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REVIEW ARTICLE

Mobile Health Applications in Weight Management: A Systematic Literature Review

Katerina Dounavi, PhD, BCBA-D,[1] Olga Tsoumani, MSc[2]

Context: Weight management is an effective strategy for controlling chronic disease and maintaining physical health, and research on this topic has risen dramatically over the past four decades. The present systematic literature review aimed to identify existing evidence on the efficacy of mobile health technology in facilitating weight management behaviors, such as healthy food consumption and physical activity.

Evidence acquisition: A systematic search was conducted in Ovid MEDLINE and Ovid PsycINFO databases with the aim to identify studies published in peer-reviewed journal articles between 2012 and 2017.

Evidence synthesis: A total of 39 studies were analyzed in spring 2018 and are presented here in terms of participant characteristics, effective technology components, additional treatments, impact on health-related behaviors, and treatment efficacy. Indicators of study quality and social validity are also provided.

Conclusions: Mobile health apps are widely considered as satisfactory, easy to use, and helpful in the pursuit of weight loss goals by patients. The potential of mobile health apps in facilitating weight loss lies in their ability to increase treatment adherence through strategies such as self-monitoring. These findings indicate that satisfactory treatment adherence and consequent weight loss and maintenance are achieved in the presence of high levels of engagement with a mobile health app. The research quality assessment of RCTs reveals a great need for following international standards both when conducting and reporting research.

CONTEXT

Among indicators of overall health lies physical health, often assessed through BMI, a simple weight for height formula. In the last 40 years, the obese population has tripled worldwide, with 13% of all adults being obese and 39% overweight; now more countries have populations at risk of overweight or obesity than at risk of underweight.[1]

It is therefore of no surprise that overweight and obesity constitute major concerns for public health worldwide. They are leading risk factors for an array of noncommunicable diseases, including diabetes, cardiovascular diseases, and some types of cancer.[2] The primary link between obesity and these chronic conditions is the consumption of energy-dense foods, high in fat and sugar, combined with insufficient physical activity; fortunately, both are modifiable at-risk behaviors that make overweight and obesity preventable.[3]

Given the alarming rates of overweight and obesity and their associated life-threatening risks but also the problem of sustaining weight loss, the need for new approaches that are effective in reaching a wider population and promoting long-term weight management in an economically viable way has emerged.

From the [1]School of Social Sciences, Education and Social Work, Queen's University of Belfast, Belfast, Northern Ireland; and [2]Imec-SMIT, Vrije Universiteit Brussel, Brussels, Belgium

Address correspondence to: Katerina Dounavi, PhD, BCBA-D, School of Social Sciences, Education and Social Work, Queen's University Belfast, 69-71 University Street, Belfast, BT7 1HL, Northern Ireland. E-mail: k.dounavi@qub.ac.uk.

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The science of behavior analysis focuses on achieving meaningful and sustainable changes in socially significant behaviors by introducing interventions at the individual level.[4] In the case of chronic medical conditions caused by a combination of genetic and environmental factors, behavior analysis is well equipped to design interventions that achieve a reduction in overall energy intake and increase in physical activity levels, through the manipulation of the environmental factors that control these behaviors. More importantly, behavior analysts have shown sustained changes in eating and exercise behavioral patterns,[5,6] including the prevention of weight regain after the initial weight loss. Such changes have been achieved through interventions that offer the greatest initial weight loss while changing key lifestyle patterns that safeguard weight maintenance. Clearly, the application of behavior-analytic interventions can promote successful weight management, including both weight loss seeking and weight gain prevention behaviors.[7]

In the last years, knowledge arising from behavioral science combined with advances in information technology has resulted in solutions that make use of mobile phones. Mobile health (mHealth) interventions are defined as the "medical and public health practice supported by mobile phones, patient-monitoring devices, PDA, and other wireless devices."[8] The mHealth market has faced a rapid growth mainly because of the increased adoption of smartphones and access to the Internet, with 1 billion global smartphone subscriptions expected by the end of 2022.[9] mHealth applications are software programs run on smartphones, tablets, and other mobile devices that target healthcare and prevention. In 2017, there were 325,000 health apps available on major app stores, representing an impressive increase of 78,000 since 2016.[10] The most popular health apps are used for tracking physical activity and diet or adherence to medication.[11]

mHealth apps present an unprecedented opportunity for behavior change interventions targeting weight management. Especially interventions requiring sustained adherence to behavioral regimens can be enhanced by the use of persuasive technology that embeds behavioral strategies to keep users engaged.[3,12] For instance, self-monitoring of health-related behaviors (e.g., tracking of dietary intake and exercise) or health-related outcomes (e.g., weight tracking); goal setting (dietary, caloric, or weight goals); activity reminders; timely and context-sensitive feedback; and peer support are already being implemented in available health apps.[13−16] Recent attempts to meaningfully summarize these behavior change strategies have led to the creation of taxonomies,[17] which are useful in endeavors to identify effective app components, but have yet to adopt a conceptually coherent behavior-analytic framework.[18] Other technology-enabled features, such as the delivery of the intervention at any time or place and for extended periods, enabling of personalized communication, tailoring to user characteristics and needs, and adoption of user-friendly design, help leverage the burden of intervention delivery and make access to effective health care universal.

Despite the large number of mHealth apps targeting weight management, the evidence for their effectiveness remains mixed. Although some studies have shown significant changes in the desired direction,[19,20] others have yielded limited or no positive outcomes. For example, a recent systematic review found limited effectiveness of mobile technology on health behaviors and identified an important risk of bias,[21] whereas others have reported mixed outcomes[11] or promising outcomes that warrant further exploration with bigger samples and higher methodological rigor.[22]

It is worth highlighting that even when mHealth apps produce outcomes equal to those of traditional interventions, apps' capacity to reach a broader audience makes them a unique tool to be researched in its own right. In this demeanor, rigorous research methods, such as systematic reviews and meta-analyses, RCTs, single-subject research designs, and methodological quality assessments, are indispensable for building a corpus of evidence that will guide healthcare best practice. To date, only a few health apps out of thousands released for smartphone use have been tested in controlled studies. Healthcare professionals and consumers need scientific evidence on the expected benefits of mHealth apps in order to make informed decisions on their use.

The present paper responds to this gap in the scientific literature by providing a systematic literature review of peer-reviewed papers studying the effectiveness of mHealth apps in weight management, accompanied by an examination of social validity and research quality indicators.

EVIDENCE ACQUISITION

Literature Search Procedure

Literature searches were conducted in Ovid MEDLINE and Ovid PsycINFO databases in April and October 2017 and were limited to peer-reviewed journal articles published between 2012 and 2017 (including an early online published version).[23] Searches followed the PRISMA statement[24] targeting the following keywords in the title or abstract: (*weight* OR *health* OR *eat** OR *food*) AND (*technology* OR *mobile* OR *app*) AND *behavio*r*. These yielded 257 studies, reduced to 195 after removal of duplicates, which were consequently assessed against inclusion and exclusion criteria. References of eligible studies were manually scanned to identify any additional studies, followed by intercoder agreement checks. A total of 39 studies were included in the review (Figure 1).

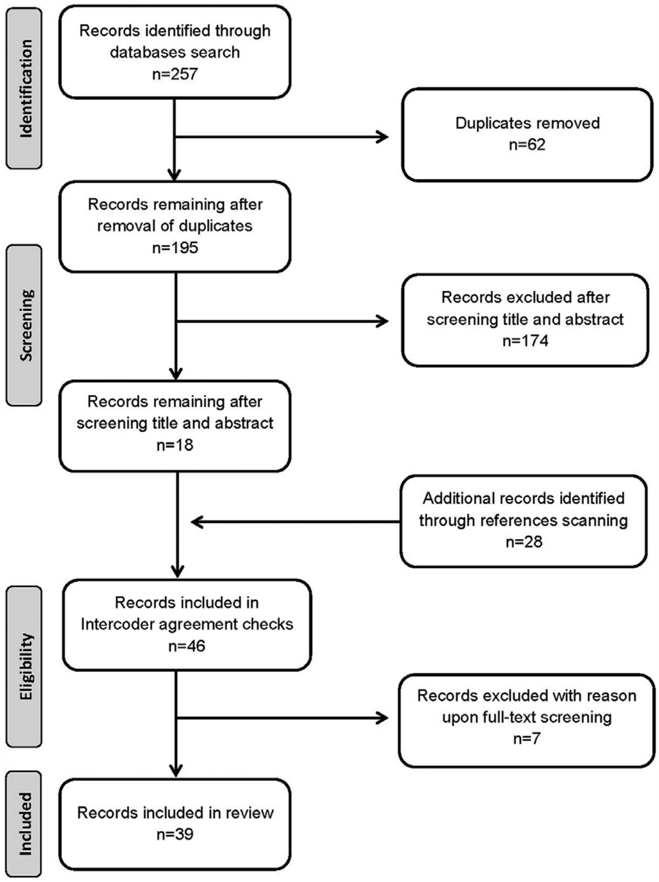

Figure 1. PRISMA 2009 flowchart illustrating inclusion process.

Inclusion and Exclusion Criteria

Identified studies were screened for eligibility if they met the following inclusion criteria: (1) adult population; (2) typical intellectual ability; (3) dependent variable: weight management behaviors; (4) independent variable: use of mobile technology including self-monitoring strategies; and (5) primary study.

Exclusion criteria leading to studies being classified as ineligible were: (1) age <18 years; (2) diagnosis of intellectual disability; (3) weight gain control in pregnancy or postpartum weight loss; (4) use of mobile technology for education/provision of information versus interactive use for self-management; and (5) lack of original data (e.g., conceptual study). Studies containing participants with underlying conditions that could affect metabolism (e.g., diabetes) were included.

Data Coding

Data extracted from studies were coded in the following categories: participant characteristics (age, sex, location, primary diagnosis, technology savviness, other); intervention (app features, feedback, reminder, other treatment); dependent variables (weight, physical activity, well-being, collateral gains); outcomes (treatment efficacy, effect size, maintenance); certainty of evidence (research design, treatment fidelity, quality assessment); and social validity. Treatment fidelity refers to the extent to which the mHealth app intervention was reliably administered as planned and whether it differed substantially from control interventions.[25,26] Social validity is inherent to treatment evaluation and can be defined as the significance of the target behavior, acceptability of the intervention, and satisfaction with obtained results.[27,28]

Study Quality Assessment

RCTs were rated following the rigor criteria established for studies included in Cochrane reviews[29] with the aim to inform healthcare decisions. For this purpose, authors independently scored a random half of RCTs against specified domains (Appendix Table 3, available online). Then, coders cross-assessed nine of 22 RCTs (41%) and reached consensus on disagreements. The quality assessment concluded by both coders re-assessing remaining studies ensuring consensus criteria had been applied.

Intercoder Agreement

During eligibility checks, the second author independently screened all studies against inclusion and exclusion criteria. Coders discussed any disagreements and reached consensus. Coding followed eligibility checks, with each author receiving a random half of studies to code. After blind coding concluded, 13 of 39 studies (33%) were blindly cross-coded. No disagreements on coding interpretations arose.

EVIDENCE SYNTHESIS

Results of eligible articles (n=39) are classified in nonrandomized studies (n=17) and RCTs (n=22), with key variables for each study presented in the following sections (Appendix Tables 1 and 2, respectively, available online). RCTs were additionally assessed for methodological quality (Appendix Table 3, available online).

Nonrandomized Studies

Participants were male or female adults (with the exception of one study that included only females)[23] predominantly from the U.S., with a few studies being conducted in the United Kingdom,[30,31] Australia,[32] New Zealand,[33] and China.[34] Participants in eight of the 17 studies had an increased BMI, with one study including cardiac rehabilitation patients.[35] All but three studies reported technology savviness (n=14), with ownership of a smartphone being the most frequent indicator; 11 studies included technology-savvy participants, whereas three included both savvy and technologically illiterate participants.

Nonrandomized studies were mainly defined as feasibility or acceptability trials and included single-armed qualitative, correlational, or secondary data analyses. Treatment fidelity was not reported in any of the studies.

Researchers tested either tailor-made apps specifically designed for the study[34] or existing apps from the public domain.[31,36] Main app components were the provision of health-related information, feedback, reminders, peer support groups, goal setting, food and physical activity logging, weight self-monitoring, digital coaching, and exceptional blood pressure tagging.[34] Additional treatments included the provision of a face-to-face coaching or assessment sessions.

Key dependent variables measured across studies were weight loss, eating and physical activity behaviors, eating and physical activity behavioral intentions, awareness of eating and physical activity goals, and glucose level. Indicators of intervention feasibility and social validity, including app use adherence, engagement, acceptability, usefulness, and satisfaction, were also measured. Collateral gains, conceptualized as gains not directly targeted by the mHealth weight management app, such as increasing social engagement with peers, were not reported in any of the studies.

Support for the efficacy of mHealth apps is provided across various weight management outcomes. Food logging frequency,[37] dietary restraint, eating concern,[38] eating goal awareness,[30] and intention to increase fruit and vegetable consumption[39] were found to increase following app use. On the other hand, overeating,[23] craving,[23] and eating disorder symptoms[38] were shown to decrease. Weight loss[36,37,39−41] as a result of app use was reported in five studies and lower glucose level[42] in one study. Physical activity level,[31,32] motivation and intention to exercise, and awareness of physical activity goals[31,32] were also shown to increase following app use. Intention to modify lifestyle behaviors and perceived control over such behaviors were also positively linked to mHealth app use.[31,34]

A few studies also support the perceived efficacy of app use in weight management. mHealth apps were more likely to be adopted by (severely) obese users for the self-management of health goals, including weight loss, and were perceived as highly effective in the self-management of such goals.[42,43] Moreover, mHealth apps were perceived as highly useful in medical care decision making, prompting medical information seeking and facilitating communication with health providers.[35,43]

Overall, the reviewed nonrandomized studies illustrate well the various benefits for weight management brought by the use of mHealth apps.

The reviewed studies lend support to the social validity of mHealth apps for weight management. Evidence is provided for validity indicators related to app use, measured in terms of app acceptability,[44,45] app engagement,[33] and adherence to self-monitoring via the app[35,40,41]; indicators related to app evaluation, such as likeability,[33] attitude toward app,[34] perceived app usefulness,[32] and ease of use and usability.[31,32] These outcomes were replicated with older patients and staff through qualitative measures.[35,46] Strong social validity is required for app effectiveness. App adherence, for example, is shown to have a positive relation with, and to also mediate the effect of app use on, eating and physical activity behaviors.[47,48]

RCTs

With the exception of one study that involved only female participants,[49] all remaining studies included both male and female adults from the U.S., Australia, the United Kingdom, Finland, South Korea, Canada, Russia, Ireland, or the Netherlands. According to their BMI, participants were overweight or obese (i.e., BMI more than 25), with the exception of a few studies that did not report BMI.[50,51] A few studies included participants with a medical condition, more specifically type 1 diabetes,[51] arterial hypertension,[46] diabetes and systolic hypertension,[52] or type 2 diabetes.[53] More than half of the studies reported technology savviness (n=13), with 11 studies including technologically savvy participants and two studies including both participants who were technologically savvy and illiterate.

RCTs involved two-, three-, and four-arm parallel groups, with participants being randomly assigned to control or intervention conditions and studies mainly aiming to compare effectiveness between these conditions by conducting prospective or post hoc analyses. Treatment fidelity was reported in only two studies.[54,55]

Participants randomly assigned to the intervention groups were granted access to apps that incorporated goal setting, food and physical activity self-monitoring, reminders/prompts for recording, tailored feedback, reinforcers, health information, social support, glucose, insulin or other medication logging, and blood pressure monitoring (Appendix Table 4 [available online] lists specific behavior change strategies). Additional treatments were offered either complementary or as alternatives to apps and included usual care, counseling, coaching, paper food diaries, printed diet booklets, visit scheduling contingent on data provided to physician through app, face-to-face intervention based on Acceptance and Commitment Therapy, financial incentives, and diet websites. A summary of behavior change strategies used across mHealth apps in RCTs can be found in Appendix Table 4 (available online), classified in antecedent and consequent.

Key dependent variables measured across RCTs were weight; BMI; physical activity; dietary intake mainly focusing on fruit and vegetable consumption, take-out meals, and sugar-sweetened beverages; anthropometric data, such as waist circumference, blood pressure, serum lipids, and glucose levels; psychological factors, such as well-being, stress, motivation, and positive or negative affect; alcohol and cigarette consumption; engagement with app; adherence to self-monitoring; and app acceptability. No collateral gains were reported in any of the studies.

Weight management behaviors mostly changed toward the desired direction. Consumption of fruits and vegetables significantly increased with app use, whereas consumption of sugar-sweetened beverages and take-out meals decreased.[54,56−60] Nonsignificant changes followed the expected direction.[61−63] Physical activity mostly increased,[50,57−59,61,64] whereas no change in physical activity was reported in two studies.[56,65]

Regarding anthropometric changes, significant weight loss (or change in the expected direction)[47,49,56,57,60,66] and reduction in BMI[59,60] and waist circumference[49,66] were reported. Absence of significant changes was also reported.[55,62−65] Moreover, reduction in glucose, blood pressure, and serum lipid levels was also found,[46,49,51,52,66] whereas two studies failed to show significant changes in blood pressure and glucose level.[64,65]

Considering user well-being, two studies revealed a decrease in depression and an increase in positive affect.[52,62] The remaining studies measuring well-being showed no change.[51,56,64,65]

mHealth apps in the reviewed studies were also characterized by strong social validity. High scores were reported for intervention acceptability,[60,67] perceived usefulness,[54,62] satisfaction,[61,65,67] and liking of and positive attitude toward the app intervention.[50,54,62] App usability, measured as ease of use and comprehensibility, also received high ratings.[50,54,62,66] Two studies showed high levels of engagement with an app (also reflecting adherence to app intervention),[51,57] whereas one study reported low engagement resulting from usability issues.[61] Support for the cost effectiveness of mHealth apps, important for user adoption and integration in healthcare practice, was provided in only one study.[65]

Only five of 22 studies (23%) presented no risk of bias across key domains.[56,57,62,64,65] All remaining 17 studies (77%) presented a high risk of bias in one or more key domains, with five (23%) presenting an unclear or high risk of bias in one or two criteria[50,52,58,61,63] and 12 (55%) presenting a high or unclear risk of bias in three or more key domains (Appendix Table 3, available online).

Upon closely analyzing quality findings, it is evident that incomplete reporting of outcome data constitutes the most frequently identified bias, with only ten studies presenting a low risk of bias. The second most frequent bias was the lack of blinding of participants and personnel, with 11 of 22 RCTs presenting a low risk. The third most frequently identified bias concerned the random sequence generation, with only 11 studies presenting a low risk of bias. Selective outcomes reporting did not present a risk of bias in any of the studies, same as blinding of outcomes assessor with the exception of two studies that presented an unclear risk. Finally, on the criterion of allocation concealment, 12 studies presented a low risk, two a high risk, and eight an unclear risk.

DISCUSSION

Social Validity

Both nonrandomized studies and RCTs reported that patients were satisfied with the use of the app, found it useful in the pursuit of their weight and physical activity goals, and easy to use. Over the course of two studies, authors reported that engagement with the app declined.[51,65] Hebden et al.[61] reported that usability issues caused a decrease in engagement with app. It is noteworthy that these positive attitudes toward app use were confirmed irrespective of participants' older age,[35,44] suggesting that mHealth technology can bring benefits to a wide population. Overall, included studies come to a concord that app use for weight management is widely accepted and regarded as useful by participants. However, this concord arises from less than half of eligible studies with the remaining studies not reporting social validity data. Social validity can be equally important to effectiveness for ensuring treatment adherence, particularly given its role in mediating the effectiveness of app use on weight management.[48,68] Therefore, future research should routinely incorporate measures of intervention acceptability and satisfaction with technology and carefully inspect their role in facilitating app efficacy.

Given the importance of reporting technology savviness of study participants for findings to be generalizable to other populations and the fact that only 69% of all studies included in the present review reported on this aspect (14 nonrandomized studies and 13 RCTs), future research should incorporate routine measurements of duration of smartphone ownership and regular access to Internet during baseline assessment in order to determine whether familiarity with the use of technology plays a role in treatment acceptability, adherence, and efficacy.

App Effectiveness

mHealth apps can be effective in the self-management of weight, such as in reducing weight, and improving health indicators, such as glucose levels and blood pressure, provided specific characteristics identified in RCTs as effective are incorporated.[32,46–50,52–54,56–59,64,66,67] These include the effortless self-monitoring of diet and physical activity, tailored feedback provision, reminders for app use, and interaction with peers.[48,63] The integration of such features increases user engagement with the treatment, which, in turn, promotes successful weight management.[69]

It is worth pointing out that although one study[63] found no significant improvements as a result of using a PDA for self-monitoring, the authors confirmed that stronger adherence is linked to higher weight loss and that adherence increases with frequent feedback, as also pointed out by others.[48] It would therefore be reasonable to assume that mobile apps can increase adherence and consequent weight loss through the provision of frequent tailored feedback, feeding in the same lifestyle change mechanism and facilitating weight management.

When focusing on the behavioral patterns that lead to changes in health indicators, such as lipid and glucose levels, it is clear that these patterns are representative of healthy eating (including high consumption of fruits and vegetables and low consumption of calorie-dense takeaway meals and sugary drinks) and regular physical activity (measured predominantly through daily steps). Furthermore, habitual behaviors, such as alcohol consumption, and behaviors with a negative impact on well-being, such as stress-causing behaviors, deserve further attention in the context of mHealth interventions as they can inhibit weight management efforts. Such behaviors, the same as any behavior that brings socially significant changes in people's lives, is the focus of the science of behavior analysis, which through decades of research has identified effective components of interventions targeting weight loss.[70] When mHealth apps incorporate some of these behavioral components as well as new technology-enabled features, they create powerful tools that help health professionals and individuals achieve their goals. These apps can be combined with traditional interventions, such as face-to-face counseling,[60] potentially boosting overall effectiveness, or be used as standalone treatments.[62] In both cases and in line with what other authors have reported,[71] this systematic review confirmed that mHealth apps are increasingly used as a cost-effective[43] and easy-to-use technological means for the delivery of behavior change interventions targeting weight loss.

Regarding measures of weight maintenance, these should be taken at 2 years' post-intervention follow-ups or later.[72] In this review, only a small proportion of RCTs included follow-up measures.[55,56] Given clinical recommendations suggest ongoing behavioral support is necessary for lifestyle changes to be sustained,[69] continuous use of mHealth apps could make this feasible and cost effective. In terms of the generalizability of these results, participants included in reported studies were male and female adults, with a BMI indicating overweight or obesity, predominantly from the U.S. or other developed countries and occasionally with a diagnosed disease, such as diabetes. Results could therefore be generalized to populations with similar characteristics and more research would be required in non-Western countries and with populations with different characteristics, such as medical condition or SES. The study of mHealth efficacy in the weight management of populations diagnosed with medical conditions related to eating behavior, such as disordered eating behavior, could greatly benefit from the use of apps capable of increasing adherence to recommended treatments.

Research Quality Limitations of Eligible Studies

Evidence-based medicine arises from methodologically rigorous studies that report replicable results. In the attempt to base clinical decision making on strong evidence combined with patient needs and wishes, the authors have reported on treatment fidelity, identifying only two RCTs that reported this measure of validity and reliability. Technology enables the automatic measurement of certain treatment fidelity aspects, while it completely eliminates the need to measure provider training. However, the need to measure treatment delivery, receipt, and enactment is still important and questionnaires specifically designed to measure these aspects should be incorporated in future trials.[26] RCTs need to be reported in a standardized manner[73] and behavior change strategies need to be rated following a coherent behavior-analytic framework.[17] Additionally, the authors have used the research quality standards published for Cochrane reviews.[29] Unfortunately, results of this research quality assessment indicated that only five of 22 studies (23%) presented no risk of bias across key domains, with remaining studies presenting a high risk of bias in one or more key domains. This outcome is a cause of concern, given RCTs have been considered the gold standard for policy-making and consequent clinical decision making.[74]

Bias can lead to an erroneous estimation of the intervention effect and corresponding flawed conclusions. For these reasons, future studies should ensure that compliance with Cochrane rigor criteria is guaranteed by verifying that research procedures follow research quality recommendations, especially in relation to outcomes data reporting, blinding of participants and personnel, and random sequence generation. Overall, the field would benefit from more detailed reporting of procedures, ensuring that risk of bias is assessable.

Limitations

Language biases might exist, because these searches were conducted in English. Additionally, relevant studies indexed in other databases may have been missed. This risk however is estimated to be low, as hand searching references of included studies yielded additional results that made this review systematic and comprehensive. Also, no gray literature studies were included, as the authors wished to limit the searches to renowned peer-reviewed journals, yet this fact might have biased the findings.

Because of the complexity and heterogeneity of included studies, no meta-analysis was conducted. A meta-analysis would quantify effect sizes of included RCTs and provide a precise estimate of treatment efficacy of mHealth apps, an important element in evidence-based medicine. Future systematic reviews should include a meta-analysis of studies.

It is worth mentioning that this review has been limited to mobile applications, without specifying whether a sensor was used together with the mHealth app. Given sensors, such as pedometers, allow for the automatic recording of behaviors and have become increasingly popular, it would be worth exploring how they might increase adherence to treatment, improve data collection precision, and maximize treatment efficacy.

CONCLUSIONS

mHealth applications seem to facilitate weight management across a wide range of measured outcomes. There is sufficient consensus across studies that mHealth apps are acceptable by patients and effective in producing weight loss through lifestyle changes in eating behaviors and physical activity patterns. The examination of social validity indicators reveals a pattern where higher engagement with mHealth applications is associated with greater treatment adherence and consequent weight loss. This study also highlights the need to obtain further empirical evidence about the role of social validity as a mechanism underlying the influence of mHealth app use on weight management behaviors. Future research should focus on weight maintenance and generalizability of results with wider populations. The present systematic review has drawn attention to the low research quality of past studies, as indicated by the use of Cochrane criteria. Methodological rigor should be ensured through compliance with evidence-based medicine standards.

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SUPPLEMENTAL MATERIAL

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