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Effectiveness of interactive technology-assisted interventions on promoting healthy food choices: a scoping review and meta-analysis

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Abstract

Making healthy food choices is crucial for health promotion and disease prevention. While there are an increasing number of technology-assisted interventions to promote healthy food choices, the underlying mechanism by which consumption behaviours and weight status change remains unclear. Our scoping review and meta-analysis of seventeen studies represents 3988 individuals with mean ages ranging from 19·2 to 54·2 years and mean BMI ranging from 24·5 kg/m^2 to 35·6 kg/m^2. Six main outcomes were identified namely weight, total calories, vegetables, fruits, healthy food, and fats and other food groups including sugar-sweetened beverages, saturated fats, snacks, wholegrains, Na, proteins, fibre, cholesterol, dairy products, carbohydrates, and takeout meals. Technology-assisted interventions were effective for weight loss (g = –0·29; 95 % CI –0·54, –0·04; I^2 = 65·7 %, t = –2·83, P = 0·03) but not for promoting healthy food choices. This highlights the complexity in creating effective interactive technology-assisted interventions and understanding its mechanisms of influence and change. We also identified that there needs to be greater application of theory to inform the development of technology-assisted interventions in this area as new and improved interventions are being developed.

Key words: Technology: Food choice: Obesity: Weight loss: Public health

By 2030, more than 38·5 % of the global adult population will be living with overweight or obesity[1], increasing one's risk of chronic diseases including cardiometabolic diseases[2], certain cancer[3], musculoskeletal disorders[4], cognitive impairment[5], and depression[6]. Local and international health organisations have implemented public campaigns, programmes and initiatives to improve population diets but remains insufficient. For example, one study found only a 16 % more people who were exposed to a public health advertisement focusing on healthy food choices and physical activity searched up on more information on weight loss as compared with the control group[7]. The authors further reported that an advertisement targeted at lifestyle preferences and sociodemographic profiles explained 49 % of the variance in responses, highlighting the intricate interactions between individual, interpersonal and environmental (micro and macro) factors[8,9]. Individual factors include biological (e.g. appetite and hunger), psychological (e.g. emotion-trigger eating) and cognitive (e.g. preference) factors and interpersonal factors include *family, cultural and peer* influence[10]. Micro-environmental factors includes schools, workplace, residential neighbourhood and community health care facilities. Macro-environmental factors include the built environment (e.g. transport and infrastructure) and food environment (e.g. food availability, accessibility and advertising)[11]. In this 21st century, technology has been integrated into our everyday lives and must be added to the obesogenic system of factors. For example, technology has been used as an obesogenic vector marketing practices leverages the power of artificial intelligence to influence consumer dietary preferences towards unhealthy food choices[12]. Food can also be conveniently, cheaply and readily obtained via smartphone food delivery apps, further promoting the consumerism culture that encourages easy consumption, overconsumption and food wastage[13]. On the other hand, technology has been used to improve eating habits through smartphone apps as an interactive interventions (requiring a two-way engagement between the user and technology system[14], and hereinafter stated as technology-assisted interventions) to enhance health promotion efforts by prolonging engagement and hence behaviour change activation[15,16]. Such apps commonly include functions of food logging, goal setting and to deliver health messages, which has been shown in various systematic reviews to result in successful weight loss[17–20]. However, the underlying mechanism by which

Abbreviations: ROB, risk of bias.

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technology-assisted interventions influence weight loss, perhaps through adopting a healthy diet, remains unclear[21].

A healthy diet generally constitutes the consumption of a balanced diet that is rich in fruits, vegetables, wholegrains, fibre, low-fat dairy products, fish, legumes, nuts, PUFA, low saturated and *trans*-fats, sugar, refined carbohydrates and sodium[22,23]. However, research studies on the effectiveness of technology-assisted interventions seldom evaluate all the food groups that contribute to a healthy diet. To our best knowledge, there is no review on the food choices that are commonly examined as outcomes of technology-assisted interventions. Knowing the effects of such interventions on various food choices would inform the underlying mechanism of weight loss arising from such intervention and inform future health promotion interventions[24,25].

Therefore, we aimed to scope the food choice-related outcomes assessed in studies to conduct a *post hoc* evaluation on the effects of technology-assisted interventions on each of the outcomes using meta-analysis, whenever statistically possible.

Methods

We conducted a scoping review according to the Arksey and O'Malley framework[26] and reported our findings according to the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist (Appendix 1)[27].

Search strategy

We searched through seven electronic databases (i.e. Embase, CINAHL, PubMed, PsycINFO, The Cochrane Library, Scopus and Web of Science) for articles published from inception through 22 March 2022. An initial search of PubMed was first conducted using keywords and medical subject headings (MeSH) terms derived from the concepts of 'food choice' and 'technology' to identify more keywords and index terms. The search was then refined according to each database using Boolean operators AND and OR and keywords shown in Appendix 2.

Study selection

Titles and abstracts screening were first performed by HSJC according to a prespecified set of eligibility criteria defined using the population, intervention, comparison, outcome and study design (PICOS) framework.

Population: Studies on adults aged above 18 years, normal or overweight were included. Studies on subjects with existing health conditions and pregnancy were excluded as the dietary requirements may be different.

Intervention: Studies on technology-assisted interventions were included. Studies that focused on food labelling, message reminders or other non-interactive provision of nutritional information were excluded. Studies that used a virtual supermarket as a test setting or an online home grocery delivery service with no other technology-assisted components were excluded.

Outcomes: Studies that measured food choice in terms of purchase or consumption were included. Studies that measured alcohol consumption only were excluded as alcohol is not a common part of one's daily diet.

Study design: Randomised controlled trials

Studies that were not in the English language or was without version in the English language were excluded. Once the duplicated articles were removed, full texts of the articles were screened independently by HSJC and SC to further shortlist the articles to be included in this review. Interrater agreement was calculated for methodological quality assessment using the Cohen's Kappa statistic.

Of a total of 1324 articles retrieved, 526 duplicated articles were removed, resulting in 798 articles screened for eligibility using titles and abstracts. After removing 749 articles and adding three articles found through reference hand searching, forty-nine full-text articles were retrieved and screened for eligibility. Thirty-two articles were removed with reasons as shown in Fig. 1, resulting in a final seventeen articles included in this review. Sixteen articles reporting thirty-five unique outcome results were included in the meta-analysis. Interrater agreement for the risk of bias (RoB) was $k = 0{\cdot}822$, $P = < 0{\cdot}001$, indicating a strong level of interrater agreement.

Data extraction

A form was created using an excel spreadsheet to extract information according to the following headings: authors, year of publication, outcomes measured, measurement unit of each outcomes measured, country, sample size, sample characteristics, programme name, intervention type, intervention components, duration, intervention group condition, control group condition, delivery mode (i.e. individual or group), mean age, percentage of male subjects, socio-economic status, educational level, baseline weight, weight measurement instrument, baseline BMI, follow-up time point(s), attrition rate by the time of analysis, presence of comparison between participants retained and lost to follow-ups, method of missing data management (e.g. intention-to-treat (ITT)/per-protocol (PP) analysis), presence of protocol registration, and presence of funding. Data extraction was first piloted on three articles, and additional headings were added. Measures of central tendency (mean or mean difference) and variance (standard deviation or standard error) on each outcome were extracted in its raw form.

Methodological quality and certainty of evidence assessment

The methodological quality of the included articles was assessed using the Cochrane's RoB tool. Articles were rated as low, unclear or high RoB according to six domains namely random sequence generation, allocation concealment, blinding of participants and personnel, blinding of outcome assessment, outcome data completeness, and selective reporting[28].

Data analysis

Effect size estimates were converted to standard mean differences expressed as Hedges' *g* and pooled using random effects models. Hedges' *g* was used to correct for the small number of studies included in the meta-analysis (four to seven studies) where a magnitude of $0{\cdot}2 =$ small, $0{\cdot}5 =$ moderate,

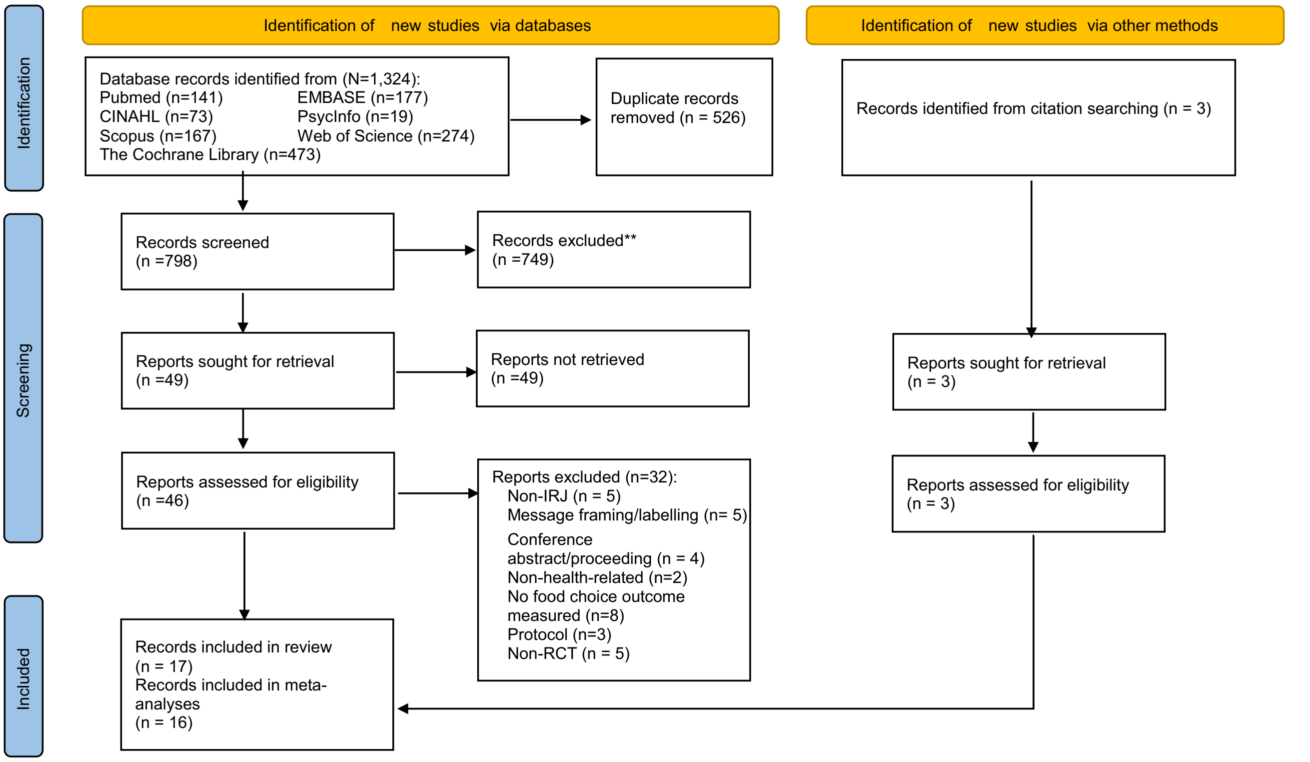

Fig. 1. PRISMA flow chart.

0·8 = large and 1·2 = very large[29]. The Hartung–Knapp–Sidik–Jonkman (HKSJ) was used for to adjust the random effects models instead of the more widely used DerSimonian–Laird (DL) method as it has been shown to result in less false-positive estimates, especially in small samples and high heterogeneity[30]. Between-study heterogeneity was assessed using Cochrane's Q statistics and quantified by I^2 statistics where a statistic of 50 % indicates heterogeneity[31].

All analyses were performed using R version 4.1.3.

Results

The seventeen included studies in this review represents 3988 individuals with mean ages ranging from 19·2[32] to 54·2[33] years and mean BMI ranging from 24·5 kg/m^2[34] to 35·6 kg/m^2[33] (one study did not report the subjects' BMI[35]) (Table 1). Most of the included studies were conducted in the USA (*n* 7, 41·2 %) and Australia (*n* 6, 35·3 %), and there was a relatively proportionate number of studies performed with subject with (*n* 8, 47·1 %) and without the criteria of having overweight (*n* 9, 52·9 %). Four articles were assessed to have a high RoB (23·5 %)[33,36–38], four articles were assessed to have a low RoB (23·5 %)[39–42] and nine had an unclear RoB (Appendix 3).

The interventional durations ranged from 2 weeks to 1 year and the attrition rates ranging from 3·9 %[32] to 76 %[35]. Various modes of delivery were used, including smartphone apps (*n* 12, 70·6 %), websites (*n* 7, 41·2 %) and hardcopy handouts (*n* 3, 7·3 %) (Table 2). The technology-assisted components of the interventions were designed to improve food choices through self-monitoring[32,33,35,37–39,41–44], goal setting[32,33,37,39,41,43], feedback[32,33,35,37,42,43], education[33,34,37,45], inhibitory control[36,40,44,46], nudging[47,48] and social support[44]. Two studies seemed to have been conducted on the same population[39,41]. Seven studies (41·2 %)[32,34,37,39,41,44,45] reported the use of a theory or framework when developing the intervention and study. All studies except two were funded[35,36], and five studies did not report the registration of the study protocol[35,36,40,45].

Weight loss

Eight studies[33,34,37,39–41,44,46] reported interventional effects on weight of which four studies[34,39–41] reported significantly higher weight loss in participants from the intervention groups. A meta-analysis of seven studies showed a significant (t = −2·83, P = 0·03) small to moderate pooled interventional effect size on weight (g = −0·29; 95 % CI −0·54, −0·04; I^2 = 65·7 %; refer to Table 3, Fig. 2). One study did not report the subjects' BMI[35].

Total calories consumption

Six studies[34,37,38,40,44,48] reported interventional effects on total calories consumed per d (one study reported the total calories of food to be consumed per d in the users' shopping cart[48]) of which two studies[37,40] reported significantly reduced total calorie consumption in participants from the intervention groups. A meta-analysis of the six studies showed a non-significant (t = −0·61, P = 0·57) pooled interventional effect size on total calories consumption per d (g = −0·08; 95 % CI −0·44, 0·27; I^2 = 87·3 %; refer to Table 3, Fig. 3).

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Table 1. Summary of sample characteristics of the seventeen studies

Authors, year	Country	Sample size	Sample characteristics	Mean age	% Males	Mean baseline BMI	Attrition rate by the time of analysis	Risk of bias rating
Allman-Farinelli *et al.*, 2016	Australia	250	General	27·6	38·7	27·0	14·4	Low
Blackburne *et al.*, 2016	Australia	58	Overweight	36·48	19	29·5	10·3	High
Coffino *et al.*, 2020	USA	53	General	46·4	74	28·6	8·6	Unclear
Eisenhauer *et al.*, 2021	USA	80	Overweight	54·2	100	35·6	7·5	High
Duncan *et al.*, 2020	Australia	116	Overweight	44·5	29·3	31·7	53·4	High
Hutchesson *et al.*, 2018	Australia	57	Overweight	27·1	0	29·4	24·6	Unclear
Irvine, *et al.* 2004	USA	517	General	42·78	27·3	NS	NS	Unclear
Kakoschke *et al.*, 2018	Australia	60	Overweight	26·93	35	30·3	NS	Unclear
Kaur *et al.*, 2020	India	732	General	52·7	24	24·5	8·7	Unclear
Lawrence, *et al.* 2015	UK	84	Overweight	50·46	26·4	28·9	3·4	Low
Lugones-Sánchez *et al.*, 2022	Spain	650	General	48·3	31·5	33·1	10	High
Mummah, *et al.* 2017	USA	135	Overweight	39·8	37·8	28·0–40·0	5·2	Low
O'Brien *et al.*, 2016	USA	154	General	19·2	32	NS	3·9	Unclear
Palacios *et al.*, 2018	USA	51	Overweight	35·3	<88	34·5	32	Unclear
Partridge *et al.*, 2015	Australia	250	General	27·6	38·7	27·0	14·4	Low
Plaete *et al.*, 2015	Belgium	529	General	31·6	40	NS	76	Unclear
Spring *et al.*, 2018	USA	212	General	40·8	23·6	34·3	17·9	Low

NS, not specified.

Vegetables consumption

Seven studies[35,38,39,43,44,47,48] reported interventional effects on vegetables consumption of which four studies[35,39,44,48] reported significantly higher vegetables consumption per d in participants from the intervention groups. A meta-analysis of five studies showed a non-significant ($t = 0{\cdot}99$, $P = 0{\cdot}37$) pooled interventional effect size on vegetables consumption per d ($g = 6{\cdot}29$; 95 % CI –10·00, 22·59; $I^2 = 97{\cdot}9$ %; refer to Table 3, Fig. 4).

Fruits consumption

Six studies[35,38,39,44,47,48] reported interventional effects on fruits consumption of which four studies[35,39,44,48] reported significantly higher fruits consumption per d in participants from the intervention groups. A meta-analysis of five studies showed a non-significant ($t = 0{\cdot}17$, $P = 0{\cdot}87$) pooled interventional effect size on fruits consumption per d ($g = 0{\cdot}06$; 95 % CI –0·85, 0·86; $I^2 = 95{\cdot}4$ %) (Table 3, Fig. 5).

Healthy food consumption

One article reported two intervention arms which were analysed as two separate studies[46], resulting in five studies that reported interventional effects on healthy food consumption[32,36,43,46]. Two studies reported significantly higher healthy food consumption per d in participants from the intervention groups[36,46]. A meta-analysis of four studies showed a non-significant ($t = 1{\cdot}00$, $P = 0{\cdot}39$) pooled interventional effect size on healthy food consumption per d ($g = 0{\cdot}20$; 95 % CI –0·42, 0·81; $I^2 = 55{\cdot}9$ %) (Table 3, Fig. 6).

Fats consumption

Four studies[34,38,45,48] reported interventional effects on fats consumption of which three studies[34,45,48] reported significantly higher fats consumption per d in participants from the intervention groups. A meta-analysis of four studies showed a non-significant ($t = 0{\cdot}99$, $P = 0{\cdot}38$) pooled interventional effect size on fats consumption per d ($g = -1{\cdot}05$; 95 % CI –2·15, 0·05; $I^2 = 98{\cdot}0$ %; refer to Table 3, Fig. 7).

Findings from other food groups

The interventional effects on other food groups were reported including that of sugar-sweetened beverages[33,38,39,47], fruits and vegetables (examined together instead of separately)[33,34,42], saturated fats[38,42,48], snacks[38,40,47], wholegrains[38,47,48], Na[34,38,48], proteins[34,38,47], fibre[34,38,48], cholesterol[38,48], dairy products[38,47], carbohydrates[34,38] and takeout meals[39,44].

Discussion

We conducted a scoping review and meta-analysis to provide an overview of the effectiveness of interactive technology-assisted interventions on commonly targeted food choice outcomes and consequently weight loss. The common food choice outcomes reported in the included articles were total calorie consumption and consumption of vegetables, fruits, healthy food and fats. Although more than 50 % of the included studies reported significant interventional effects on their respective outcomes, our meta-analysis only found significant interventional effects on weight loss.

Given that weight loss results from a caloric deficit either from a decrease in caloric intake or an increase in caloric expenditure, the non-significant interventional effect on total caloric consumption remains unclear. Though four studies reported findings on both weight loss and total calorie intake, only one study reported consistent findings for the effectiveness of an interactive technology-assisted intervention resulting in a decrease in total calorie intake and significant weight loss[40]. One study[39] reported a significant weight loss but non-significant change in total calorie intake, while two studies reported the opposite[34,37]. One reason for this inconsistency could be due to the small number of studies included in the

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Table 2. Intervention characteristics of the seventeen studies

Authors, year	Intervention name	Underlying components	Theoretical framework	Single or multi-component	Duration	Follow-up time points	Mode of delivery	Intervention group condition	Control group condition
Allman-Farinelli *et al.*, 2016	TXT2BFiT	Improve self-monitoring and goal setting	Control theory, TTM and MI	Multicomponent	3 months	9 months	f2f, smartphone app, website and handout	Coaching calls, text messages, emails, apps and downloadable resources from the study website.	No coaching and no app.
Blackburne *et al.*, 2016	NoGo iOS app	Inhibitory control training	NS	Single	2 weeks	3 weeks	Smartphone app	Go/No-go task	Waitlist control
Coffino *et al.*, 2020	Supplemental Nutrition Assistance Program (SNAP)	Nudging through default options	NS	Single	NS	NS	Website	SNAP and nutrition education	Nutrition education only
Duncan *et al.*, 2020	'Balanced' smartphone app and CalorieKing Wellness Solutions Inc	Improve self-monitoring education, goal setting, and feedback on behaviour	Social cognitive and self-regulatory theories	Multicomponent	12 months	6 months and 12 months	Smartphone app	Personalised dietary recommendations, 'Balanced' smartphone app, CalorieKing website or the Control My Weight app by CalorieKing, body weight scale, Fitbit activity tracker and a participant handbook.	Waitlist control
Eisenhauer *et al.*, 2021	Lose-It! premium version	Improve self-monitoring education, goal setting and feedback on behaviour	NS	Multicomponent	6 months	3 months and 6 months	Smartphone app	Lose-It! premium (additional insight trend reports, text message prompts, Wi-Fi weight scale, peer interaction, Internet connection troubleshooting and re-engagement support)	Lose-It! basic
Hutchesson *et al.*, 2018	Be Positive Be Health (BPBH)	Improve self-monitoring, stimulus control, cognitive restructuring and social support	Social cognitive theory and control theory	Multicomponent	6 months	6 months	Website, Smartphone app, email and text messages	Using BPBH programme	Waitlist control
Irvine, *et al.* 2004	NS	Education	TTM	Single	2 months	60 d	Videos audio, video, graphics and handout	Interactive multimedia (IMM)	Waitlist control
Kakoschke *et al.*, 2018 (three-arm study)	Approach-avoidance training (AAT) and episodic future thinking (EFT)	Inhibitory control training	NS	Single	6 weeks	6 week	Smartphone app	AAT and EFT	No intervention
Kaur *et al.*, 2020	SMART Eating Program	Education	PRECEDE-PROCEED model	Single	6 months	6 months	Smartphone app	IT-enabled nutrition education	Pictorial pamphlet on the dietary recommendations
Lawrence, *et al.* 2015	Go/No-go task	Inhibitory control training	NS	Single	6 months	1 month and 6 months	Website	Go/No-go task with food items	Go/No-go task with food items
Lugones-Sánchez *et al.*, 2022	Evident 3 app	Improve self-monitoring	NS	Multicomponent	3 months	3 and 12 months	Smartphone app	App and activity tracker wristband	No app and activity tracker wristband

Table 2. (*Continued*)

Authors, year	Intervention name	Underlying components	Theoretical framework	Single or multi-component	Duration	Follow-up time points	Mode of delivery	Intervention group condition	Control group condition
Mummah, *et al.* 2017	Vegethon	Improve self-monitoring, goal setting and feedback on behaviour	Unclear	Multicomponent	12 months	8 weeks	Smartphone app	Vegethon mobile app	Waitlist control
O'Brien *et al.*, 2016	NS	Personalised feedback, motivational enhancement and self-regulation strategies	Self-regulation and goal systems theory	Multicomponent	NS	1 month	Website	Web intervention + SMS and web-based-only intervention	Assessment-only condition
Palacios *et al.*, 2018	MyNutriCart	Nudging	NS	Single	2 months	NS	Smartphone app	MyNutriCart app	Dietary counselling
Partridge *et al.*, 2015	TXT2BFiT	Improve self-monitoring and goal setting	Control theory, TTM and MI	Multicomponent	3 months	9 months	Smartphone app, website and handouts	Coaching calls, text messages, emails, apps and downloadable resources from the study website.	No coaching and no app.
Plaete *et al.*, 2015	MyPlan	Action planning, problem-solving, self-monitoring, personalised feedback and dynamic tailoring	NS	Multicomponent	1 month	1 month	Website	Survey	No intervention
Spring *et al.*, 2018 (Three-arm study)	Make Better Choices 2 (MBC2)	Self-monitoring and feedback	NS	Multicomponent	9 months	6 months and 9 month	Smartphone app	App content focused on MVPA either simultaneously with (simultaneous) or sequentially after (sequential) other diet and activity risk behaviours (fruits and vegetables, and sedentary leisure screen time)	App content focused on stress and sleep

MI, motivational interviewing; MVPA, moderate to vigorous physical activity; NS, not specified; RCT, randomized controlled trial; TTM, transtheoretical model.

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Table 3. Meta-analyses of the effects of interactive technology-assisted interventions on weight, total calories, vegetables, fruits, healthy food and fats

Outcomes	Number of studies combined	Effect size (*g*)	95 % CI†	*t*	*P*	Heterogeneity (I^2)
Weight	7	–0·29	–0·54, –0·04	–2·83	0·03*	65·7 %
Total calories	6	–0·08	–0·44, 0·27	–0·61	0·57	87·3 %
Vegetables	6	6·29	–10·00, 22·59	0·99	0·37	97·9 %
Fruits	5	0·06	–0·85, 0·86	0·17	0·87	95·4 %
Healthy food	4	0·20	–0·42, 0·81	1·00	0·39	55·9 %
Fats	4	–1·05	–2·15, 0·05	–3·04	0·06	98·0 %

g, Hedges' g; *t*, t-statistic.
* $P < 0·05$.
† Hartung–Knapp–Sidik–Jonkman (HKSJ) method for random effects meta-analysis.

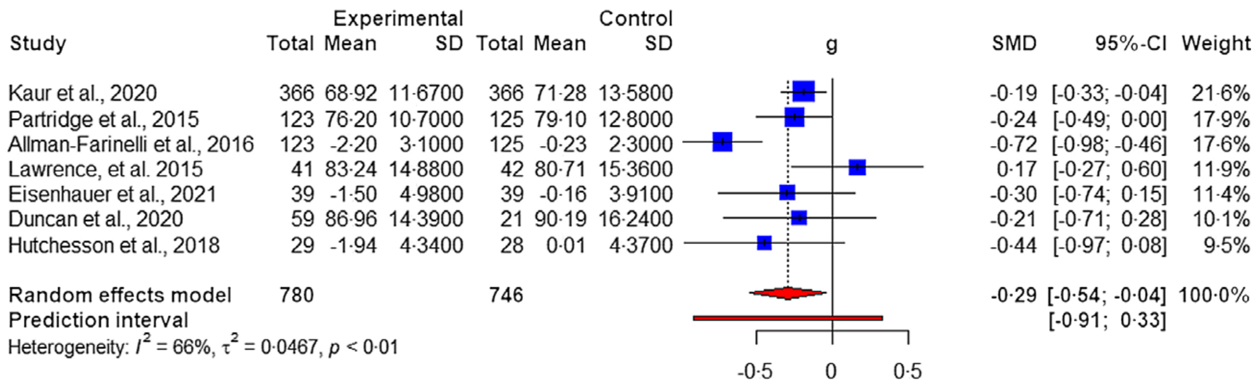

Fig. 2. Forest plot of the pooled effect sizes of seven studies on weight expressed in Hedges' *g*.

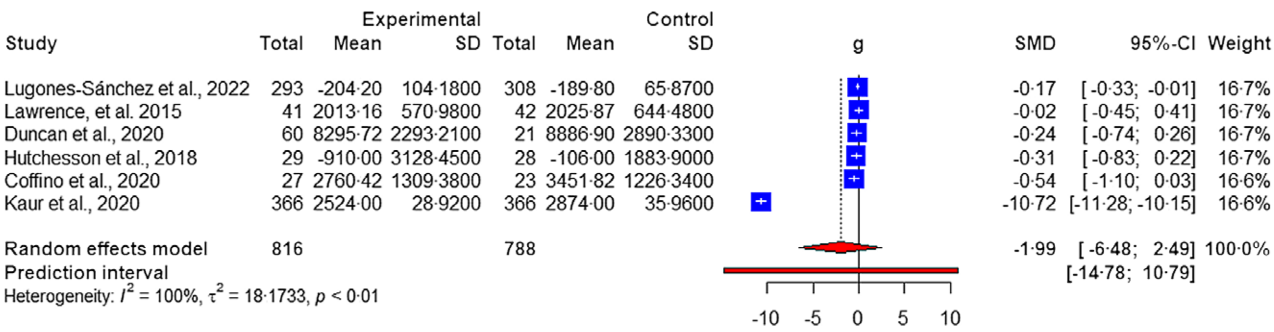

Fig. 3. Forest plot of the pooled effect sizes of six studies on total calories consumption per d expressed in Hedges' *g*.

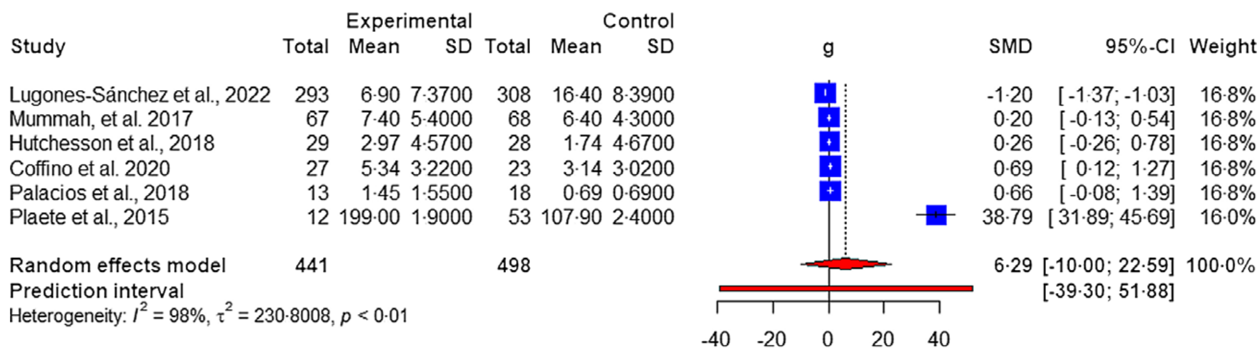

Fig. 4. Forest plot of the pooled effect sizes of six studies on vegetables consumption per d expressed in Hedges' *g*.

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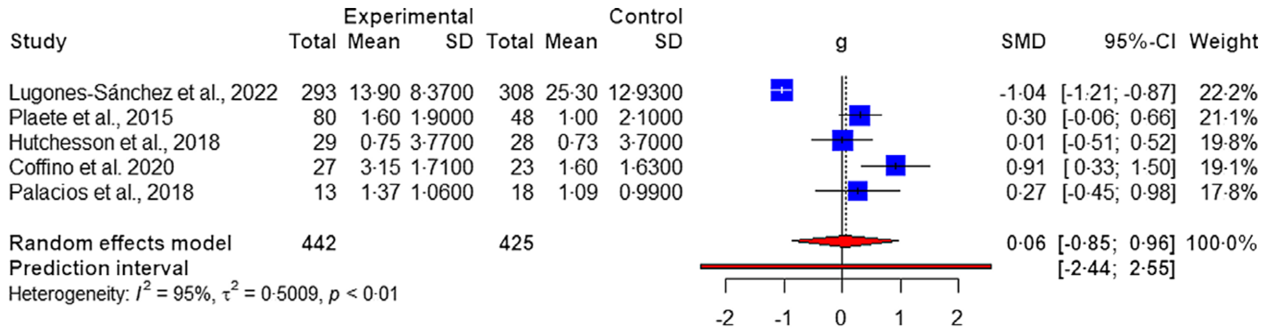

Fig. 5. Forest plot of the pooled effect sizes of six studies on fruits consumption per d expressed in Hedges' *g*.

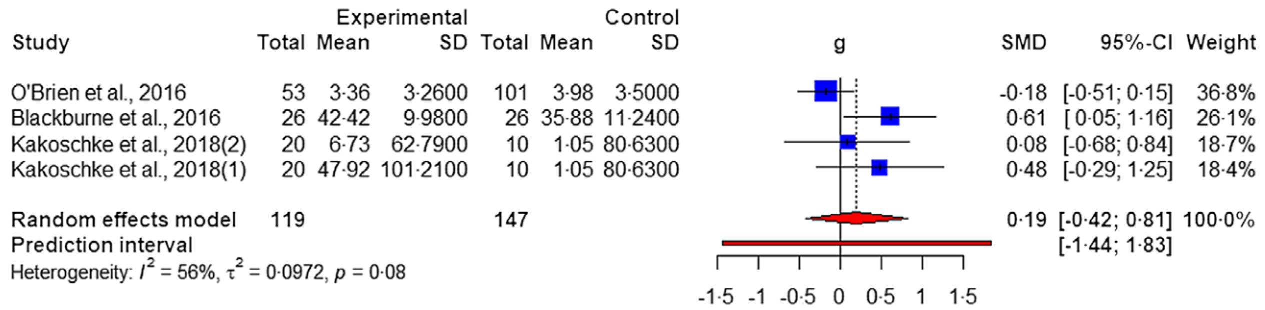

Fig. 6. Forest plot of the pooled effect sizes of six studies on healthy food consumption per d expressed in Hedges' *g*.

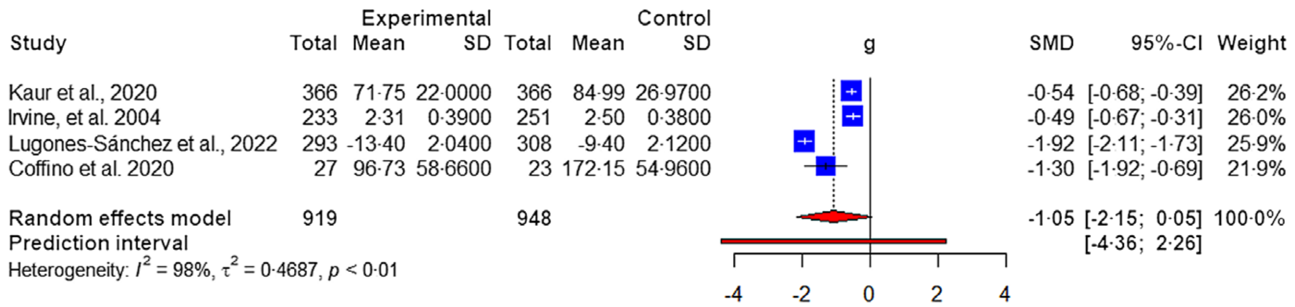

Fig. 7. Forest plot of the pooled effect sizes of six studies on fat consumption per d expressed in Hedges'.

meta-analysis, and the fact that there was a wide range of sample sizes thus the statistical weight could not be proportionally distributed by sample size. Another reason could be due to the proportionate increase in healthy food consumption (especially energy-dense food groups like protein and wholegrain instead of calorie-light food groups like vegetables) and decrease in unhealthy food consumption, leading to no change in calorie intake when aggregated[49]. Lastly, this could indicate the complexity in weight loss such that it should not be understood merely as an equation of calories intake and output, but also as an outcome of food quality. Further studies are necessary to ascertain the optimal dietary composition for weight loss, considering important biopsychosocial factors such as demographics[50], environments, lifestyles (i.e. sleep, meal frequency and physical activity)[51], resources, genetics[52] and gut health[53] which may not be as effectively influenced, if possible at all to do so, by interactive technology-assisted interventions.

Given the general prevalence of technology in our daily lives, it was surprising to have identified only a small number of studies that have developed, piloted and evaluated the use of technology-assisted interventions to influence food choices and consequently weight loss outcomes. Nevertheless, from the studies identified, 53 % were published in the last 4 years (from 2018), indicating a clear trend of more technology-assisted interventions being explored. In particular, the use of smartphone app-based intervention is the dominant choice, moving away from website-based and mobile text message-based interventions. It was not possible, in this scoping review, to analyse the effectiveness of the different types of technology-assisted interventions because of the heterogeneity of the interventions, but as a critical mass of similar interventions are tested and published this analysis should be conducted in future reviews to evaluate the effectiveness of these interventions.

From our reviewed studies, we also identified that the development of the technology-assisted interventions and the studies evaluating them should be more theoretically informed. Majority of the studies (58·8 %) did not use or specify an underpinning theory or framework. Greater and effective use of theory going forward would be important in advancing the research and development of interventions in this area. The technology employed in the interventions are a means of delivering interventions, but these interventions should be theoretically informed to target specific levers of informed behaviour change. Introducing a technology without clearly understanding how it might lead to behaviour change should not be an intervention.

This scoping review is not without limitations. Firstly, it might have been possible that some studies on the effects of interactive technology-assisted interventions on the consumption of various foods may have been excluded due to lack of mention about food choice, leading us to preclude these relevant studies. However, when identifying studies in this review, we searched using a list of commonly targeted food groups to ensure that we were able to identify the relevant studies. Secondly, with the small number of studies reviewed, an even smaller number of studies was included in the meta-analysis, and thus this could have introduced biased estimates. We tackled this problem by adjusting the random effects models with the HKSJ method, which is a well-established method for such situations[54]. Thirdly, due to the heterogeneity of the technology-assisted interventions identified, we were not able to conduct further needed analysis to compare between the types of interventions. Lastly, the studies reviewed here spanned a wide age range. Given that there might be differences in the level of affinity with technology and across age groups, this could have been an influential in some studies included in this review. Future intervention studies might consider exploring potential age differences as part of their evaluation process. This, together with the heterogeneity of interventions identified will be the remit of a similar review conducted in the future as the body of knowledge expands.

The above notwithstanding, in this scoping review, we have provided an overview of the available evidence on the use of technology-assisted interventions to improve food choices and its effectiveness on weight-related outcomes. Our meta-analysis found that technology-assisted interventions were effective for weight loss outcomes but not for improving food choices. This could be due to the heterogeneity within the small number of interventions identified in this review as this field is still in its nascency. We identified that there needs to be greater application of theory to inform the development of technology-assisted interventions in this area as new and improved interventions are being developed.

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Supplementary material

For supplementary material accompanying this paper visit https://doi.org/10.1017/S0007114523000193

References

1. Kelly T, Yang W, Chen C-S, *et al.* (2008) Global burden of obesity in 2005 and projections to 2030. *Int J Obes* **32**, 1431–1437.
2. Da Costa LA, Arora P, García-Bailo B, *et al.* (2012) The association between obesity, cardiometabolic disease biomarkers, and innate immunity-related inflammation in Canadian adults. *Diabetes Metab Syndrome Obes: Target Ther* **5**, 347.
3. Arnold M, Leitzmann M, Freisling H, *et al.* (2016) Obesity and cancer: an update of the global impact. *Cancer Epidemiol* **41**, 8–15.
4. Collins KH, Herzog W, MacDonald GZ, *et al.* (2018) Obesity, metabolic syndrome, and musculoskeletal disease: common inflammatory pathways suggest a central role for loss of muscle integrity. *Front Physiol* **9**, 112.
5. Sellbom KS & Gunstad J (2012) Cognitive function and decline in obesity. *J Alzheimer's Disease* **30**, S89–S95.
6. Jantaratnotai N, Mosikanon K, Lee Y, *et al.* (2017) The interface of depression and obesity. *Obes Res Clin Pract* **11**, 1–10.
7. Yom-Tov E, Shembekar J, Barclay S, *et al.* (2018) The effectiveness of public health advertisements to promote health: a randomized-controlled trial on 7 94 000 participants. *Npj Digital Med* **1**, 1–6.
8. Swinburn B & Egger G (2002) Preventive strategies against weight gain and obesity. *Obes Rev* **3**, 289–301.
9. Blüher M (2019) Obesity: global epidemiology and pathogenesis. *Nat Rev Endocrinol* **15**, 288–298.
10. Rolls BJ, Keller KL, Hayes JE, *et al.* (2021) Food choice: behavioral aspects. Reference Module in Food Science, Elsevier. ISBN 9780081005965.
11. Lake A & Townshend T (2006) Obesogenic environments: exploring the built and food environments. *J Royal Soc Promot Health* **126**, 262–267.
12. Kumar V, Rajan B, Venkatesan R, *et al.* (2019) Understanding the role of artificial intelligence in personalized engagement marketing. *California Manage Rev* **61**, 135–155.
13. Gupta M (2019) A study on impact of online food delivery app on restaurant business special reference to zomato and swiggy. *Int J Res Anal Rev* **6**, 889–893.
14. Chew HSJ (2022) The use of artificial intelligence-based conversational agents (chatbots) for weight loss: a scoping review and practical recommendations. *J Med Internet Res* **10**(4), 1–14, e32578.
15. Chew HSJ, Ang WHD, Lau Y (2021) The potential of artificial intelligence in enhancing adult weight loss: a scoping review. *Public Health Nutr.* **24**(8), 1993–2020.
16. Michie S, Ashford S, Sniehotta FF, *et al.* (2011) A refined taxonomy of behaviour change techniques to help people change their physical activity and healthy eating behaviours: the CALO-RE taxonomy. *Psychol Health* **26**, 1479–1498.
17. Chew HSJ, Lim SL, Kim G, Kayambu G, So JBY, Shabbir A, Gao Y (2023) Essential elements of weight loss apps for a multi-ethnic population with high BMI: a qualitative study with practical recommendations. *Transl Behav Med*, in press.
18. Cheatham SW, Stull KR, Fantigrassi M, *et al.* (2018) The efficacy of wearable activity tracking technology as part of a weight loss

program: a systematic review. *J Sports Med Phys Fitness* **58**, 534–548.
19. Chew HSJ, Koh WL, Ng JSHY, *et al.* (2022) The sustainability of weight loss through smartphone apps: a systematic review and meta-analysis on anthropometric, metabolic, and dietary outcomes. *J Med Int Res* **24**, e40141.
20. Dounavi K & Tsoumani O (2019) Mobile health applications in weight management: a systematic literature review. *Am J Prev Med* **56**, 894–903.
21. Caudwell P, Hopkins M, King NA, *et al.* (2009) Exercise alone is not enough: weight loss also needs a healthy (Mediterranean) diet? *Public Health Nutr* **12**, 1663–1666.
22. de Ridder D, Kroese F, Evers C, *et al.* (2017) Healthy diet: health impact, prevalence, correlates, and interventions. *Psychol Health* **32**, 907–941.
23. Rong S, Liao Y, Zhou J, *et al.* (2021) Comparison of dietary guidelines among 96 countries worldwide. *Trends Food Sci Tech* **109**, 219–229.
24. Tobi RC, Harris F, Rana R, *et al.* (2019) Sustainable diet dimensions. Comparing consumer preference for nutrition, environmental and social responsibility food labelling: a systematic review. *Sustainability* **11**, 6575.
25. Cecchini M & Warin L (2016) Impact of food labelling systems on food choices and eating behaviours: a systematic review and meta-analysis of randomized studies. *Obes Rev* **17**, 201–210.
26. Arksey H & O'Malley L (2005) Scoping studies: towards a methodological framework. *Int J Soc Res Methodol* **8**, 19–32.
27. Tricco AC, Lillie E, Zarin W, *et al.* (2018) PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. *Ann Int Med* **169**, 467–473.
28. Higgins JP, Altman DG, Gøtzsche PC, *et al.* (2011) The Cochrane Collaboration's tool for assessing risk of bias in randomised trials. *BMJ* 343.
29. Hedges LV & Olkin I (2014) *Statistical Methods for Meta-Analysis*. London: Academic Press.
30. IntHout J, Ioannidis JP & Borm GF (2014) The Hartung-Knapp-Sidik-Jonkman method for random effects meta-analysis is straightforward and considerably outperforms the standard DerSimonian-Laird method. *BMC Med Res Method* **14**, 1–12.
31. Higgins JP, Thomas J, Chandler J, *et al.* (2019) *Cochrane Handbook for Systematic Reviews of Interventions*. Glascow: John Wiley & Sons.
32. O'Brien LM & Palfai TP (2016) Efficacy of a brief web-based intervention with and without SMS to enhance healthy eating behaviors among university students. *Eat Behav* **23**, 104–109.
33. Eisenhauer CM, Brito F, Kupzyk K, *et al.* (2021) Mobile health assisted self-monitoring is acceptable for supporting weight loss in rural men: a pragmatic randomized controlled feasibility trial. *BMC Public Health* **21**, 1568.
34. Kaur J, Kaur M, Chakrapani V, *et al.* (2020) Effectiveness of information technology–enabled 'SMART Eating'health promotion intervention: a cluster randomized controlled trial. *PLoS One* **15**, e0225892.
35. Plaete J, De Bourdeaudhuij I, Verloigne M, *et al.* (2015) Acceptability, feasibility and effectiveness of an eHealth behaviour intervention using self-regulation:'MyPlan'. *Patient Educ Counsel* **98**, 1617–1624.
36. Blackburne T, Rodriguez A & Johnstone SJ (2016) A serious game to increase healthy food consumption in overweight or obese adults: randomized controlled trial. *JMIR Serious Games* **4**, e10.
37. Duncan MJ, Fenton S, Brown WJ, *et al.* (2020) Efficacy of a multi-component m-health weight-loss intervention in overweight and obese adults: a randomised controlled trial. *Int J Environ Res Public Health* **17**, 6200.
38. Lugones-Sánchez C, Recio-Rodríguez JI, Menéndez-Suárez M, *et al.* (2022) Effect of a multicomponent mhealth intervention on the composition of diet in a population with overweight and obesity—randomized clinical trial EVIDENT 3. *Nutrients* **14**, 270.
39. Allman-Farinelli M, Partridge SR, McGeechan K, *et al.* (2016) A mobile health lifestyle program for prevention of weight gain in young adults (TXT2BFiT): nine-month outcomes of a randomized controlled trial. *JMIR mHealth uHealth* **4**, e5768.
40. Lawrence NS, O'Sullivan J, Parslow D, *et al.* (2015) Training response inhibition to food is associated with weight loss and reduced energy intake. *Appetite* **95**, 17–28.
41. Partridge SR, McGeechan K, Hebden L, *et al.* (2015) Effectiveness of a mHealth lifestyle program with telephone support (TXT2BFiT) to prevent unhealthy weight gain in young adults: randomized controlled trial. *JMIR mHealth uHealth* **3**, e4530.
42. Spring B, Pellegrini C, McFadden HG, *et al.* (2018) Multicomponent mHealth intervention for large, sustained change in multiple diet and activity risk behaviors: the make better choices 2 randomized controlled trial. *J Med Int Res* **20**, e10528.
43. Mummah S, Robinson TN, Mathur M, *et al.* (2017) Effect of a mobile app intervention on vegetable consumption in overweight adults: a randomized controlled trial. *Int J Behav Nutr Phys Act* **14**, 1–10.
44. Hutchesson MJ, Callister R, Morgan PJ, *et al.* (2018) A targeted and tailored ehealth weight loss program for young women: the be positive be health e randomized controlled trial. *Healthcare* **6**, 39.
45. Irvine AB, Ary DV, Grove DA, *et al.* (2004) The effectiveness of an interactive multimedia program to influence eating habits. *Health Educ Res* **19**, 290–305.
46. Kakoschke N, Hawker C, Castine B, *et al.* (2018) Smartphone-based cognitive bias modification training improves healthy food choice in obesity: a pilot study. *Eur Eat Disord Rev* **26**, 526–532.
47. Palacios C, Torres M, López D, *et al.* (2018) Effectiveness of the nutritional app "MyNutriCart" on food choices related to purchase and dietary behavior: a pilot randomized controlled trial. *Nutrients* **10**, 1967.
48. Coffino JA, Han GT, Evans EW, *et al.* (2021) A default option to improve nutrition for adults with low income using a prefilled online grocery shopping cart. *J Nutr Educ Behav* **53**, 759–769.
49. Basciani S, Camajani E, Contini S, *et al.* (2020) Very-low-calorie ketogenic diets with whey, vegetable, or animal protein in patients with obesity: a randomized pilot study. *J Clin Endocrinol Metabolism* **105**, 2939–2949.
50. Jambhekar A, Maselli A, Robinson S, *et al.* (2018) Demographics and socioeconomic status as predictors of weight loss after laparoscopic sleeve gastrectomy: a prospective cohort study. *Int J Surgery* **54**, 163–169.
51. Paoli A, Tinsley G, Bianco A, *et al.* (2019) The influence of meal frequency and timing on health in humans: the role of fasting. *Nutrients* **11**, 719.
52. Goodarzi MO (2018) Genetics of obesity: what genetic association studies have taught us about the biology of obesity and its complications. *Lancet Diabetes Endocrinol* **6**, 223–236.
53. Crovesy L, Masterson D & Rosado EL (2020) Profile of the gut microbiota of adults with obesity: a systematic review. *Eur J Clin Nutr* **74**, 1251–1262.
54. Mathes T & Kuss O (2018) A comparison of methods for meta-analysis of a small number of studies with binary outcomes. *Res Synth Methods* **9**, 366–381.