Is the uptake, engagement, and effectiveness of exclusively mobile interventions for the promotion of weight-related behaviors equal for all? A systematic review

Szinay, D.; Forbes, C.C.; Busse, H.; DeSmet, A.; Smit, E.S.; König, L.M.

DOI
10.1111/obr.13542

Publication date
2023

Document Version
Final published version

Published in
Obesity Reviews

Received: 15 June 2022 | Revised: 28 September 2022 | Accepted: 6 December 2022

DOI: 10.1111/obr.13542

OBESITY Reviews WILEY

REVIEW

Public Health / Intervention

Is the uptake, engagement, and effectiveness of exclusively mobile interventions for the promotion of weight-related behaviors equal for all? A systematic review

Dorothy Szinay[1,2] | Cynthia C. Forbes[3] | Heide Busse[4,5] | Ann DeSmet[6,7] | Eline S. Smit[8] | Laura M. König[9,10]

[1]Behaviour and Implementation Science, School of Health Sciences, University of East Anglia, Norwich, UK

[2]Department of Behaviour Science and Health, University College London, London, UK

[3]Wolfson Palliative Care Research Centre, Hull York Medical School, University of Hull, Hull, UK

[4]Leibniz Institute of Prevention Research and Epidemiology - BIPS, Bremen, Germany

[5]Leibniz ScienceCampus Digital Public Health Bremen, Bremen, Germany

[6]Faculty of Psychology and Educational Sciences, Université Libre de Bruxelles, Brussels, Belgium

[7]Department of Communication Studies, University of Antwerp, Antwerp, Belgium

[8]Amsterdam School of Communication Research/ASCoR, Department of Communication Science, University of Amsterdam, Amsterdam, The Netherlands

[9]Faculty of Life Sciences, University of Bayreuth, Bayreuth, Germany

[10]Behavioural Science Group, Cambridge Institute of Public Health, University of Cambridge School of Clinical Medicine, Cambridge, UK

Correspondence
Laura M. König, University of Bayreuth, Campus Kulmbach, Faculty of Life Sciences: Food, Nutrition and Health, Fritz-Hornschuch-Straße 13, 93526 Kulmbach, Germany.
Email: laura.koenig@uni-bayreuth.de

Funding information
LK was supported by a research fellowship from the German Research Foundation (grant no. KO 6018/1-1). ES received funding from the Innovational Research Incentives Scheme Veni from NWO-MaGW (Netherlands Organization for Scientific Research - Division for the Social Sciences; project number 451-15-028). CF is funded by a Career Development Research Fellowship from Yorkshire Cancer Research (HEND405CF). Covidence license funded by Hull York Medical School INSPIRE program.

Summary

Mobile health interventions are promising behavior change tools. However, there is a concern that they may benefit some populations less than others and thus widen inequalities in health. This systematic review investigated differences in uptake of, engagement with, and effectiveness of mobile interventions for weight-related behaviors (i.e., diet, physical activity, and sedentary behavior) based on a range of inequality indicators including age, gender, race/ethnicity, and socioeconomic status. The protocol was registered on PROSPERO (CRD42020192473). Six databases (CINAHL, EMBASE, ProQuest, PsycINFO, Pubmed, and Web of Science) were searched from inception to July 2021. Publications were eligible for inclusion if they reported the results of an exclusively mobile intervention and examined outcomes by at least one inequality indicator. Sixteen publications reporting on 13 studies were included with most reporting on multiple behaviors and inequality indicators. Uptake was investigated in one study with no differences reported by the inequality indicators studied. Studies investigating engagement ($n = 7$) reported differences by age ($n = 1$), gender ($n = 3$), ethnicity ($n = 2$), and education ($n = 2$), while those investigating effectiveness ($n = 9$) reported differences by age ($n = 3$), gender ($n = 5$),

Abbreviations: EPHPP, Effective Public Healthcare Panacea Project; PDA, personal digital assistant; PRISMA, Preferred Reporting Items of Systematic Reviews and Meta-analysis; SD, standard deviation.

education ($n = 2$), occupation ($n = 1$), and geographical location ($n = 1$). Given the limited number of studies and their inconsistent findings, evidence of the presence of a digital divide in mobile interventions targeting weight-related behaviors is inconclusive. Therefore, we recommend that inequality indicators are specifically addressed, analyzed, and reported when evaluating mobile interventions.

KEYWORDS
body weight, health promotion, mHealth, social inequality

1 | INTRODUCTION

Mobile health (mHealth) interventions are interventions that use mobile, often Internet-supported, tools such as smartphone applications, tablets, wearables (e.g., smart watches and pedometers), and personal digital assistants (PDAs) to promote health, illness self-management, or remotely support treatment. As Internet use and smartphone ownership are common, mHealth interventions may reach a large number of people[1] and, in doing so, may increase access to health care.[2] They are available to the user at any time and in any place, enable the user to self-monitor and self-manage health, and consequently have the technical affordances to empower users in taking ownership of their health.[3] As such, mHealth interventions carry the added potential of a higher retention rate at population scale compared to non-mHealth interventions.[1,2,4] The commonly used techniques of self-monitoring and feedback in mHealth tools have shown high levels of user satisfaction,[5,6] long-term engagement with the tool,[7] and high levels of self-efficacy in changing health behavior.[8] The World Health Organization has consequently proposed that such innovative digital technologies present a potential to improve health care coverage, health risk protection, and enhance health and well-being for all.[9] Indeed, mHealth interventions are becoming increasingly popular in healthcare. For instance, in 2019, Germany introduced its Digital Healthcare Act. Among others, this policy allows physicians to prescribe digital health applications, which are usually delivered exclusively mobile, to allow for monitoring and provision of care without contact to service providers.[10]

To date, mHealth interventions have been applied to a wide range of health domains such as HIV prevention, smoking cessation, diabetes self-management, and depression self-management.[11–14] Furthermore, a large number of mHealth interventions have been studied in relation to weight-related behaviors, such as sufficient physical activity, low levels of sedentary behavior and a healthy diet.[15,16] These behaviors are important determinants of lower morbidity and mortality[17–19] and contribute to both optimal physical and mental health.[20,21]

For an intervention to have impact on population health, it should reach the target group, the users should show sufficient objective (e.g., uptake and continued usage) and subjective engagement (e.g., enjoyment and perceived usefulness) with the tool, and it must be effective.[22] mHealth interventions were found to be as effective as face-to-face interventions in increasing physical activity[23,24] and reducing sedentary behavior.[25] Yet, other aspects needed to achieve long-term health behavior change, such as uptake, followed by engagement, are reported less often in studies on mHealth interventions for physical activity[26] and other weight-related behaviors. Whereas uptake is reported by the majority of studies, the information usually relates to sample size, and not to the representativeness of the sample, that is, the number of people who accepted the invitation to take part compared to all contacted persons.[27]

Despite the potential of digital technologies, questions remain about the actual public health impact of mHealth interventions in their ability to reduce health inequalities.[28] Certain groups of the population are known to have a lower adoption of health behaviors and to experience lower access to health care and/or higher morbidity, including people from ethnic minorities,[29] from economically disadvantaged backgrounds,[29] from sexual minorities,[30] people with lower health literacy levels,[31] with a lower educational status,[32] or women in certain patriarchy cultures.[33] Moreover, these groups of the population may also experience more barriers to using mobile health apps. As technology literacy is related to age, digital experience, overall health literacy, education, cultural background,[34] and urban or rural residency,[4] people might differ in their ability to engage with mHealth interventions as a result of these demographic and personal characteristics. It has thus been proposed that mHealth interventions may actually widen health inequalities.[35,36] This is also commonly referred to as the "digital health divide."[36]

Inequalities may arise during different stages of an intervention and may relate to access, uptake, objective and subjective engagement, different types of usage, and efficacy.[4] Several studies support the existence of a digital health divide. A rapid evidence synthesis, including seven reviews and eight individual studies, found that the uptake of digital health interventions in primary care is low and that those who use such tools are more often female, younger, more educated and have a higher income.[37,38] A secondary data analysis of a large study showed that younger individuals, with higher income were more likely to have health apps installed, while those of Hispanic ethnicity background and who are less educated were less likely.[39] Similarly, racial and ethnic minorities are less likely to enroll in clinical trials of digital interventions.[40] A narrative review found that there is lack of diversity in studies in dietary self-monitoring health apps, with study participants being predominantly white and female.[41] In support of this, a review of 83 studies on mHealth interventions found that the diversity of low socioeconomic position and ethnic minorities were not reflected in the included studies, neglecting factors that may widen a digital divide.[42] This idea finds support in the findings from a recent meta-analysis that showed that digital interventions are not effective in changing physical activity in low socioeconomic position populations.[43] There is also a lack of research and evidence on the effect of mHealth interventions in rural populations.[38]

To the best of our knowledge, no systematic review has investigated the digital health divide as related to the uptake, engagement, and effectiveness of exclusively mobile interventions for weight-related behaviors. Mobile interventions are especially promising in increasing access to health care for all, as they may solve the structural barriers to access to care.[44] Though many behaviors have shown to impact body weight, we decided to focus on physical activity, diet, and sedentary behavior for this review, as these are commonly targeted in interventions for managing body weight in studies using mobile interventions[15,45]; and body weight has been repeatedly found to be an important predictor of morbidities and premature mortality.[46] We defined "uptake" as the act of downloading and installing a mobile intervention device[47]; in the context of this review, this also included the act of receiving or buying a mobile intervention. As a lot of terms are used interchangeably in relation to "engagement," and as measures of engagement focused predominantly on certain metrics, a more comprehensive approach to measure in-app engagement is suggested.[48] We defined "engagement" as "(1) the extent (e.g., amount, frequency, duration, and depth) of usage and (2) a subjective experience characterized by attention, interest and affect."[49] Finally, "effectiveness" refers to the extent to which an intervention leads to a desired outcome in the real world compared to a comparison condition (e.g., comparing pre-and post-intervention scores within subjects and comparison with a group receiving no intervention or usual care).[50]

Therefore, this review aimed to address the following research questions: Does the (1) uptake, (2) engagement, and (3) effectiveness of mobile interventions for diet, physical activity, or sedentary behavior differ depending on inequality indicators, that is, users' socioeconomic position, age, gender, level of education, health and digital literacy, sexual orientation, health services accessibility, or geographical location?

2 | METHODS

This review followed the Preferred Reporting Items of Systematic Reviews and Meta-analysis (PRISMA) guidelines.[51] The completed PRISMA checklist can be found in Supporting Information S1. The study protocol was registered on the International Prospective Register of Systematic Reviews (PROSPERO: CRD42020192473). Raw extracted data can be downloaded from the project's Open Science Framework page (https://osf.io/kdmz8/).

2.1 | Eligible studies

We included studies conducted among adults aged 18 and over, with no apparent pre-existing medical condition, where the intervention was delivered exclusively in a mobile format (e.g., using a smartphone, PDA, or wearable, without any intervention components being delivered face-to-face or using other digital tools such as computers or websites) and targeted at least one weight-related behavior, that is, diet, physical activity and sedentary behavior, and/or weight loss resulting from changing these behaviors. Studies that additionally contained coaching calls or social media as an optional intervention component that was also delivered fully mobile (i.e., not via access to a computer) were also considered. Studies were eligible if the results reported data on at least one of the following inequality indicators: age, gender, socioeconomic position (including occupation, from unskilled to skilled labor or profession; income; employment, considering employed versus unemployed individuals), level of education, health service accessibility, geographical indicators, sexual orientation, health, or digital literacy. Studies where the primary or secondary outcomes were the uptake of or the engagement with, or the effectiveness of the interventions, were included. Any real-life test of the intervention was included, and no control group was required for the interventions; therefore, single-group designs with pre-post-tests were also considered.

Studies focusing exclusively on a clinical population, that is, a population with a medical condition other than overweight or obesity (e.g., diabetes), were excluded. Yet, interventions that focused on a health risk factor (e.g., overweight) were included. Studies examining infants, children, or adolescents, or where the intervention was part of the treatment of a pre-existing condition, were excluded. Interventions that solely focused on text messaging were excluded since they could also be delivered on mobile phones, which provide fewer opportunities for tailoring and personalization, which is typically seen as an advantage of smartphone-based interventions.[5] Phoning or using video calling were excluded since they can also be delivered without using a smartphone (i.e., landline phones or a computer) and require in-person contact (in comparison to purely digital interventions that can be delivered in a purely automated form without immediate response from a person). Finally, interventions that used a combination with other elements such as information material, a website, or a face-to-face element were excluded. Finally, systematic reviews and meta-analyses were also excluded.

2.2 | Search strategies

2.2.1 | Electronic search

The electronic search was conducted by CF in consultation with an Information Specialist from the University of Hull in the following databases: PsycINFO (Ovid), MEDLINE (Ovid), EMBASE (Ovid), CINAHL (EBSCO), Web of Science Core Collection, and ProQuest

Dissertations and Theses (for the full MEDLINE search strategy see Supporting Information S2). MeSH terms were developed to search for all key concepts and modified for each database. Keyword searches restricted to abstract, title, and keyword headings were also completed. Boolean logic was used to combine the terms. Databases were initially searched from inception to May 2020 with no language or country limits applied. Later, the databases were searched again to include studies from May 2020 to July 2021.

2.2.2 | Searching other resources

Additionally, a search for unpublished work (i.e., manuscripts in preparation or submitted to a journal) was conducted via mailing lists of the European Health Psychology Society, the Association for Researchers in Psychology and Health, the Netherlands Flanders Communication Association, the German Psychological Society, and the British Psychological Society.

2.2.3 | Citation search

A backward and forward citation search of all initially included studies through the electronic search and gray literature search was conducted using Google Scholar. Screening was performed by two independent authors (AD, CF, ES, HB, or LK).

2.3 | Screening

All records identified by the search strategy were exported to Endnote X9, deduplicated and uploaded into Covidence software (Covidence Systematic Review Software, Veritas Health Innovation, Melbourne, Australia). To reduce the likelihood of reviewer selection bias, titles and abstracts of all studies were screened independently by at least two reviewers (CF, HB, DS, or LK). Full texts were screened by at least two reviewers (AD, ES, HB, or LK). Inter-rater reliability based on the number of eligible and ineligible studies was tested at the full text screening phase using Cohen's Kappa statistics.[52] The following cut-offs were used: 0.41–0.60 indicated moderate agreement, 0.61–0.80 substantial agreement and 0.81–0.99 almost perfect agreement.[52] Disagreements were resolved by discussion. During full text screening "moderate agreement" was achieved between the three independent reviewers (Kappa = 0.45).

2.4 | Data extraction

A data extraction form was developed following the existing guidelines from the Cochrane Collaboration.[53] Study characteristics (author, date of publication, location of the study, aim of the study, sample size and type, target behavior of the study, methodological characteristics, such as design, recruitment, and participants, intervention development, and type) and the main findings related to the research questions of this systematic review were extracted. The data extraction was performed independently by two reviewers (LK and DS); disagreements were resolved by discussion.

2.5 | Quality assessment

The quality of included studies was assessed through assessments of the risk of bias randomized studies, using the Cochrane Risk of Bias 2.0 tool (RoB 2.0),[54] and of study quality for nonrandomized studies with the Effective Public Healthcare Panacea Project (EPHPP) tool[55] respectively. The RoB 2.0 tool evaluates biases in selection, performance, detection, attrition, reporting, and other sources of bias.[54] Based on the individual domains, an overall risk of bias rating is derived. Studies scored with RoB 2.0 can be rated as low risk of bias, some concern of risk of bias, and high risk of bias. A high risk of bias is attributed to studies that show a high risk of bias in at least one domain of the quality appraisal. Equally, a rating of some concern of risk of bias is given if at least one domain is rated to be of some concern for risk of bias. The EPHPP tool assessed bias due to selection of participants into the study, type of study, confounders, blinding, measurement of outcomes, and withdrawals from and drop-out of the study. Based on the individual domains, an overall quality rating is derived. Studies scored with the EPHPP tool can receive a rating of high quality, moderate quality, or weak quality. The overall quality rating of weak quality is given to studies that have a weak rating in at least two domains of the quality appraisal. To stay true to the purpose of each tool, we refer to study quality for nonrandomized studies and risk of bias for randomized studies. However, in the discussion, when looking at overarching patterns, both quality and risk of bias may be mentioned jointly. The risk of bias or quality assessments of the studies were assessed independently by two reviewers per study (LK, DS, AD, or HB).

2.6 | Data synthesis

Narrative synthesis was conducted to synthesize the findings of the studies for the identified inequality indicators. Due to design heterogeneity of the included studies, as well as the limited number of studies per inequality indicator, a meta-analysis was not considered possible.

3 | RESULTS

3.1 | Study selection

After removing duplicates, 2201 studies were retrieved, with 176 studies included in the full text screening. Nine papers were eligible for inclusion. Another seven records were identified through

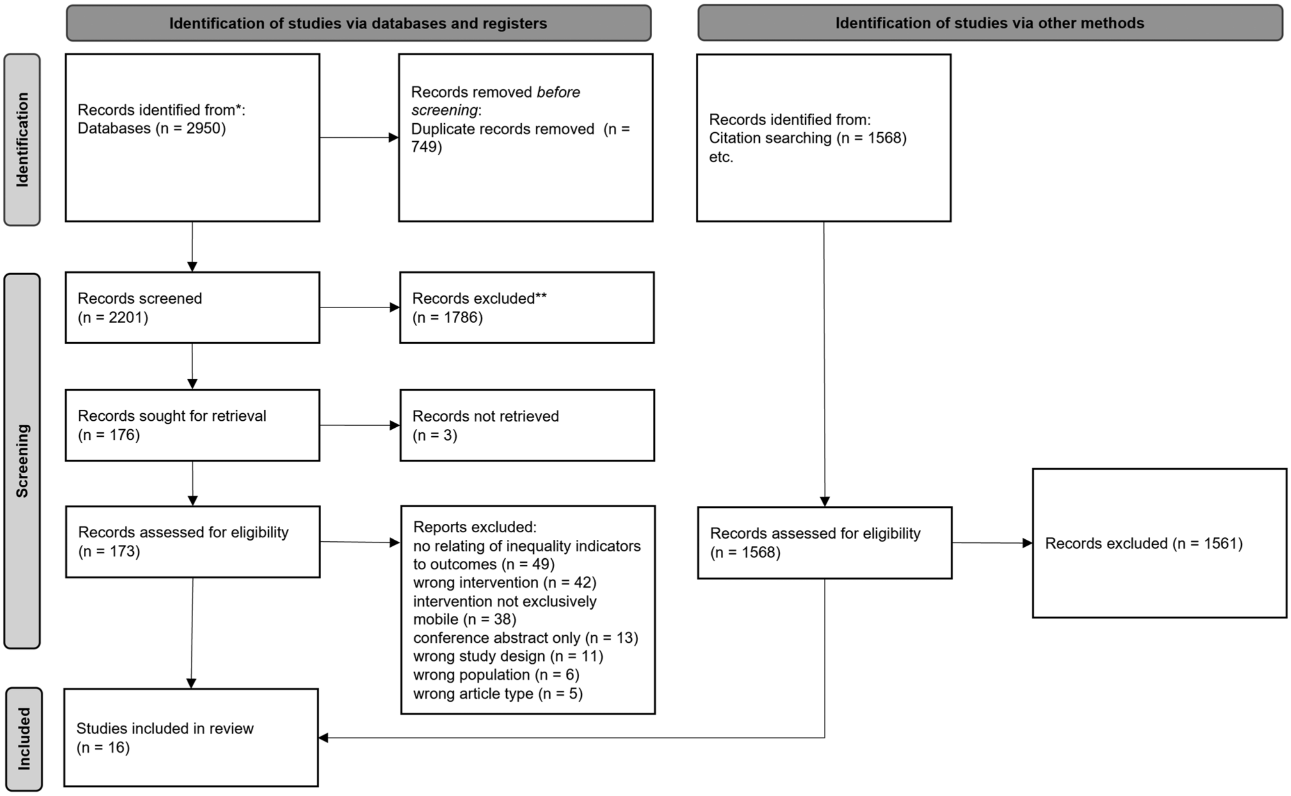

FIGURE 1 Preferred Reporting Items of Systematic Reviews and Meta-analysis (PRISMA) flowchart illustrating the inclusion and exclusion of the studies[47]

backward and forward citation searches. A total of 16 articles reporting on 13 studies were included in the narrative synthesis (see Figure 1). The list of studies excluded in the full text screening stage can be downloaded from the project's Open Science Framework page (https://osf.io/kdmz8/).

3.2 | Study characteristics

Studies were conducted in the USA ($n = 6$),[56–61] the UK ($n = 3$),[62–64] India ($n = 1$),[65] Japan ($n = 1$),[66] Germany ($n = 1$),[67] and Saudi Arabia ($n = 1$).[68] The included studies were randomized controlled trials ($n = 10$),[56–59,61–65,68] quasi-experimental nonrandomized longitudinal designs ($n = 2$),[60,66] single group studies ($n = 2$),[67,69] a mixed-method study ($n = 1$)[70] and a retrospective cohort study ($n = 1$).[71]

The number of participants included in the studies ranged between 48 and 251,718. Ten studies targeted diet or weight management,[57–60,64–66,68,71,72] two targeted physical activity,[56,67] and four studies targeted both.[61–63,70] No study targeted sedentary behavior. The interventions targeted employees,[62,63,66] patients,[56] university students,[68] general population,[57–59,61,64,65,67] and existing app users.[71] The inequality indicators assessed by the included studies for uptake, engagement or effectiveness were age ($n = 12$),[56,57,59–64,67,68,71,72] gender ($n = 13$),[56,57,59–64,66,67,70–72] ethnicity or race ($n = 8$),[56–59,61–64] educational attainment ($n = 6$),[57,59,63–65,68] occupation ($n = 2$),[62,63] income ($n = 2$),[57,59] employment type ($n = 4$),[56,57,59,64] and health literacy ($n = 1$).[59] See Table 1 for the characteristics of the included studies.

3.3 | Intervention characteristics

Intervention duration ranged from 4 weeks to 24 months. The theoretical basis for the interventions was reported in seven of the 16 studies, which included the Transtheoretical Model and Social Cognitive Theory,[61,68] self-regulation theories,[57] Self-Determination Theory,[67] and Habit Formation Theory.[64] See Supporting Information S3 for the characteristics of the mHealth interventions and inequality indicators.

3.4 | Quality assessment of included studies

Of the 10 randomized studies, assessed with the RoB 2.0 tool, nine showed some concern for risk of bias[56–59,61–64,68] whereas one showed a high risk of bias.[65] Two studies only showed some risk of bias in one domain[58,64]; four studies showed some risk of bias in two domains[56,57,59,63]; with the remaining three showing concerns for a risk of bias in more than two domains. Some concerns of risk of bias were mostly detected in a selective reporting of results (for eight out

TABLE 1 Characteristics of the included studies

First author (year)	Country	Target behavior	Study design	Population	Recruitment strategy	Sample size	Mean age (SD or age range)	% Female	Mode of delivery
Alssafi (2018)[68]	Saudi Arabia	Weight management	Two-arm randomized control trial	University students in Riyadh, Saudi Arabia	Through professors and student center	103	Not reported (age group 18–24)	Not reported	Smartphone app, activity tracker, social media
AlZuhaibi K. (2017)[70]	UK and Oman	Diet, weight management and physical activity	Mixed methods study, with pre-post design	Omani adults living in the UK	Through email to Omani adults living in Nottingham, registered with the Omani society enrolled in the student Union (University of Nottingham)	21	34 (3.9)	24%	Smartphone apps
Carter (2013)[62]	UK	Diet, weight management physical activity	Three-arm randomized trial	Employees (Leeds, UK)	Email sent to employers, use of intranet, distribution of posters, and newsletters	128	App group: 41.2 (8.5) Diary group: 42.5 (8.3) Website group: 41.9 (10.6)	77%	Smartphone app
Carter (2017)[63]	UK	Diet, weight management physical activity	Three-arm randomized trial	Employees (Leeds, UK)	Email sent to employers, use of intranet, distribution of posters, and newsletters	43	41.2 (8.5)	77%	Smartphone app
Chin (2016)[71]	N/A	Weight management	Retrospective cohort study	Noom Coach app users	N/A Data was received from the app developer company	35,831	33.3 (0.1)	78%	Smartphone app
Glenn (2019)[66]	Japan	Diet	Quasi-experimental, single-arm, nonrandomized, longitudinal design	Employees and parents of employees of a Japanese insurance company (Sompo Holdings, Tokyo, Japan)	Email outreach, flyers, and word of mouth throughout the company	559	Not reported	51.7%	Smartphone app
Klenk (2017)[67]	Germany	Physical activity	Single group design	Participants of a larger study, users of Runtastic app	From a larger study on fitness app use	31	44 (age range 26–66)	58%	Smartphone app
Kliemann (2019)[64]	UK	Weight management	Pilot three-arm randomized control trial	General population with overweight or obesity	Through recruitment posters, social media, recruitment	81	43.6 (13)	86%	Smartphone app

TABLE 1 (Continued)

First author (year)	Country	Target behavior	Study design	Population	Recruitment strategy	Sample size	Mean age (SD or age range)	% Female	Mode of delivery
					websites, and snowball sampling via personal contacts.				
Martin (2015)[56]	USA	Physical activity	Two-arm randomized control trial	Outpatients of an academic cardiovascular disease prevention center (Baltimore, Maryland, USA)	Not reported	48	58 (8)	46%	Smartphone app, activity tracker (Fitbug Orb), text messaging
Muralidharan (2019)[65]	India	Weight management	Two-arm randomized control trial	Convenience sample of Indian adults	Two-step recruitment using community-based screening in parks, residential colonies, corporates, and through direct clinic references	741	Intervention group 37.8 (9.2); control group 37.8 (9.6)	Intervention group 43.9%; control group 42.1%	Smartphone app
Patel (2019)[57]	USA	Diet, weight management	Three-arm randomized control trial	Convenience sample of adults (central North Carolina, USA)	Through University associated website, social media postings, clinicaltrials.gov registry, online community advertisements, and community flyers	84	43.7 (11.6)	81%	Smartphone app
Patel (2019) b[58]	USA	Diet, weight management	Three-arm randomized control trial	Convenience sample of adults (central North Carolina, USA)	Through University associated website, social media postings, clinicaltrials.gov registry, online community advertisements, and community flyers	105	42.7 (11.7)	84%	Smartphone app
Patel (2020)[56,59]	USA	Diet, weight management	Three-arm randomized control trial	Convenience sample of adults (central North Carolina, USA)	Through University associated website, social media postings,	100	42.7 (11.7)	84%	Smartphone app

(Continues)

TABLE 1 (Continued)

First author (year)	Country	Target behavior	Study design	Population	Recruitment strategy	Sample size	Mean age (SD or age range)	% Female	Mode of delivery
					clinicaltrials.gov registry, online community advertisements, and community flyers				
Senecal (2020)[72]	China	Diet, weight management	Retrospective observational analysis	Existing app users	N/A	251,718	37.3 (9.9)	78.6%	Smartphone app, wireless scale
Stein (2017)[60]	USA	Diet, weight management	Single-arm, nonrandomized, longitudinal design	Convenience sample (Nevada and Southern California)	Through six primary care offices in Nevada and Southern California	70	46.9 (1.89)	74.5%	Smartphone app
Svetkey (2015)[61]	USA	Diet, weight management physical activity	Three-arm randomized control trial	Convenience sample	Through advertising and mass mailing	365	29.4 (4.3)	69.6%	Smartphone app and smartphone app with personal coaching

of 10 studies)[56–59,63,65,68] and bias from deviating from the intended interventions (for five out of 10 studies).[57,59,61,62,68] High risk of bias was found for one study in the domain of bias due to missingness of data.[65]

The six non-randomized studies assessed using the EPHPP tool were judged to be of weak quality rating.[60,67,70–72] One study scored weak in two domains[70]; one study scored weak in three domains[60]; two studies scored weak in four domains[67,72]; and two scored weak in five out of six quality rating domains.[66,71] All six studies scored weak on reducing risk of confounders; five scored weak on reducing risk due to withdrawals and drop-outs[60,66,67,71,72]; and these also scored weak on reducing risk due to study design.

The quality assessment can be found in Supporting Information S4.

3.5 | Uptake

Only one study (of moderate quality/showing some concern of risk of bias) examined differences in age, gender, ethnicity, education, and employment between those who downloaded the app and those who did not, and reported no differences.[64]

3.6 | Engagement

Seven studies reported on engagement in relation to inequality indicators.[56,59,62,65–67,72] Out of the five studies, four did not find any difference in engagement by age.[59,62,63,66] One study reported that older participants (versus younger participants) engaged more often with features that allowed sharing information in Facebook groups.[67] This one study finding differences showed a high risk of bias/weak quality, whereas the four that showed no difference had a moderate quality rating/some concern of risk of bias.

Six studies investigated gender differences in engagement,[59,62,63,66,67,72] of which three studies did not find any difference.[59,62,63] One study reported that the frequency of nutrition tracking and meditation features tracking was higher for females (mean = 36, SD = 48) than for males (mean = 22, SD = 34).[66] A different study reported that females were more likely than males to participate longer in the intervention.[72] Another study only found gender differences when age was not included in the model; once age was accounted for in the model, gender differences ceased to be significant.[67] The three studies where a difference was found, were of weak quality/high risk of bias, whereas the remaining three were rated as moderate quality/some concern of risk of bias.

In terms of ethnicity,[58,59,62,63] two studies out of four did not find any difference.[62,63] The other two publications, both reporting on the same sample of participants, found significant differences between participants who inconsistently versus consistently used the tracking feature of the intervention app.[56,64] Non-Hispanic white participants were more consistent in app usage (67% non-Hispanic white and 80% non-Hispanic white, respectively).[59] Furthermore, this study reported differences between completers and non-completers at 3 months, with non-Hispanic white participants (16%) being more likely to complete the study than participants of other race or ethnic minorities (39%).[58] All four studies had received a moderate quality/some concern of risk of bias rating.

Four of the included studies examined differences in education levels of participants,[59,63,65,68] out of which three studies did not find any difference.[59,63,68] One study reported that more educated individuals engaged more with the available features (including video lessons and coach calls), while those with shorter time spent in formal education engaged predominantly in coaching calls (66%).[65] The one study that reported a difference had a weak quality/high risk of bias rating, whereas the other three studies had a moderate quality/some concern of risk of bias rating.

Two studies reporting on the same sample investigated the difference based on occupation and no significant difference was found.[62,63] Both studies were scored as of moderate quality/some concern of risk of bias.

Finally, one study (moderate quality/some concern of risk of bias) examined differences in employment status (i.e., whether participants worked full-time, part-time or were unemployed), income, and health literacy and no differences were found between consistent and inconsistent trackers.[59]

3.7 | Effectiveness

Nine studies examined differences in effectiveness due to inequality indicators.[56,57,60,61,65,66,70–72] Out of six studies assessing age differences, three studies found no difference.[56,57,61] Two studies found that younger age contributed to greater weight loss.[71,72] However, one study reported that older age was associated with more weight loss during the intervention period.[60] The three studies that reported differences were of weak quality/high risk of bias, whereas the other three studies were of moderate quality/some concern of risk of bias.

Eight studies reported on gender differences.[56,57,60,61,66,70–72] Two studies found no difference.[57,61] One study reported marginal differences at $p = 0.05$, with females having better results in step counts.[56] Another study reported significant gender differences regarding nutritional scores (mean value of nutritional scores for females of 36, SD = 48; versus males 22, SD = 10), but not regarding minutes spent exercising.[66] In contrast, one study reported better results in weight loss for males[71] and increased step count for males, although no difference was found in the weight between males and females.[70] One study found greater absolute weight loss for males, however, when compared to baseline a greater proportion of females achieved 5% weight loss.[72] Finally, one study reported significant gender differences for weight loss but did not provide information on which gender benefitted more.[60] The five studies reporting differences were of weak quality/high risk of bias, whereas the rest of the studies were of moderate quality/some concern of risk of bias.

Three studies (all moderate quality/some concern of risk of bias) reported on ethnicity and no differences were found.[56,57,61] Out of the two studies reported on education, one found no differences.[57] The other study reported that individuals with a degree or postgraduate degree, compared to having completed primary school (5th grade), reported greater weight loss.[65] The study reporting differences was of weak quality/high risk of bias, as opposed to the one reporting no differences, which was of moderate quality/some concern of risk of bias.

Only one study (weak quality/high risk of bias) examined occupation and found that individuals in professional, managerial, or executive jobs, compared to being self-employed or working in agriculture, achieved greater weight loss.[65] Two studies (both moderate quality/some concern of risk of bias) examined differences in employment status in relation to effectiveness, with no differences found.[56,57] One study (moderate quality/some concern of risk of bias) that investigated income found no difference.[57] The one study (weak quality/high risk of bias) that investigated geographical location found that individuals who lived in the capital as opposed to those living outside of the capital reported greater weight loss.[65]

Finally, one study (moderate quality/some concern of risk of bias) investigated differences in health literacy and found no difference.[57] The summary of results based on the inequality indicators investigated can be found in Table 2.

4 | DISCUSSION

4.1 | Principal findings

This review synthesized the available evidence for a potential digital health divide, defined by a range of inequality indicators, focusing on uptake, engagement, and effectiveness of exclusively mobile interventions for weight-related behaviors in adults. Overall, with 16 included papers reporting on 13 interventions, literature on the topic was limited. This finding is in line with previous reviews underlining that potential indicators for inequality are often not taken into account or are not reported in mHealth interventions.[38,42] Inequalities most often studied were age, gender, ethnicity/race, and education; however, the reported relationships were heterogeneous. The limited literature suggests scarce and unclear evidence for digital health inequalities. Throughout the uptake of, engagement with and effectiveness of mobile health interventions most studies found no difference, mixed findings, or contradictory evidence on the inequality indicators explored.

The difference in the quality of the included studies could provide an indication for the mixed or contradicting evidence. None of the included studies were of high quality/low risk of bias. All non-randomized studies were of weak quality, whereas most of the randomized studies were of moderate quality (some concerns of risk of bias). A pattern across findings on health inequality in uptake, engagement and effectiveness suggest no evidence of health inequality in

TABLE 2 Summary of results per outcome: Number of studies that reported significant differences in the outcome based on the inequality indicator vs the total number of studies that investigated this inequality indicator in relation to the outcome

Inequality indicator	Uptake	Engagement	Effectiveness
Age	0/1	1/4	3/6
Education	0/1	1/4	1/2
Ethnicity and race	0/1	2/4	0/3
Gender	0/1	3/6	5/8[a]
Health literacy		1/1	0/1
Income		0/1	0/1
Location			1/1
Occupation		0/2	1/1
Socioeconomic status			

Note: Empty cells indicate that the inequality indicator was not studied in relation to the outcome.[1]
[a]One additional study, not included in those 5, labeled the result as marginally significant.

studies of moderate quality, and evidence of health inequality only in poor quality/high risk of bias studies.

4.2 | Inequalities in uptake of exclusively mobile interventions

Given only one study included in this review investigated uptake, no conclusions can be drawn regarding a potential digital divide in the uptake of mHealth interventions. This lack of evidence may partly be attributable to the context of the included studies. The present review focused on intervention studies, which included experimental tests of interventions in RCTs and similar study designs. In this context, information on potential participants who decided not enroll in the study is presumably more difficult to obtain and not typically reported. However, recent systematic reviews suggest that, in the context of digital health studies, participants are typically younger and comprise fewer males and ethnic minority participants than the general population, suggesting potential inequalities in uptake.[40,47,73] Not only in intervention studies but also in survey studies that report on characteristics of people who engage with mHealth apps spontaneously, users are often younger. Evidence on other possible indicators of social inequality, such as gender or education, however, are mixed so far.[74–76]

4.3 | Inequalities in engagement with exclusively mobile interventions

Findings of this review regarding the inequalities in terms of engagement are mixed. Almost half of the included studies investigated different indicators of engagement, including how often participants engaged with different features and whether they were using the intervention consistently across longer periods of time. The inequality indicators of gender, age, and education were studied most frequently in relation to engagement. Where gender differences were reported, females were found to engage more with the intervention compared to males. This is in line with research on other types of digital health interventions that found women to be more active engagers in health research.[77] Understanding the possible mechanisms and other factors that include but are not limited to individual characteristics (e.g., interest in health-related topics, motivation, and design of the app) could help gain insight into why females, compared to males, seem to engage more with mHealth interventions. Given that higher engagement does not automatically lead to higher effectiveness, however, further research on how to increase effective forms of engagement among all users is needed.[78]

Only one study reported significant differences in engagement for age. In this study, older participants were more likely to share their data on Facebook compared to younger participants.[67] These findings contrast with the assumption that younger participants are more likely to engage with digital interventions because of higher digital literacy[76] and self-efficacy.[79] Furthermore, one out of four studies reported differences in education, indicating that individuals with a higher level of formal education (e.g., university degree) engaged more with the intervention.[65] This mirrors the results of previous studies indicating that higher levels of education are associated, for instance, with more frequent use of digital services to access health-related information[80] or treatment[81] and better health in general.[82] However, since the majority of studies included in this review did not report differences in engagement based on education, results could indicate that mobile interventions might reduce the digital divide induced by education, although this assumption requires further testing.

4.4 | Inequalities in the effectiveness of exclusively mobile interventions

The findings of this review on the inequality indicators on effectiveness are also inconclusive. The majority of studies focused on gender, age, and ethnicity. Most studies reported gender differences; however, results were mixed regarding which gender benefited more from the intervention. Since the included studies were diverse in terms of target behaviors and intervention components, the present review cannot provide indicators on when an intervention may be more beneficial for one gender than for another. Among the studies that explored ethnicity as a potential influence on intervention effectiveness, no study found differences in effectiveness for the different ethnicities investigated. This perhaps suggests that mHealth interventions may be a tool to reduce or to limit the increase of existing health disparities related to ethnic background.[83] It may also be that mHealth interventions help reduce structural barriers related to socioeconomic position (e.g., cost of in-person interventions and difficulty attending an appointment—all these could be overcome through mHealth interventions) that are more prevalent among ethnic minorities, however, these types of inequality indicators have been largely neglected by previous research making this determination difficult.[84] However, survey-based research has identified a digital divide in ethnicity regarding the use of digital health technology more broadly, with Blacks and Hispanics being less likely to use this technology than white participants.[85] However, this study was conducted in older adults only, who may be less likely to use digital health technology.[76] Nevertheless, the few studies included in this review might need to be supported by evidence from future research in this area to drawn firm conclusions.

4.5 | Implications and future research

Although evidence for a digital divide in exclusively mobile interventions was inconclusive, this systematic review found that engagement with and effectiveness of mobile interventions may be influenced by certain sociodemographic variables. It may thus be important for the success of mHealth interventions to further investigate these differences in high quality research designs and identify means to reduce these disparities. Integrating sub-group analyses regarding inequality indicators and reporting of their results should therefore become standard in mHealth research. The mixed evidence found across studies suggests there may also be intervention-specific characteristics that cause heterogeneity in effectiveness, which are useful to explore in future experimental studies. The results of the present review are in line with the findings of a recent review on mental health apps, which also indicated that evaluation frameworks for mental health apps rarely include indicators for diversity and inclusion, such as cost or using simple language.[86] Including inequality indicators such as the PROGRESS-plus criteria[87] in evaluation frameworks would be an important step toward making mHealth interventions accessible to marginalized groups, which may be in greater need of support.[29–32]

Another potential reason for the divergence in findings reported by individual studies may be the study design: RCTs included in this review did not report significant differences in engagement and effectiveness based on age or gender, while studies using other designs (e.g., single arm trials with pre–post comparisons) consistently reported significant differences. Due to randomization, the inclusion of control groups, and the possibility to draw causal conclusions, RCTs are usually considered to be of higher methodological quality than cohort studies, single arm trials or case–control studies.[88] Accordingly, more weight is usually put on the results from RCTs compared to other study designs. On the other hand, participation in RCTs especially may involve barriers such as information about the trial being difficult to understand for people with low levels of (health) literacy, and burden due to time commitment.[89] Consequently, samples in trials are rarely representative of the general population.[73] Using existing data from freely available mobile interventions, as applied in a small number of studies included in this review,[67,71,72] may thus provide a more realistic picture of intervention uptake, engagement, and effectiveness in real-life settings. However, the non-randomized studies included in this review suffered from biases in several domains other than randomization, such as low representativeness of the sample and high drop-out, which means these studies do not necessarily fulfill the potential of giving a more realistic picture of digital health inequalities.

Although it is often assumed that digital health technology including mobile interventions are used more often and are more effective in younger compared to older adults,[76,90] the present review only found limited evidence supporting this claim. Previous studies stated that reduced effectiveness of digital interventions in older adults may be because they are less familiar with digital technology in general and thus perceive more barriers.[91] However, age differences may be partly due to generational effects[92] and may thus diminish in the future. This development may be further accelerated by the increased use of smartphones and other digital devices in older age groups.[93] More research is needed to disentangle age and generational effects to determine whether differential preferences of younger and older adults, for example, regarding behavior change techniques included in the intervention, are actually due to age-related changes such as changes in physical abilities,[94] or rather due to generational differences.

Certain inequality indicators such as socioeconomic position, health literacy, or geographical location have hardly been studied in the context of exclusively mobile interventions. This limited our ability to draw meaningful conclusions from the presented data. A recent meta-analysis on digital interventions for physical activity more broadly reports that digital interventions are ineffective in people with lower socioeconomic position.[43] However, Western and colleagues were unable to test differences in uptake and engagement, which are considered a necessary and important prerequisite for intervention effectiveness[43]: if an intervention is not taken up and used as intended, it will most likely not induce any effects.[78] The divergent findings may thus underline the importance of studying a potential digital divide not only regarding effectiveness but also regarding uptake and engagement (see also the work of Birch and colleagues, for weight loss interventions more broadly[27]). Moreover, other inequality indicators such as sexual orientation and health services accessibility have not been studied at all in any of the identified studies. Previous research has demonstrated links between belonging to a sexual minority and reporting poorer physical health outcomes such as obesity and chronic conditions.[95,96] It would thus be important to investigate whether exclusively mobile interventions may reduce or widen these disparities. Furthermore, digital interventions are seen as a promising tool to overcome disparities due to geographical location or lack of health care providers in the area.[97,98] Therefore, more research is needed to test whether mHealth interventions actually improve access to health care among geographically challenged populations.

Additionally, future research is needed on potential inequalities in the uptake of mHealth interventions, both within (e.g., by reporting on potential participants approached versus participants enrolled) and especially outside the research context, to provide potential guidance for intervention development and clinical practice. This review mainly included studies that measured engagement objectively, for example, how often specific intervention features were used. A future systematic review may want to complement findings of this review and investigate subjective engagement. Future research may want to further address the interplay of different inequality indicators on mHealth intervention uptake, engagement, and effectiveness.

Although in its early stages, research has already identified starting points for making mHealth interventions more equitable. For instance, mHealth interventions should use plain language and simple labels to benefit users with low health and digital literacy.[99] Also, uptake and engagement may be improved by tailoring apps to the users' cultural backgrounds.[5,100–102] Tailoring the use of different behavior change techniques to age group-specific needs may increase the effectiveness of mHealth interventions across age groups, especially when age group-specific motivational barriers are addressed.[103,104] Additionally, to make mHealth interventions more equitable, required time and financial costs may need to be reduced, since these are resources of which socioeconomically advantaged individuals tend to have more of.[105]

Finally, the present review focused on exclusively mobile interventions only, which is why only a small number of studies were identified. While mobile interventions often include non-mobile components (e.g., an accompanying website, counseling via telephone or in face-to-face consultations[69,106,107]), exclusively mobile interventions become increasingly common. For instance, the German Digital Healthcare act allows medical professionals to prescribe digital interventions as they would prescribe medication.[10] These interventions are often delivered exclusively mobile. However, research suggests that exclusively digital interventions may be less effective than interventions including face-to-face components.[108] This difference may be elevated in deprived populations who might need more support to sustain engagement and thus benefit from the intervention. However, this assumption needs to be investigated in future research.

4.6 | Strength and limitations

This review is the first to investigate a wide range of inequality indicators in the context of uptake of, engagement with and effectiveness of exclusively mobile interventions, which are becoming increasingly popular in health promotion and care. However, the PROGRESS-Plus criteria indicate further potential sources of inequality such as culture, language, or disability,[87] which should be taken into account in future empirical research and systematic reviews. Another strength is the focus not only on effectiveness of the digital interventions, but also on uptake and engagement as two further important dimensions of a digital divide. Finally, the comprehensive search strategy was complemented with backward and forward citation tracking to ensure completeness. However, it is important to acknowledge that due to the heterogeneity of the studies included in terms of which inequality indicators were assessed, we were unable to conduct a meta-analysis. The aim of this review focused on health promotion and primary prevention, therefore, excluded participants with pre-existing medical conditions. However, these populations are more likely to be part of a disadvantaged group, which may have led to further indicators of a potential digital divide. Future reviews could focus on groups with existing conditions to explore this. Furthermore, the studies included in this review provided only limited quantitative data on differences based on the inequality indicators, and the indicators were often limited to common demographic variables such as gender, age, and ethnicity. Lastly, included studies were not specifically designed to test for a potential digital divide; accordingly, they might not have been adequately powered to detect these interaction effects, and relevant tests were often not preregistered. These caveats limit the conclusions that can currently be drawn regarding a potential digital divide in exclusively mobile interventions.

5 | CONCLUSION

There is limited to mixed evidence of a digital divide in exclusively mobile interventions targeting weight-related behaviors. This review highlights the need for researchers to address, analyze, and report on a broad range of potential sources of inequality when evaluating mHealth interventions to test whether they reduce or widen existing health disparities and to identify starting points for developing more inclusive mHealth interventions.

ACKNOWLEDGMENTS

The authors would like to thank Sarah L Greenley, information specialist from the University of Hull, for their input on the search strategy. Open Access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST

None declared.

AUTHOR CONTRIBUTIONS

LK wrote the study protocol with contributions from all authors and registered the protocol on PROSPERO. CF performed the searches and the de-duplication. CF, DS, HB, and LK conducted the title and abstract screening. AD, ES, HB, and LK conducted the full-text screening. CF, ES, LK, AD, and HB conducted the backward and forward citation searches. LK and DS extracted the data. AD, HB, LK, and DS assessed the quality of the studies. Data synthesis was undertaken by DS and LK. DS, LK, and AD prepared the first draft of the manuscript. All authors read, commented, and contributed to the final version of the manuscript.

ORCID

Dorothy Szinay https://orcid.org/0000-0003-2722-6758
Cynthia C. Forbes https://orcid.org/0000-0002-3259-1832
Heide Busse https://orcid.org/0000-0001-6043-9072
Ann DeSmet https://orcid.org/0000-0002-7473-140X
Eline S. Smit https://orcid.org/0000-0001-8588-6194
Laura M. König https://orcid.org/0000-0003-3655-8842

REFERENCES

1. Zhao J, Freeman B, Li M. Can Mobile phone apps influence People's health behavior change? An evidence review. *J Med Internet Res*. 2016;18:e287. doi:10.2196/jmir.5692
2. Lustria ML, Smith SA, Hinnant CC. Exploring digital divides: an examination of eHealth technology use in health information seeking, communication and personal health information management in the USA. *Health Informatics J*. 2011;17:224-243. doi:10.1177/1460458211414843
3. Hamberger M, Ikonomi N, Schwab JD, et al. Interaction empowerment in mobile health: concepts, challenges, and perspectives. *JMIR Mhealth Uhealth*. 2022;10:e32696. doi:10.2196/32696
4. van Deursen AJAM, van Dijk JAGM. The digital divide shifts to differences in usage. *New Media Soc*. 2013;16(3):507-526. doi:10.1177/1461444813487959
5. König LM, Attig C, Franke T, Renner B. Barriers to and facilitators for using nutrition apps: systematic review and conceptual framework. *JMIR Mhealth Uhealth*. 2021;9(6):e20037. doi:10.2196/20037
6. Sharp DB, Allman-Farinelli M. Feasibility and validity of mobile phones to assess dietary intake. *Nutrition*. 2014;30(11-12):1257-1266. doi:10.1016/j.nut.2014.02.020
7. Lee K, Kwon H, Lee B, et al. Effect of self-monitoring on long-term patient engagement with mobile health applications. *PLoS ONE*. 2018;13(7):e0201166. doi:10.1371/journal.pone.0201166
8. Compernolle S, DeSmet A, Poppe L, et al. Effectiveness of interventions using self-monitoring to reduce sedentary behavior in adults: a systematic review and meta-analysis. *Int J Behav Nutr Phys Act*. 2019;16(1):63. doi:10.1186/s12966-019-0824-3
9. World Health Organisation. Global strategy on digital health 2020–2025.
10. Gerke S, Stern AD, Minssen T. Germany's digital health reforms in the COVID-19 era: lessons and opportunities for other countries. *NPJ Dig Med*. 2020;3(1):94. doi:10.1038/s41746-020-0306-7
11. Catalani C, Philbrick W, Fraser H, et al. mHealth for HIV treatment & prevention: a systematic review of the literature. *Open AIDS J*. 2013;7:17-41. doi:10.2174/1874613620130812003
12. Ghorai K, Akter S, Khatun F, Ray P. mHealth for smoking cessation programs: a systematic review. *J Pers Med*. 2014;4(3):412-423. doi:10.3390/jpm4030412
13. Hamine S, Gerth-Guyette E, Faulx D, et al. Impact of mHealth chronic disease management on treatment adherence and patient outcomes: a systematic review. *J Med Internet Res*. 2015;17:e52. doi:10.2196/jmir.3951
14. Seppälä J, De Vita I, Jämsä T, et al. Mobile phone and wearable sensor-based mHealth approaches for psychiatric disorders and symptoms: systematic review. *JMIR Ment Health*. 2019;6:e9819. doi:10.2196/mental.9819
15. Müller AM, Maher CA, Vandelanotte C, et al. Physical activity, sedentary behavior, and diet-related eHealth and mHealth research: bibliometric analysis. *J Med Internet Res*. 2018;20:e122. doi:10.2196/jmir.8954
16. Villinger K, Wahl DR, Boeing H, et al. The effectiveness of app-based mobile interventions on nutrition behaviours and nutrition-related health outcomes: a systematic review and meta-analysis. *Obes Rev*. 2019;20:1465-1484. doi:10.1111/obr.12903
17. Biddle SJ, Bennie JA, Bauman AE, et al. Too much sitting and all-cause mortality: is there a causal link? *BMC Public Health*. 2016;16:635. doi:10.1186/s12889-016-3307-3
18. Blair SN, Morris JN. Healthy hearts--and the universal benefits of being physically active: physical activity and health. *Ann Epidemiol*. 2009;19:253-256. doi:10.1016/j.annepidem.2009.01.019
19. Oyebode O, Gordon-Dseagu V, Walker A, et al. Fruit and vegetable consumption and all-cause, cancer and CVD mortality: analysis of health survey for England data. *J Epidemiol Community Health*. 2014;68:856-862. doi:10.1136/jech-2013-203500
20. Collins S, Dash S, Allender S, Jacka F, Hoare E. Diet and mental health during emerging adulthood: a systematic review. *Emerg Adulthood*. 2020;10(3):2167696820943028. doi:10.1177/2167696820943028
21. Hoare E, Milton K, Foster C, et al. The associations between sedentary behaviour and mental health among adolescents: a systematic review. *Int J Behav Nutr Phys Act*. 2016;13:108. doi:10.1186/s12966-016-0432-4
22. Perski O, Blandford A, West R, Michie S. Conceptualising engagement with digital behaviour change interventions: a systematic review using principles from critical interpretive synthesis. *Transl Behav Med*. 2017;7(2):254-267. Systematic Rev. doi:10.1007/s13142-016-0453-1
23. Hakala S, Rintala A, Immonen J, et al. Effectiveness of technology-based distance interventions promoting physical activity: systematic review, meta-analysis and meta-regression. *J Rehabil Med*. 2017;49:97-105. doi:10.2340/16501977-2195
24. Direito A, Carraca E, Rawstorn J, et al. mHealth technologies to influence physical activity and sedentary behaviors: behavior change techniques, systematic review and meta-analysis of randomized controlled trials. *Ann Behav Med*. 2017;51:226-239. doi:10.1007/s12160-016-9846-0
25. Stephenson A, McDonough SM, Murphy MH, et al. Using computer, mobile and wearable technology enhanced interventions to reduce sedentary behaviour: a systematic review and meta-analysis. *Int J Behav Nutr Phys Act*. 2017;14(1):105. doi:10.1186/s12966-017-0561-4
26. Blackman KC, Zoellner J, Berrey LM, et al. Assessing the internal and external validity of mobile health physical activity promotion interventions: a systematic literature review using the RE-AIM framework. *J Med Internet Res*. 2013;15:e224. doi:10.2196/jmir.2745
27. Birch JM, Jones RA, Mueller J, et al. A systematic review of inequalities in the uptake of, adherence to, and effectiveness of behavioral weight management interventions in adults. *Obes Rev*. 2022;23(6):e13438. doi:10.1111/obr.13438
28. Vandelanotte C, Müller AM, Short CE, et al. Past, present, and future of eHealth and mHealth research to improve physical activity and dietary behaviors. *J Nutr Educ Behav*. 2016;48:219-228.e211. doi:10.1016/j.jneb.2015.12.006
29. Latulippe K, Hamel C, Giroux D. Social health inequalities and eHealth: a literature review with qualitative synthesis of theoretical and empirical studies. *J Med Internet Res*. 2017;19(4):e136. doi:10.2196/jmir.6731
30. Blosnich JR, Farmer GW, Lee JG, et al. Health inequalities among sexual minority adults: evidence from ten U.S. states, 2010. *Am J Prev Med*. 2014;46:337-349. doi:10.1016/j.amepre.2013.11.010
31. Gibney S, Bruton L, Ryan C, Doyle G, Rowlands G. Increasing health literacy may reduce health inequalities: evidence from a National Population Survey in Ireland. *Int J Environ Res Public Health*. 2020;17(16):5891. doi:10.3390/ijerph17165891
32. Mackenbach JP, Hu Y, Artnik B, et al. Trends in inequalities in mortality amenable to health care in 17 European countries. *Health Aff (Millwood)*. 2017;36:1110-1118. doi:10.1377/hlthaff.2016.1674
33. Jennings L, Gagliardi L. Influence of mHealth interventions on gender relations in developing countries: a systematic literature review. *Int J Equity Health*. 2013;12:85. doi:10.1186/1475-9276-12-85
34. Chesser A, Burke A, Reyes J, et al. Navigating the digital divide: a systematic review of eHealth literacy in underserved populations in the United States. *Inform Health Soc Care*. 2016;41:1-19. doi:10.3109/17538157.2014.948171
35. Huh J, Koola J, Contreras A, et al. Consumer health informatics adoption among underserved populations: thinking beyond the

digital divide. *Yearb Med Inform*. 2018;27:146-155. doi:10.1055/s-0038-1641217
36. Cornejo Müller A, Wachtler B, Lampert T. Digital divide-social inequalities in the utilisation of digital healthcare. *Bundesgesundheitsblatt Gesundheitsforschung Gesundheitsschutz*. 2020;63:185-191. doi:10.1007/s00103-019-03081-y
37. Rodgers M, Raine G, Thomas S, et al. Health Services and Delivery Research. In: *Informing NHS Policy in 'Digital-First Primary Care': A Rapid Evidence Synthesis*. Southampton (UK): NIHR Journals Library.
38. Chesser A, Burke A, Reyes J, Rohrberg T. Navigating the digital divide: a systematic review of eHealth literacy in underserved populations in the United States. *Inform Health Soc Care*. 2016;41(1):1-19. doi:10.3109/17538157.2014.948171
39. Chae J. A comprehensive profile of those who have health-related apps. *Health Educ Behav*. 2018;45(4):591-598. doi:10.1177/1090198117752784
40. Rosenbaum DL, Piers AD, Schumacher LM, Kase CA, Butryn ML. Racial and ethnic minority enrollment in randomized clinical trials of behavioural weight loss utilizing technology: a systematic review. *Obes Rev*. 2017;18(7):808-817. doi:10.1111/obr.12545
41. Payne JE, Turk MT, Kalarchian MA, et al. Defining adherence to dietary self-monitoring using a Mobile app: a narrative review. *J Acad Nutr Diet*. 2018;118:2094-2119. doi:10.1016/j.jand.2018.05.011
42. Stowell E, Lyson MC, Saksono H, et al. Designing and Evaluating mHealth Interventions for Vulnerable Populations: A Systematic Review. In: *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. Montreal QC, Canada: Association for Computing Machinery; 2018:Paper 15.
43. Western MJ, Armstrong MEG, Islam I, Morgan K, Jones UF, Kelson MJ. The effectiveness of digital interventions for increasing physical activity in individuals of low socioeconomic status: a systematic review and meta-analysis. *Int J Behav Nutr Phys Act*. 2021;18(1):148. doi:10.1186/s12966-021-01218-4
44. Tomlinson M, Rotheram-Borus MJ, Swartz L, Tsai AC. Scaling up mHealth: where is the evidence? *PLoS Med*. 2013;10(2):e1001382. doi:10.1371/journal.pmed.1001382
45. Hruby A, Manson JE, Qi L, et al. Determinants and consequences of obesity. *Am J Public Health*. 2016;106:1656-1662. doi:10.2105/ajph.2016.303326
46. Adair T, Lopez AD. The role of overweight and obesity in adverse cardiovascular disease mortality trends: an analysis of multiple cause of death data from Australia and the USA. *BMC Med*. 2020;18(1):199. doi:10.1186/s12916-020-01666-y
47. Szinay D, Jones A, Chadborn T, Brown J, Naughton F. Influences on the uptake of and engagement with health and well-being smartphone apps: systematic review. *J Med Internet Res*. 2020;22(5):e17572. doi:10.2196/17572
48. O'Brien HL, Morton E, Kampen A, et al. Beyond clicks and downloads: a call for a more comprehensive approach to measuring mobile-health app engagement. *BJPsych Open*. 2020;6:e86. doi:10.1192/bjo.2020.72
49. Perski O, Blandford A, West R, et al. Conceptualising engagement with digital behaviour change interventions: a systematic review using principles from critical interpretive synthesis. *Transl Behav Med*. 2017;7:254-267. doi:10.1007/s13142-016-0453-1
50. Haynes B. Can it work? Does it work? Is it worth it? *BMJ*. 1999;319(7211):652-653. doi:10.1136/bmj.319.7211.652
51. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*. 2021;372:n71. doi:10.1136/bmj.n71
52. Viera AJ, Garrett JM. Understanding interobserver agreement: the kappa statistic. *Fam Med*. 2005;37:360-363.
53. Higgins J, Green S (Eds). *Cochrane Handbook for Systematic Reviews of Interventions Version 5.1.0 [updated March 2011]*. The Cochrane Collaboration; 2011.
54. Sterne JAC, Savović J, Page MJ, et al. RoB 2: a revised tool for assessing risk of bias in randomised trials. *BMJ*. 2019;366:l4898. doi:10.1136/bmj.l4898
55. Thomas BH, Ciliska D, Dobbins M, et al. A process for systematically reviewing the literature: providing the research evidence for public health nursing interventions. *Worldviews Evid Based Nurs*. 2004;1:176-184. doi:10.1111/j.1524-475X.2004.04006.x
56. Martin SS, Feldman DI, Blumenthal RS, et al. mActive: a randomized clinical trial of an automated mHealth intervention for physical activity promotion. *J Am Heart Assoc*. 2015;4. doi:10.1161/jaha.115.002239
57. Patel ML, Hopkins CM, Bennett GG. Early weight loss in a standalone mHealth intervention predicting treatment success. *Obes Sci Pract*. 2019;5(3):231-237. doi:10.1002/osp4.329
58. Patel ML, Hopkins CM, Brooks TL, Bennett GG. Comparing self-monitoring strategies for weight loss in a smartphone app: randomized controlled trial. *JMIR Mhealth Uhealth*. 2019;7(2):e12209. doi:10.2196/12209
59. Patel ML, Brooks TL, Bennett GG. Consistent self-monitoring in a commercial app-based intervention for weight loss: results from a randomized trial. *J Behav Med*. 2020;43:391-401. doi:10.1007/s10865-019-00091-8
60. Stein N, Brooks K. A fully automated conversational artificial intelligence for weight loss: longitudinal observational study among overweight and obese adults. *JMIR Diabetes*. 2017;2:e28. doi:10.2196/diabetes.8590
61. Svetkey LP, Batch BC, Lin PH, et al. Cell phone intervention for you (CITY): a randomized, controlled trial of behavioral weight loss intervention for young adults using mobile technology. *Obesity (Silver Spring)*. 2015;23:2133-2141. doi:10.1002/oby.21226
62. Carter MC, Burley VJ, Nykjaer C, Cade JE. Adherence to a smartphone application for weight loss compared to website and paper diary: pilot randomized controlled trial. *J Med Internet Res*. 2013;15(4):e32. doi:10.2196/jmir.2283
63. Carter MC, Burley VJ, Cade JE. Weight loss associated with different patterns of self-monitoring using the Mobile phone app my meal mate. *JMIR Mhealth Uhealth*. 2017;5:e8. doi:10.2196/mhealth.4520
64. Kliemann N, Croker H, Johnson F, et al. Development of the top tips habit-based weight loss app and preliminary indications of its usage, effectiveness, and acceptability: mixed-methods pilot study. *JMIR Mhealth Uhealth*. 2019;7:e12326. doi:10.2196/12326
65. Muralidharan S, Ranjani H, Mohan Anjana R, et al. Engagement and weight loss: results from the Mobile health and diabetes trial. *Diabetes Technol Ther*. 2019;21:507-513. doi:10.1089/dia.2019.0134
66. Glenn J, Madero EN, Gray M, et al. Engagement with a digital platform for multimodal cognitive assessment and multidomain intervention in a Japanese population: pilot, quasi-experimental, longitudinal study. *JMIR Mhealth Uhealth*. 2019;7(10):e15733. doi:10.2196/15733
67. Klenk S, Reifegerste D, Renatus R. Gender differences in gratifications from fitness app use and implications for health interventions. *Mob Media Commun*. 2017;5(2):178-193. doi:10.1177/2050157917691557
68. Alssafi AH. *A Mobile-Based Intervention for Obesity Prevention Among Female College Students in Saudi Arabia: A Randomized Controlled Trial*. FIU Electronic Theses and Dissertations; 2018:3877.
69. Olfert MD, Barr ML, Hagedorn RL, et al. Feasibility of a mHealth approach to nutrition counseling in an Appalachian state. *J Pers Med*. 2019;9(4):50. doi:10.3390/jpm9040050
70. AlZuhaibi K. *Impact of Dietary Practices and Physical Activity on Obesity and Overweight in Omani Adults and effectiveness of lifestyle interventions using Smart Phone Applications*. Nottingham, United Kingdom: University of Nottingham; 2017.

71. Chin SO, Keum C, Woo J, et al. Successful weight reduction and maintenance by using a smartphone application in those with overweight and obesity. *Sci Rep*. 2016;6(1):34563. doi:10.1038/srep34563
72. Senecal C, Widmer RJ, Larrabee BR, et al. A digital health weight loss program in 250,000 individuals. *J Obes*. 2020;2020:9497164. doi:10.1155/2020/9497164
73. Pratap A, Neto EC, Snyder P, et al. Indicators of retention in remote digital health studies: a cross-study evaluation of 100,000 participants. *NPJ Dig Med*. 2020;3(1):21. doi:10.1038/s41746-020-0224-8
74. Bender MS, Choi J, Arai S, et al. Digital technology ownership, usage, and factors predicting downloading health apps among Caucasian, Filipino, Korean, and Latino Americans: the digital link to health survey. *JMIR Mhealth Uhealth*. 2014;2:e43. doi:10.2196/mhealth.3710
75. Carroll JK, Moorhead A, Bond R, LeBlanc WG, Petrella RJ, Fiscella K. Who uses Mobile phone health apps and does use matter? A secondary data analytics approach. *J Med Internet Res*. 2017;19(4):e125. doi:10.2196/jmir.5604
76. König LM, Sproesser G, Schupp HT, et al. Describing the process of adopting nutrition and fitness apps: behavior stage model approach. *JMIR Mhealth Uhealth*. 2018;6:e55. doi:10.2196/mhealth.8261
77. Freyne J, Saunders I, Brindal E, et al. Factors associated with persistent participation in an online diet intervention. In: *CHI '12 Extended Abstracts on Human Factors in Computing Systems*. Austin, Texas, USA: Association for Computing Machinery; 2012:2375-2380.
78. Yardley L, Spring BJ, Riper H, et al. Understanding and promoting effective engagement with digital behavior change interventions. *Am J Prev Med*. 2016;51(5):833-842. doi:10.1016/j.amepre.2016.06.015
79. Hall AK, Bernhardt JM, Dodd V, Vollrath MW. The digital health divide: evaluating online health information access and use among older adults. *Health Educ Behav*. 2014;42(2):202-209. doi:10.1177/1090198114547815
80. Xiao N, Sharman R, Rao HR, Upadhyaya S. Factors influencing online health information search: an empirical analysis of a national cancer-related survey. *Decis Support Syst*. 2014;57:417-427. doi:10.1016/j.dss.2012.10.047
81. Amo L. Education-based gaps in eHealth: a weighted logistic regression approach. *J Med Internet Res*. 2016;18(10):e267. doi:10.2196/jmir.5188
82. Raghupathi V, Raghupathi W. The influence of education on health: an empirical assessment of OECD countries for the period 1995–2015. *Arch Public Health*. 2020;78(1):20. doi:10.1186/s13690-020-00402-5
83. Armstrong S, Wong CA, Perrin E, et al. Association of Physical Activity with Income, race/ethnicity, and sex among adolescents and young adults in the United States: findings from the National Health and nutrition examination survey, 2007-2016. *JAMA Pediatr*. 2018;172:732-740. doi:10.1001/jamapediatrics.2018.1273
84. Dressler WW, Oths KS, Gravlee CC. RACE AND ETHNICITY IN PUBLIC HEALTH RESEARCH: models to explain health disparities. *Ann Rev Anthropol*. 2005;34(1):231-252. doi:10.1146/annurev.anthro.34.081804.120505
85. Mitchell UA, Chebli PG, Ruggiero L, et al. The digital divide in health-related technology use: the significance of race/ethnicity. *Gerontologist*. 2019;59:6-14. doi:10.1093/geront/gny138
86. Ramos G, Ponting C, Labao JP, Sobowale K. Considerations of diversity, equity, and inclusion in mental health apps: a scoping review of evaluation frameworks. *Behav Res Ther*. 2021;147:103990. doi:10.1016/j.brat.2021.103990
87. Attwood S, van Sluijs E, Sutton S. Exploring equity in primary-care-based physical activity interventions using PROGRESS-plus: a systematic review and evidence synthesis. *Int J Behav Nutr Phys Act*. 2016;13(1):60. doi:10.1186/s12966-016-0384-8
88. Bonita R, Beaglehole R, Kjellström T, et al. *Basic Epidemiology*. 2nd ed. Geneva: World Health Organization; 2006.
89. Houghton C, Dowling M, Meskell P, et al. Factors that impact on recruitment to randomised trials in health care: a qualitative evidence synthesis. *Cochrane Database Syst Rev*. 2020;2020(10):MR000045. doi:10.1002/14651858.MR000045.pub2
90. French DP, Olander EK, Chisholm A, et al. Which behaviour change techniques are most effective at increasing older adults' self-efficacy and physical activity behaviour? A systematic review. *Ann Behav Med*. 2014;48:225-234. doi:10.1007/s12160-014-9593-z
91. Franke T, Attig C, Wessel D. A personal resource for technology interaction: development and validation of the affinity for technology interaction (ATI) scale. *International Journal of Human–Computer Interaction*. 2019;35:456-467. doi:10.1080/10447318.2018.1456150
92. Alkire L, O'Connor GE, Myrden S, et al. Patient experience in the digital age: an investigation into the effect of generational cohorts. *J Retail Consum Serv*. 2020;57:102221. doi:10.1016/j.jretconser.2020.102221
93. American Association of Retired Persons (AARP). *Older Adults Keep Pace on Tech Usage*. https://www.aarp.org/research/topics/technology/info-2019/2020-technology-trends-older-americans.html (2020, accessed 23.10.2021).
94. Wildenbos GA, Maasri K, Jaspers M, Peute L. Older adults using a patient portal: registration and experiences, one year after implementation. *Dig Health*. 2018;4:2055207618797883. doi:10.1177/2055207618797883
95. Dyar C, Taggart TC, Rodriguez-Seijas C, et al. Physical health disparities across dimensions of sexual orientation, race/ethnicity, and sex: evidence for increased risk among bisexual adults. *Arch Sex Behav*. 2019;48:225-242. doi:10.1007/s10508-018-1169-8
96. Gonzales G, Henning-Smith C. Health disparities by sexual orientation: results and implications from the behavioral risk factor surveillance system. *J Community Health*. 2017;42:1163-1172. doi:10.1007/s10900-017-0366-z
97. Bucci S, Berry N, Morris R, et al. They are not hard-to-reach clients. We have just got hard-to-reach services. Staff views of digital health tools in specialist mental health services. *Front Psychiatry*. 2019;10:344. doi:10.3389/fpsyt.2019.00344
98. World Health Organisation. *WHO Guideline: Recommendations on Digital Interventions for health system strengthening*, https://www.who.int/publications/i/item/9789241550505 (2019).
99. Caburnay CA, Graff K, Harris JK, et al. Evaluating diabetes mobile applications for health literate designs and functionality, 2014. *Prev Chronic Dis*. 2015;12:E61. doi:10.5888/pcd12.140433
100. McKay FH, Wright A, Shill J, et al. Using health and well-being apps for behavior change: a systematic search and rating of apps. *JMIR Mhealth Uhealth*. 2019;7(7):e11926. doi:10.2196/11926
101. Coughlin SS, Hardy D, Caplan LS. The need for culturally-tailored smartphone applications for weight control. *J Ga Public Health Assoc*. 2016;5:228-232.
102. Lyzwinski LN, Caffery LJ, Bambling M, et al. Consumer perspectives on mHealth for weight loss: a review of qualitative studies. *J Telemed Telecare*. 2018;24:290-302. doi:10.1177/1357633x17692722
103. French DP, Olander EK, Chisholm A, Mc Sharry J. Which behaviour change techniques are Most effective at increasing older Adults' self-efficacy and physical activity behaviour? A systematic review. *Ann Behav Med*. 2014;48(2):225-234. doi:10.1007/s12160-014-9593-z
104. Wildenbos GA, Peute L, Jaspers M. Aging barriers influencing mobile health usability for older adults: a literature based framework (MOLD-US). *Int J Med Inform*. 2018;114:66-75. doi:10.1016/j.ijmedinf.2018.03.012

105. Adams J, Mytton O, White M, Monsivais P. Why are some population interventions for diet and obesity more equitable and effective than others? The role of individual agency. *PLoS Med*. 2016;13(4):e1001990. doi:10.1371/journal.pmed.1001990
106. Partridge SR, McGeechan K, Bauman A, Phongsavan P, Allman-Farinelli M. Improved eating behaviours mediate weight gain prevention of young adults: moderation and mediation results of a randomised controlled trial of TXT2BFiT, mHealth program. *Int J Behav Nutr Phys Act*. 2016;13(1):44. doi:10.1186/s12966-016-0368-8
107. Partridge SR, McGeechan K, Bauman A, et al. Improved confidence in performing nutrition and physical activity behaviours mediates behavioural change in young adults: mediation results of a randomised controlled mHealth intervention. *Appetite*. 2017;108:425-433. doi:10.1016/j.appet.2016.11.005
108. Dombrowski S, Whitcomb E, Olthuis J, Witherspoon R, Hebert J. Syetemactire review of RCTs comparing face-to-face vs remote behaviour change interventions for weight management. In: *35th Conference of the European Health Psychology Society*; 2021.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Szinay D, Forbes CC, Busse H, DeSmet A, Smit ES, König LM. Is the uptake, engagement, and effectiveness of exclusively mobile interventions for the promotion of weight-related behaviors equal for all? A systematic review. *Obesity Reviews*. 2023;24(3):e13542. doi:10.1111/obr.13542