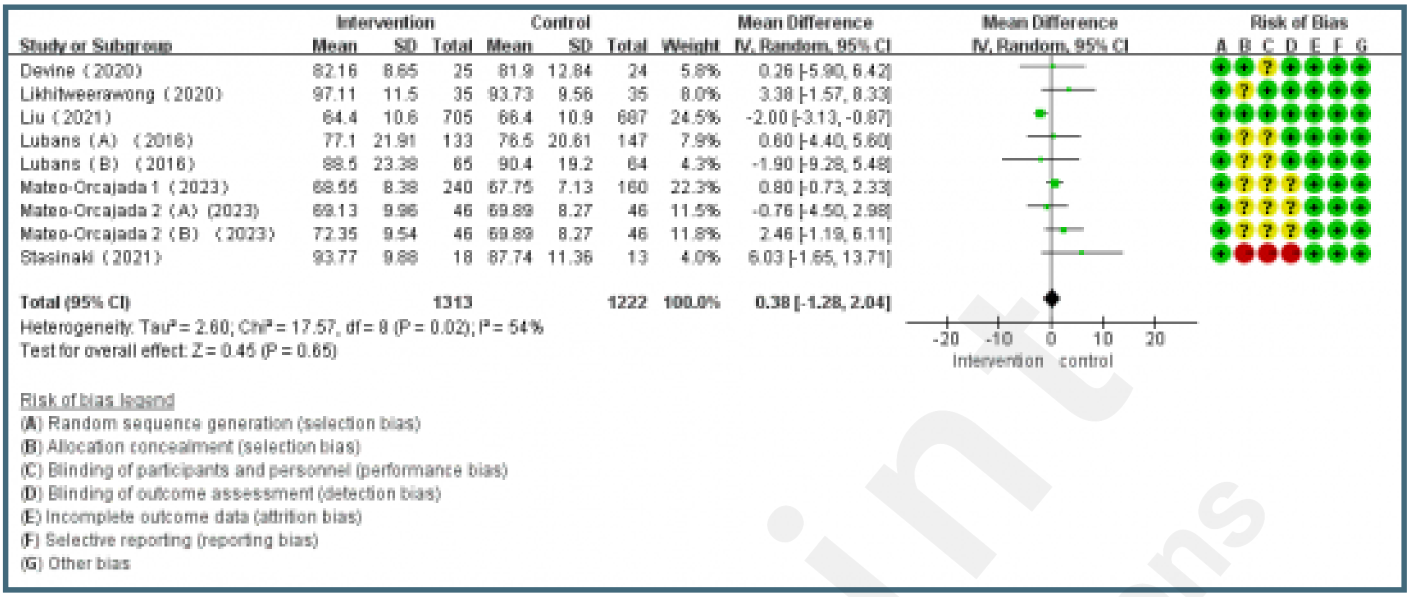
Intervention
Control
Mean Difference
Study or Subgroup
Mean
SD
Total
Mean
SD
Total
Weight
IV, Random, 95% CI
Devine（2020） 82.16 8.65 25 81.9 12.84 24 5.8% 0.26 [-5.90, 6.42]
Likhitweerawong（2020） 97.11 11.5 35 93.73 9.56 35 8.0% 3.38 [-1.57, 8.33]
Liu（2021） 64.4 10.6 705 66.4 10.9 687 24.5% -2.00 [-3.13, -0.87]
Lubans（A）（2016） 77.1 21.91 133 76.5 20.61 147 7.9% 0.60 [-4.40, 5.60]
Lubans（B）（2016） 88.5 23.38 65 90.4 19.2 64 4.3% -1.90 [-9.28, 5.48]
Mateo-Orcajada 1（2023） 68.55 8.38 240 67.75 7.13 160 22.3% 0.80 [-0.73, 2.33]
Mateo-Orcajada 2（A）(2023) 69.13 9.96 46 69.89 8.27 46 11.5% -0.76 [-4.50, 2.98]
Mateo-Orcajada 2（B）（2023） 72.35 9.54 46 69.89 8.27 46 11.8% 2.46 [-1.19, 6.11]
Stasinaki（2021） 93.77 9.88 18 87.74 11.36 13 4.0% 6.03 [-1.65, 13.71]
Total (95% CI) 1313 1222 100.0% 0.38 [-1.28, 2.04]
Heterogeneity: Tau² = 2.60; Chi² = 17.57, df = 8 (P = 0.02); I² = 54%
Test for overall effect: Z = 0.45 (P = 0.65)
Mean Difference
IV, Random, 95% CI
-20
-10
0
10
20
Intervention
control
Risk of Bias
A B C D E F G
Risk of bias legend
(A) Random sequence generation (selection bias)
(B) Allocation concealment (selection bias)
(C) Blinding of participants and personnel (performance bias)
(D) Blinding of outcome assessment (detection bias)
(E) Incomplete outcome data (attrition bias)
(F) Selective reporting (reporting bias)
(G) Other bias

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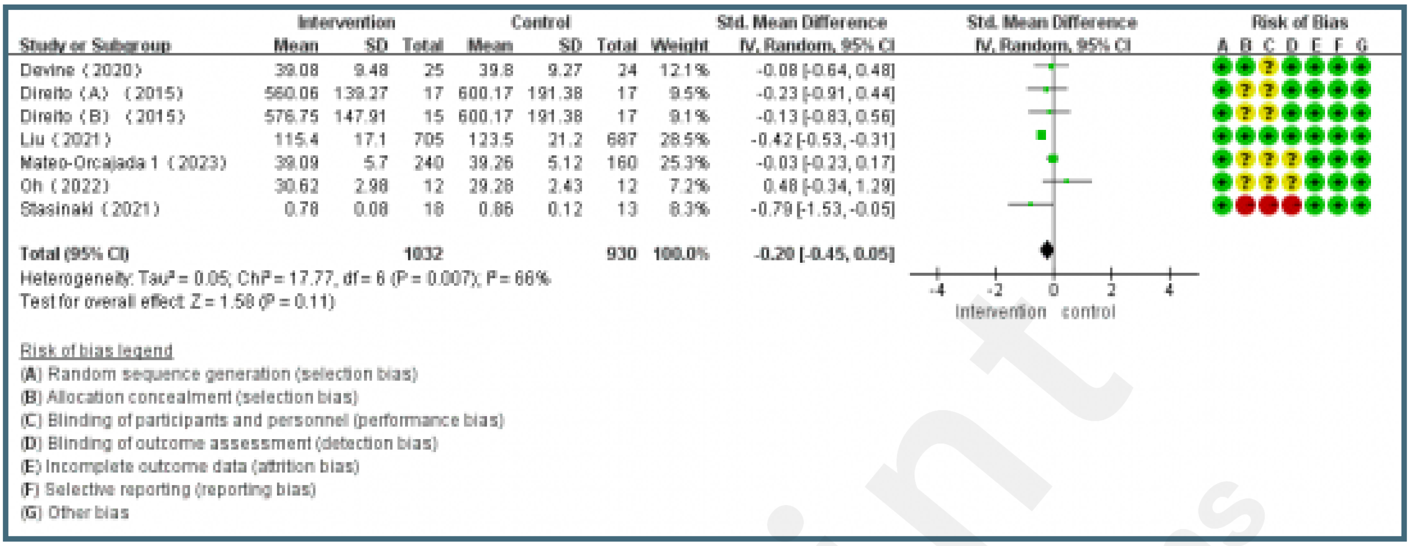

Study or Subgroup	Intervention Mean	Intervention SD	Intervention Total	Control Mean	Control SD	Control Total	Weight	Std. Mean Difference IV, Random, 95% CI
Devine（2020）	39.08	9.48	25	39.8	9.27	24	12.1%	-0.08 [-0.64, 0.48]
Direito（A）（2015）	560.06	139.27	17	600.17	191.38	17	9.5%	-0.23 [-0.91, 0.44]
Direito（B）（2015）	576.75	147.91	15	600.17	191.38	17	9.1%	-0.13 [-0.83, 0.56]
Liu（2021）	115.4	17.1	705	123.5	21.2	687	28.5%	-0.42 [-0.53, -0.31]
Mateo-Orcajada 1（2023）	39.09	5.7	240	39.26	5.12	160	25.3%	-0.03 [-0.23, 0.17]
Oh（2022）	30.62	2.98	12	29.28	2.43	12	7.2%	0.48 [-0.34, 1.29]
Stasinaki（2021）	0.78	0.08	18	0.86	0.12	13	8.3%	-0.79 [-1.53, -0.05]
Total (95% CI)			**1032**			**930**	**100.0%**	**-0.20 [-0.45, 0.05]**

Heterogeneity: $Tau^2 = 0.05$; $Chi^2 = 17.77$, $df = 6$ ($P = 0.007$); $I^2 = 66\%$

Test for overall effect: $Z = 1.58$ ($P = 0.11$)

Risk of bias legend

(A) Random sequence generation (selection bias)

(B) Allocation concealment (selection bias)

(C) Blinding of participants and personnel (performance bias)

(D) Blinding of outcome assessment (detection bias)

(E) Incomplete outcome data (attrition bias)

(F) Selective reporting (reporting bias)

(G) Other bias

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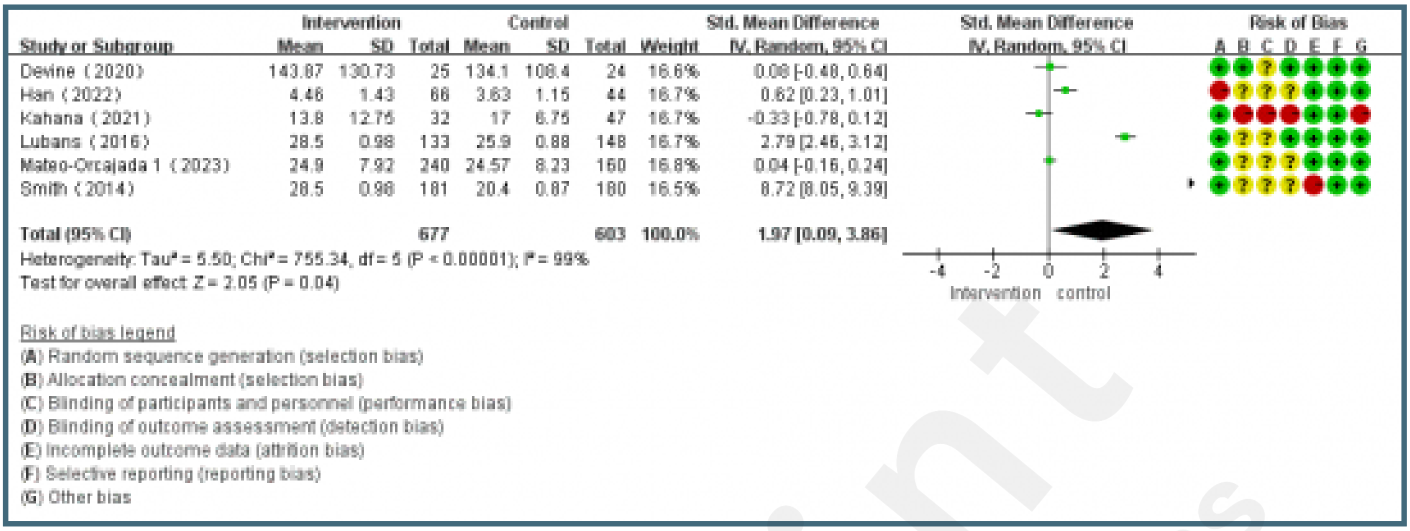
Intervention
Control
Std. Mean Difference
Study or Subgroup
Mean SD Total Mean SD Total Weight IV, Random, 95% CI
Devine (2020) 143.87 130.73 25 134.1 108.4 24 16.6% 0.08 [-0.48, 0.64]
Han (2022) 4.46 1.43 66 3.63 1.15 44 16.7% 0.62 [0.23, 1.01]
Kahana (2021) 13.8 12.75 32 17 6.75 47 16.7% -0.33 [-0.78, 0.12]
Lubans (2016) 28.5 0.98 133 25.9 0.88 148 16.7% 2.79 [2.46, 3.12]
Mateo-Orcajada 1 (2023) 24.9 7.92 240 24.57 8.23 160 16.8% 0.04 [-0.16, 0.24]
Smith (2014) 28.5 0.98 181 20.4 0.87 180 16.5% 8.72 [8.05, 9.39]
Total (95% CI) 677 603 100.0% 1.97 [0.09, 3.86]
Heterogeneity: Tau² = 5.50; Chi² = 755.34, df = 5 (P < 0.00001); I² = 99%
Test for overall effect: Z = 2.05 (P = 0.04)
Std. Mean Difference
IV, Random, 95% CI
-4
-2
0
2
4
Intervention
control
Risk of Bias
A B C D E F G
Risk of bias legend
(A) Random sequence generation (selection bias)
(B) Allocation concealment (selection bias)
(C) Blinding of participants and personnel (performance bias)
(D) Blinding of outcome assessment (detection bias)
(E) Incomplete outcome data (attrition bias)
(F) Selective reporting (reporting bias)
(G) Other bias

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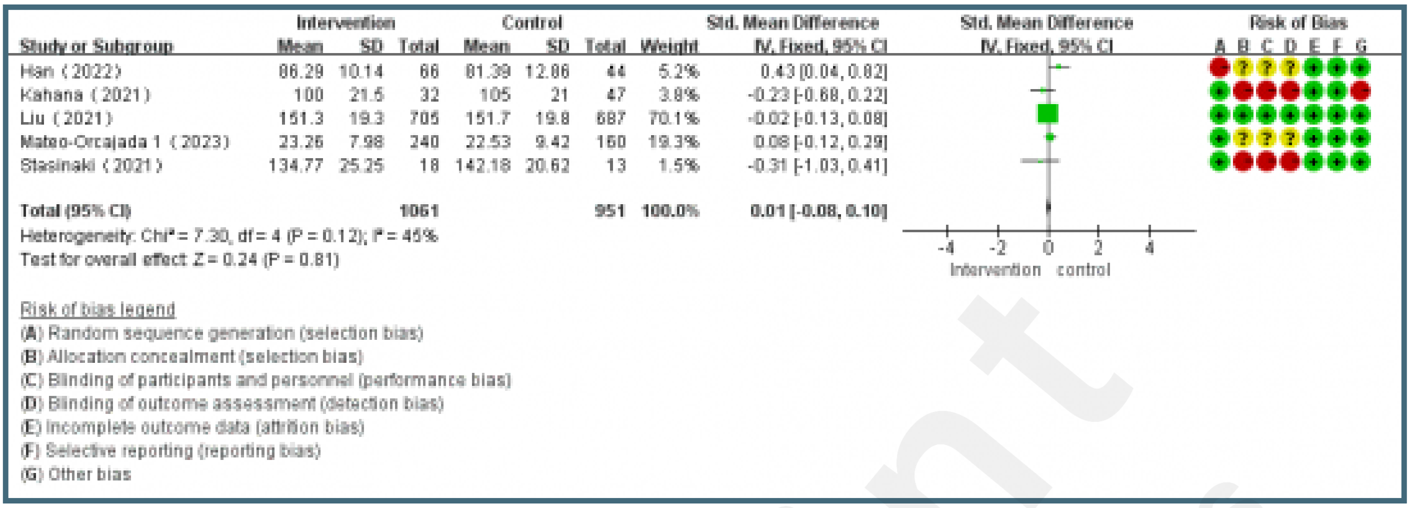
Intervention
Control
Std. Mean Difference
Std. Mean Difference
Risk of Bias
Study or Subgroup
Mean SD Total
Mean SD Total Weight
IV, Fixed, 95% CI
IV, Fixed, 95% CI
A B C D E F G
Han（2022） 86.29 10.14 66 81.39 12.86 44 5.2% 0.43 [0.04, 0.82]
Kahana（2021） 100 21.5 32 105 21 47 3.8% -0.23 [-0.68, 0.22]
Liu（2021） 151.3 19.3 705 151.7 19.8 687 70.1% -0.02 [-0.13, 0.08]
Mateo-Orcajada 1（2023） 23.26 7.98 240 22.53 9.42 160 19.3% 0.08 [-0.12, 0.29]
Stasinaki（2021） 134.77 25.25 18 142.18 20.62 13 1.5% -0.31 [-1.03, 0.41]
Total (95% CI) 1061 951 100.0% 0.01 [-0.08, 0.10]
Heterogeneity: Chi² = 7.30, df = 4 (P = 0.12); I² = 45%
Test for overall effect: Z = 0.24 (P = 0.81)
-4 -2 0 2 4
Intervention control
Risk of bias legend
(A) Random sequence generation (selection bias)
(B) Allocation concealment (selection bias)
(C) Blinding of participants and personnel (performance bias)
(D) Blinding of outcome assessment (detection bias)
(E) Incomplete outcome data (attrition bias)
(F) Selective reporting (reporting bias)
(G) Other bias

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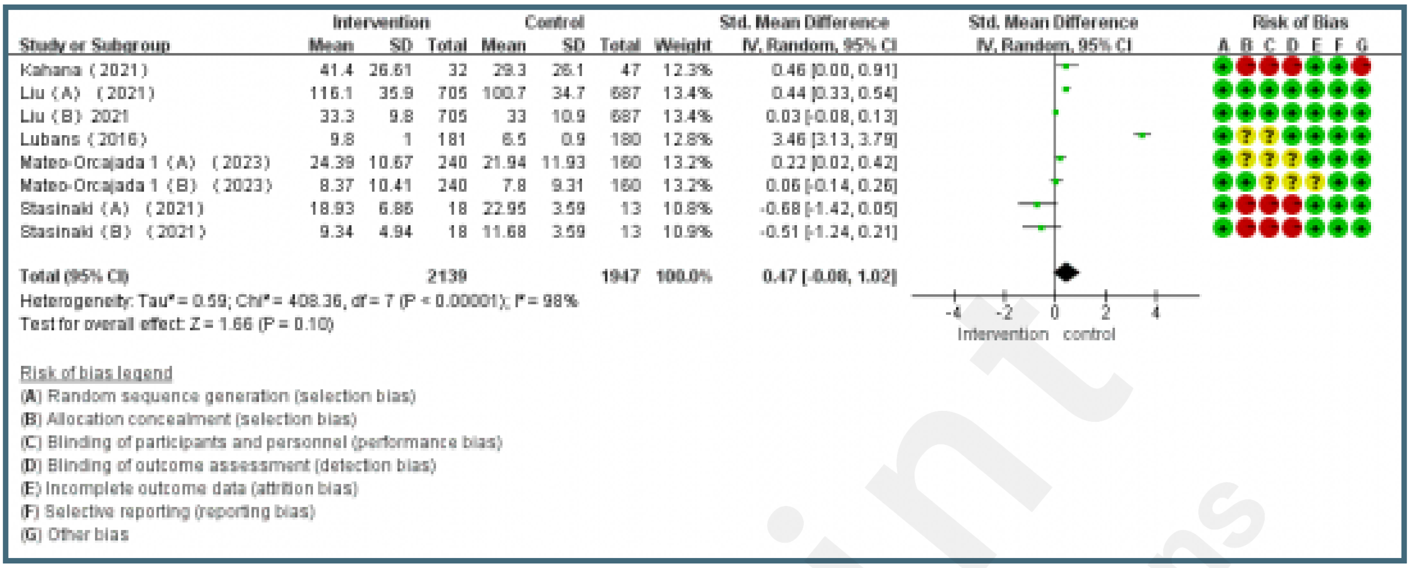

Study or Subgroup	Intervention Mean	Intervention SD	Intervention Total	Control Mean	Control SD	Control Total	Weight	Std. Mean Difference IV, Random, 95% CI
Kahana (2021)	41.4	26.61	32	29.3	26.1	47	12.3%	0.46 [0.00, 0.91]
Liu (A) (2021)	116.1	35.9	705	100.7	34.7	687	13.4%	0.44 [0.33, 0.54]
Liu (B) 2021	33.3	9.8	705	33	10.9	687	13.4%	0.03 [-0.08, 0.13]
Lubans (2016)	9.8	1	181	6.5	0.9	180	12.8%	3.46 [3.13, 3.79]
Mateo-Orcajada 1 (A) (2023)	24.39	10.67	240	21.94	11.93	160	13.2%	0.22 [0.02, 0.42]
Mateo-Orcajada 1 (B) (2023)	8.37	10.41	240	7.8	9.31	160	13.2%	0.06 [-0.14, 0.26]
Stasinaki (A) (2021)	18.93	6.86	18	22.95	3.59	13	10.8%	-0.68 [-1.42, 0.05]
Stasinaki (B) (2021)	9.34	4.94	18	11.68	3.59	13	10.9%	-0.51 [-1.24, 0.21]
Total (95% CI)			**2139**			**1947**	**100.0%**	**0.47 [-0.08, 1.02]**

Heterogeneity: $Tau^2 = 0.59$; $Chi^2 = 408.36$, df = 7 (P < 0.00001); $I^2 = 98\%$

Test for overall effect: Z = 1.66 (P = 0.10)

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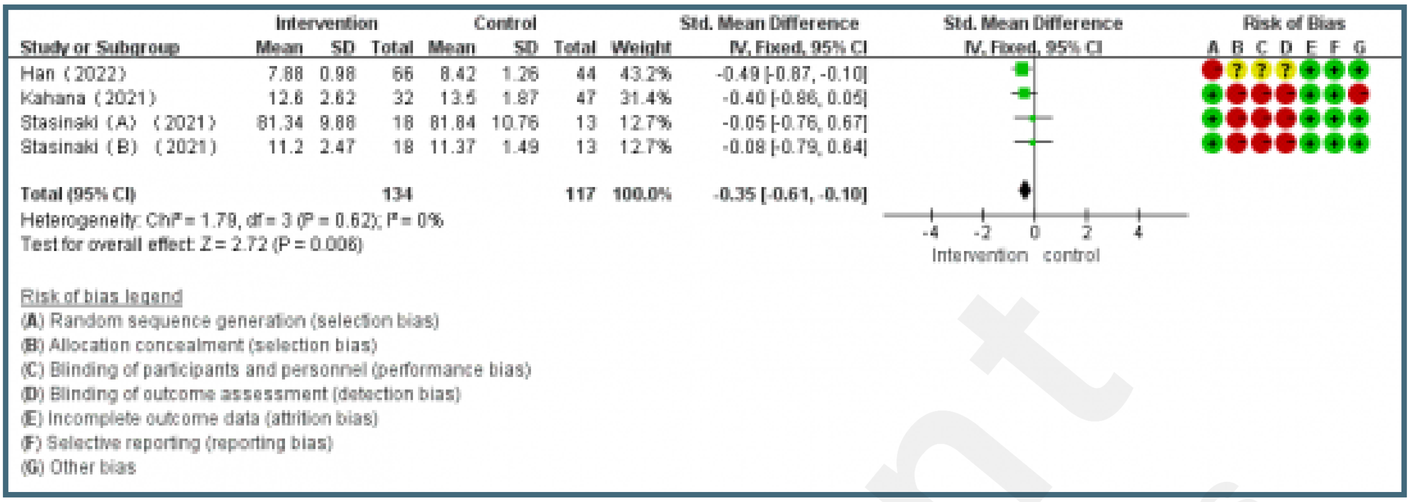
Intervention
Control
Std. Mean Difference
Std. Mean Difference
Risk of Bias
Study or Subgroup
Mean SD Total Mean SD Total Weight
IV, Fixed, 95% CI
IV, Fixed, 95% CI
A B C D E F G
Han（2022） 7.88 0.98 66 8.42 1.26 44 43.2% -0.49 [-0.87, -0.10]
Kahana（2021） 12.6 2.62 32 13.5 1.87 47 31.4% -0.40 [-0.86, 0.05]
Stasinaki（A）（2021） 81.34 9.88 18 81.84 10.76 13 12.7% -0.05 [-0.76, 0.67]
Stasinaki（B）（2021） 11.2 2.47 18 11.37 1.49 13 12.7% -0.08 [-0.79, 0.64]
Total (95% CI) 134 117 100.0% -0.35 [-0.61, -0.10]
Heterogeneity: Chi² = 1.79, df = 3 (P = 0.62); I² = 0%
Test for overall effect: Z = 2.72 (P = 0.006)
-4 -2 0 2 4
Intervention control
Risk of bias legend
(A) Random sequence generation (selection bias)
(B) Allocation concealment (selection bias)
(C) Blinding of participants and personnel (performance bias)
(D) Blinding of outcome assessment (detection bias)
(E) Incomplete outcome data (attrition bias)
(F) Selective reporting (reporting bias)
(G) Other bias

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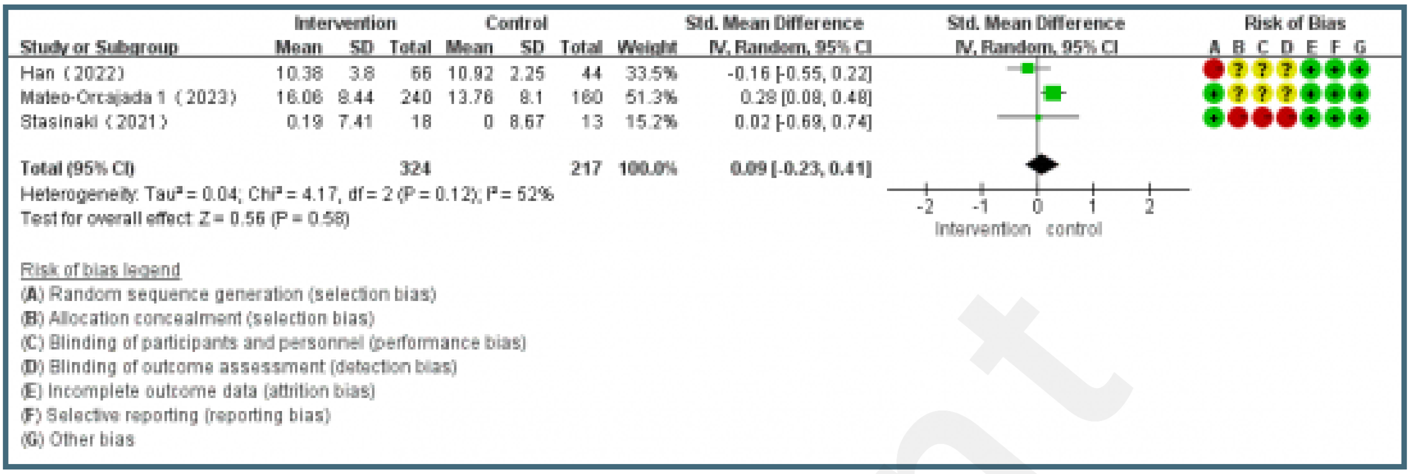
Intervention
Control
Std. Mean Difference
Std. Mean Difference
Risk of Bias
Study or Subgroup Mean SD Total Mean SD Total Weight IV, Random, 95% CI IV, Random, 95% CI A B C D E F G
Han (2022) 10.38 3.8 66 10.92 2.25 44 33.5% -0.16 [-0.55, 0.22]
Mateo-Orcajada 1 (2023) 16.06 8.44 240 13.76 8.1 160 51.3% 0.28 [0.08, 0.48]
Stasinaki (2021) 0.19 7.41 18 0 8.67 13 15.2% 0.02 [-0.69, 0.74]
Total (95% CI) 324 217 100.0% 0.09 [-0.23, 0.41]
Heterogeneity: Tau² = 0.04; Chi² = 4.17, df = 2 (P = 0.12); I² = 52%
Test for overall effect: Z = 0.56 (P = 0.58)
-2 -1 0 1 2
Intervention control
Risk of bias legend
(A) Random sequence generation (selection bias)
(B) Allocation concealment (selection bias)
(C) Blinding of participants and personnel (performance bias)
(D) Blinding of outcome assessment (detection bias)
(E) Incomplete outcome data (attrition bias)
(F) Selective reporting (reporting bias)
(G) Other bias

Multimedia Appendixes

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