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Review Article

Precision health in behaviour change interventions: A scoping review

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ABSTRACT

Precision health seeks to optimise behavioural interventions by delivering personalised support to those in need, when and where they need it. Conceptualised a decade ago, progress toward this vision of personally relevant and effective population-wide interventions continues to evolve. This scoping review aimed to map the state of precision health behaviour change intervention research.

This review included studies from a broader precision health review. Six databases were searched for studies published between January 2010 and June 2020, using the terms 'precision health' or its synonyms, and including an intervention targeting modifiable health behaviour(s) that was evaluated experimentally.

Thirty-one studies were included, 12 being RCTs (39%), and 17 with weak study design (55%). Most interventions targeted physical activity (27/31, 87%) and/or diet (24/31, 77%), with 74% (23/31) targeting two to four health behaviours. Interventions were personalised via human interaction in 55% (17/31) and digitally in 35% (11/31). Data used for personalising interventions was largely self-reported, by survey or diary (14/31, 45%), or digitally (14/31, 45%). Data was mostly behavioural or lifestyle (20/31, 65%), and physiologic, biochemical or clinical (15/31, 48%), with no studies utilising genetic/genomic data.

This review demonstrated that precision health behaviour change interventions remain dependent on human-led, low-tech personalisation, and have not fully considered the interaction between behaviour and the social and environmental contexts of individuals. Further research is needed to understand the relationship between personalisation and intervention effectiveness, working toward the development of sophisticated and scalable behaviour change interventions that have tangible public health impact.

1. Introduction

Non-communicable diseases (NCDs) such as cardiovascular disease, type 2 diabetes, chronic respiratory disease, and cancers are leading causes of death, illness, and disability globally (World Health Organization, 2018). These conditions are driven by modifiable lifestyle behaviours including physical inactivity, unhealthy diet, smoking, and alcohol consumption, which are causally linked to NCD development by increasing blood pressure, glucose and lipid levels, and weight (World Health Organization, 2018). The Global Burden of Disease study found that more than 11 million deaths were attributed to suboptimal diets in 2017 (Afshin et al., 2019); while a further 6 million were attributed to tobacco smoking alone (Reitsma et al., 2017). NCDs threaten the health and well-being of populations globally and convey large social, medical,

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and economic costs (Ghebreyesus, 2018; Bloom et al., 2012; WHO, 2020). These costs are projected to exceed a cumulative output loss of $47 trillion by 2030, with lower- and middle- income countries contributing an increasing share of the burden (Bloom et al., 2012). In addition to unhealthy lifestyle behaviours, NCDs are also influenced by a complex range of interrelated factors including individual psychological and physiological (genetic, epigenetic, microbiome, metabolomic, cardiovascular, etc.) profile, and the social determinants of health - the social, economic, cultural, and physical environments in which people live and work (Marmot and Bell, 2019; Prüss-Ustün et al., 2019; Glasgow et al., 2018; Olstad and McIntyre, 2019).

Public health seeks to improve health and reduce health disparities on a population scale (Binns and Low, 2015). Prevention of NCDs by targeting modifiable lifestyle behaviours with cost-effective population-wide interventions is therefore a cornerstone of public health (Masters et al., 2017; Bertram et al., 2018). Research has shown that primary prevention interventions targeting nutrition, physical activity, smoking status, and medication adherence are effective in preventing or reducing the severity of NCDs (Schellenberg et al., 2013; Abbate et al., 2020). However, prevalence of NCDs and their associated impact on public health continues to be a major concern (World Health Organization, 2013). Traditionally, public health behaviour change interventions have taken a 'one-size-fits-all' approach where the same intervention is provided to each person, regardless of their personal or contextual risk factors. However, NCD risk factors are dynamic and interrelated, meaning that each person has a unique and complex risk profile that varies over time. Thus, the public health impact of population-wide interventions could be enhanced by personalising them to generally accepted indicators of health, making them more personally relevant, and therefore engaging and effective (Schoeppe et al., 2016; Tong et al., 2021).

Precision health is one such approach to optimizing interventions by ensuring the delivery of the right support, to the right individual, at the right time (Weeramanthri et al., 2018; Hekler et al., 2020; Kee and Taylor-Robinson, 2020; Bayer and Galea, 2015; Chen and Snyder, 2013; Collins and Varmus, 2015). Precision health seeks to reduce NCDs by personalising interventions to an individual's genetic, omic (genomic, transcriptomic, lipidomic, proteomic, metabolomic, phenomic, radiomic, and microbiomic), clinical, behavioural, social, and environmental risk profile (Gambhir et al., 2018; Hickey et al., 2019). In the early stages of precision medicine, which was considered as the predecessor of precision health (Juengst and McGowan, 2018), pharmacologic interventions were personalised using an individual's genetic profile, such as using *BRCA1* status for predicting response to chemotherapy treatment (Narod, 2010). Recent advances in precision health and unprecedented access to big data has presented new opportunities for personalisation. These advances make it possible to move beyond personalisation by static subgroup characteristics toward the integration of multiple data types, including those relating to social determinants of health, for individual-level tailoring (Viana et al., 2021a). For example, a recent initiative has integrated metabolomics with microbiome, inflammation and behavioural information, to develop pathways for better management of disease symptoms, such as cancer fatigue (Sleight et al., 2022). New and emerging technologies including smartphone devices, wearable sensors, virtual and augmented reality, smart home sensors, and applications of artificial intelligence have also played an increasingly central role in the operationalisation of precision health (Silvera-Tawil et al., 2020). These technologies are becoming a focal point for precision health due to their role in enabling the collection, analysis, and actionability of health, behavioural, and environmental information (Silvera-Tawil et al., 2020). In order for precision health interventions to be effective and equitable, they must simultaneously take interindividual variability into account while retaining the potential to be delivered on a population-wide scale to maximise their public health impact by reducing the economic, social, and health-related burdens of NCDs (Hekler et al., 2020; Kee and Taylor-Robinson, 2020; Khoury et al., 2016; Payne and Detmer, 2020).

Leading examples of precision health initiatives highlight the potential future impact of this approach. The United States Centers for Disease Control's Tier 1 Genomic Applications (Centers for Disease Control Prevention, 2020) leverages genomic data to achieve early detection and intervention of serious health conditions such as hereditary breast and ovarian cancer syndrome (HBOC). The initiative includes pre-specified pathways to impact that consider the individual's socioeconomic factors and that include counselling, behaviour change, and education interventions. This initiative, in context with complementary initiatives to increase the impact of cancer prevention programs, has been attributed to substantial increases in disease prevention activities and impact, such as a two-fold increase in genetic counselling for individuals at risk of HBOC (Green et al., 2019).

Questions remain, however, as to what extent the vision of an integrative precision health future has been realised in health behaviour or preventive health research. Although the term 'precision health' was conceptualised a decade ago, to what extent do corresponding health behaviour interventions tailor their content based on individual-level omic data, personal, and environmental characteristics? To what extent has the 'precision' of this approach been realised, and is it successful in improving the health of populations? To answer these questions and identify both promising lines of research as well as current gaps, a scoping review was undertaken.

1.1. Aims

The primary objective of this scoping review is to map the current state of precision health behaviour change intervention research. More specifically, this study addresses the following questions: (1) What are the health behaviours being targeted by precision health behavioural interventions?; (2) How are the interventions personalised?; and (3) How successful are they at changing behaviour?

2. Methods

This review follows the methodological and reporting guidelines set by the Joanna Briggs Institute (Peters et al., 2015) and the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) Extension for Scoping Reviews (PRISMA-ScR) (Tricco et al., 2018).

2.1. Protocol and registration

This review is part of a broader study, the Precision Health Scoping Review, which sought to identify and describe all studies labelled as precision health research, evaluate the extent to which they have collected different data types, and determine which of the key stages of the Gambhir et al. 2018 precision healthcare model they address; risk assessment, customised monitoring, data analytics, and/or personalised intervention (Gambhir et al., 2018). The Precision Health Scoping Review and its protocol have been published elsewhere (Ryan et al., 2021; Viana et al., 2021b). The current paper extensively presents and appraises results from studies included in the original review that experimentally evaluated an intervention targeting at least one modifiable health behaviour.

2.2. Eligibility criteria

The aim of the original precision health scoping review was to provide a broad overview of 'precision health' in publications using this term; therefore, few restrictions were placed on eligible studies. Studies were eligible if they were (1) published between 1st of January 2010 (when precision health was distinguished from precision medicine) and 30th of June 2020; (2) included the term 'precision health' or its synonyms ('personalised health', 'stratified health', 'tailored health', and 'individualised health') (Ali-Khan et al., 2016) in the title or abstract and

(3) in the introduction, methods, or results sections. As an example, the search strategy for Scopus was as follows: '(TITLE ((precision OR personali* OR individuali* OR stratif* OR tailo*) PRE/0 health) OR ABS ((precision OR personali* OR individuali* OR stratif* OR tailo*) PRE/0 health)).' Lastly, (4) studies were required to have a clearly defined health or medical outcome. Although we acknowledge various modalities (e.g. genomic medicine, precision oncology) and large-scale initiatives (e.g. UK Biobank, All of Us, Million Veteran Program) that relate to and/or enable a precision health system by collecting and integrating multiple data types, we designed our original search strategy to broadly capture studies characterised by the authors as 'precision health'.

Studies were eligible for inclusion in the present review if they (5) targeted one or more health behaviours and (6) experimentally evaluated the intervention. Eligibility was not limited to a certain population, concept (e.g., chronic disease, non-communicable disease), or context (e.g., high income countries, community settings).

2.3. Search strategy and information sources

To ensure optimal coverage of health and medical literature (Bramer et al., 2017), searches were performed in six databases covering peer-reviewed scientific literature and grey literature: Medline (via Ovid), Embase, Scopus, Web of Science, PsycINFO, and Google Scholar (first 300 results only). The reference lists of relevant primary studies and reviews, and publication lists on websites of precision health research groups were hand searched. Search results were exported into the systematic review software Covidence (Veritas Health Innovation), where duplicates were removed, and all stages of article screening were conducted in independent duplicate. Discrepancies were resolved through discussion between the two reviewers and a third independent team member. Articles were screened first by title, then abstract, and finally, full text.

2.4. Data charting

A data charting template with item definitions was drafted and piloted on two studies by three review team members. Data were charted independently in duplicate, and disagreements were resolved by a third independent review team member. Data were extracted on study characteristics (e.g., design), participant characteristics (e.g., age, sex), intervention features (e.g., behaviour(s) targeted, duration), personalisation features (e.g., how the personalisation was done), outcome

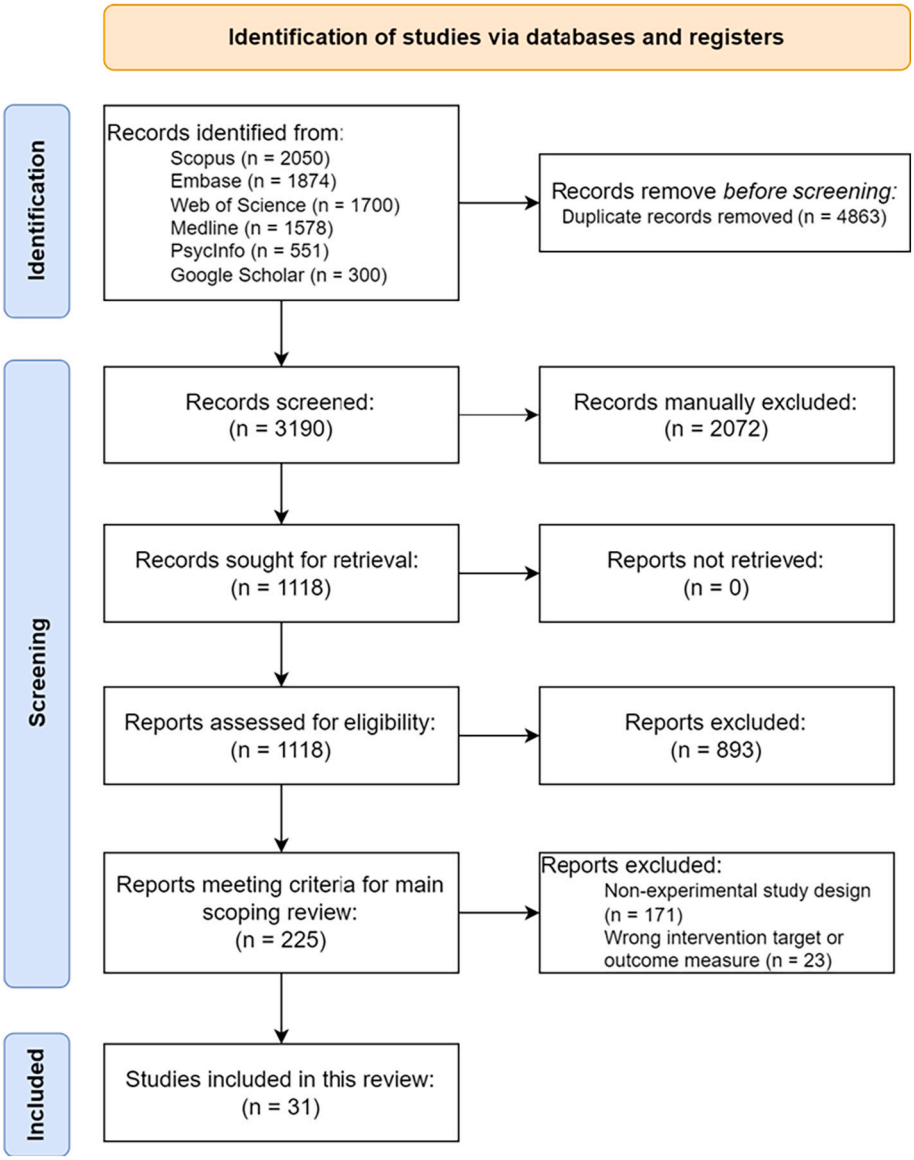

Fig. 1. Preferred reporting items for systematic review and meta-analyses (PRISMA) statement flow diagram.

measures (measurement tool and timing), and key study results.

Quality of the included studies was assessed using the 11 items from the Effective Public Healthcare Panacea Project (Thomas et al., 2004) which gives a global quality rating of weak, moderate or strong, based on selection bias, study design, confounders, blinding, data collection tools, reporting of withdrawals, and dropouts. The 4-item intervention intensity assessment tool was used to assess the overall intensity of each included intervention in relation to intervention duration, numbers of touchpoints, levels of contact, and settlings/reach (Hendrie et al., 2013). The full data charting template is included in Appendix A.

3. Results

Of the 225 studies included in the primary scoping review, 31 (13.8%) were eligible for the present study (Fig. 1). (An et al., 2013; Anderson et al., 2015; Arens et al., 2018; Berks et al., 2019; Chua et al., 2011; Colkesen et al., 2011; de Vries et al., 2012; Dreer et al., 2016; Elbert et al., 2016; Gilmore et al., 2017; Haslam et al., 2019; Kim et al., 2015; Lee et al., 2012; Leinonen et al., 2017; Lim et al., 2011; Liu, 2018; Liu et al., 2019; McHugh and Suggs, 2012; Nakamura et al., 2018; Oh et al., 2014; Qin et al., 2019; Rabbi et al., 2015; Sadat Rezai et al., 2019; Samaan et al., 2013; Sun et al., 2019; Tucker et al., 2016; van den Brekel-Dijkstra et al., 2016; van Limpt et al., 2011; Youm and Liu, 2017; Zhou et al., 2010; Drake et al., 2018)

3.1. Summary of studies

Table 1 summarises the included studies. Just under half of the studies (12/31, 39%) were randomised controlled trials (RCTs). In terms of methodological rigour, only seven studies (23%) were scored as strong, seven as moderate (23%), and the remaining 17 (55%) were weak. Sample size varied from 11 to more than 47,000 participants, although 12 studies (39%) recruited less than 100 participants. Almost half (13/31, 42%) of the studies had a sample with a mean age between 51 and 70 years. Of the 30 studies reporting the sex of participants, the average percentage of female participants was 59.1% (SD 27.3%), with six studies including only females and one study only males. Half of the studies (15/31, 48%) were focused on improving health behaviour or related outcomes in a general population, with the remaining half (16/31, 52%) targeting people with specific health conditions. Mean intervention duration was around six months (25 weeks, SD 20), ranging from a one-off interaction, to two years.

Table 1
Summary of included studies targeting health behaviour ($N = 31$).

Characteristic	Category	n (%)
Country of sample population	USA	9 (29)
	The Netherlands	6 (19)
	Korea	5 (16)
	China	4 (13)
	Others	7 (23)
Sample age in years (mean)[a]	18–30	4 (14)
	31–50	11 (38)
	51–70	13 (45)
	71+	1 (3)
Sample size	0–100	12 (39)
	101–500	13 (42)
	501+	6 (19)
Study design	Randomised controlled trial	12 (39)
	Case-control study	7 (23)
	Cohort study	5 (16)
	Others	7 (23)
Clinical condition of sample	No condition / general population	15 (48)
	Heart disease	4 (13)
	Type 2 diabetes	3 (10)
	People with overweight or obesity	3 (10)
	Others	6 (19)
Health behaviour targeted[b]	Physical activity	27 (87)
	Dietary intake	24 (77)
	Smoking	11 (35)
	Alcohol or drug use	6 (19)
	Medication adherence	5 (16)
	Sleep	4 (13)
	Others	8 (26)
Quality score	Weak	17 (55)
	Moderate	7 (23)
	Strong	7 (23)

[a] Mean age of sample not reported in $n = 2$ studies.
[b] Most studies (74%) targeted more than 1 health behaviour.

3.2. Study characteristics

Table 2 describes individual study characteristics. Most interventions targeted weight-related behaviours including physical activity (27/31, 87%) and dietary intake (24/31, 77%), with the majority (23/31, 74%) targeting two to four health behaviours. Few studies solely focused on one health behaviour (4/31, 13%). Around 40% of the studies (12/31) were conducted with the explicit aim of changing health behaviour, while a quarter (8/31, 26%) aimed to prevent or manage a medical condition. Half (16/32, 52%) of the studies delivered high-intensity interventions, as measured by intervention duration, frequency of contact, type of contact, and reach.

3.2.1. Intervention personalisation process

Table 3 describes the personalised components of the interventions across the included studies. Intervention content was personalised manually (i.e., via human interaction) in over half of the studies (17/31, 55%), and automatically via a digital platform with inbuilt algorithms or decision rules in just over a third of studies (11/31, 35%). Advice or coaching in relation to lifestyle and behavioural factors was the intervention component personalised most often (23/31, 74%). Intervention delivery occurred in a single setting, such as an app or individual consultations, around half of the time (14/31, 45%) (Table 2). The most common delivery methods were websites (12/31, 39%) and telephone (12/31, 39%), followed by face-to-face individual consultations or interviews (11/31, 35%) and mobile applications (8/31, 26%). Personalisation occurred on a daily basis in eight studies (26%) and weekly to fortnightly in seven studies (23%), while nine studies (29%) did not specify the frequency of personalisation of intervention content. Information used to personalise interventions was most commonly behavioural or lifestyle data (20/31, 65%); physiologic, biochemical or clinical data (15/31, 48%); psychological or psychiatric data (12/31, 39%); or anthropometric data (12/31, 39%). Most (23/31, 74%) studies used two to four data types to personalise intervention content, with the mean (SD) being 2.8 (1.4). Genetic or genomic data was not utilised in any of the included studies. Data were largely obtained via self-report, either by survey or diary (14/31, 45%) or digitally (14/31, 45%).

3.3. Digitally personalised versus human-led personalised interventions

Digital interventions more commonly personalised 'feedback on behaviour' (7/11, 64% of studies) compared with those interventions personalised by humans (1/17, 6%) (data not presented). Interventions personalised by humans more frequently made use of psychologic or psychiatric data (8/17, 47%), and perspective or opinion data (7/17, 41%), than those personalised digitally (4/11, 36% and 3/11, 27% respectively). Digitally personalised interventions utilised a greater number of data types compared with those personalised manually (i.e. by human interaction) (mean ± SD of 3.4 ± 1.1 versus 2.6 ± 1.5, respectively).

3.4. Intervention efficacy

Around 60% of the studies (18/31) reported a statistically significant result in favour of the intervention relating to the primary outcome measure or equivalent (see Appendix B). Only half of the 12 RCTs

Table 2
Characteristics of precision health studies targeting health behaviour ($N = 31$).

Study	Country	Design	Quality Score[a]	Sample age in yrs (M ± SD)[b]	Sample size (I gp(s)/C)[c]	Clinical sample	Int type	Int intensity	Primary health outcome/Behavioural target	Health behaviour targets						
										PA	Diet	Smoking	Alcohol/ drugs	Med adherence	Sleep	Other[d]
An 2013 (An et al., 2013)	USA	RCT	W	24.1	566/565/567	N	D,T	Low	Smoking	✓	✓	✓	✓			
Anderson 2015 (Anderson et al., 2015)	AUS	RCT	S	49.2 ± 6.2	26/29	Y	D,W,T	High	Menopausal symptoms	✓	✓	✓	✓		✓	
Arens 2018 (Arens et al., 2018)	DEU	Cohort	W	49.6 ± 9.3	109/57	Y	G,D	High	Weight	✓	✓					
Berks 2019 (Berks et al., 2019)	NLD	Cohort	W	31.6 ± 4.2	144/62	Y	I,D,T	High	CVD risk	✓	✓	✓				
Chua 2011 (Chua et al., 2011)	USA	Pre-post	W	37.5 ± 11.5	91/0	N	I,T,M, W	High	Smoking			✓				
Colkesen 2011 (Colkesen et al., 2011)	NLD	Cohort	W	46.0 ± 7.8	368/404	N	D,I	Low	CVD risk	✓	✓	✓				
deVries 2012 (de Vries et al., 2012)	NLD	Pre-post	W	46.2	387/0	Y	D	Low	Skin protection							✓
Drake 2018 (Drake et al., 2018)	USA	CCT	W	59.4 ± 10.5	17/16	Y	I,G	High	T2DM management	✓	✓			✓		✓
Dreer 2016 (Dreer et al., 2016)	USA	Pre-post	M	61.0 ± 7.0	11/0	Y	I,T	Medium	Glaucoma med adherence					✓		
Elbert 2016 (Elbert et al., 2016)	NLD	RCT	M	41.4 ± 14.6	114/113/115	N	D	Low	Dietary intake		✓					
Gilmore 2017 (Gilmore et al., 2017)	USA	RCT	W	26.0 ± 5.2	20/20	Y	D,T	Medium	Weight	✓	✓				✓	
Haslam 2019 (Haslam et al., 2019)	GBR	NRCT	W	42.1 ± 10.5	431/471/218	N	W	High	Physical activity	✓						✓
Kim 2015 (Kim et al., 2015)	KOR	CCT	S	65.7 ± 5.0	35/35	Y	D,T,I	High	T2DM management	✓	✓			✓		
Lee 2012 (Lee et al., 2012)	KOR	Pre-post	S	53.4 ± 14.3	69/0	N	D	Low	Weight & blood pressure	✓	✓					✓
Leinonen 2017 (Leinonen et al., 2017)	FIN	RCT	S	17.8 ± 0.6	250/246	N	D	High	Physical activity	✓						✓
Lim 2011 (Lim et al., 2011)	KOR	RCT	S	67.2 ± 4.1	51/51/52	Y	D	High	T2DM management	✓	✓					✓
Liu 2018 (Liu, 2018)	USA	Pre-post	M	48.0 ± 10.7	297/0	Y	I,T,D	Medium	Depression	✓	✓	✓	✓			✓
Liu 2019 (Liu et al., 2019)	CHN	CCT	W	53.5 ± 6.3	49/49	Y	D	Low	Burden & fatigue	✓	✓					
McHugh 2012 (McHugh and Suggs, 2012)	USA	CCT	M	41.0 ± 9.3	101/137	Y	D,W	Medium	Weight	✓	✓					
Nakamura 2018 (Nakamura et al., 2018)	JPN	Cohort	M	53.1[e]	4683/2392/31202/9450	Y	I,T,W, D	High	Smoking	✓	✓	✓	✓		✓	
Oh 2014 (Oh et al., 2014)	KOR	RCT	S	66.2 ± 8.2	21/20	N	G,M	High	Bone health	✓	✓			✓		
Qin 2019 (Qin et al., 2019)	CHN	CCT	M	53.5 ± 9.4	49/49	Y	D	Low	Burden & fatigue	✓	✓			✓		
Rabbi 2015 (Rabbi et al., 2015)	USA	Pre-post	W	NS	16/0	N	D	High	Weight	✓	✓					
Rezai 2019 (Sadat Rezai et al., 2019)	CAN	CCT	W	23.6 ± 5.8	40/40/40	N	D	Low	Physical activity	✓						
Samaan 2013 (Samaan et al., 2013)	CAN	RCT	M	53.8 ± 11.4	182/185	N	D	Medium	CVD risk	✓	✓	✓				✓
Sun 2019 (Sun et al., 2019)	CHN	RCT	W	68.2 ± 4.7	50/50	Y	I,T,D	High	Physical activity	✓	✓			✓		
Tucker 2016 (Tucker et al., 2016)	USA	RCT	W	43.0 ± 12.4	27/13/0	N	D	High	Physical activity	✓						✓

(*continued on next page*)

Table 2 (*continued*)

Study	Country	Design	Quality Score[a]	Sample age in yrs (M ± SD)[b]	Sample size (I gp(s)/C)[c]	Clinical sample	Int type	Int intensity	Primary health outcome/Behavioural target	Health behaviour targets					
										PA	Diet	Smoking	Alcohol/ drugs	Med adher-ence	Sleep	Other[d]
van den Brekel-Dijkstra 2015 (van den Brekel-Dijkstra et al., 2016)	NLD	Cohort	W	52.2 ± 6.3	230/0	N	D	Low	CVD risk	✓	✓	✓	✓			
van Limpt 2011 (van Limpt et al., 2011)	NLD	RCT	W	62.2	618/657	Y	I,T	High	CVD risk	✓	✓	✓		✓		
Youm 2017 (Youm and Liu, 2017)	KOR	CCT	W	NS	143	N	D	Medium	Physical activity	✓	✓				✓	
Zhou 2010 (Zhou et al., 2010)	CHN	RCT	S	71.5 ± 7.4	1156/1038	N	I	High	General lifestyle / QOL	✓	✓	✓	✓			

CCT = controlled clinical trial; NRCT = non-randomised controlled trial; RCT = randomised controlled trial; G = group; I = individual (face-to-face consultations/interviews); D = digital, i.e. website, app, text message; T = telephone; W = written materials; M = medication or supplements; CVD = cardiovascular disease; NS = not specified; QOL = quality of life.

[a] Assessed using the Effective Public Health Practice Project Quality Assessment Tool for Quantitative Studies (ref): W = weak; M = moderate; S = strong.

[b] Mean age of intervention group only where mean age of total sample was not reported.

[c] Total sample size reported where size of intervention / control groups were not reported separately.

[d] Other includes: sedentary time, stress reduction/management, skin protection & self-monitoring of blood glucose levels.

[e] Mean age of the males in the sample.

Table 3
Personalisation details of study interventions targeting health behaviour (N = 31).

Personalisation aspect	Category	n (%)
Personalisation process	Human – Practitioner/interventionist led	17 (55)
	Digital – Algorithm/decision rule based	11 (35)
	Digital & human	2 (6)
	Not specified / unclear	1 (3)
Personalised intervention components	Lifestyle/behavioural advice or coaching	23 (74)
	Health education content	14 (45)
	Goal setting	11 (35)
	Feedback on behaviour or health	10 (32)
Delivery of personalised content	Website	12 (39)
	Telephone	12 (39)
	Face-to-face – Individual	11 (35)
	Mobile application	8 (26)
	Email	5 (16)
	Written materials	5 (16)
	Face-to-face – Group	3 (10)
	Text message	3 (10)
	Computer software	1 (3)
	Tracking device	1 (3)
Frequency of personalisation[a]	Daily	8 (26)
	Weekly to fortnightly	7 (23)
	Monthly	4 (13)
	Once	3 (10)
	Not specified	9 (29)
Data types used[b]	Behavioural / lifestyle	20 (65)
	Physiologic / biochemical / clinical markers	15 (48)
	Psychologic / psychiatric	12 (39)
	Anthropometric	12 (39)
	Perspective / opinion	11 (35)
	Sociodemographic / economic	10 (32)
	Diet / nutritional	8 (26)
	Socioenvironmental	1 (3)
Source of data	Self-report via survey/diary	14 (45)
	Self-report via app input or web	14 (45)
	Self-report at interview (incl via telephone)	9 (29)
	Tracking/monitoring/smart device	5 (16)
	In-person health assessment	2 (6)

[a] Where frequency varied across the intervention, the most frequent period of intervention is reported.

[b] Data type category descriptions/examples: Behavioural / lifestyle = physical activity, smoking, drinking, sleep; Physiologic / biochemical / clinical markers = blood pressure, blood glucose, metabolites; Psychologic / psychiatric = quality of life, depression, anxiety; Anthropometric = height, weight, body mass index (BMI); Perspective / opinion = opinion on or evaluation of a particular technology/concept; life/lived experiences; Sociodemographic / economic = age, sex, income; Diet / nutritional = food or nutrient intake; Socio-environmental = exposure to pollutants, housing conditions, size of household/ family.

reported significant primary outcomes in favour of the intervention group. A quarter of the studies (8/31, 26%) did not measure or report on any health behaviours targeted by the interventions, while 45% (14/31) reported outcomes relating to all of the health behaviour targets.

4. Discussion

4.1. Summary

The bold vision of precision health – to personalise and thus transform preventive health care through the integration of multiple data types – is expected to take decades to fully realise (Gambhir et al., 2018). In this review, we included studies characterised as 'precision health' that evaluated a personalised health intervention. Although no study on its own fully reflected precision health's vision of integrating a wide range of information for health promotion, isolated components of this model were evident throughout the included studies (Gambhir et al., 2018). The majority of studies evaluated interventions that were multi-component, typically targeting a combination of behavioural risk factors including physical activity, diet, and/or smoking. Intervention personalisation typically involved personalised lifestyle advice, behavioural goals, and/or feedback on behaviour or health condition(s). In most cases, the personalisation process was human-led or involved human interaction, while a smaller group of studies employed digital personalisation processes, such as the provision of personalised feedback on past or current health behaviour entered into an app or website. While most studies reported statistically significant effects in favour of the intervention, they were mainly of weak or moderate quality and just 12 RCTs were identified in the sample of 31. This review has identified the outstanding questions that must be answered to truly make progress toward a precision healthcare future.

4.2. Comparison with previous literature

Precision health interventions should be holistic, delivering behavioural support to those in need when and where they need it most. Interventions included in this review were multi-component, often targeting two to four behaviours simultaneously. This is consistent with previous reviews that have also identified a high prevalence of multi-component health behaviour change interventions (Roberts et al., 2017; Booth et al., 2014; Ryan et al., 2019). The co-occurrence of unhealthy lifestyle behaviours related to energy balance (e.g. dietary intake and activity) and addiction (e.g. smoking and alcohol intake) (Samaan et al., 2013) means that multi-component interventions are key to maximising impact upon downstream health outcomes. Although the outcomes of multi-component health behaviour change interventions remain mixed, the largest effects have so far been seen in at-risk populations (Samaan et al., 2013; Sun et al., 2019). Precision health interventions utilising continuous health monitoring and big data analytics are well placed to improve the health behaviour of these populations through enhanced risk assessment and early disease detection. However, study efficacy with respect to multiple health behaviour change was difficult to assess in the included studies, due to the lack of reporting of behavioural outcomes relating to some or all of the health behaviours targets, along with substantial heterogeneity in study design. Thus, the efficacy of precision health interventions in addressing multiple, co-occurring health behaviours remains unclear.

In this review, precision health was most commonly operationalised as the delivery of personalised intervention content based on inputs of behavioural and lifestyle information (e.g., physical activity levels), clinical and biochemical markers, psychological information, or anthropometric data. The reviewed studies did not realise the vision of precision health for behavioural interventions, wherein genetic or genomic, and contextual information, such as the social and built environment, are integrated to deliver personally relevant interventions (Gambhir et al., 2018). Current approaches appear to reflect next generation personalised interventions focusing primarily on the previous or current health behaviour of the individual and/or personalisation according to discrete subgroup characteristics. The social and environmental contexts of individuals, and how these change over the life course, along with their genetic profile, have not been fully considered. It is worth noting that the lack of studies that utilise genetic/genomic information and other data types for behavioural interventions does not mean that these studies do not exist. Since our initial scoping review primarily captured studies that explicitly use the term 'precision health', different labelling of these studies (such as precision medicine) may have meant they were not captured within our search strategy.

Previously, evaluations of personalised health interventions have focused on either clinical, one-to-one (patient-centred) care (Booth et al., 2014), or digital health that utilises computer algorithms and other automated processes to deliver a personalised program (Ryan et al., 2019; Sahin et al., 2019). This review suggests that in precision health, both human-led personalisation and digital personalisation processes requiring human input (e.g. of behavioural data) continue to dominate. 'Hands off' approaches harnessing health-monitoring devices for data collection and intelligent algorithms for personalisation of health interventions are often regarded as an ideal approach, due to their scalability and potential cost-effectiveness (Kostkova, 2015). This is despite the well-documented challenges in achieving sufficient user engagement in digital interventions (Yardley et al., 2016; Yeager and Benight, 2018). In the reviewed studies, reliance on human-led, low-tech personalisation may limit the potential for cost-effective scale-up of behaviour change interventions. However human contact and input could lead to greater engagement and long-term behaviour change, whilst also being more relevant and acceptable to populations experiencing the digital divide (Makri, 2019; Mubarak and Suomi, 2022) and those with mistrust of digital technologies (Figueroa et al., 2022). The optimal balance between human and digital input for maximising intervention efficacy and cost-effectiveness requires further exploration in RCTs and health economic assessments (Michie et al., 2017).

Despite the popularity of digital intervention delivery evident in this study, risk assessment, monitoring, and data analytics remain largely reliant on research participants via self-reported data and health practitioners. The precision healthcare model proposed by Gambhir et al. 2018 demonstrates how digital technologies could contribute to data collection and monitoring, risk assessment and data analytics (Gambhir et al., 2018). Future behavioural interventions could leverage advances in wearables to simplify data collection and monitoring, while machine learning and predictive modelling could be used to enhance data analytics and risk assessment. More objective, technology-driven measurement and assessment of human health, behaviour, and context would improve intervention scalability and support the delivery of timely and relevant precision health behavioural interventions.

Only half of the 12 RCTs in this study reported statistically significant outcomes in favour of the intervention, and less than half reported outcomes on all relevant behavioural targets. This may reflect the mainly weak study design of the included studies, but perhaps also the early stage of research in which the field currently stands. Thus, precision health behavioural intervention research should employ more rigorous and efficient study design to fully understand the effects of individual intervention components on relevant behavioural outcomes. Just-in-the-Moment Adaptive Interventions (Wang and Miller, 2020), Multiphase Optimization Strategy or Sequential Multiple Assignment Randomised Trials with factorial experiments (Collins et al., 2007) would support more efficient testing and optimisation of complex behavioural interventions. Pragmatic or real-world trials would also ensure the successful translation and community implementation of research in the rapidly advancing field of precision health.

4.3. Outstanding research questions

This review highlights some outstanding research questions with respect to precision health in behaviour change interventions which should be addressed in future research:

1. How can precision health interventions effectively target multiple, co-occurring health behaviours?

2. What is the effectiveness of interventions that are personalised by humans, an algorithm, or a combination of both? Furthermore, what is the best metric to judge effectiveness?
3. Can 'light touch' digital interventions achieve the same level of precision that can be achieved via human-led personalisation? And if not, what is the necessary balance between digital and human-led personalisation to maximise efficacy, scalability and cost-effectiveness?
4. What are the barriers and enablers to the integration of genetic, social and environmental data *with* behavioural, psychologic and user preference data?

4.4. Strength and limitations

Strengths of this review included our broad search criteria, which did not limit the included studies to those with a specific mode of delivery (such as digital) or target population (such as those with a specific health condition). Our search criteria also included numerous synonyms of precision health (Ali-Khan et al., 2016), broadening the scope of this review and facilitating richer analysis on how various 'precision health' studies integrate multiple types of information and personalise behavioural interventions. Finally, all stages of the review, from article screening to data extraction, were conducted rigorously in independent duplicate with discrepancies resolved through discussion with a third adjudicator.

This study was not a systematic review; therefore, we did not consider effect size or all study outcomes reported. Substantial heterogeneity in study design and outcomes assessment meant that our work was limited to a frequency count of intervention efficacy. Due to variability in the terminology used to define precision health, it is unlikely that we captured all precision or personalised interventions targeting health behaviour. The search strategy used in our initial scoping review did not include several terms associated with precision health such as 'precision medicine', or subfields of precision health, such as 'precision nutrition', 'precision oncology', and 'precision public health'. This might have limited retrieval of articles using alternative terminology. Finally, progress in the field of precision health and behavioural interventions is ongoing and future reviews will be needed to capture the most recent evidence and to keep track of how these fields of research are evolving over time.

5. Conclusion

Precision health offers new opportunities for optimizing complex behaviour change interventions to improve health and prevent disease. With the majority of studies reviewed focusing on human-led, low tech personalisation, additional work is needed to facilitate more automated and objective means of collecting and interpreting user data. To realise the true vision of precision health, behaviour change interventions must also go beyond personalisation according to current behaviour to consider the genetic profile of individuals, along with their social and environmental context. Finally, more rigorous and efficient study designs would improve our understanding of the relationship between personalisation and intervention effectiveness, supporting the development of more sophisticated and scalable behaviour change interventions that have tangible public health impacts.

Author contributions

JNV conceptualised the original scoping review from which this sample was taken. CEM, SME, JCR conceptualised and managed the project, and drafted the manuscript. All authors contributed to the collection and curation of data, and CEM, SME, JCR, DDN and SJB undertook analysis and interpretation of data. All authors critically reviewed the drafted manuscript and approved the final version for submission. No financial disclosures or conflicts of interest were reported by the authors of this paper.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ypmed.2022.107192.

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