Understanding the uptake of, and the engagement with, health and wellbeing smartphone apps.

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Abstract

Background

Health and wellbeing smartphone apps are promising tools in behaviour change, however, the uptake with these is low and the engagement with them is suboptimal.

Objectives

The research objectives were to 1) better understand factors influencing the uptake of and the engagement with health and wellbeing apps, 2) explore the factors influencing how and why individuals choose health and wellbeing apps online, including curated health app portals, and 3) investigate the attributes of smoking cessation apps that are likely to affect their uptake.

Methods

Three integrated research studies using qualitative and quantitative methods were conducted. Firstly, a systematic literature review was undertaken to investigate factors influencing the uptake of, and engagement with, health and wellbeing apps. Secondly, a think-aloud and interview study was undertaken to gain a deeper understanding of previously identified factors from the systematic review and to explore participants' views on curated health app portals. The final study involved the development and delivery of a discrete choice experiment to elicit smokers' preferences for the uptake of a hypothetical smoking cessation smartphone app.

Findings

The systematic review identified twenty-six factors that influence the uptake and engagement with health and wellbeing apps, with one of the most important factors being health practitioner support. The qualitative study found that social influences and the perceived utility of an app may be core factors influencing their uptake. Engagement appeared to be influenced by the need for apps to contain clear user guidance, create low cognitive demands and support self-monitoring, have tailored technology, include peer and professional support, and goal setting features with action planning. Findings from the discrete choice experiment suggest that uptake of a smoking cessation app is most likely if the app has a high star rating, followed by if it is developed by a trusted organisation, the image of the app includes screenshots of how the app appears, and if the app is low cost.

Conclusion

Easy to use health and wellbeing apps which convey their social approval and practical benefits of use have the greatest potential to be adopted.

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List of abbreviations

AI: Artificial Intelligence

BCT: Behaviour Change Techniques

BCTTv1: Behaviour Change Technique Taxonomy version 1

BCW: Behaviour Change Wheel

CBPR: Community-based Participatory Research

COM-B model: Capability, Opportunity, Motivation – Behaviour model

COVID-19: Corona Virus Disease 2019

DCE: Discrete choice experiment

HIV: Human Immunodeficiency Virus

LGBTQ+: Lesbian, Gay, Bisexual, Transgender, Queer and other spectrum of sexuality and gender

mhealth: mobile health

MMAT: Mixed Methods Appraisal Tool

MOST: Multiphase Optimisation Strategy

NHS: National Health Service

NICE: National Institute for Health and Care Excellence

OSF: Open Science Framework

PHE: Public Health England

PPI: Patient and Public Involvement

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PROSPERO: International prospective register of systematic reviews

TDF: Theoretical Domains Framework

UK: United Kingdom

US: United States

WHO: World Health Organisation

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Impact statement

My key contribution to knowledge is the comprehensive synthesis of factors that influence an under-researched and highly important aspect of digital health, the uptake of health and wellbeing apps, and better understanding factors influencing the engagement with them. This statement summarises areas where my research created the most apparent impact.

The work presented in this thesis underpinned webinars and talks delivered to Public Health England (PHE), NHS Digital and the Good Thinking digital wellbeing service providers. My research informed how to improve the information presented to the public to enhance the uptake of mental health apps included on the Good Thinking website. In the last few months of my PhD, I have been employed by PHE and involved in work commissioned by NHS Digital, developing a health promotion digital tool where I could directly apply findings from my research.

Furthermore, this PhD project was presented to GPs and wider health professionals to highlight the importance of conveying the value and possible mechanisms of change to the end-user, which will help with the uptake and engagement of health apps and is now part of the wider digital transformation in health. The findings of this thesis informed the content of the 'Digital navigator course' for Primary Care Professionals, including Social Prescribing Link Workers. My work also informed the development of a community-based health promotion website of Norfolk County Council.

I have provided industry consultancy to two national and one international company for smoking cessation and mental health and wellbeing apps, directly applying my research to real-life issues with the uptake of, and engagement with, health apps.

Furthermore, my work has led to national and international collaborations with researchers from University College London (UK), University of Hull (UK), University of Brussels (Belgium), University of Bayreuth (Germany), University of Amsterdam (Netherlands), and the Leibniz Institute, Bremen (Germany) to investigate a potential digital divide in the use of health apps targeting sedentary behaviour.

Finally, the findings from this thesis have been published, or submitted for publication in peer-reviewed journals. They have been presented at several conferences in the UK and abroad. The dissemination of each of the studies presented in this thesis is described at the beginning of Chapters 2 to 6.

Statement of jointly authored publications

The research reported is my own work, which was carried out in collaboration with others as follows:

Chapter 1. Written by Dorothy Szinay.

Chapter 2. Dorothy Szinay was the lead author of the following published paper:

> Szinay, D., Jones, A., Chadborn, T., Brown, J., Naughton, F. Influences on the uptake of, and engagement with, health and wellbeing smartphone apps: systematic review (2020). *Journal of Medical Internet Research.* 22(5): e17572. DOI 10.2196/17572. Available from: https://www.jmir.org/2020/5/e17572/
>
> DS led and designed the study with FN, AJ, TC and JB. DS wrote the study protocol with contributions from FN, AJ, TC and JB. DS registered the study protocol on PROSPERO. DS undertook the data collection (literature search, screening, data extraction, and quality appraisal), compiled the quantitative and qualitative data, conducted the data synthesis, interpretated the findings. FN double checked the study selection, data extraction, and data coding. FN and AJ double assessed the quality of the included studies. DS prepared the manuscript. All authors read, commented, and contributed to the final version of the chapter. DS responded to peer review comments with advice from FN, AJ, JB and TC.

Chapter 3. Dorothy Szinay was the lead author of the following published paper:

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>
> DS led and designed this study with contributions from OP, FN, AJ, TC, JB. DS registered the study protocol on the Open Science Framework. DS collected the data, analysed the data with support from OP. DS prepared the manuscript. All authors contributed to and approved the final version of the chapter. DS responded to peer review comments with advice from FN, AJ, OP, JB and TC.

Chapter 4. Dorothy Szinay was the lead author of the following published paper:

> Szinay, D., Perski, O., Jones, A., Chadborn, T., Brown, J., Naughton, F. Perceptions of factors influencing engagement with health and wellbeing apps: a

qualitative study using the COM-B model and Theoretical Domains Framework. Preprint (2021). JMIR mHealth and uHealth. 9(12):e29098. DOI: 10.2196/29098. Available from: https://mhealth.jmir.org/2021/12/e29098/

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DS prepared the manuscript. All authors reviewed the draft for important intellectual content and approved the final version. DS responded to peer review comments with advice from FN, AJ, JW and JB.

Chapter 6: Dorothy Szinay was the lead author of the following submitted paper:

Szinay, D., Cameron, R., Jones, A., Whitty, J.A., Chadborn, T., Brown, J., Naughton, F. Eliciting preferences for the uptake of smoking cessation apps: A Discrete Choice Experiment. Manuscript submitted for publication to *Addiction* (October 2021).

DS conceptualised the study design with FN, AJ, JW, JB and TC. DS wrote the study protocol with contribution from FN, AJ, JW, JB, TC. DS registered the study protocol on the Open Science Framework. DS generated the choice sets with support from JW. DS analysed the data of the pilot phase. DS recruited the participants, collected the data, analysed the final data with statistical support from RC. DS prepared the manuscript. All authors reviewed and contributed to the final version of the chapter.

Chapter 7: Written by Dorothy Szinay.

Chapter 1. General Introduction

The Global Burden of Disease Study (GBD) reported that 73.4% of total deaths worldwide in 2017 were caused by non-communicable diseases (1). In terms of the UK, the leading cause of age-adjusted years-of-life-lost, were ischaemic heart disease, lung cancers, cerebrovascular disease and chronic pulmonary disease (2). In the same report several behavioural, environmental and occupational, and metabolic risk factors were further identified. However, some metabolic risk factors, such as high blood pressure and high body-mass index, are consequences of unhealthy behaviours (3, 4). It is therefore the case that, smoking, alcohol and other substance misuse, physical inactivity, unhealthy diet are the major behavioural factors that contributes to all-cause death. Moreover, poor mental health represents an additional risk factor for disease (1).

Unhealthy behaviours are associated with a range of adverse health outcomes and also have financial consequences and societal costs, including, but not limited to, National Health Service (NHS) costs, productivity loss (sickness absence), and in case of behaviours such as alcohol consumption on the consumption of banned substances, the cost of related crimes (5). The quantification of these costs suggests the substantial impact of unhealthy behaviours on society. For example, according to Action on Smoking and Health (ASH), smoking related diseases cost the NHS around £2.5 billion a year (6), while treating alcohol related illnesses costs £3.5 billion a year with further £7 billion to lost productivity, such as unemployment or sickness (7). However, these are modifiable behaviours. Therefore, it is clear that necessary measures must be taken to reduce the burden of the non-communicable disease by promoting and implementing behaviour change interventions. Indeed, investing in these in the short term could provide cost improvements for NHS in the long term.

1.1. Behaviour change interventions

Behaviour change interventions include a set of active components or techniques, known as behaviour change techniques, used together to change the health-related behaviour of people, groups or entire populations (8). The Behaviour Change Guidance produced by the National Institute for Health and Care Excellence (NICE) outlines that interventions designed to change behaviour offer a part solution to alter present patterns of disease (9). Interventions, ideally based on behaviour change theories and models, such as the COM-B model, could therefore reduce the risk of illness (10).

Primary care interventions targeting health behaviours, such as those targeting physical inactivity (11), alcohol consumption (12) and smoking cessation (13), have been shown to be effective in changing the behaviour. For example, the NHS Health Check programme is a multiple health behaviour change intervention that aims to reduce cardiovascular disease risk factors by addressing four behavioural areas: diet and weight management, promoting physical activity, providing smoking cessation and reducing excessive alcohol consumption (14). Indeed, individuals attending the health check programme show a decrease in CVD risk factors scores (15). Nevertheless, although participation increased between 2011 and 2015, the rate of uptake remains below those expected by the Department of Health (15). Reported barriers in delivering primary care interventions include high workload and lack of time, as well as insufficient knowledge to deliver behaviour change interventions (14). Therefore, funding cuts in staff and financial pressure (16), and barriers to implementing brief interventions in primary care, such as lack of time (17) or lack of support and training offered to health care professionals responsible for the delivery of these interventions (18), suggest that more flexible and cost effective solutions are needed. Digital technology, such as mobile phones and relevant health and wellbeing smartphone apps, could be an important key component to address these issues by offering a flexible, cost effective and cost reducing way to decrease unhealthy behaviours. However, the potential reach and impact of these interventions is not well understood.

1.2. Digital behaviour change interventions

Digital behaviour change interventions (DBCI) focused on health behaviours have been described as “an intervention that employs digital technology to promote and maintain health, through primary or secondary prevention and management of health problems” (19). At present, DBCIs are mainly based on mobile phone applications and websites, nonetheless they can also be found in other technologies like text messaging, email, social media or online patient portals (20).

Behaviour change based on digital technology appears promising. Smartphone ownership is continuously growing globally. According to the Global Mobile Consumer Survey 2017 (UK), 85% of the respondents across all countries own or had access to smartphones in 2017 (21). In 2018 95% of those under 35 owned a smartphone, with this dropping to 51% among those aged 55-64 and to 18% among those over 65 (22). Nevertheless, statistics on the smartphone user penetration in the UK suggest that smartphone ownership is continuing to grow, and is expected to reach around 80% by 2022, an increase of 16% from 62% in 2014 (23). Therefore, the increasing number and use of smartphones and the rapid development in technology represents a noteworthy opportunity for a global impact on health behaviours (10, 24). The continued growth in smartphone ownership therefore provides a clear opportunity to positively influence health behaviours (10).

There are two aspects that highlight the importance of DBCIs: the results from the efficacy testing of behaviour change interventions and the reported acceptability of DBCIs among users. Testing interventions, specifically those conducted in healthcare, involves the consideration of three concepts that were first defined by Archie Cochrane, the British pioneer clinical epidemiologist: efficacy, effectiveness and efficiency (25).

Efficacy considers whether an intervention can work in ideal conditions (26). Evidence supports the efficacy of DBCIs using mobile phones, such as in the case of smoking cessation (27), in reducing hazardous drinking (28) and to promote healthy diet and address physical inactivity (29). There is evidence that efficacy studies maximise the probability of an intervention effect if one exists yet often overestimate the effect of a trial when implemented in practice (30). This is because the participants in an efficacy study are typically more homogenous than the population being sampled from, they are selected based on several inclusion and exclusion criteria, the intervention is delivered in a highly standardised way, and participation in the study is heavily maintained.

The second concept, effectiveness, refers to the extent to which the intervention could work in ‘real world’ practice, that is under usual conditions as opposed to the ideal ones (26). As opposed to efficacy studies, the population is typically less homogenous, and participants are selected based on fewer inclusion and exclusion criteria in effectiveness research. Whilst effectiveness studies standardise the availability of interventions in the sample, they do not typically reinforce implementation or participation at the same level as an efficacy study often would. DBCIs have been shown to be effective in improving healthy eating (31, 32), addressing sedentary behaviour (32), enhancing physical activity (20, 33). It was found that to maintain weight loss, DBCIs are better than usual care and as effective as face-to-face interventions (24, 34, 35). Although, a literature review on apps for behavioural interventions for risky alcohol consumption argues that there is a lack of convincing evidence of effective apps (36), in the case of non-dependent drinkers, DBCIs are as effective as brief interventions (37, 38).

Finally, the third concept of testing interventions, efficiency, represents the cost-effectiveness of an intervention in relation to the resources expended (26). Reviews have highlighted the low-cost nature of DBCIs. For instance, they are cost-effective in improving diet and nutrition and to tackle obesity (39). The recent National Institute for Care and Excellence (NICE) guideline on digital behaviour change interventions reviewed the cost effectiveness of DBCIs addressing health behaviours, such as smoking, alcohol consumption, diet, physical activity and sedentary behaviour. It found limited evidence on the cost-effective nature of the smoking cessation tools (40). However, it is noteworthy, that the number of studies considered for cost-effectiveness was low, ranging from one for reducing alcohol consumption, to six for all other behaviours, limiting the certainty of evidence.

There is good evidence that all three constructs (efficacy, effectiveness and efficiency), are important for public health impact. Intervention evaluation is considered as a 'continuum', progressing from efficacy study to effectiveness and efficiency trials (30). So, while the literature suggests that DBCIs could be an effective way to change behaviour, there is lack of evidence on their cost-effective nature.

Another important aspect is the acceptability of DBCIs among users, that is how receptive the population is towards DBCIs as opposed to other interventions, e.g. face-to-face ones. A systematic review targeting the behavioural functionality of the mobile apps in health interventions found that the acceptability of apps among users was high, and therefore the potential for delivering behavioural interventions is encouraging (41).

This thesis focuses particularly on digital interventions delivered by smartphone apps. Smartphone apps are usually inexpensive, can offer anonymity for the user, and can be accessed at any time from practically anywhere (37, 42). Overall, they appear to be an ideal platform to deliver behavioural interventions (10) because of their easy access (42), the potential for constant connectivity to the internet and their capacity to store and run different smartphone apps. For example, health app downloads increased by 16% between 2016 and 2017, representing around 3.7 billion downloads, with the growth rate of health apps being higher than the number of downloads (43).

Despite their promise, the overall uptake of digital interventions delivered by smartphone apps are low and the engagement with these remain suboptimal to promote behaviour change. Therefore, this thesis focuses on these two key behaviours that might limit the potential public health impact of the health and wellbeing smartphone apps, the uptake of and the engagement with these, while exploring views on curated health app portals.

1.3. The problem

1.3.1. The uptake of health and wellbeing apps

Uptake of a health app refers to the act of downloading and installing it (44). The majority of health and wellbeing apps are selected from a commercial platform, predominantly from ‘Google Play’ developed for mobile phones operating on Android operational system users, and the ‘App Store’ for those operating on iOS operating system (29, 45).

The list of apps yielded through commercial app store search are dominated by the search algorithm applied by these platforms. The search algorithm can be shaped by developers by applying search engine optimisation strategies, for example by using specific keywords, whereas the app store’s search ranking is based on the text relevance (such as app’s title, keywords, category) and user behaviour (number and intensity of downloads, the popularity factors represented by quality ratings and reviews left) (46, 47). Existing evidence suggests that ratings and rankings are influential during app selection (45), and individuals typically choose a top positioned and popular app (48-51). Individuals also tend to select an app based on their look and feel, rather than a cognitive elaboration by considering at a deeper level the utility of the selected apps (52). Further, engagement tends to be low (53), and users tend to disengage with health apps within a week (54, 55). Understanding engagement is important, as it represents the next stage in the process of producing behaviour change through a digital intervention, following the uptake of such tools.

1.3.2. Poor engagement

Engagement with DBCIs has been recently conceptualised in a systematic-review conducted by Perski et al. (56), and is defined as ‘(1) the extent (e.g. amount, frequency, duration, depth) of usage and (2) a subjective experience characterised by attention, interest and affect’ (56). Engagement with DBCIs is necessary for their effectiveness (57). Only 20% of health and fitness apps users use the app one day after installation, and only 8% after seven days after installation (54). The median app retention rate of mental health apps at 15 days after installation was 3.9% (55).

In the past few years, there have been several studies carried out to investigate the reasons for poor engagement. For example, in a survey conducted in the US a few key explanations for poor engagement have been previously identified, such as prolonged time to enter user data, loss of interest, poor usability, exchanging to a better app and a lack of social media connections within the app (45). A systematic review and content analysis of remote measurement technology has found that poor health status or change in health status, technical malfunction, poor data reliability, concerns regarding privacy, costs, forgetfulness of the users, excessive notifications and lack of intrinsic motivation are the main barriers to engagement (58). A think-aloud study has shown that people have different preferences for features such as self-monitoring, goal-settings and rewards, and lack of flexibility of these features are off putting (59).

Furthermore, the level of engagement often depends on the quality of the app represented by the features based on behaviour change techniques relevant for the target behaviour. High quality apps may more likely encourage behaviour change than others, and therefore improve the effectiveness of the app (60). For example, apps that have used behaviour change techniques associated with effectiveness provided better quality of information for the users (61).

Therefore, the poor matching between users' needs and the app they select might be one of the causes of poor engagement and may lead to disengagement. This might be triggered by the selection of apps, described previously. Therefore, improving engagement is crucial, and this could also improve health and wellbeing smartphone apps' effectiveness (57). However, the uptake on the commercial app marketplace could further hinder the engagement with health and wellbeing apps.

1.3.3. The commercial marketplace

Most health and wellbeing apps listed on commercial app stores are not evidence based. Indeed, several content analyses have found that the majority of health and wellbeing smartphone apps listed in commercial platforms are lacking well-researched and appropriate evidence-based content represented by behaviour change techniques (60, 62-68). It is of particular concern that it has been shown that there is an inverse association between popularity and effectiveness in apps listed on commercial app stores developed for weight management (62). A study analysing anti-tobacco videogames found that even though these contain effective features, behaviour change techniques are absent (65). Less than one percent (0.39%) of the available stress-management apps had included all three widely used and recommended precede- proceed framework theoretical constructs (i.e. predisposing, enabling and reinforcing factors) for self-management of stress (66). Overall, the majority of health apps do not have theoretical constructs, or behaviour change techniques, explicitly incorporated (63, 67) and lack evidence-based content (64, 68). A review and content analysis of apps targeting depression found that only a third were in fact addressing depression and 61.7% failed to mention their organisational affiliation and content source (69). Furthermore, content analyses found that out of 40 apps targeting alcohol consumption only one app demonstrated application of evidence-based approach (68), while the most popular cannabis smartphone apps fail to address the issue of addiction (70).

It is therefore the case that there are thousands of health and wellbeing apps on the marketplace targeting different behaviours, but only a small percent of these are of sufficient quality that would potentially promote behaviour change (71). Furthermore, due lack of guidance or recommendation of which apps are of sufficient quality, these apps are likely to be hard to find when the selection relies on app-store search only and, usually, the most popular apps are showcased rather than the highest quality ones. This suggests that these commercial platforms may be unsuitable to search for effective health and wellbeing smartphone apps as DBCIs, without prior professional recommendation. Unsurprisingly, health apps are often deleted as they fail to meet users' expectations (72). This leads to poor engagement with apps and rapid disengagement after uptake.

One potential solution to these problems is represented by curated health app portals. These websites pool health and wellbeing apps curated by either governmental bodies (e.g. NHS Apps Library) or private companies (e.g. ORCHA). These portals aim to list evidence-based, quality assured, safe and tested health apps. However, the use and the popularity of these is under researched.

1.3.4. Smoking

Smoking is one of the leading risk factors of noncommunicable diseases worldwide (1). The UK government has committed to creating a smoke-free generation and improving smoking cessation services. Supporting people to quit smoking is a public health priority (5). Digital behaviour change interventions, such as smartphone apps, have shown promise for smoking cessation (27).

1.4. Theoretical frameworks

The structure that can hold or endorse a theory of a research study is the theoretical context, or framework. The theoretical framework is a collection of interrelated concepts that connects the researcher to existing knowledge. The COM-B model of behaviour, together with the Theoretical Domains Framework (TDF), were identified as the appropriate theoretical frameworks for the thesis. The benefit of employing the COM-B model with the TDF, over other types of behaviour change theories and models, is that TDF offers several explanatory components to help understand the behaviour, while the COM-B model helps to synthesize these (73). These are presented below.

1.4.1. The COM-B model of behaviour

The COM-B (Capability, Opportunity, Motivation – Behaviour) model is a behaviour change model, and its purpose is to guide understanding of human behaviour in the context in which it occurs (74). It relies on the interaction of three components: capability (C), opportunity (O) and motivation (M) that shapes the behaviour (B) (74). It is believed that these components together are the necessary conditions for the behaviour to happen (74). In this “behaviour system” (74) the first component, *capability*, is represented by the individuals’ physical and psychological capacity to engage with the behaviour. This includes knowledge, as well as skills. The second component is *opportunity*, which includes all the physical and social determinants that could influence and prompt the behaviour. The last component, *motivation*, is defined as brain processes that fuel and guide the behaviour. This can be reflective motivation, such as conscious and analytical decision-making, or automatic motivation, for example habits or emotional responses.

These components do not just directly influence behaviour, but also interact with each other, as is represented in Figure 1. The COM-B model can be expanded by using the Theoretical Domains Framework.

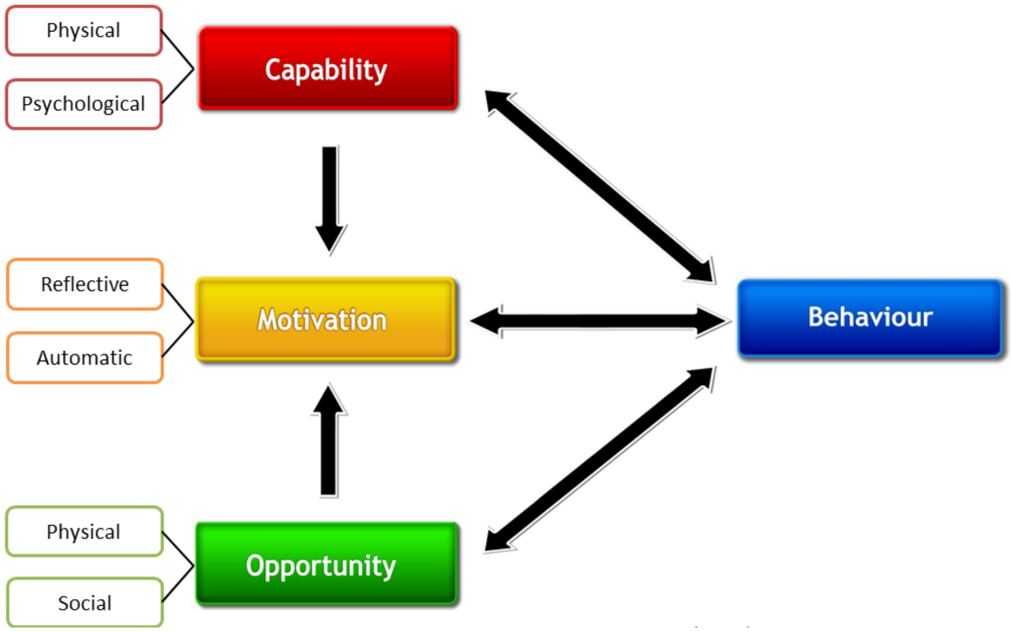

Figure 1. The COM-B model of behaviour (reproduced with permission from (74)).

1.4.2. Theoretical Domains Framework (TDF)

The TDF is a framework that offers a ‘theoretical lens’ (75) through which to view cognitive, social, emotional and environmental influences on behaviour (75). It was developed as a synthesis of 33 behaviour change theories and pooled together into 14 domains with one or more constructs in each domain (75) (see Appendix 1). There is a strong connection between the COM-B model and the TDF. The TDF is a variant of the COM-B model where the domains of the TDF were mapped onto the components of the COM-B model (see Figure 2).

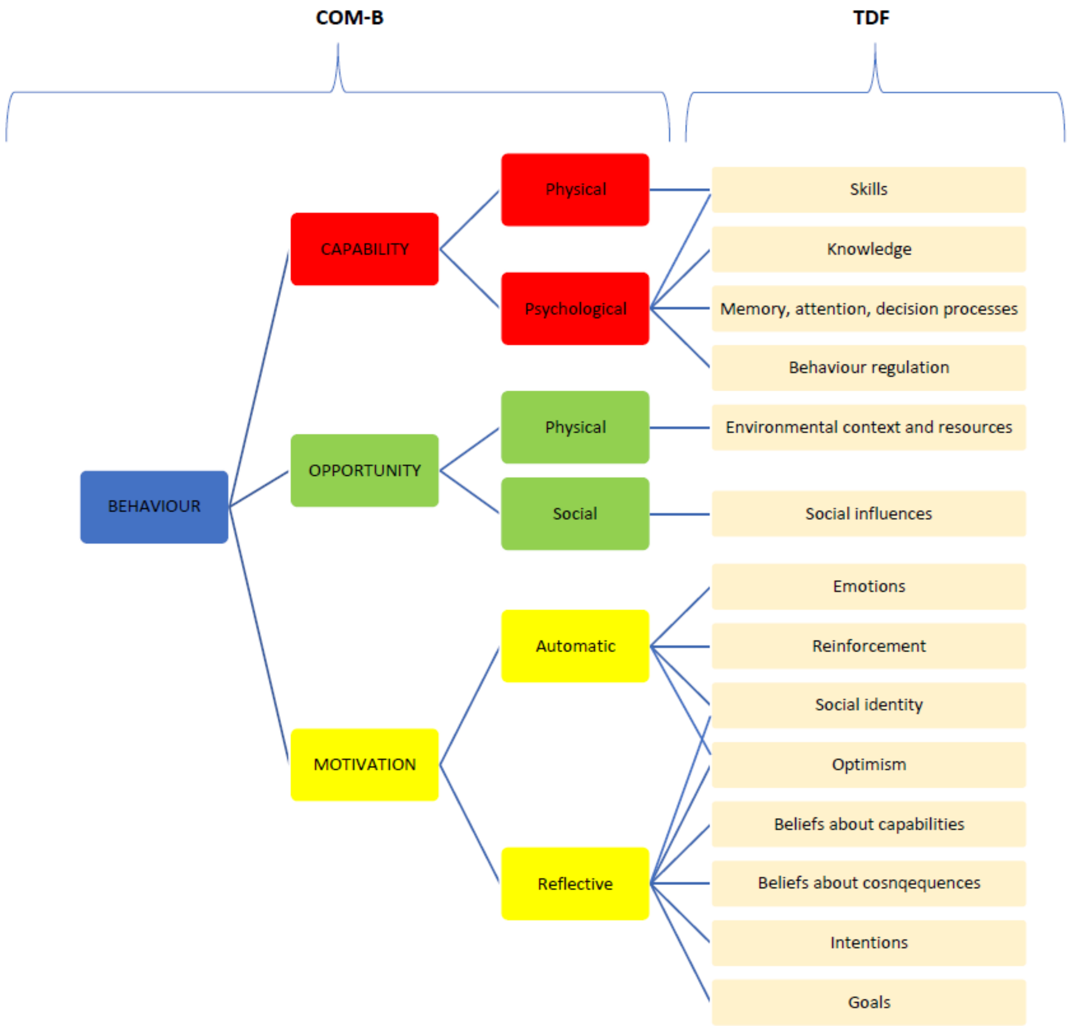

Figure 2. Mapping constructs of the theoretical domains framework onto the COM-B model of behaviour change (44).

Even though the main role of the COM-B model is to guide intervention design (73), its associated theoretical framework, the TDF, has been applied in numerous synthesis frameworks for systematic reviews (76-78) and as a coding guide for qualitative studies (79, 80). When a more comprehensive understanding of the behaviour is needed the TDF can expand the COM-B and, therefore, can help identify a specific construct of the TDF under a component of the COM-B model (81). The more precise the analysis of the behaviour is, the more likely that the intervention will change the behaviour (74).

1.4.3. The Behaviour Change Wheel (BCW)

The COM-B model and the TDF together can be considered as complementary tools to more fully understand the problem of the uptake of and the engagement with health and wellbeing apps in behavioural terms. In particular, when taken together they allow researchers to select intervention functions by using the Behaviour Change Wheel (BCW) approach to design behaviour change interventions in practice (74). The core of the BCW is represented by the COM-B model (i.e. sources of behaviour), followed by the constructs of the TDF in the next layer, intervention functions representing the third layer, and with policy categories in the outer layer of the wheel (Figure 3).

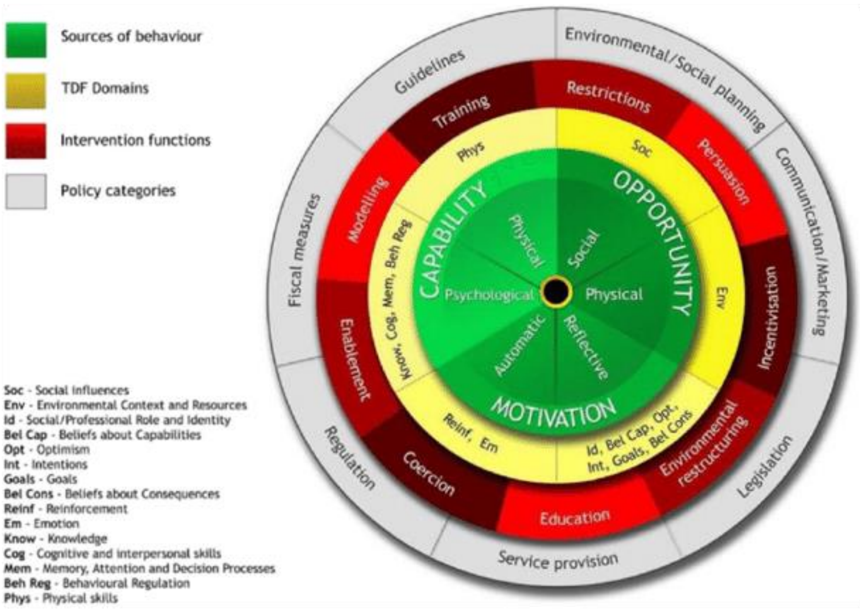

Figure 3. Behaviour Change Wheel (reproduced with permission from (81)).

There are several steps to follow when applying the BCW. Firstly, the identification of the target behaviour is needed: that is what behaviour needs to be changed, in whom and in what way? This thesis focusses on two target behaviours: the *uptake* of and the *engagement* with health and wellbeing apps. This led to the recognition of which components could be changed, in other words the identification of psychological variables that shape the behaviour (capability, opportunity, motivation) (74), by identifying potential factors that may influence the uptake and engagement with health apps. The next step would be to select one or more intervention functions (e.g. education) followed by the selection of a policy category to address long-term implementation (e.g. regulation). Additionally, specific behaviour change techniques can be applied for the chosen intervention function(s) and policy categories. The Behaviour Change Technique Taxonomy v1 (BCTTv1) was developed, featuring 93 hierarchically clustered techniques (82) due to a need for standardised definitions and labels for the active components of behaviour change interventions. The development of the BCTTv1 has simplified the process of selecting specific behaviour change techniques to bring about changes in the targets of the intervention. Once the behaviour change techniques are chosen, the final step is to develop an intervention plan with a specification covering aspects related to content and delivery of the intervention (81).

The COM-B model, together with the TDF, have assimilated the most important constructs of the most commonly used behaviour change models and theories (83), including those relating to societal factors, beliefs, attitudes, habits, self-control, norms and intentions. All these concepts were suggested to be relevant in the uptake and engagement with health and wellbeing apps. Therefore, unlike the other behaviour change models and theories, the COM-B with the TDF, the core of the BCW, provides a comprehensive way of exploring how these constructs interact with each other, hence, proves to be the most suitable theoretical framework to apply in this thesis.

1.5. Stakeholder engagement

Stakeholders are groups of individuals interested in, or affected by, a project. Stakeholder engagement is a method of shaping a range of outcomes through collaboration, consultation and consensus. Stakeholder engagement ensures the acceptability of research, that is to what extent will it be accepted by developers and users, and how meaningful and useful research findings would be for them. The stakeholders of this project are represented by those who have an interest in improving public health and those who are affected by policy decision makers, end-users represented by the general public. Therefore, stakeholder engagement was achieved by continuous stakeholder dialogue with the representatives of the Public Health England (PHE) and the Patient and Public Involvement group (PPI). This allowed the project to be compatible with, or inform, ongoing digital tool development within PHE and NHS Digital, both organisations that aim to provide the public with effective evidence-based digital tools to help the general public manage their physical and mental health. It also involved end-user participation through PPI to ensure that the relevance of the research was fulfilled from a lay person's perspective.

1.5.1. Public Health England

The project fits closely with the digital public health agenda and the NHS's long-term plan (84) , 'digital first' (85). It is expected that from 2024, individuals in England will have the opportunity to access digital primary care services (84). Furthermore, the expectation is that digital care using wearables, electronic services and digital tools will become standard care by the end of the ten year period (86). The research findings within this thesis are, therefore, compatible with and inform ongoing digital tool activities within PHE and NHS Digital. The development of the qualitative research, as well as the experimental development phase, was based on continuous stakeholder dialogues with Dr Tim Chadborn, Behaviour Insight Team Lead at PHE, who has been involved in the development of this thesis as a tertiary supervisor, and with endorsement from the Deputy Director of PHE Digital, the PHE Strategy and Innovation Lead, and the PHE Strategy and Planning lead.

Towards the end of this project part of PHE was replaced with a UK-wide health protection institute the UK Health Security Agency, while another part joined the Department of Health and Social Care. The team led by Dr Tim Chadborn was absorbed by the Department of Health and Social Care. However, to reflect the chronological order of the conducted studies, this thesis will continue to use PHE as reference for the work undertaken.

1.5.2. Patient and Public Involvement (PPI)

The aim of PPI was to involve end-users in planning, conducting and evaluating research (87). The importance of this lays in the fact that PPI has a potential benefit for researchers to ensure that the research itself is designed in a participant-friendly manner and that all relevant aspects of the research is relevant to the public (88). Therefore, undertaking effective and meaningful PPI is crucial and this project aims to consider these aspects.

Whilst conducting a secondary data synthesis, a systematic review, is less relevant for PPI input, involvement of members of the public was crucial for the rest of the project. Following the advice of Gray-Burrows and colleagues (87) PPI representatives were involved in: 1) planning the research by informing the content of the research materials (e.g. they helped refine the topic guide for the interview study); 2) interpreting findings by reviewing how the research is progressing; 3) providing knowledge by sharing personal experiences, which was especially useful in the development of the DCE.

Advice from PPI representatives, who have used behaviour change apps before, had already been sought prior to the start of the PhD by reviewing and commenting on the application for research funding.

1.6. Aim and objectives

The thesis aimed to understand factors influencing the uptake of, and engagement with, health and wellbeing smartphone apps and to serve as a starting point of the development of interventions that aim to increase the uptake and engagement of such apps. The ultimate aim of the project is to inform the optimisation of digital service tools, such as the Public Health England (PHE) 'One You' portal and the NHS apps library, that promote uptake and engagement with evidence-based health and wellbeing apps. While part of the thesis focuses on a wide range of physical and mental health apps, focusing on a single behaviour to test key principles was considered most practical. Smoking is a highly appropriate single behaviour to focus on as it is one of the leading risk factors of noncommunicable diseases worldwide (89) and the UK government have committed to creating a smoke-free generation and improving smoking cessation. Furthermore, it would allow the translation of findings to other types of health apps as the way individuals assess the utility of apps during uptake tends to be similar (52).

The key objectives of the thesis were:

1. To gain a better understanding of the factors influencing uptake of, and engagement with, health and wellbeing apps
2. To explore how and why individuals select a health and wellbeing app, including routes for identifying apps other than commercial smartphone app stores, as well as reasons for engagement and non-engagement with apps
3. To determine the factors likely to influence the uptake of smoking cessation apps and to identify factors which may potentially influence adults' engagement with health and wellbeing apps.

1.7. The structure of the thesis

This thesis reports three original research studies that used qualitative and quantitative methodologies. These three studies yielded five research papers described in the '*Statement of jointly authored publications*' that are either published or submitted and under review at the time of completion of this thesis.

This thesis involved three stages of work. The first stage of work is focused on the identification of factors influencing the uptake of, and engagement with, health and wellbeing apps and included two studies:

- A theory informed comprehensive systematic review of the digital health literature, including all types of study design that aimed to identify factors influencing the uptake of, and engagement with, a wide range of health and wellbeing smartphone apps (Chapter 2).
- A think aloud and interview study to explore what potential app users consider to be important for the uptake of health and wellbeing apps and to investigate the potential of curated health app portals as a way of choosing health and wellbeing apps (Chapter 3) and perceptions of factors influencing engagement with health and wellbeing apps (Chapter 4).

The second stage of this thesis focuses on the development of a discrete choice experiment based on the findings reported in Chapters 2 to 4:

- A methodological description of how the discrete choice experiment was developed and serves as a guide to those with limited knowledge of this method (Chapter 5).

The final stage of this thesis describes the findings of an experimental study that investigated the uptake of smoking cessation apps:

- A discrete choice experiment to determine the attributes that may influence the uptake of a smoking cessation app and their relative importance. The study also assessed factors influencing the uptake of, and engagement with, smoking cessation apps to better understand to what extent are these facilitators or barriers (Chapter 6).

Note on the final two stages of the thesis.

The second stage of this thesis initially was planned as a development of a web-based intervention that aimed to investigate the most preferred features of a prototype health app portal, and the third stage being a feasibility study to test the intervention. The development stage was ongoing when the COVID-19 pandemic started and should have been based on a close collaboration with PHE. However, because of COVID, PHE's priorities have changed, and this collaboration was no longer feasible. The decision to find a different methodology was made and a DCE was developed instead.

Chapter 2. Influences on the uptake of, and engagement with, health and wellbeing smartphone apps

2.1. Dissemination

This chapter was presented at the Behavioural Science and Public Health Network Annual Conference (2019), at the University College London Centre for Behaviour Change Digital Health Conference (2019), at the Norwich Science Festival (2019), at the Public Health England Annual Conference (2019), accepted at the European Health Psychology Society's Annual Conference (2020 – cancelled due to the COVID-19 pandemic) and at the International Society of Physical Activity and Health Virtual Congress (2021).

A version of this chapter has been published in the Journal of Medical Internet Research (44). See Appendix 2 for the published peer reviewed journal article.

2.2. Abstract

Background. The public health impact of health and wellbeing digital interventions is dependent upon sufficient real-world uptake and engagement. Uptake is currently dependent largely on popularity indicators (e.g. ranking and user ratings on app stores), which may not correspond with effectiveness, and rapid disengagement is common. Therefore, there is an urgent need to identify factors that influence uptake and engagement with health and wellbeing apps to inform new approaches that promote the effective use of such tools.

Objective. To synthesise what is known about influences on the uptake of, and engagement with, health and wellbeing smartphone apps amongst adults.

Methods. A systematic review of quantitative, qualitative and mixed-methods studies. Studies conducted on adults were included if they focused on health and wellbeing smartphone apps reporting on uptake and engagement behaviour. Studies identified through a systematic search in MEDLINE, EMBASE, CINAHL, PsychINFO, Scopus, Cochrane library databases, DBLP and ACM Digital library were screened, with a proportion screened independently by two authors. Data synthesis and interpretation was undertaken using a deductive iterative process. External validity checking was undertaken by an independent researcher. A narrative synthesis of the findings was structured around the components of the COM-B behaviour change model and the Theoretical Domains Framework.

Results. Out of 7640 identified studies, 41 were included in the review. Identified factors related to uptake (U), engagement (E) or both (B). Under ‘Capability’, the main factors identified were app literacy skills (B), user knowledge, including app awareness (U), available user guidance (B), health information (E), statistical information on progress (E), well-designed reminders (E), features to reduce cognitive load (E), and self-monitoring features (E). Availability at low cost (U), positive tone and personalisation (E) were identified as physical ‘Opportunity’ factors, while recommendations for health and wellbeing apps (U), embedded health professional support (E) together with social networking (E) possibilities were social ‘Opportunity’ factors. Finally, ‘Motivation’ factors included positive feedback (E), available rewards (E), goal setting (E) and the perceived utility of the app (E).

Conclusions. Across a wide range of populations and behaviours, twenty-six factors relating to capability, opportunity and motivation appear to influence the uptake of, and engagement with, health and wellbeing smartphone apps. Recommendations at the end of this chapter may help app developers, health app portal developers and policy makers in the optimisation of health and wellbeing apps.

2.3. Introduction

2.3.1. Background

Digital behaviour change interventions, such as smartphone apps, can be effective and cost-effective tools to change a range of health-related behaviours (90, 91), described in detail in Chapter 1. For example, there have been promising studies of apps to deliver health prevention messages for men who have sex with men (92), to help self-manage diabetes (93) and cardiovascular diseases (94), in weight management (61, 95, 96), alcohol reduction (37, 97, 98), mental health interventions (99), and in the management of long-term conditions (100). For certain behaviours such as alcohol reduction, they could also address the barriers experienced by health professionals when delivering brief interventions in person, such as lack of necessary training (37) and to reduce the stigma associated with the behaviour (91). The public health implications are substantial because of their potential to have a low incremental cost and broad reach.

Despite their promise, effect sizes reported in evaluations of app-based interventions are often small. One potential explanation is the level of uptake and engagement. Uptake refers to the act of downloading and installing a smartphone app. Engagement has been defined as '(1) the extent (e.g. amount, frequency, duration, depth) of usage and (2) a subjective experience characterised by attention, interest and affect' (56). To date, low uptake and poor engagement are commonly observed with digital interventions which is often insufficient to sustain behaviour change (101, 102). However, there is a lack of evidence as to the main factors in contributing to problem.

Systematic reviews that focussed on one specific behaviour or a certain type of health or wellbeing app suggest that the effectiveness of evidence-based smartphone apps can be improved by targeting the design and engagement features, such as user-friendly design, individualised and culturally tailored content or health professional support (39, 103, 104). A review based on experiential and behavioural perspectives conceptualised key factors that might affect engagement with digital behaviour change interventions: the content (e.g. behaviour change techniques, social support, reminders), and how the content is delivered (e.g. professional support, personalisation, aesthetic features) (56).

To date, no systematic review that primarily seeks to identify factors that influence the uptake of, and engagement with, a wide range of health and wellbeing smartphone apps has yet been conducted. To narrow the focus of this review, the four public health priority behaviours related to prevention (smoking, alcohol consumption, physical activity and diet) along with mental health and wellbeing were targeted.

2.3.2. Theoretical framework

The COM-B model (74) and the Theoretical Domains Framework (TDF) (75) described in Chapter 1 were used as a coding framework, where the constructs of the TDF were applied as subthemes under the components of the COM-B model.

2.3.3. Objectives

This systematic review aimed to synthesise factors identified in studies that influence the uptake of, and engagement with, health and wellbeing smartphone apps among adults targeting public health priority behaviours (smoking, alcohol consumption, physical activity and diet) and mental health and wellbeing and mapped these factors under the components of the COM-B model and constructs of the TDF. This could help inform stakeholders in public health and policymakers, digital behaviour change intervention developers, and providers of health and wellbeing smartphone app portals to better target uptake and engagement.

2.4. Methods

The review was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (105) (see Appendix 3), and the protocol was registered on the International Prospective Register of Systematic Reviews (PROSPERO: CRD42019120312). The review used a mixed-methods approach to generate different, but complementary knowledge about users' views from qualitative findings, and predictors and patterns of behaviour from quantitative findings.

2.4.1. Eligibility criteria

Eligible studies had to explore factors that influence uptake or engagement with health and wellbeing smartphone apps among adults. Table 1 summarises the inclusion/exclusion criteria.

Table 1. List of inclusion/exclusion criteria.

	Inclusion criteria	Exclusion criteria
Participants	Adults aged 18 and over. Studies including individuals aged 16 and over were included if at least 70% of the participants were 18 or over.	Apps targeting health professionals.
Intervention/ context	Studies investigating digital interventions using smartphone health and wellbeing apps on the following behaviours and outcome: smoking, alcohol consumption, physical activity, diet and mental health and wellbeing.	Studies where the smartphone was not the primary intervention component.
Outcomes	Qualitative: Findings described as facilitators, barriers, determinants of uptake or engagement with health or wellbeing apps (either already existing or planned to be developed), including perceptions, beliefs, experiences, interest, etc. of the participants. Quantitative: Uptake, measured as number of downloads; engagement measured as number of logins, frequency of use or any other relevant measure that tracks user engagement.	Usability and user-testing studies, where functionality and app design were exclusively investigated for specific apps.
Study design	All study designs were included.	Not applicable.

2.4.2. Search strategy

2.4.2.1. Electronic search

A systematic literature search was developed in consultation with a specialist librarian from the University of East Anglia and a senior information scientist from PHE. An iterative process helped to define the final search terms while ensuring a balance between sensitivity and specificity. A systematic literature search was performed in eight electronic databases: MEDLINE, Embase, CINAHL, PsycINFO, Scopus, Cochrane Library database, DBLP and ACM Digital library. The databases were searched with no data limit, no publication or geographical restriction, but limited to English language. Synonyms of three concepts were searched: (mhealth) AND (behaviour change) AND (uptake or engagement) (see Appendix 4 for MEDLINE search strategy). The electronic search was performed in November 2018 initially and it was updated in August 2019.

2.4.2.2. Searching for other resources

Additionally, the search also included a manual search in key journals, such as 'Journal of Medical Internet Research' (JMIR) and 'Computers in Human Behaviour', and in Google Scholar. Reference lists of all included studies were hand searched for additional studies. The search for grey literature included dissertations and theses, as well as unpublished research data and material sought from government bodies and policy makers during stakeholder communication (PHE, NHS in England).

2.4.3. Identification of studies

All records identified by the search strategy were exported to Endnote X9 and deduplicated. To reduce the likelihood of reviewer selection bias and to assess how reliably the study eligibility criteria were applied, a subsample (10%) of records were additionally screened by FN during the title and abstract screening. Inter-rater reliability based on the number of eligible and ineligible studies was tested using Cohen's Kappa statistics (106), with the following cut-offs being used: 0.41-0.60 to indicate moderate agreement, 0.61-0.80 substantial agreement and 0.81-0.99 almost perfect agreement (106). The full texts of potentially eligible studies were independently screened by the lead author with 20% randomly selected and double screened by FN. The exclusions of the studies were justified and recorded.

2.4.4. Data extraction

A data extraction proforma was developed by the lead author following the existing Cochrane guidelines (107) and the subsequent data were extracted: study characteristics (author, date of publication, sample size and type, location of the study, type of the app investigated in the study, aim of the study, methodological characteristics (design, data collection, participants), main findings related to the research question of this systematic review (including participants' quotations and authors' interpretations in the qualitative studies and reported results of the quantitative studies) and conclusion of each study. The data extraction was performed by the lead author and was checked for accuracy by FN.

2.4.5. Quality assessment

To assess the quality of the studies, critical appraisal was conducted using the latest version of the Mixed Methods Appraisal Tool (MMAT) (108). MMAT is a unique tool (108) that was developed by pooling together the core relevant methodological criteria found in different well-known and widely used qualitative and quantitative critical appraisal tools (109-111).

The quality of all studies was assessed by the lead author and checked for accuracy by FN and AJ. The tool is not intended to score the studies or to exclude papers, but to offer a guide of how to interpret findings (108).

2.4.6. Data synthesis and analysis

Integrative synthesis was applied to analyse the data (112, 113). The focus of the synthesis was on interpreting the data using specific concepts of the TDF as a deductive coding framework which, for ease of interpretation, is summarised under the components of the COM-B model. Using the integrated approach, the data were pooled together by findings viewed as answering the same research questions, rather than by methods (e.g. quantitative vs qualitative) (112, 113).

Deductive thematic synthesis, a methodology designed to enhance the transparency of synthesising qualitative data (114), was used to conduct the data synthesis of the findings of the qualitative studies and the qualitative component of the mixed-methods studies. Using line-by-line coding, the findings were coded deductively into the domains of the TDF. The coding was conducted by the lead author, and a randomly selected 10% of the coding was checked for accuracy by FN. Regular coding meetings took place to maintain consistency. Expert opinion of an independent researcher with extensive experience in systematic reviewing was sought on data synthesis. The integrative approach includes interpretation of the quantitative findings by ‘qualitizing’ (113), which refers to the textual interpretation of the findings of the quantitative studies (regardless of the interpretation of the author) so they can be combined narratively with the qualitative data (113).

2.5. Results

2.5.1. Included studies

A total of 7633 studies were initially retrieved, with a further six identified through manual search and reference check. An additional unpublished research report was received from stakeholders as part of grey literature searching process. No non-English papers were identified. A total of 2138 duplicates were removed. Further 5429 studies were excluded based on the review of their titles and abstracts (Figure 4).

PRISMA 2009 Flow Diagram

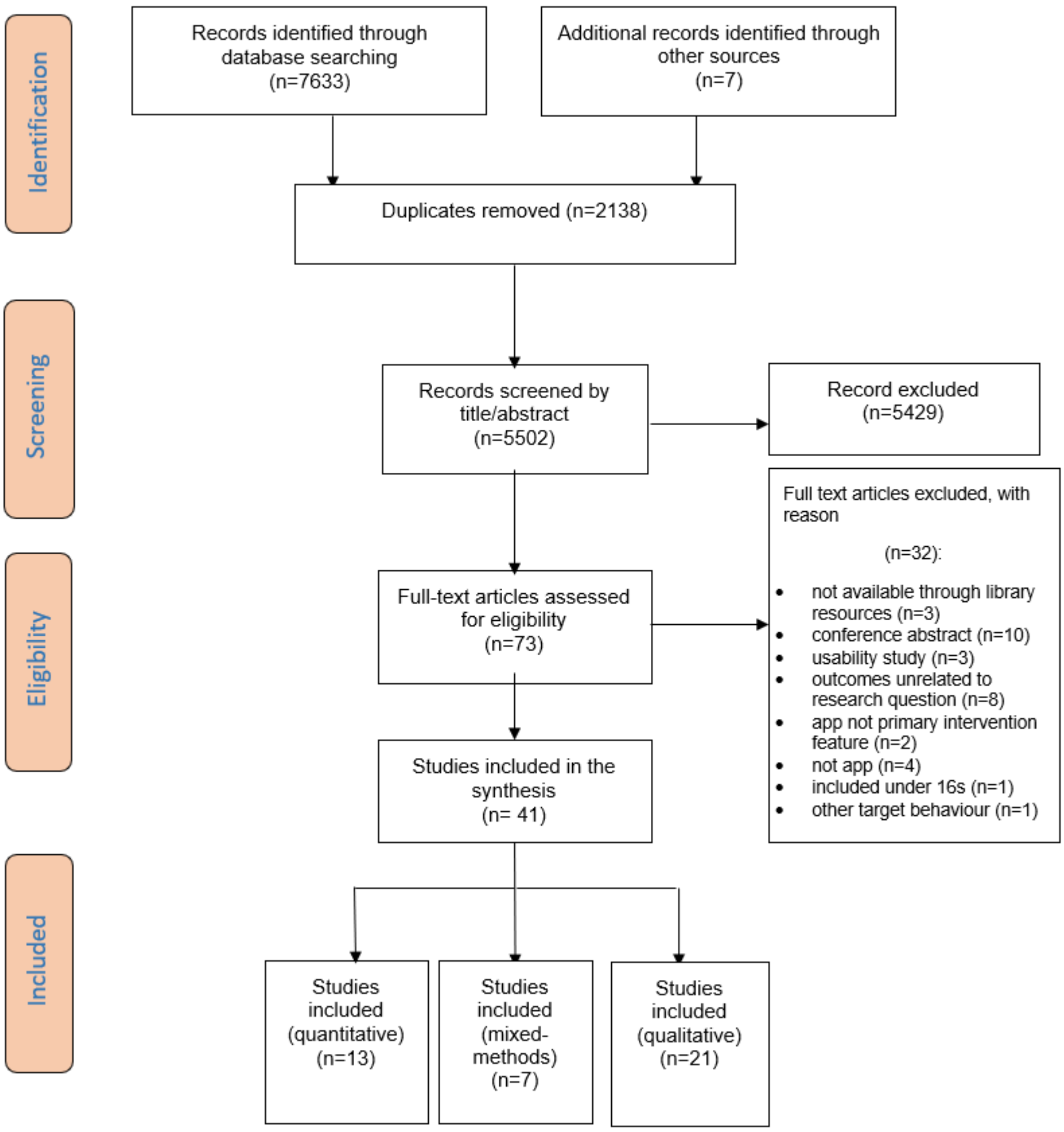

Figure 4. PRISMA flowchart illustrating the inclusion and exclusion of the studies (105).

During title and abstract screening 'substantial' agreement was achieved between the two independent reviewers (Kappa = 0.63) (106). There were two types of disagreements identified (one reviewer included studies that targeted app use in conjunction with a connected device, and purely user research studies) that limited agreement between the reviewers during the selection process, which were resolved through discussion and with the consultation with a co-author. After disagreements were resolved and the eligibility criteria updated accordingly, seventy-three studies were identified as potentially meeting the inclusion criteria. All remaining titles and abstracts of records were assessed by the lead author. From these, 41 studies were included in the review (52, 115-154), out of which thirteen were quantitative (119, 120, 122, 127, 131, 133, 140, 142, 145, 153-156), seven were mixed-methods (116, 125, 136, 139, 147, 151, 157) and twenty-one were qualitative studies (52, 115, 117, 118, 123-125, 128-130, 132, 134, 135, 137, 138, 143, 144, 146, 148, 149, 152).

2.5.2. Description of included studies

The study characteristics are summarised in Appendix 5. The end users of the studies were described as the general public (52, 115, 117, 120, 122, 124, 125, 128-132, 134-136, 142, 148, 149, 152, 153), college students (126), existing app users (116, 124, 127, 133, 140, 144, 147, 154, 155), male workers of male-dominated industry (137), LBGTQ+ communities (118), rural communities (135), Asian ethnic minorities (119), pregnant women (157), patients in primary care (123, 138, 151), adult cancer survivors (139), adults with diabetes (135), those infected with HIV (156), those with chronic disease (145) and bipolar disorder (146). The focus of some studies was very specific and targeted a certain health behaviour or condition, including alcohol reduction (52, 116, 124, 132, 136, 156), smoking cessation (52, 118, 144, 149, 154), increasing physical activity (117, 123, 126, 127, 131, 139, 142, 145), weight management (125, 126, 129, 131, 140, 142, 143, 147, 148), depression (130, 138), mindfulness (128), diabetes management (135) and health management in pregnancy (157). Other studies were less specific and targeted a more general mental health app (137, 146, 155), and a more general health app (115, 119, 120, 122, 133, 134, 151-153). Fifteen studies were investigating factors influencing one particular app (116, 117, 123, 124, 127, 128, 132, 133, 140, 143, 144, 147, 149, 154, 155). The remaining twenty-seven studies examined users' perceptions of a wide range of apps or of a hypothetical app not yet developed.
The studies were published between 2011 and 2019 and were carried out in Australia (115, 127, 137, 138, 147), Belgium (146), Canada (118, 129, 133, 144),

China (145, 153, 157), Czech Republic (142), Ireland (123), Italy (117), New Zealand (125), Norway (152), Sweden (130), the United Kingdom (52, 116, 124, 128, 132, 136, 139, 143, 148, 149, 151), and the United States (119, 120, 122, 126, 131, 134, 135, 140, 154-156).

2.5.3. Quality assessment of the studies included

Based on the MMAT (108) the majority of the studies employing qualitative methodology were deemed to be of high quality. Concerns related to the sample were identified across many quantitative studies. This included issues around sampling, lack of clarity as to whether the groups were comparable at baseline or whether the sample was representative for the general population. In four non-randomised studies confounders were not accounted for by the design and analysis. Two out of seven mixed-methods studies were judged to be of low quality, out of which one is an unpublished report (grey literature) and the other one is a published short report. See Appendix 6 for details of quality assessment for each study.

2.5.4. Data analysis and thematic synthesis

While not all the studies presented data for all the aspects of this review, all studies presented some data that could be included in the synthesis. Evidence that was considered weakly explained, or was judged to be unclear, was not included in the summary of findings. An overview of the identified factors, the level of influence (uptake, engagement or both) along with a brief description of each factor can be found in Table 2. Examples of supporting evidence are provided in the form of quotes.

Table 2. Factors identified in the systematic review.

COM-B component and TDF construct	Identified factor (source)*	U, E or B**	Short description of the factor
Physical capability			
TDF construct: Skills			
	App literacy [124, 128, 135, 138, 142]	B	Technological competency
Psychological capability			
TDF construct: Knowledge			
	App awareness [132, 134, 135, 138, 152]	U	Knowledge of the existence of health and wellbeing apps
	User guidance [115, 117, 124, 128, 136, 149]	B	Instructions on how to effectively use the app
	Health Information [52, 125, 129, 131, 132, 134, 135, 139, 146, 147, 149, 152]	E	Educational information related to health and wellbeing aspects
	Statistical information [115-117, 124, 130, 132, 135, 143, 144, 148, 149, 152]	E	A visual or numerical summary of progress
TDF construct: Memory, attention, and decision processes			
	Well-designed reminders [52, 115-118, 124, 126, 129, 130, 132, 134, 135, 139, 143, 144, 146-148, 155]	E	The ability to customize reminders
	Less cognitive load [52, 115, 117, 124, 126, 128, 129, 132, 134, 135, 137, 143, 146, 148, 149, 152]	E	The app is not too time consuming, easy to use, and requires minimal input
	Coping games [118, 137, 144, 149]	E	Distraction activities within the app
TDF construct: Behavioural regulation			
	Self-monitoring [115-118, 123, 126, 129, 130, 133, 135-137]	E	The ability of the app to help self-regulation of the target behaviour
	Established routines [116, 126, 128, 132, 143]	E	Regularity in using the app
	Safety netting [115, 138, 143, 157]	E	Retaining the app for a potential precipitating event in the future
Physical opportunity			
TDF construct: Environmental context and resources			
	Availability accessibility [115, 118, 123, 127, 130, 135, 147, 149]	U	The ability to use a smartphone anytime anywhere
	Low cost [115, 118, 125, 126, 134, 145, 149, 151]	U	The price of the app
	Interactive and positive tone [52, 124, 129, 135-137, 146, 148, 149]	E	Encouraging communication style
	Personalisation to needs [115, 116, 118, 125, 128, 130, 134, 135, 137-139, 146-149, 152]	E	The possibility to use an app that is tailored to a user's needs

*Studies where the factors were identified; **U, E or B: uptake, engagement, or both.

Table 2. (Continued) Factors identified in the systematic review.

COM-B component and TDF construct	Identified factor (source)*	U, E or B**	Short description of the factor
Social opportunity			
TDF construct: Social influences			
	Recommendations (52, 134, 135, 138, 151)	U	Suggestions received from other users
	Health practitioner support (115, 118, 129, 130, 135, 136, 139, 144, 146, 149, 157)	E	Possibility to get in touch with health professionals and practitioners within the app
	Community networking (115, 117, 118, 125, 134, 136, 139, 143, 144, 146, 148, 149, 152, 157)	E	Social interaction with users with similar needs within the app or within their community
	Social media (52, 117, 118, 126, 132, 134, 138, 143, 144, 147-149, 152)	E	A choice to connect to social media platforms
	Social competition (115, 117, 126, 134, 136, 143, 144)	E	Competitive nature of the app with others or with themselves
	Personification of the app (117, 123, 125, 126, 128, 134)	E	Applying human attributes to the app
Automatic motivation			
TDF construct: Reinforcement			
	Feedback (52, 115, 117, 123-126, 129, 130, 132, 134, 139, 144, 149)	E	Feedback regarding the user's performance
	Rewards (52, 115, 118, 123, 124, 134-136, 143, 146, 148, 152)	E	Tangible and intangible reward in response to the user's effort
TDF construct: Emotions			
	Curiosity (116, 130, 132, 138)	U	Desire to acquire knowledge and skills to use a behaviour change tool
Reflective motivation			
TDF construct: Goals			
	Goal setting (52, 116, 117, 123, 126, 129, 132, 134, 136, 143, 148, 151)	E	Establishing what the user would like to accomplish
TDF construct: Beliefs about consequences			
	Perceived utility of the app (115, 124, 130, 136, 138, 151)	E	Discrepancy of what the users are looking for and what the app offers

Note. *Studies where the factors were identified; **U, E or B: uptake, engagement, or both.

2.5.5. Physical Capability

2.5.5.1. TDF domain: Skills

Skills refer to one's ability to perform an action, and include constructs such as competencies, interpersonal skills, skill development and practice. App literacy (124, 128, 135, 138, 142), defined as technological competency to use a smartphone app, was reported by participants as being of high importance for both uptake and engagement. A basic level of app literacy is required to be able to download and initiate engagement with an app, whilst adequate app literacy skills would enhance users' intentions to engage with an app (124, 128).

> *"I'd be happy to do it if I knew how to do it [but] I don't know how to download apps...I need help with technology. Like, I'm 58 and I didn't grow up in a technological age and so do find that I lack confidence with technology." (138)*

> *"I've never used it [these apps] because I never got it to work the way I wanted it to." (135)*

In a cross-sectional study, advanced app literacy was associated with the increased use of the social functions of an app, such as networking, but not with the functions that target action planning and goal management (142). This suggests that app literacy might be an important aspect for successful uptake, but this alone might not be enough to maintain engagement. In contrast, users have reported that lack of app literacy skills could trigger negative emotions towards themselves (e.g. self-blame, disappointment of not being able to use an app) (124, 128, 138), and could contribute to their perceived low self-confidence in using technology (138).

2.5.6. Psychological Capability

2.5.6.1. TDF domain: Knowledge

There were multiple factors identified under the TDF domain that covers rational, procedural and other types of knowledge, information and awareness of the existence of something. App awareness (132, 134, 135, 138, 152), such as information on the existence of health and wellbeing apps, would positively influence uptake of health and wellbeing smartphone apps.

> *"I didn't realize that they had an app."* (135)

It was suggested that many participants were not aware of the availability of such tools, and some found the disorganised nature of the commercial app stores confusing, and represented a barrier for uptake (138).

User guidance (115, 117, 124, 128, 136, 149), namely instructions on how to effectively use an app, such as how to create achievable goals, influenced uptake and initial engagement. It was proposed that by having a guide on how to use an app could positively affect the users' intention to be engaged with it, and hence users might be able to better regulate their behaviour (124, 136).

> *"I want something to tell me 'Do number 1 first, then number 2. When you've done this go here" so I don't have to think too much about it. Once I've got it up and running, I'm fine.'"* (124)

However, the presence of a guide was reported off-putting and unnecessary for long-term engagement by producing negative emotions (e.g. annoyance) once the knowledge regarding app functionality has been gathered (136).

> *"Just at the beginning of the app, when you've downloaded it and you're using it for the first time, it should tell you what to do. But not every time. You don't need guidance how to use it and where things are, because I think it would just be annoying."* (136)

Available health information within the app was perceived by users as beneficial and positively influenced their engagement in several studies (52, 125, 129, 131, 132, 134, 135, 139, 144, 146, 147, 149, 152).

> *'[It is] important and really helps me to learn about bipolar disorder and read about stuff'*. (144)

> *"I... enjoy learning something new. It's quite informative and makes you think about what you're doing. [QG] helps you to understand a bit more about what's going on...what could go wrong by continuing [to smoke]."* (149)

Depending on the target behaviour, end users wished to: 1) access advice on exercise routines (117, 134, 139, 143); 2) seek nutritional education (117, 129, 134, 135, 143, 147); 3) widen their knowledge of health consequences (52, 144, 149); 4) find out more about healthy living whilst living with a medical condition (139, 157); 5) know more about the condition they are living with (146, 152, 157); 6) improve their health literacy (152); 7) demystify myths (149); 8) receive health news updates, such as on smoking taxes and bans (149); 9) better understand alcohol units (UK) (132).

However, the quality of information was identified as potentially affecting engagement (149). Some users wanted a credible source, a trustworthy and evidence-based guide with references to the information they receive (139, 147, 157).

> *“I personally am scared of getting lymphedema, and still don’t know sometimes what exercises are good to prevent it, so I think that maybe educating people about […] consequences of not exercising from a really good NHS source would be helpful.”* (139)

Health information that focuses on negative aspects of the past behaviour that cannot be modified (e.g. smoking or alcohol consumption) would trigger negative emotions (e.g. regrets) (52). It was suggested that better quality of information would increase the likelihood of maintaining users’ engagement with an app and consequently they would better self-monitor their behaviour (134, 144). This could be achieved by providing a wide range of information that everyone could relate to rather than facts that are already known (149).

> “*I think everyone has heard that information many times. It’s actually quite patronizing...shallow stuff, not hard-hitting useful facts. It obviously isn’t a tailored app to each person, but it gives enough information that each person can relate to it in a tailored way. I find it really engaging, I suppose that’s why I stuck with it.”* (149)

For example, one qualitative study suggested the use of health quizzes to promote engagement (152). Health quizzes were also found promising by a large study that evaluated the uptake of a loyalty points-based health app conducted in Canada (133). One of the intermediate objectives of that study was to improve the Canadian population’s health literacy by using health information related to quizzes. The app usage data included quiz completion rates, and the results showed that 60% of the users were highly engaged with the app by having more than 75% of health quizzes completed. Furthermore, better health literacy might enhance beliefs about consequences (e.g. health outcome expectancies) (144, 149) and the users’ intention to stay engaged with an app and subsequently with the behaviour they target to change (149, 152). Mackert and colleagues also found that adequate health literacy was associated with increased engagement with fitness and nutrition apps (131).

Users valued available statistical information (115-117, 124, 130, 132, 135, 143, 144, 148, 149, 152) that was a visual or numerical summary of progress or a trend in their behaviour. This included features like step counting (148, 152), the number of calories consumed (132, 148), number of days spent abstinent from smoking (144), the amount of money saved by quitting smoking (149) or by reducing drinking (132), a trend in their alcohol consumption and how is it changing over time (116, 124, 132), as well a way to allow analysis of user data (115, 152). Being able to check their progress helped users better monitor their behaviour (115-117, 148, 149) and for some individuals, a positive trajectory acted as a behavioural reinforcement (124, 144).

> "*I like the numbers. I like to track stuff and have some figures behind it rather than just like, oh, I'll go for a run today. I'll be like, well, I'll go for a run today but what's my time from last time and how can I beat it? And I think that's why this kind of app appeals to me. If I just put the drinks in and it just said you're drinking too much but didn't give any numbers behind it, I'd probably delete it within a few days."* (116)

> *"It was like a visual of my day of smoking. And every day, you'd look at it, it went down and down and down, like it got better every day. So, it was like a motivational thing to just look, like positive reinforcement."* (144)

In two studies, participants reported that a lack of visual representation of progress led to disengagement with the alcohol reduction app (116, 124), and one study on smoking cessation reported negative emotions associated with progress viewing during 'a few bad days', suggesting discouragement (144).

> *"I couldn't find any graph that's reflected the mood so therefore I didn't see the point of having to fill that part out and I stopped filling it out."* (124)

> *"If you're having a bad day or a couple of bad days, seeing it on [the app] as a reflection [of your bad days] just like kicks you in the face even more, you know?"* (144)

2.5.6.2. TDF domain: Memory, Attention and Decision Processes

This domain focuses on the ability to retain and select information, including aspects of attention, memory, decision making and cognitive overload. Reminders (52, 115-118, 124, 126, 129, 130, 132, 134, 135, 139, 143, 144, 146-148, 155) to engage with an app were reported as being useful for people with busy schedules, and for those who tend to forget engaging with the app and, therefore, with the target behaviour (115, 117, 134, 144, 155). Individuals described being inclined to check their phones when receiving a notification (115, 116, 118). Reminders positively affected behavioural regulation by prompting engagement with self-monitoring and the tracking features of the app (115, 117, 118, 129, 132, 139, 144, 146-148), as well as reinforcing the users by reminding them about their positive progress (118, 126, 129).

> *"I found it was almost like having my girlfriend there, in a good way. So you're like, oh I haven't done this in two days, I didn't even realize, but my phone just reminded me. Better keep it going."* (144)

A micro-randomised trial found that a push notification that contained a tailored health message resulted in a small increase in the engagement with a health app (155). A large study conducted on engagement with a weight loss app found that 16% of the most engaged group used reminders, compared to 1% of the least engaged group (140). However, not all users found reminders useful (52, 115, 117, 129, 134, 135, 143). In the case of behaviours that are associated with stigma (e.g. alcohol consumption), reminders would threaten the users' social identity when these are received at an inappropriate time or wrong place (116, 124, 132).

> "*I think because they were just pinging… and I was just thinking, I don't really want to read this right now. Obviously, and I don't know whether they do but I guess most people check their phone when something pings in and you can be with your friends and actually maybe you wouldn't want to be saying to your friends, I've just got a notification from Drinkaware*". (116)

Therefore, the timing of when the reminders were sent, as well as the language used, appeared to be important conditions. If these conditions were not met, users were more likely to turn the notifications off (115, 116, 144) or ignore them (134, 143, 144).

> *"I completely ignored them [notifications]. Actually, I'm pretty sure I had the notifications that were from the app all turned off. It just felt like a pop up, like another thing for me to click close on throughout the day. I completely paid no attention to it."* (144)

Regarding attention and decision processes, the findings of the studies included in the review proposed that cognitive overload should be avoided to maintain engagement with an app. An app that is less time-consuming, requires minimal input, is easy to use and log into was preferred (52, 115, 117, 124, 126, 128, 129, 132, 134, 135, 137, 143, 146, 148, 149, 152).

> *"I really loved it [Couch to 5K], there was no excessive login, it was really easy you just downloaded and start you have to have your email, no password, no nothing like that, they don't send you a bunch emails that annoy the crap out of me. Nothing."* (126)

Additional functions that decrease the time spent on a task using an app were highly appreciated (115, 117, 126, 128, 132, 134, 148, 149, 152). The automatization of data collection, for example, by linking apps to wearables (115) or by using the camera function for scanning the barcodes to input calories (148) was found particularly useful for physical activity and weight management apps. An app that is easy to use and does not require extra effort would increase the intention to engage with it (117, 124, 126, 132, 134, 135, 151), and would improve users' self-monitoring and self-management strategies (126, 129, 143, 152). Conversely, using a difficult and time-consuming app would affect the users' perceived competence in engaging with it (128).

> *"What I'm thinking is, this better be easy, because otherwise I'm probably not going to do it. If there are too many obstacles in the way I won't. Even though I know I need to do this, I probably won't."* (124)

Such an app often would be deleted or replaced with another one that is perceived to be easier to use (124, 126, 134, 143, 148). Only one study found that users who are highly committed to change behaviour (in this case to reduce alcohol consumption) would be willing to overcome this barrier (132).

Including coping games (118, 137, 144, 149) as distraction activities was suggested as a helpful way to cope with cravings (smoking) (118, 144, 149) or with distress (137). Some users indicated that by using their hands and minds, they expected to be preoccupied, instead of engaging with the undesirable behaviour, while keeping them engaged with the app itself.

> *"If there was a bunch of games on the app that were there to distract you from smoking, (you could) go play five minutes of a quick game instead of smoking."* (118)

> *"Maybe if they had prior to like some type of like a mini game or something in there that would keep the mind occupied rather than telling you, 'Don't smoke.'"* (149)

2.5.6.3. TDF domain: Behavioural Regulation

Behavioural regulation refers to managing, monitoring or changing actions or behaviour. Self-monitoring, the ability of an app to help monitor and regulate the target behaviour (116-118, 123, 126, 129, 130, 133, 135-137), was found to be important to support behaviour change. A self-monitoring feature was able to raise awareness on the number of cigarettes smoked (52, 118), the amount of alcohol consumed (52), the number of steps they made (123), the mood they have (137), or on users' calorie intake (126, 134).

> *"You get a chance to see what you do on a daily basis, something you're probably not aware of."* (134)

It also enhanced users' intention to engage with an app (52, 129, 130), provided 'self-reinforcement' (130), helped increase self-efficacy (134, 138, 148), and evoked feelings of 'control, security, health, empowerment and autonomy' (132).

> *"Because I can see I'm getting better, I use the app now, but I can see myself in the future not having to use it. Kind of like a stepping stone I guess."* (148)

An established routine or regularly using an app (116, 126, 128, 132, 143) positively affected the intention to engage with an app (128) and to maintain the engagement.

> *"Because I've got a couple of other little apps that I look at on a daily, not all apps, but a little regime of four or five, you know, I check the weather and I look at my drink app, and various things like that, a little routine, so pretty much daily."* (116)

Further, safety netting (115, 138, 143, 157) defined as the ability of an app to provide 'aftercare' (143), and an option to retain an app for a potential precipitating event in the future and for relapse prevention, was found useful to maintain the behaviour, even when the target behaviour has been achieved.

> *"I think the migraine one's probably outlived its usefulness for me, but the back pain one, I could still go back to that at any time. If I started to need to monitor my pain again in a systematic way, I'd still go back to it."* (115)

2.5.7. Physical Opportunity

2.5.7.1. TDF domain: Environmental Context and Resources

This domain refers to the circumstances of an individual's situation or environment that positively or negatively affects the uptake of or engagement with health and wellbeing smartphone apps. Availability and accessibility of a smartphone (115, 118, 123, 127, 130, 135, 147, 149) facilitates both uptake and engagement by having a behaviour change device in close proximity.

> *"It was really easy you just put it in your pocket and off you go and… you could do it at your own pace."* (123)

Although a smartphone or tablet enhances portability and accessibility of health apps, the development of an accompanied website was suggested to reduce the inequality for those who might not have the opportunity to own a smartphone (118).

> *"I feel like there would need to be a website equivalent with it (for) people who don't have access to smartphones but do have access to public libraries. A lot of smokers are LGBTQ, and a lot of LGBTQ are in poverty and homeless. The people that you want to access might not be able to access the program."* (118)

Furthermore, the results of a digital behaviour change intervention study examining engagement and non-usage attrition with a physical activity programme suggested that when the app was used together with the accompanying website, a higher engagement rate was observed versus those who used the app only or the web only versions (127).

The low cost of an app was found to be an influential factor for uptake (115, 118, 125, 126, 134, 145, 149, 151), so that low income individuals would be able to afford them (125).

> *"I wouldn't pay money for an app. I think that's kinda stupid."* (126)

In a questionnaire study in China, one of the top barriers of using a health app was the extra cost, having a total of 83% of patients reporting that they would not be willing to pay for a health app (145). Nevertheless, a few participants expressed their willingness to pay a small extra fee (i.e. under $5) if this way they would unlock unique features otherwise not available with the free version (115, 126, 134, 151).

> *"I'm prepared to pay for applications. As well as being in the software industry, I understand that it's people's livelihoods are attached to this. I use some free applications, but I often will pay for the upgraded or the purchased option."* (115)

Numerous studies found that interactivity and positivity of tone may be efficacious for engagement, especially when attempting to change behaviours associated with self-blame (e.g. weight management) (52, 124, 129, 135-137, 146, 148, 149). Three studies provided evidence that an encouraging rather than condescending tone was important (52, 124, 146).

> *"I had a chocolate bar today and It would say, this chocolate bar contained this much saturated fat and... I just feel really guilty now."* (148)

Evidence from one study suggested shame should be avoided and praise emphasised (129), and another study provided evidence that a relaxed tone may be beneficial and may include jokes (124). Several studies suggested that demanding or annoying language would be ignored (52, 135, 136), although a study of nutrition apps reported the occasional need for a tougher attitude to achieve goals (129).

> *"I think I'm more likely to listen to practical advice rather than finger wagging…"* (52)

> *"I just see it as a way to help me monitor what I'm doing and maybe give me a little kick in the pants every now again to be like, 'By the way, that donut had five hundred calories in it. Maybe make a better choice at dinner.'"* (129)

Nevertheless, careful selection of the terminology used to understand the app and what it does, such as using simple and clear language, was suggested to make a noteworthy difference in the effectiveness of the content (137, 149). Terminology around certain behaviours might make a difference. For example, it was reported that using 'non-smoker' label as opposed to an 'ex-smoker' label would increase people's self-confidence (149). It was suggested that unsupportive language would evoke negative emotions (e.g. guilt, regret) and that would affect the intention to engage with an app (124, 136, 148).

A personalised app was highly valued for engagement (115, 116, 118, 125, 128, 130, 134, 135, 137-139, 146-149, 152). Users would want to have control over the app (136, 143, 146). They would like to switch off features they do not use (115), use external incentives, such as uploaded photos or quotes (143, 144), to personalise their goal and how to achieve it (118).

> *"The more I would be able to manipulate the app to be and do what I wanted or needed, for my own circumstances, the more likely I am to use it." (136)*

Users would also like to choose a level at which to start using a particular app. For example, a more experienced user would want to have the possibility to start a mindfulness practice at the intermediate level rather than at the beginner level (128). Users were seeking to receive more personalised information about their current behavioural habits, demographic characteristics, long term effect of the current behaviour (116, 134, 137, 147), and recommendations based on their tracked data (135). Personalisation can be extended to their identity as well.

> *"It must be very personalized, it's easy to find things on the Internet, but it's mostly for normal people."* (152)

Participants were looking for an app that is tailored to their culture and social identity, such as LGBTQ+ people or cancer survivors, or other patients, who are predisposed to have other struggles and mental health issues (118).

> *"Assuming that it's customised to LGBTQ (and) it incorporates the kinds of struggles that we've lived through, it wouldn't be any average quit-smoking app. The fact that it's specific to a community... the fact that it's LGBTQ-specific, that would help us more than if it was just a general quit-smoking app."* (118)

Personalisation to users' needs and preferences suggested better engagement (52, 136, 138), while lack of flexibility in content was found to be a reason for stopping engagement (130), and in some cases created frustration (148). Furthermore, a large study found that 30% of the most frequently engaged group customised the app more, for example, uploaded pictures, than the least engaged group (2%) (140).

2.5.8. Social Opportunity

2.5.8.1. TDF domain: Social Influences

Social influences are interpersonal influences (received from other individuals) that could impact on the individual's behaviours, decisions, thoughts and feelings. In five studies, recommendations to use an app (52, 134, 135, 138, 151), received from health care practitioners or trusted providers (135, 138, 151), friends and families (134, 137, 151), or by reading user reviews (52, 134, 151), positively affected the uptake of health and wellbeing apps.

> *"I'd rather ask a counsellor or a doctor what they would recommend."* (138)

> *"Most of mine [my apps] are friend recommendations, people with similar activities."* (134)

> *"…if an app has a good rating, despite the one or two people who are not satisfied, I think it would mean that it works for the majority of people."* (52)

Connections between an app and health practitioner support were highly valued (115, 118, 129, 130, 135, 136, 139, 144, 146, 149, 157). Participants reported that counselling services should be linked to an app (118, 144, 146), such as an 'emergency button' feature (146), while others have emphasised the importance to link an app to their health care provider (115, 139).

> *"It would help in times of crisis to be able to be in touch with a professional, or if I needed to ask health questions related to alcoholism."* (136)

“I want to let others know when I’m not well, the app would help me.” (146)

“The therapist helped me to find my motivation every now and then, and then I was on top of it for about a week or so, and eventually the application sort of became a part of my everyday life. Then it was pretty obvious that I would use it and then I didn't even think about whether it was hard to use it, I just did it.” (130)

Health practitioner support could i) help overcome potential barriers caused by lack of skills, such as app literacy (130), ii) enhance self-monitoring (130, 139) and iii) act as reinforcement (130), having the potential to enhance intentions to engage with the app (130, 139, 149). In one study, health practitioner support was suggested as being the most important factor for continuous engagement (158).

“The therapist helped me to find my motivation every now and then, and then I was on top of it for about a week or so, and eventually the application sort of became a part of my everyday life. Then it was pretty obvious that I would use it and then I didn't even think about whether it was hard to use it, I just did it.” (130)

The possibility for community networking within apps with other users or other people with similar needs was identified in multiple studies (115, 117, 118, 125, 134, 136, 139, 143, 144, 146, 148, 149, 152, 157). It was considered important social support by reinforcing behaviour change (125, 134, 136, 139, 146, 149, 157) and by sharing knowledge and experiences (115, 146, 152, 157). This was found to increase their intention to engage with the app and subsequently, the behaviour (139).

“It is so important to get in touch with people who went through the same thing as you have. […] I think that if an app for cancer survivors had a forum on it as a part of the application to motivate each other, that would be amazing.” (139)

“I don't think I would share on the social media, but within the app community I think it is important to like inspire and be motivated by others.” (143)

A large study found that the most engaged group had a mean number of 24 friends within the app, as opposed to the least engaged group (one friend) (140). The users’ potential social role or group identity, and personal preference should be taken into consideration. For instance, individuals from the LGBTQ+ community (118) and cancer survivors (139), would wish to interact with people who face similar challenges.

"It is so important to get in touch with people who went through the same thing as you have. […] I think that if an app for cancer survivors had a forum on it as a part of the application to motivate each other, that would be amazing." (139)

Also, some users would not want to share information with strangers due to fear of social comparison (117, 136) or social stigma (132), while others were more open to connecting with strangers rather than with friends or family (134).

"I don't think I would share on the social media, but within the app community I think it is important to like inspire and be motivated by others." (143)

"So, having some sort of platform where everyone can just say, 'This is how I stopped' or 'This is how I'm trying to stop' and then other people giving feedback saying, 'This is good' or, 'This is not'." (149)

"Being able to exchange feedback with strangers with the same goal could be supportive but non-judgemental as you will probably not know the other users." (136)

Evidence for the importance of embedded social media for engagement was mixed (52, 117, 118, 126, 132, 134, 138, 143, 144, 147-149, 152, 158). It largely depends on the individual's attitude towards these channels and as well as on the target behaviour. Some users found this reinforcing (118, 138, 148, 152), while others did not want to engage with such features due to social stigma (e.g. smoking, alcohol consumption or weight management) (52, 117, 126, 132, 134, 144, 149).

"Integrating it with the social media is definitely a great thing to do because they can always fall back to Facebook, Twitter, etc. And through this, people can get to share their experiences and keep an update and tell whatever experiences they may have to share. So, it's like ongoing support." (118)

"Yeah, you can share on Facebook and stuff, but I hate that. I hate when apps sync to like every form of social media. I'm like really weird about social media, so, no I don't want to share it." (126)

"Don't want to share progress on social media in case you fail." (149)

Social competition (115, 117, 126, 134, 136, 143, 144) includes the possibility for individuals to compete with themselves (i.e. their previous achievements or breaking their own records), or with others app users.

> *"Whenever we do a weekend challenge, you always have a look at what the other person's doing and [their] competitive side. I just want to beat the other people I see on there, so [using the app] is quite a good motivator."* (115)

> *"It made me want to exercise more just, as like, kinda like, a competition to see how many calories because it takes your calories off whenever you exercise so I'm like let's see how many I can get off this time."* (126)

Five studies suggest that the reinforcing nature of social competitions might increase the intention to engage with an app (115, 126, 134, 136, 143). The increased engagement was anticipated when the competition is based on support by receiving encouragement from others (117, 144), rather than on defeating each other, which might prompt discouragement to use the app (144).

> *"Someone who's successful and quit smoking isn't any better than someone that's struggling with it. Like, no, I didn't-I don't like that aspect… it just makes someone feel bad."* (144)

Several studies described that some participants felt apps can impersonate a little person (117, 123, 125, 126, 128, 134) which increased the intention to use the app (123, 126, 128).

> *"It's like a 'little boss in my pocket' … that's sort of saying "you know you need to get out and do this"."* (123)

> *"It's like your own little motivator, in a way. And it definitely, it's like, okay it's like a little person, but it doesn't talk, but it's like, you shouldn't eat that, or it's like you should. So, I don't know it's, I like it—I mean, I think it's cool. It's like my own little motivation."* (126)

It was also suggested that if the app is too impersonal, it would not offer the social support the users need (125). In contrast, in two studies the participants were concerned about having a machine telling them what to do (125, 134).

> *"I don't want an electronic device telling me what to do."* (134)

Finally, personal experience related to noncommunicable diseases might increase the chances of the uptake of apps. One study conducted on Latino and Asian subgroups in the US found that the odds of downloading a health app was twice as high for those who had a family history of heart attack (OR 2.02, 95% CI 1.16-3.51), compared to those who have not (119).

2.5.9. Automatic motivation

2.5.9.1. TDF domain: Reinforcement

Reinforcement is a process or action of encouragement of a pattern of behaviour. Users reported better engagement when positive feedback was received (52, 115, 117, 123-126, 129, 130, 132, 134, 139, 144, 149).

> *"I liked how it gave notifications, like every day I've got a notification saying; You're on day four of your smoking quitting history. You could do this, don't give up. Stay loyal and stuff like that. That was quite impressive."* (149)

Visual feedback of progress made users aware of their advancement of reaching their goal (115, 123, 124), while auditory feedback was seen as encouraging during physical activity (e.g. running) (115, 126).

> *"The big green 'continue' at the bottom and when it moves on to the next thing I feel great, I've achieved something, I've filled something in correctly. I like that. And a nice little noise which made me think, Oh, I'm not an idiot."* (124)

For some, instant feedback on their progress, even if it is of a positive nature, was perceived to cause pressure and potential disappointment if they were not able to reach their goal (123, 134).

> *"The progress I didn't make—it shows [and thus is demotivating]."* (134)

Offering rewards (52, 115, 118, 123, 124, 134-136, 143, 146, 148, 152) was found to be a useful way to increase engagement. Participants suggested including gamification elements in apps to enhance engagement (115, 134, 146, 148, 152). Some users found intangible rewards (e.g. badges) motivating (52, 124, 134, 136, 143, 148)

> *"Earning badges [was] important when I was doing it…We learned as a kid, to consider [it] as [an] accomplishment."* (134)

Others would want to receive tangible rewards instead (e.g. free t-shirt, gift cards, cash, reduction in health insurance or vouchers provided by hospitals or doctor's office) (52, 118, 134, 143).

> *"Each time you try, you get the points. And if these points can be converted to something else. Because you know, you're not really working for the badge but if the virtual badge can turn into something tangible, I would want that."* (135)

> *"Well, both of them are a kind of 'well done for doing this', they're both a reward, they both make you feel a bit better. But a badge, it's a cool fact, but it's not the same as having vouchers, where you can go and treat yourself to something you want."* (136)

This has been partly supported by two quantitative studies. In one study having health insurance was associated with uptake of, but not with the engagement with, health apps (120). Another study found that when offering loyalty points, engagement increased for at least three months (133).

2.5.9.2. TDF domain: Emotions

Emotions, based on previous experiences and behaviour, are a complex reaction by which people tend to respond to a personally important event or matter. Curiosity (116, 130, 132, 138) would positively influence uptake of health and wellbeing smartphone apps.

> *"It was more like seeing an ad and just, okay I should try this — and then I found it on the internet and signed up. It was more like a fun thing. We'll see if it works. More like that."* (130)

However, in two studies, both targeting alcohol consumption reduction, this factor was only relevant for a specific user type: for those who were characterised as 'low risk' drinkers (116) and 'noncommitters' (i.e. users who did not commit to engage with the app, hence did not gain any benefit from it) of the app (132).

2.5.10. Reflective motivation

2.5.10.1. TDF domain: Goals

Goals are outcomes that an individual would like to achieve in order to change a certain behaviour. Goal setting (52, 116, 117, 123, 126, 129, 132, 134, 136, 143, 148, 151) was related to sustained engagement with health and wellbeing apps.

> *"I'm not good at self-discipline and exercise, so maybe this [goal setting in the app] can help me get to my goal."* (134)

Some users chose to set a goal and mostly this was only one goal at a time, so their focus would remain on one single aspect of change of the behaviour, while others were more reluctant to use this feature due to fears of not being able to achieve their set goal and to avoid disappointing themselves (116).

> *"I only set one goal because I was very keen to kind of remain focused on one thing. I didn't want to come and get lost in the app using it like a game. You*

know, I wanted to use it for one very specific thing... I think I set it to drink probably within guidelines." (116)

"No, it didn't appeal - probably because I thought if I put some goals in, I'm probably not going to stick to it, which probably makes me sound a bit naughty." (116)

In general, the studies suggest that users were more determined to engage in behaviour change when they had set goals (123) and believed they had successfully achieved or could achieve their goals with the help of an app by increasing their intention to use the app and by better monitoring the target behaviour (52, 126, 132, 134, 136).

"If you set those manageable goals, so you could achieve it, if you feel like you're actually progressing, getting something, then you're more likely to go back." (52)

"It would encourage me to open the app on a daily basis." (136)

2.5.10.2. TDF domain: Beliefs about consequences

This domain includes aspects related to outcome expectancies. Perceived utility of the app (115, 124, 130, 136, 138, 151) refers to where there is a discrepancy between what the users are looking for and what an app actually offers. It was suggested that the unmet expectations of an app would lead to disengagement and frustration with the app.

"I do have some apps I don't use often, mainly because they've kind of bored me in a way. I'll just do an example: one fitness app shows you how to lose weight, but the way it's describing it, it's not what I'm after. It's one of those free apps I bought that—I thought [the fitness app] would be great, but when you actually use it, it's not the same." (115)

"I think that's where it let itself down for me. Once I'd played with it, once I tried the game, done the identity and whatnot, there wasn't much else there for me." (124)

"It [mindfulness app] didn't add anything...I guess it didn't detract, it didn't make anything worse, but it didn't add anything to my armoury, I guess, my tool kit, as keeping myself sane, I suppose, it didn't add." (138)

2.5.11. Other factors

There were a number of sociodemographic factors that did not fit clearly under the components of the COM-B model.

2.5.11.1. Sociodemographic factors

Apps were more frequently downloaded by women than men, with the percentage ranging from 59% to 74% (116, 119, 127, 131, 133, 140) though one study found that being male was associated with using an app to manage alcohol consumption (156). Being less than 44 years old was associated with a higher level of uptake and engagement (116, 119, 120, 122, 127, 131, 133, 140, 156) than older adults. Living in an urban area (120, 122, 133), with better education level, such as having high school education or higher (119, 120, 122, 156) and college degree or higher (119, 131) and having a higher income (122) was also associated with better engagement with health and wellbeing apps.

2.6. Discussion

2.6.1. Principal findings

This is the first systematic review to conduct a theoretical analysis using the COM-B model of factors influencing the uptake of, and engagement with, health and wellbeing apps. Findings from this review suggest that there are 26 key factors across the constructs of capability, opportunity and motivation that influence the uptake of, and engagement with, these types of apps, which were found to be important for a wide range of populations and behaviours.

This review replicates previous findings in the wider literature on digital behaviour change interventions. The core findings of this review suggest that attention should be perhaps shifted mainly on the support and guidance offered to new and existing users of health and wellbeing apps. Furthermore, support and guidance of uptake can be targeted by increasing their awareness of health apps through, for example, recommendations received from health practitioners. In line with findings of previous reviews, help with initial engagement could be achieved by improving the users' app literacy skills and by providing knowledge (10, 56). This review presents knowledge in a novel way by breaking it down to: i) instructions of how to use it (i.e. user guidance), ii) advice related to the target behaviour or condition (i.e. health information), and iii) information on their progress or data (i.e. statistical information). This suggest that allowing user access to different information that serves different purposes (e.g. health benefits vs progress data) would enhance their engagement through different channels, such as guidance, support and education.

Potentially, one of the most important factors for engagement identified in this review is health practitioner support. In line with the emerging evidence from the human-computer interaction literature, this study found that an app coupled with human support (10, 56) was likely to be more effective by increasing the intervention effectiveness and engagement (159, 160). Alternatively, human support can be impersonated by embedded artificial intelligence (AI) features. A recent experimental study found that a supportive artificial intelligence powered chatbot doubled the engagement with a smoking cessation app and increased its effectiveness (161). This suggests that embedded human support or features that mimic human support might lead to greater engagement with digital behaviour change tools.

Behaviour change techniques, widely reported by others previously (10, 39, 56, 104), were also identified as important factors to sustain engagement, including self-monitoring, feedback, goal setting, reminders, rewards, social support. However, not all of these have a positive effect. Reminders and social support factors (embedded social media and social competition) are not universally useful and might cause disengagement or even harm by triggering negative emotions. One plausible explanation is that the participants of the studies included may or may not have real life experience with health and wellbeing apps. Some of the included studies examined the participants' perceptions about a hypothetical app or an app that was planned to be developed. These studies relied on the participants' opinion of what they thought it would be important for them in terms of uptake of, and engagement with, health and wellbeing apps, rather than sharing their lived experiences with such tools. For example, reminders were found useful in all the studies targeting a hypothetical app, as opposed to those that were researching engagement with an app that had been used by the participants, where opinions about reminders were mixed, with some users finding them annoying. Another explanation is that the importance of these factors might be dependent on the target behaviour. For example, people using apps that target mental health might not want to engage with a social competition feature or to share their progress or experiences on social media. This suggests that some of the identified factors in this review might be behaviour dependent.

Another interesting finding, not identified in previous literature, is the safety netting characteristic of an app. This characteristic could promote long-term engagement, rather than short goal-oriented engagement. The user could disengage at any time and re-engage at a later stage when needed. This feature might be particularly useful for addiction research targeting relapse prevention strategies.

No factors were coded directly under four out of fourteen TDF domains (optimism, social identity, beliefs about capabilities, intentions). However, two of these were highlighted in this review. It was described how several factors coded under different domains affect intentions (e.g. having adequate app literacy skills, user guidance provided to the user, etc.), in the similar way of how emotions, other than curiosity, affect engagement with an app (e.g. lack of app literacy skills triggers negative emotions, some found reminders annoying, or some fear of social comparison related to sharing on social media, etc.). It was also found that aspects of the factor 'personalisation to needs' also included social identity aspects. Some communities (LGBTQ+, cancer patients) prefer an app that is personalised to their social identity. Although social identity, in this case, was judged to be too weak a factor to list it independently. In terms of the other two absent domains, factors under beliefs in their capabilities and optimism might be less relevant for uptake and engagement with health apps, or the studies may have missed them out, or, potentially, this review failed to identify them from the included studies.

The importance of promoting equality and embracing cultural diversity was partially identified previously (39). Several studies in this review reported that apps should be provided at low cost to users. It was suggested that multiculturalism should be embraced, and regional languages added. The concern of inequality for those who do not own a smartphone was also raised in this review (118). An accompanying website was suggested as an alternative for homeless people who would not have access to a smartphone but may have access to the internet through non-profit organisations, charities or community libraries.

2.6.2. Strengths and Limitations

One major strength of this review is that it adhered to the best practice processes for undertaking reviews by following the PRISMA guidance and Cochrane handbook (105, 107). By including all study designs we were able to pool together and triangulate evidence and provide a novel and powerful synthesis of different study designs.

The use of theoretical frameworks is another strength. Other theoretical models were considered for this review, including the technology acceptance model (162) and the human-computer interaction models and theories (163). However, the

COM-B and TDF present advantages by their dynamic nature and by explaining the influences between components as they were developed from, and to represent, all theoretical components in behaviour change-related models and theories. COM-B was explicitly developed to inform behaviour change interventions through its connection to the BCW (81), a tool that provides guidance on designing behaviour change interventions as described in Chapter 1. Therefore, the factors identified under the components of the COM-B model allow easy identification of the intervention functions to target increased uptake of, and engagement with, health and wellbeing smartphone apps.

The review has several limitations. The review focused on four major behaviours related to prevention (smoking, alcohol consumption, physical activity, diet) and mental health and wellbeing and could not capture other prevention type behaviours (e.g. fall prevention). Factors relating to the uptake and engagement of apps focusing on other behaviours or conditions may differ from those found in this review and warrant further investigation.

Although this review captured a wide range of populations, most of the studies included were carried out in high income countries. Therefore, the findings might not be transferable to low- and middle-income countries or to other cultures. The quality of the studies was mixed. In some qualitative studies, the authors provided interpretations of their findings without an explicit quotation to support them. These interpretations were handled with care and often ignored when no further explanation was provided about a concept. This might have led to losing some potentially important factors, not identified otherwise.

2.6.3. Policy and Practice: Recommendations and Implications

The findings of this review can inform app developers and researchers on how to develop health and wellbeing smartphone apps to better support behaviour change and manage and monitor different physical and mental health conditions in adults.

This review may also have implications for policies that target prevention using digital technologies. Apps are an easy way to provide health-promoting behaviours and may play an important role in prevention strategies. For example, the UK government has recently published a Green Paper entitled ‘Advancing our health: prevention in the 2020s’ which shifted their focus from ‘cure to prevention’ committing to encourage the population to live a healthier life (164). Additionally, the ‘Long Term Plan’ policy document of the NHS in the UK dedicates an entire chapter to prevention programmes and includes plans on digitally delivered methods to improve access to information, education and intervention (84).

As part of prevention and health management strategies, the NHS and partners have created a pool of health and wellbeing apps for the individuals to access (the NHS Apps Library). This research could help people access effective apps that people will remain engaged with, though to extent to which the population is open to use these portals for uptake is yet unknown, and something worth investigating in the future.

A number of important themes are described in the projects and policy documents mentioned above. Some relate to digital health, for example with an aim to reduce health inequalities (164) or to improve population health with personalised content and tailored lifestyle advice (84). For example, this review suggests that app literacy skills are important for uptake. Enhancing app literacy skills for the elderly (e.g. drop-in sessions in community settings) might be a feasible way to reduce health inequalities. Furthermore, some of the engagement-related factors might suggest use of tailored lifestyle advice to address health behaviours. For example, by receiving personalised content within the app, and online or offline help or advice from health practitioners, as well as receiving recommendations for health apps from their healthcare professionals and GP practices.

Therefore, the findings of this review could inform stakeholders in public health and policymakers, and providers of health and wellbeing smartphone app portals to provide additional support for the uptake of, and engagement with, these digital interventions for adults.

Recommendations for stakeholders in public health and policy makers, and health and wellbeing app developers derived from the findings of this review can be found in Table 3.

Table 3. Recommendations for stakeholders in public health, policy, industry, health care, and health and wellbeing app development.

Policy makers/industry/health care providers might want to consider:	App developers might want to consider:
Capability	
• Improving app literacy skills • Increasing awareness of effective health and wellbeing apps, by advertising offline (e.g. GP practices) and online (e.g. social media)	• Promoting less cognitive load by enabling automatization of data collection • Including user guidance that can be deactivated once the functionality of the app has been achieved (e.g. help button) • Including content that targets education, health prevention, and health consequences related to the behaviour that is targeted to change • Including statistical information (e.g. graphs, percentages, numbers), about the user's progress • Including well-designed reminders where the user can choose the time and frequency of receiving it • Including self-monitoring feature that enables users to create routines • To provide long term use of an app, a 'safety netting' feature that allows users to fall back on, even though the target behaviour has been achieved
Opportunity	
• Providing online or offline health practitioner support • Providing recommendations for health and wellbeing apps by health care professionals • Offering apps for free or at low-cost	• Allowing the provision of health professional support within the app • Allowing community networking within the app with other users • Organising competition and challenges for users to opt in to • Avoiding automatic synching with the embedded social media (when applicable) • Personification of the app, by designing human-type attributes • Offering apps for free or at low-cost • Offering personalisation of the app according to their demographics, individual and cultural needs
Motivation	
• Offering tangible rewards, such as points that could be used as a discount in pharmacies or at other health and wellbeing related domains, or health insurance providers • Providing a meaningful title and clear description of what the app does and what can offer, and how can help the user	• Providing positive, non-judgemental, constructive and informative feedback • Include gamification elements and offering rewards • Including goal setting features (when applicable) • Providing a meaningful title and clear description of what the app does and what can offer, and how can help the user

2.6.4. Future research

While some of the factors identified and presented in the results section appear to provide a positive influence on uptake and engagement, there are mixed findings that might benefit from further investigation, such as reminders, embedded social media, and social competition. In the studies included in the review, descriptions of notification-type-messages, such as reminders, feedback, push-notifications and other notifications, were used interchangeably and it was not always clear which were being referred to. Consistent terminology would help eliminate doubt around these concepts in the future. Issues around equality and diversity were highlighted in a few studies as something future research should address. Further work is also needed to aid our understanding as to how to avoid digital health widening inequalities through the exclusion of individuals that face a financial barrier to owning a smartphone or one with a relatively up to date operating system or to purchasing an app, or who do not possess the skills to use one.

2.6.5. Conclusions

This is the first systematic review to investigate factors that influence uptake of, and engagement with, health and wellbeing smartphone apps. Twenty-six factors that are relevant to a wide range of populations and different behaviours were identified. These have clear implications for improving population health and targeting health inequalities. The list of recommendations provided are built on the identified factors to guide app developers, health app portal developers and policy makers when commissioning, developing and optimising health and wellbeing smartphone apps. These can help with addressing the issues of suboptimal uptake and engagement which currently constrain the public health benefit of apps.

2.7. Next steps

The next steps of the thesis were to provide an in depth understanding of factors influencing the uptake and engagement with health and wellbeing apps. The next chapter of the thesis presents the factors influencing the uptake of health and wellbeing smartphone apps in general following an unguided search for a suitable app, and the uptake of health and wellbeing apps on curated health app portals (Chapter 3).

Chapter 3. Influences on the uptake of health and wellbeing apps and curated app portals: a think aloud and interview study.

3.1. Dissemination

Findings of this chapter were presented at the UK Society of Behavioural Medicine's Annual Meeting (2020), at the Society of Behavioural Medicine (2020 – cancelled due to COVID, but disseminated virtually), at the UCL Centre for Behaviour Change Digital Health Virtual Conference (2020), at the European Health Psychology Society's Annual Virtual Conference (2021) and at the International Society of Physical Activity and Health Virtual Congress (2021).

A version of Chapter 3 has been published in the Journal of Medical Internet Research mHealth and uHealth (165). See Appendix 7 for the published peer reviewed journal article.

3.2. Abstract

Background. Health and wellbeing smartphone apps could provide a cost-effective solution to addressing unhealthy behaviours. The selection of these apps tends to occur in commercial app stores, where thousands of health apps are available. Their uptake is often influenced by popularity indicators. However, these indicators are not necessarily associated with app effectiveness and evidence-based content. Alternative routes to app selection are increasingly available, such as via curated app portals, but little is known about people's experiences of them.

Objectives. To explore how people select health apps online and their views on curated app portals.

Methods. Eighteen UK-based adults were recruited through social media and asked during an in-person meeting to verbalise their thoughts whilst searching for a health or wellbeing app online on a platform of their choice, then repeat the search on two curated health app portals: the 'NHS Apps Library', and the PHE 'One You' App portal. This was followed by a semi-structured interview. Data were analysed using Framework Analysis, informed by the Capability, Opportunity, Motivation – Behaviour (COM-B) model and the Theoretical Domains Framework.

Results. Searching for health and wellbeing apps online was described as a ‘minefield’. App uptake appeared to be influenced by participants’ *capabilities*, such as app literacy skills, health and app awareness, and *opportunities*, including the availability of apps, app aesthetics, the price of an app and social influences. *Motivation* factors that seemed to affect uptake were perceived competence, time efficiency, the perceived utility and accuracy of the app, transparency about data protection, commitment and social identity, and a wide range of emotions. Social influences and the perceived utility of an app were highlighted as particularly important. Participants were not previously aware of curated portals but found the concept appealing. Curated health app portals appeared to engender trust and alleviate data protection concerns. While apps listed on these were perceived as more trustworthy, their presentation was considered disappointing. This disappointment seemed to stem from the functionality of the portals, the lack of user guidance and lack of tailored content to an individual’s needs.

Conclusions. The uptake of health and wellbeing apps appear to be primarily affected by social influences and the perceived utility of an app. App uptake via curated health app portals perceived as credible may mitigate concerns related to data protection and accuracy, providing their implementation meets user needs and expectations.

3.3. Introduction

3.3.1. Background

Noncommunicable diseases (e.g. diabetes, heart disease, cancer, poor mental health), are considered key threats to global health (166), and are driven by factors such as physical inactivity, poor diet, tobacco smoking, and excessive alcohol consumption. A key global public health policy priority is to enact policies to ensure the best possible health is available for all (167). In the UK, aims of the NHS long term plan (84) and priorities of UK Government executives agencies such as PHE are to provide a smoke-free society, to encourage healthier diets and to improve mental health (168). Encouraging the use of digital health interventions, such as smartphone apps, may be one (cost-) effective way of contributing.

Health and wellbeing smartphone apps can be cost-effective solutions for changing health behaviours (24, 39). Such tools can act as ideal platforms to deliver behaviour change interventions (10) because of their availability, portability and easy access (42). Research has demonstrated early evidence of effectiveness of smartphone apps for smoking cessation (27), healthy dietary and physical activity promotion (29, 31, 32, 39), weight loss (34, 35, 39), alcohol reduction among non-dependent drinkers (36) and mental health promotion (169). In addition, health apps can reach those resistant to help-seeking in person (e.g. due to stigma) by improving access to behaviour change interventions (170). However, this thesis highlighted in Chapter 1 that low uptake and poor engagement over time compromise the potential of health and wellbeing apps.

'Uptake' refers to the decision to select and install a health app (44). The search for, and selection of, health apps tends to take place in commercial app stores, such as Google Play for android operating systems and the Apple App Store for iOS (29, 45). Thousands of health and wellbeing smartphone apps are available in the major app stores, a number that continues to grow (10). Research shows that the uptake of apps from commercial app stores tends to be influenced by indicators of popularity, such as the app's rank order, ratings and/or reviews, and its total number of downloads (45). However, such popularity indicators are not necessarily positively associated with app effectiveness (171), and indeed may even be negatively related (172). An associated problem with app uptake is that the vast majority of apps listed in commercial stores lack evidence about their efficacy (173) or effectiveness (174). The need for quality marks in commercial app stores has been raised (71), as well as the need for regulation of health apps and evidence for their effectiveness (169). Better transparency in an app's description to help people make an informed choice, including how the user's data are handled, how the app was developed, benefits explained in lay terms, as well as descriptions of the app content has been recommended (175-177).

A barrier to the uptake of evidence-informed apps is that not all apps are available to the public, or prominently displayed, via commercial app stores (71, 173). Therefore, fewer people may benefit from available high-quality tools. Evidence-informed apps tend to be promoted within community or health care settings (often targeting a specific geographic region/country), or on curated health app portals. These portals are websites presenting a list of selected health apps (178). Health app portals can be government-funded, such as the UK NHS' 'Apps Library' or PHE's 'One You Apps' portal, or curated by private organisations, such as 'App Script' by IQVIA in the United States, the UK and the United Arab Emirates, the 'MyHealthApps' by PatientView's in Europe and the UK, or 'ORCHA' in the UK. These organisations can lend credibility to, and have the potential to promote, the uptake of selected health apps (179) by providing a list of safe, evidence-informed, tested and, where possible, clinically effective health apps for the general public to choose from.

As described in Chapter 2 research has focused on the identification of factors that influence uptake of health apps in commercial app stores. There is an urgent need to explore whether the general public would be willing to use curated health app portals, which could improve the uptake of evidence-informed health and wellbeing apps (44). Despite this need, little is known about views on curated health app portals. This study aimed to explore potential users' views on factors influencing the uptake of health apps in general, and on curated health app portals in particular, using think aloud and interview methodology.

3.3.2. Theoretical framework

The COM-B model (74) and the Theoretical Domains Framework (TDF) (75) described in Chapter 1 were continued to be used as a coding framework. Together, the COM-B model and the TDF allow for a detailed analysis of data and identification of key factors influencing uptake in general and on curated health app portals in particular.

3.3.3. Aims

This qualitative study applied a theoretical framework informed by the COM-B model and the TDF to explore 1) factors influencing potential users' uptake of health and wellbeing smartphone apps through online searching and 2) their views on available curated health app portals.

3.4. Methods

3.4.1. Study design

This research elicited views and preferences of a sample of members of the public. The Consolidated Criteria for Reporting Qualitative Research (COREQ) checklist guided the design of the study (180). The checklist can be found in Appendix 8. Think aloud methodology (181) was applied to collect real-time data about online health app selection, and involves asking participants to verbalise their thoughts and impressions throughout the selection process. The lead author only intervened when a prompt was considered necessary (e.g. during silent moments, asking questions such as 'What are you thinking now?). Following the think aloud tasks, follow-up questions were asked to better understand statements/utterances made during the tasks. Finally, semi-structured interview techniques were used. The think aloud tasks and the topic guide were informed by stakeholder consultation which included views and opinion of lay persons (PPI representatives) and expert opinion of policy makers of this research. The study protocol was pre-registered on the Open Science Framework (182). The Faculty of Medicine and Health Sciences Ethics Committee at the University of East Anglia approved this study (Reference number: 201819 – 089, see Appendix 9). The collected data is stored following the European Union General Data Protection Regulation (GDPR) and the University of East Anglia Research Data Management Policy. The data was anonymised, and all personal identifiers were removed. All participants read the participant information sheet and provided consent prior taking part in this study.

3.4.2. Participants and recruitment

Participants were recruited through paid advertisements on Facebook. Adults in the general population were eligible if they 1) were aged 18 or over; 2) were able to provide consent; 3) owned a smartphone; 4) would consider using a smartphone app to change their behaviour in the future; 5) were able to attend an interview in Norwich, England, where the work took place. As a standard practice in qualitative research, the aim of the study was to gain better understanding of the phenomenon of interest and to increase the coverage of perspectives rather than to necessarily recruit a population-representative sample (183). Hence, purposive sampling was used to promote the diversity of the sample (i.e. age, gender, ethnicity, educational level, employment) (184). This included targeted adverts on Facebook, which encompassed monitoring and adjusting the variables which allowed the selection of participants to ensure the diversity of the sample. 114 individuals responded to the Facebook adverts and read a brief participant information sheet and completed the screening questionnaire. Out of 38 participants invited to an interview, 14 did not respond and 24 agreed to participate. Six of these 24 cancelled for various reasons. The recruitment and the interviews took place in batches of 3 or 4, and the recruitment stopped when data saturation was reached.

3.4.3. Procedure

Prior to completing the online screening survey, participants were asked to read a brief participant information sheet describing the study. Once read and agreed to participate, participants were asked to complete an online questionnaire to assess their eligibility and to collect descriptive data (see Appendix 10). Data were collected on 1) age, 2) gender, 3) ethnicity, measured using the Office for National Statistics' index, 4) level of education, 5) employment status, 6) whether they have ever used health or wellbeing app, 7) whether they currently use a health or wellbeing app, 8) last time they had downloaded an app, and 9) frequency of app use. Participants who met the inclusion criteria were sent an email with a comprehensive participant information sheet (see Appendix 11) and were invited for an interview. On the day of the interview, interviewees received a printed copy of the participant information sheet, and written consent was obtained (see Appendix 12).

Face-to-face interviews were conducted between July and August 2019 and took place at the University of East Anglia (n=17) or the participants' home in Norwich (n=1). The interviews were conducted by a female lead author and no one else was present during the sessions. The session started with a think aloud exercise, with participants being instructed on how to verbalise their thoughts. First, they were asked to perform a search for an app they would potentially use to change a health behaviour of their choice. They had a choice of using either a study laptop or their smartphone. Second, the lead author asked them if they were familiar with curated app portals. If they were not, the lead author briefly explained the principle and asked people to repeat the search using the 'NHS Apps Library' and the PHE 'One You Apps' curated health app portals (Figure 5). During the think aloud sessions, positive reinforcement using verbal (e.g. 'You are doing great', 'Right') and non-verbal (e.g. nodding) communication was used to encourage participants to continue to express their views. In quiet moments, prompts were used (e.g. 'What are you thinking now?', 'Tell me what is on your mind'). Following the think aloud task, questions regarding their experience with the uptake of, and engagement with, apps were asked (see Appendix 13 for the topic guide). The sessions lasted between 26 and 63 minutes. Participants received a £20 gift voucher as compensation for their time.

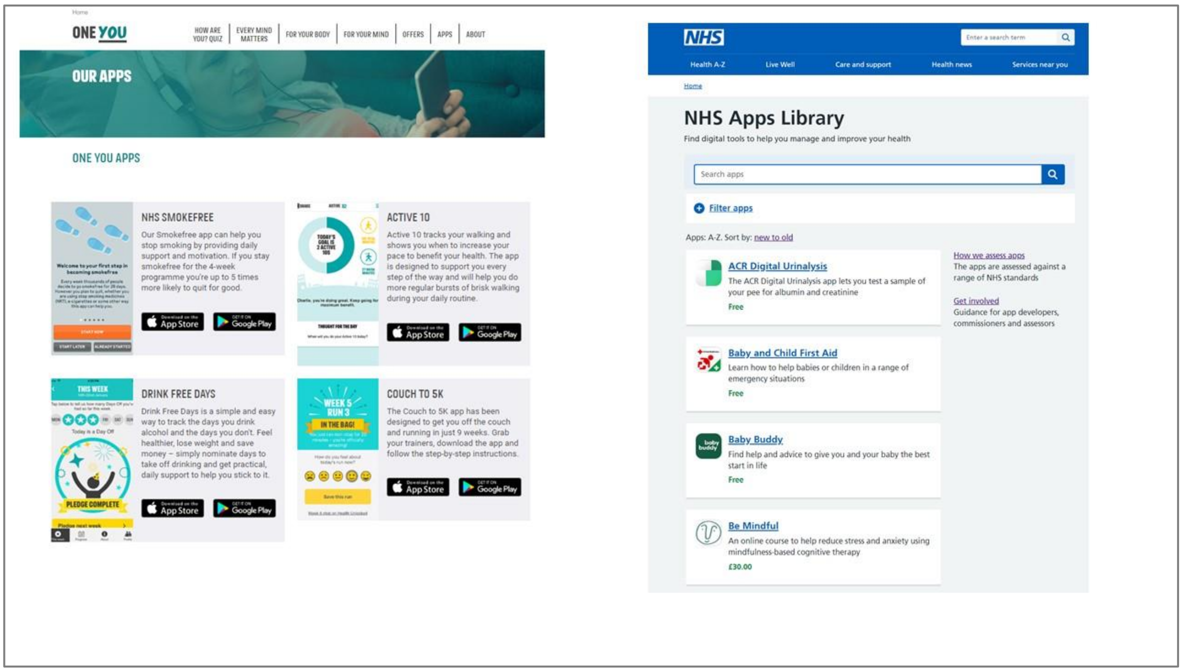

Figure 5. Screenshot of the Public Health England's 'One You Apps' portal and the 'National Health Service's Apps Library'.

3.4.4. Data analysis

The sessions were audio-recorded and transcribed verbatim by an external company. Transcriptions were checked for accuracy by the lead author undertaking the interviews. The data were analysed using framework analysis following the stages of familiarisation, identification of thematic framework, indexing, charting, mapping and interpretation (185). To ensure rigour, trustworthiness and consistency, a percentage of randomly selected transcripts (15%) were independently coded by OP. The deductive thematic framework based on the TDF was refined iteratively through repeated discussions with OP, and any discrepancies were resolved through discussion with FN. Indexing was completed by the lead author using QSR NVivo 12. The data were charted, and the responses were grouped according to the finalised thematic framework. During mapping and interpretation, the grouped data were examined by the lead author to identify patterns. During mapping, identified factors were classified according to their organic position rather than what they affect (e.g. an opportunity factor may indirectly influence the behaviour through increasing the motivation for uptake of a health app, as well as influencing it directly). To aid comprehension of the findings for uptake in general and on health app portals in particular, data were analysed and presented separately for these two topics. Findings on the engagement factors are presented in Chapter 4. To increase the trustworthiness of the findings, peer debriefing by the University College London Tobacco and Alcohol research group, with extensive experience of the application of the COM-B model and TDF in health research, was used to ensure the accuracy of data interpretation and data analysis. Peer debriefing is a form of analytical triangulation where researchers not directly involved in the study are prompted to provide input and critical opinions on various aspects of a project (186). The use of the TDF in the deductive framework analysis approach was particularly useful for coding the results under several factors, which may otherwise have been overlooked. It was expected to explore a large number of factors as the TDF has 14 constructs, as opposed to other well-known methods. However, the authors were aware that findings would not be coded under all available constructs. Constructs under which no findings were coded were omitted from the results section.

3.4.5. External validity

To enhance the credibility and trustworthiness of the results (187), six participants (30%) were randomly selected and requested via email to provide feedback on a document with a summary of the findings and conclusions (‘member checking’). They were asked whether they recognised their opinions and whether they agreed with the interpretation of the findings. Two participants responded to our request and confirmed that their opinions had been captured. In one case, our email failed to be delivered.

3.4.6. Reflexivity

The authors involved in this study are mixed-methods researchers with experience applying the COM-B model and the TDF to qualitative data. The lead author disclosed her research interest to participants on the day of the interview and no prior relationship was established between her and participants. The interviews were conducted by the lead author, a PhD candidate who has undertaken extensive training in the collection and analysis of qualitative data. Participants were encouraged to share their thoughts (both positive or negative) and to be honest. The interviewer felt that good rapport was built with the interviewees, and most participants (n=16) expressed their interest in learning more about the findings of the research. Field notes and a research journal was kept during data collection.

3.5. Results

A total of 18 participants completed the interview. The average age of participants was 43 years (SD=14), 9 (50%) were females, 14 (78%) were of white British ethnicity, (13) 72% were employed full time, 2 (11%) had postgraduate qualifications, 17 (94%) had used health apps before, and 11 (61%) were using health apps at the time of the interviews, out of which 8 (73%) reported daily health app usage. Most participants were interested in changing more than one behaviour (e.g. losing weight, getting more active, managing mood) and only 16% of participants expressed a desire to change only one behaviour. Two participants were satisfied with the app they were already using and did not wish to take part in the think aloud exercise to look for a different app. The remaining 16 participants searched for apps targeting physical activity (n=6), weight management (n=4), mood and mental wellbeing (n=3), smoking cessation (n=1), alcohol reduction (n=1) and sleep (n=1). Participants' characteristics are presented in Table 4.

The findings pertaining to factors relevant for both the uptake of health apps and views on curated health app portals are presented under the components of the COM-B model: Capability, Opportunity, Motivation. Higher order themes and subthemes informed by the COM-B model and the TDF are reported in Table 5.

Table 4. Characteristics of the participants.

ID	Gender	Age	Ethnic group	Highest education	Employment	Health or wellbeing topic of interest	Current use of health app	Last time downloaded a health app	Frequency of health app use
P1	M	28	Mixed	Degree	Part-time	Physical Activity, Depression, Anxiety, Mood	No	> 6 months ago	Infrequently
P2	F	44	British	Prof. qual.	Full-time	Diet, Physical Activity, Depression, Anxiety, Mood	Yes	< 30 days	Daily
P3	F	44	Other	Degree	Full-time	Diet, Physical Activity, Depression, Anxiety, Mood	No	> 6 months ago	None
P4	M	46	British	Degree	Full-time	Diet, Physical Activity, Depression, Anxiety, Mood	No	> 6 months ago	None
P5	M	37	British	A levels	Full-time	Alcohol consumption, Diet, Physical Activity, Mood	No	> 6 months ago	None
P6	F	53	British	PGT	Full-time	Diet, Physical Activity, Depression, Mood	Yes	< 30 days	Daily
P7	M	22	Mixed	A levels	Student	Physical Activity, Depression, Mood	No	> 6 months ago	Biweekly
P8	M	52	British	Degree	Full-time	Diet, Physical Activity	Yes	< 30 days	Daily
P9	M	38	British	PGT	Full-time	Diet, Depression	Yes	< 30 days	Daily
P10	F	48	British	GCSE	Part-time	Diet, Physical Activity, Depression, Anxiety, Mood	No	> 6 months ago	Weekly
P11	F	68	British	GCSE	Retired	Depression, Anxiety, Mood	Yes	< 30 days	Daily
P12	M	57	British	GCSE	Retired	Alcohol consumption	No	*NA*	*NA*
P13	M	28	British	Degree	Full-time	Smoking, Diet, Physical Activity, Mood	Yes	< 30 days	Weekly
P14	F	64	British	GCSE	Full-time	Diet	Yes	< 6 months ago	Weekly
P15	F	56	British	GCSE	Full-time	Diet, Physical Activity	Yes	> 6 months ago	Daily
P16	F	34	Other	A levels	Full-time	Smoking, Diet, Physical Activity, Depression, Anxiety, Mood	Yes	< 3 months ago	Weekly
P17	M	31	British	Degree	Full-time	Diet, Physical Activity, Depression	Yes	> 6 months ago	Daily
P18	F	21	British	A levels	Full-time	Diet	Yes	< 6 months ago	Daily

Note. F – female, M – male, Prof. Qual - professional qualifications, PG – postgraduate; GSCE – General Certificate of Secondary Education (in the UK), A levels – General Certificate of Education Advanced Level (in the UK), NA – not applicable

Table 5. Factors influencing uptake of health apps in general and on health app portals mapped onto the components of the COM-B model and TDF constructs.

COM-B component and *TDF construct*, and the identified factors	Uptake in general (description of the factor)	Uptake on health app portals (description of the factor)
Physical Capability		
TDF construct: Skills		
App literacy	Technological competency	-
Psychological Capability		
TDF construct: Knowledge		
Health awareness	General health consciousness or having family members diagnosed with a condition or disease, or concerns regarding a behaviour or health outcome	-
App awareness	Knowledge of the existence of health and wellbeing apps	Knowledge of the existence of health and wellbeing apps listed on health app portals
User guidance	-	Instructions on how to effectively use a health app portal
Health information	-	Educational information related to health and wellbeing
TDF construct: Memory, attention, decision processes		
Cognitive load	-	The manner in which apps are presented on the portal; The complexity of the search or to access a relevant health app
Physical Opportunity		
TDF construct: Environmental resources		
Availability	The ability to use a smartphone anytime, anywhere Availability of an app on all major commercial app stores	-
Portal tailored to individuals needs	-	Personalised listing of apps targeting age, gender, health condition
Cost of an app	Low cost and apps that are free for users	Low cost and apps that are free for users
Aesthetics	The look and design of an app	User-friendly and design related characteristics of the portal

Table 5. (Continued) Factors influencing uptake of health apps in general and on health app portals mapped onto the components of the COM-B model and TDF constructs.

COM-B component and *TDF construct*, and the identified factors	Uptake in general (description of the factor)	Uptake on health app portals (description of the factor)
Social Opportunity		
TDF construct: Social influences		
Social influences	The importance of reviews and ratings in the commercial app stores, as well as of apps promoted as 'editor's choice' Identified credible sources: apps developed or endorsed by trusted app developers, organisations, universities, or promoted by respected celebrities (e.g. athletes) Recommendations received from health practitioners or from friends and family	Health app portals perceived as credible source Recommendations of health app portals needed mainly in primary care Clarity about the recommended apps on health app portals Explanations about any required GP referral
Reflective Motivation		
TDF construct: Beliefs about capabilities		
Perceived competence	App preferred over face-to-face intervention when the user feels that they can engage with the app on their own	-
TDF construct: Beliefs about consequences		
Time efficiency	The ability of a health app to be interacted with a minimum amount of time	-
The perceived utility of the app	Discrepancy between what the users are looking for and what the app offers, characterised by a relevant title, description, pictures, adaptation to individual characteristics and users' previous experience with health apps	Discrepancy between what the users are looking for and what the app listed on health app portal offers, characterised by a relevant title, description, pictures
Perceived accuracy	The perceived effectiveness of apps before the selection of an app	Potential app users' perceived effectiveness of apps listed on health app portals
Data protection	Concern regarding the handling of personal data	Concern over the handling of personal data
TDF construct: Intentions		
Commitment	The level of commitment when deciding to download a health app	-
TDF construct: Social identity		
Social identity	Identity related to app use (e.g. trends and gender specificity)	Identity related to app use (e.g. feeling like a 'patient')

Table 5. (Continued) Factors influencing uptake of health apps in general and on health app portals mapped onto the components of the COM-B model and TDF constructs.

COM-B component and *TDF construct*, and the identified factors	Uptake in general (description of the factor)	Uptake on health app portals (description of the factor)
Automatic Motivation		
TDF construct: Emotions		
Positive emotions	Triggered by curiosity in trying a health app, and by the time-efficiency characteristic of an app as opposed to face-to-face interventions, as well as by being provided by a credible source	Triggered by curiosity in choosing a behaviour change tool from a curated health app portal, and from a credible source
Negative emotions	Triggered by lack of availability on all major app stores Preferred over a face-to-face intervention if feeling anxiety (e.g. caused by an unhealthy behaviour or unhealthy state), and pressure (to succeed or to show progress)	Triggered by lack of search features on the portal, or when the search yields irrelevant results; when an app requires GP referral without further explanation, when an app is only available in one major app store
Mixed emotions	Triggered by the aesthetics (design) of the apps and by adaptation to individual characteristics (judged by the title, description, pictures, gender specificity)	Triggered by the aesthetics and features of the portal and the perceived utility of the apps

3.5.1. Factors influencing the uptake of health and wellbeing apps

Half of participants who agreed to search for a health app (n=8) used Google Search as their first choice to find a suitable app, while the other half opened a commercial app store. The latter search among hundreds of available apps was described by most participants as difficult or a "*minefield*" (P2, P4, P6). One participant described this task as being "*far more complicated than I thought it would be*" (P2). By the end of this exercise, only three participants found an app that they were willing to download and engage with further to change their behaviour.

3.5.1.1. Capability factors related to the uptake of health and wellbeing apps in general

Participants who presented a higher level of technological competency were able to better navigate on their phones, thus highlighting that app literacy skills are necessary when selecting a health app. One participant, who had never used a health app before, showed signs of technical difficulties (i.e. lack of skills) during the think aloud exercise while searching for an alcohol reduction app in a commercial app store.

> *"I wouldn't know how to do that [refining the search to find a suitable app]." (P12)*

Additionally, two participants expressed their concern toward the older generation and stated that training should be provided for those with insufficient technological and app literacy skills.

> *"My nanny is diabetic and if there was an app to help her with her diabetes, then I'm sure she would be happy to use it but it's just someone would need to explain it to her." (P18)*

All participants expressed their decision to look for an app for health reasons, such as getting healthier or to prevent illness. This included reasons of being diagnosed, or having a family member diagnosed, with a medical condition (e.g. diabetes, high blood pressure), concern of the negative effect a current behaviour may have (e.g. smoking, alcohol consumption), to better manage or improve their mental health (e.g. anxiety, self-confidence) and general wellbeing (e.g. sleep quality):

> *"I'm trying to avoid having type 2 diabetes, or getting it, so there's a background, my mother, in my family, there's a heart conditions background, which is why I'm really wanting to do something about my health." (P3*)

While most participants were aware of the existence of some apps, three participants were surprised by the existence of health apps for smoking cessation and mental health issues.

> *"It didn't cross my mind that I could use an app for stopping smoking, so it is new." (P16)*

3.5.1.2. Opportunity factors related to the uptake of health and wellbeing apps in general

Some participants expressed their preference to look for a health app as a digital behaviour change intervention instead of a face-to-face intervention because of the availability and the low cost of an app. However, concerns around widening inequalities were raised by one participant who showed signs of worry about the limited access to digital aids for individuals living in deprived areas.

> *"So, if they [people living in deprived areas] do not have the smart phone, they won't be able to use it, so it's not going to work, is it? It's what happened with the Universal Credit, so it's not going to work. I mean issue everyone a smart phone." (P16)*

A few participants highlighted the importance of the availability of health apps in both major commercial app stores (Apple App Store and Google Play), not just one or the other.

Most participants stated that apps should be available at no cost. Only six participants expressed their willingness to pay a small fee for an app if, for example, it would be “almost life-changing” (P4) or if it would include online professional support.

The specific design and colour scheme preferred by participants appeared to be unique and dependent on the individual’s taste. However, the majority were looking for a “simple” looking app.

Social influences appeared to be one of the core factors that shaped the selection of apps for all participants during the think aloud exercise. This includes ratings and reviews of the app, how credible the source of the app is, and recommendations of apps received from others. Within app stores, most participants described looking at the star ratings and the number of downloads of each app, and whether the apps were listed as an ‘editor’s choice’. Three participants acknowledged that reviews were subjective, they still reported feeling influenced by the ratings of the app. Additionally, two participants reported that they were sceptical of the reviews, which they believed may have been paid for, and that reviews are not enough, as more information is necessary to make an informed choice.

> *“You know, so you're having to make all these judgements about people’s reviews and then you know deep down that the reviews might be paid for and, you know, it’s a bit of a minefield which is why I would only take a free sample and then see if it works for me.” (P6)*

A credible source was also important. Apps developed or recommended by trusted organisations or respected celebrities seemed more appealing to all participants. Participants who used Google Search to find an app aimed to look for websites they were familiar with or had used before, or for websites that would post ‘Top 10 apps for …’ type of articles. Additionally, word of mouth was another identified source of social influence for many.

> *“I see two different specialists, I have a lung problem as well and I see a lung specialist at a hospital near me and she said to me, the best thing that I could do, which was downloading the Couch to 5k app.” (P14)*

3.5.1.3. Motivational factors related to the uptake of health and wellbeing apps in general

Health or wellbeing apps were preferred over face-to-face options because participants reported feeling competent changing their behaviour through the use of an app, requiring less time commitment and avoiding the anxiety and pressure of interacting with others. Time appeared to be a particularly valuable resource for all participants, and they believed apps to have this advantage.

Another core factor in the selection of an app was the way users perceived its utility. This was found to be based on two aspects. First, they appeared to judge how the app is adapted to the individual by reading the title and the description of the app, and by looking at pictures (i.e. screenshots). Twelve participants reported the need for enough information about an app to make an informed choice.

> *"I would definitely judge more from the pictures more than anything and I think that just nowadays everyone does, is you get an idea of the app from the pictures. (…) I mean I think when you see an older person on a picture and you're a lot younger, it makes you think, I mean it's the wrong think to think but it makes you think maybe it's not for me." (P7)*

Second, it seemed that twelve participants relied on their past experiences with health apps. Whether those experiences were positive or negative may have shaped their beliefs about health apps in general.

> *"So that's why My Fitness Pal is the first app that I've ever had that's actually worked." (P9)*

Additionally, seven participants expressed their scepticism about the accuracy and effectiveness of some apps (e.g. mental health apps), and concerns about data protection were mixed.

> *"These mindful ones, I've never downloaded one and I'm sceptical." (P17)*

Participants mentioned that commitment to the behaviour change would influence uptake and future engagement.

> *"So, I think the committed ones seek out the ones that are the right ones for them, the best ones, rather than necessarily the trendy ones." (P4)*

Participants' social identity also shaped their selections. Many reported that they did not wish to select apps that promoted groups they do not seem themselves fitting in with (e.g. athletic body image or individuals of the hipster subculture).

"They've got a kind of hipster bloke and now they've got a kind of sexy female image with tattoos down her arm, sexy, trendy, female image. Okay, so they are obviously aiming at younger, sort of people in their twenties and thirties, yeah, another sexy female image. It's quite interesting isn't it, I'm looking at the images and not the words and getting a sense, is this for me, middle aged, well older woman?!" (P6)

Curiosity, defined here as a desire to learn something, was the only stand-alone positive emotion, and appeared to positively influence the uptake of health apps for many participants.

"I thought out of curiosity I'd have a look, so I just typed in quit smoking in Google play store and there's hundreds of apps from various people with varying degrees of credibility, and they all were pretty similar to be honest." (P13)

Apps linked to a credible source were important with people unimpressed when an app was not available on all major app stores.

3.5.2. Views on curated health app portals

None of the participants spontaneously used a curated portal. Curated portals were then introduced to the participants, but none were previously aware of them. Curated health app portals were appealing to all participants and they believed the portals would be likely to engender trust. However, searching for a health app on NHS Apps Library and the One You App portal was a generally disappointing experience. Only two participants chose a health app from a health app portal (One You Apps), while the rest of the participants decided to continue the search in commercial app stores.

3.5.2.1. Capability factors related to the uptake of health and wellbeing apps on health portals

All participants had heard of widely advertised apps (e.g. Couch to 5k), but none were aware before study participation of the existence of curated health app portals.

"I think they're brilliant [apps on health app portals]; I didn't know they existed." (P11)

Navigating on the NHS Apps Library seemed easy for some. However, a few participants mentioned that a user guide or help section would be a useful added feature of the portal. Two participants reported that they did not find it easy to use the filter features, and in many cases, they felt the search yielded irrelevant results (e.g. while searching for a physical activity app the results also listed apps for mental health). A few participants reported that navigating on curated app portals felt difficult, characterised as “*cumbersome*” (P4, P12).

> *“It’s not clear, it’s suggests that they are independent apps but maybe they should have some guidelines about design, you know, of their sort of landing pages.” (P6)*

3.5.2.2. Opportunity factors related to uptake on health portals

All participants indicated that they would want a portal tailored to their needs with categories related to their gender, age group, and medical conditions they may have.

> *“So, something like that, this is suitable if you’re over 65, this would be more suitable for you if you’re under 40 or with these ones that you don’t have to go and see your GP, that you can pay for, if you have any concerns, visit your GP or speak to a health professional because some people don’t have that common sense.” (P14)*

Participants had different opinions about the layout of these portals. Some liked the NHS Apps Library design better, with simple colours, while others enjoyed the more colourful One You App portal. Most participants felt that a fusion between these two designs (the searchability and filters of NHS Apps Library and the look and presentation of the One You App portal) and a better functionality would create the ideal curated health app portal. “*Why they are not combined?”* (P8)

While many participants expressed their wish to access apps for free, a few participants were more open to pay for an app that was listed on a curated health app portal.

> *“This is fabulous, and I’d be much more inclined to pay money. This is really, really good.” (P6)*

Participants found the NHS and PHE trustworthy and believed these portals would provide safe and effective digital aids. Some indicated a desire to receive further recommendations for using this portal from their primary care physicians.

> *“If GPs knew that they could say ‘well this could help you’ I’m sure that they would recommend it to people.” (P11)*

However, they also wanted to avoid putting unnecessary pressure on GP practices.

“You’ve got ‘free but requires GP referral’ and when you’re thinking the NHS is under so much financial strain and pressure at the moment, why do I need a GP referral to obtain an app?” (P2)

Additionally, the One You App portal lists a few apps that are recommended, but participants expressed their confusion and lack of clarity of why some apps are ‘recommended’, and by whom.

3.5.2.3. Motivation factors related to uptake on health portals

While searching on curated health app portals none of the participants expressed signs of concern about data protection and accuracy of apps, although two participants reported that they would want to read more about how these apps were developed and tested.

“How long it takes, how many sessions and the fact that it’s been tested in clinical trials and evaluated by NICE which, to me, is probably quite an important thing.” (P1)

Social identity was also important. Some participants had identified themselves as individuals living with a medical condition. These participants were keen to look for an app that targets the behaviour change of individuals with pre-existing medical conditions. Others stated that they do not wish to feel “like a patient” (P7) and seemed reluctant to continue the search on a curated health app portal.

“So, it would be nice to have one specific for maybe people with medical problems or age-related problems, etc.” (P15)

3.6. Discussion

3.6.1. Principal Findings

The online search for health and wellbeing apps was found to be difficult. Factors influencing uptake of health apps were mapped under the COM-B model and the TDF. It was found that social influences and participants’ beliefs about consequences (the perceived utility of the app) are key factors influencing the uptake of health apps. This conclusion was based on the frequency and salience of themes as these occurred during the interview. Curated health portals were found appealing to all despite of the lack of awareness of their existence. However, the way apps are currently presented on these portals did not meet users’ needs due to a lack of certain features, such as lack of tailoring to the users’ requirements.

In line with previous research, the findings revealed the importance of the capability and opportunity factors, such as app literacy skills, health awareness and app awareness, the aesthetics of the app, the low cost of an app, reading reviews and checking ratings, the credible source, and recommendations of apps from others including health professionals (44, 59, 173, 188). Interestingly, the perception of the cost of an app appeared to be related to the perceived utility and the credibility of the source. Although, at the start, some participants were against paying for apps, the more useful an app was perceived, the more inclined participants felt to pay a fee. This phenomenon was observed for apps listed on health app portals which were considered a credible source. More importantly, unlike apps listed on commercial app stores, there was implied trust in apps listed on curated health app portals by participants. Additionally, some health apps are not available to download in both commercial app stores. Participants found it disappointing that some apps were only available for iPhone users. This is in line with previous research which found that out of eighteen investigated health apps, only one third were available to download on both major commercial app stores (178).

In terms of motivational factors, it was found that the perceived utility included aspects related to the individuals' perceptions about the presentation of an app as well as their previous experiences with health apps. Together these shaped the way participants judged the usefulness of an app. This characterisation underlines the need expressed by others previously for a better way to present health apps through a description that would lead to an informed choice (e.g. the content of the app) (175-177), and potentially positively affect other motivational factors, such as the accuracy of an app and data protection (189). Notably, concern about data protection and the accuracy of a health app was minimal when participants navigated on health app portals as opposed to commercial app stores.

There is a need to understand what design aspects generate positive or negative emotions, and for whom. Emotions are powerful driver of a behaviour, which affect decision making (e.g. app uptake) (190). A key emotion identified in this research directly influencing uptake was curiosity. However, this study emphasised the importance of positive emotions triggered by, for example, the credible source of an app, and negative emotions triggered by restriction of information (e.g. lack of understanding of the necessity of GP referral to download an app). Taking these into consideration may lead to better uptake with such tools.

Uptake and engagement are connected. Engagement without uptake is not possible, and uptake without taking into consideration factors that are important for engagement is impractical. Some factors might influence both uptake and engagement; for example, this research suggests that the perceived utility of an app is one of the main factors for uptake and the study presented in Chapter 2 (44) and a previous study found that perceived utility was a predictor for engagement with an alcohol reduction app (191). Hence, where possible, uptake and engagement should be considered together as two linked constructs.

3.6.2. Strengths and Limitations

The main strength of this study lies in the methodology; given the aim of this study was to explore uptake with health apps and by applying a user-centred approach, the think aloud methodology was the appropriate technique to use (181, 192) as it will minimise recall bias when investigating uptake factors. To ensure that the study was as meaningful as possible, the study protocol was developed with policymakers and patient and public representative involvement in the design of the topic guide. Furthermore, the research was informed by well-established theoretical models; the COM-B and the TDF and peer debriefing was used to help the data interpretation and data analysis (186). Additionally, purposive sampling was used to attempt to recruit a diverse sample regarding their gender, educational level and employment status. Finally, member checking was conducted, a technique used to establish the credibility of the findings by sending a brief summary of it to randomly selected participants (187).

The study has several limitations, and some may directly affect interpretation of the findings. First, for a qualitative study exploring such a broad topic. Information saturation was felt to have been reached, but it is possible that additional participants with more varied characteristics would have allowed identification of additional concepts. Second, during external validation a randomly selected subsample of participants was asked via email to provide feedback on the summary of findings. Three participants (50%) did not reply, and it is unclear whether these participants ignored our request or did not agree with the interpretation of the results. In terms of the uptake factors identified in this study, asking participants to perform the think aloud task under observation may not be fully analogous to how they would perform a search when on their own. Furthermore, some identified factors were difficult to define and describe due to lack of specificity of the description provided by participants. These include aesthetics of apps, often described vaguely (‘nice’, ‘elegant’) and the cognitive load associated with engagement with these (‘easy to use’).

3.6.3. Implications for research, policy and practice

This research has important implications for stakeholders in public health and policymakers that target prevention and health promotion using digital technologies, and governmental bodies and trusted health organisations that provide curated health app portals. Low awareness, low app literacy skills, lack of availability on all major app stores, and lack of recommendation in primary care were identified as factors limiting the uptake of health apps in general and on curated app portals. These are factors are important to consider for improving the uptake of health apps. The selection was described as difficult. Hence, there is a need for public guidance on how to identify evidence-based tools (44, 173), and for health practitioners to promote and advise their patients on how to select appropriate health and wellbeing apps (188). Raising awareness of such tools through both online and offline promotion channels might provide better access to effective apps.

Findings of this study could also help developers reconsider the ways in which apps are currently presented on commercial app stores and app portals, which might in turn increase the uptake of evidence-informed health apps. The idea of selecting an app from a health app portal was appealing to all participants, although individuals' needs were not currently met. These findings describe essential barriers and facilitators related to participants' capability, opportunity and motivation to take up health and wellbeing apps. For example, app descriptions and presentations that better align with individuals' needs may increase the uptake of health apps on health app portals. These findings can also be used to inform the development of interventions that specifically aim to promote the uptake of, and engagement with, evidence-informed health and wellbeing apps, a priority within the NHS Long Term Plan (i.e. 'digital first'). By targeting the identified psychological influences on app uptake through further interventional work, organisations that provide app portals (e.g. the NHS, PHE) should be able to increase their impact through helping people to better select appropriate apps. A summary of recommendations for policy makers, providers and developers is presented in Table 6.

Table 6. Recommendations for policy makers, industry, health care providers and app developers for a better uptake of health and wellbeing apps.

COM-B component	Recommendations for policy makers, health app portal providers, app developers
1. Capability	1.1. Improve app literacy skills with a focus on elderly and marginalised populations and continue working towards reducing the digital divide (e.g. through the use of an outreach approach to target elderly, migrant and homeless populations) 1.2. Increase awareness of effective health apps and curated health app portals through promotion online and offline in primary care, mass media and public spaces 1.3. Provide guidance on how to use a health app portal (e.g. through incorporating an extensive help section) and additional physical and mental health related evidence-based articles 1.4. Promote reduced cognitive load on curated health app portals (e.g. through the use of images and short app descriptions)
2. Opportunity	2.1. Ensure evidence-informed apps are available for free or at low cost to everyone 2.2. Make apps available on all major app stores simultaneously 2.3. Offer the possibility to tailor the health app portal to target certain demographics (e.g. apps for physical activity for women aged 60 and over) 2.4. Offer apps at low cost and provide explanation for those that require referrals and justifications for the cost of paid apps on curated health app portals 2.5. Collaborate with interaction design experts and end-users to enhance the aesthetics of health app portals 2.6. Promote evidence-informed apps via trusted organisations and provide information on how the apps were developed and tested 2.7. Encourage health professionals and practitioners of promotion of evidence-informed health apps and health app portals
3. Motivation	3.1. Provide relevant and realistic titles and avoid general app descriptions. Descriptions should be short, but contain details of what the app offers and how it is able to help the user 3.2. Provide pictures of the app (e.g. screenshots) and avoid pictures that promote an unrealistic body image 3.3. Provide information about the accuracy and effectiveness of the app (e.g. details about development and developers), as well as about how the users' data are handled 3.4. Take into account the user's emotions about certain features by constantly involving users in the development of health apps

3.6.4. Future research

Future research is needed to minimise factors limiting uptake, such as low awareness, low app literacy skills and a lack of recommendation in primary care. Our results suggest that there is a need to better tailor the design and content of health app portals to better meet individuals' needs. However, the mixed views on specific app designs indicates that more research is needed to investigate whether there are general design principles that are missed and could be followed to accommodate the majority of people, or whether better tailoring and/or adaptive interventions should be considered instead. Future research may also want to consider comparing curated health app portals developed by private organisations with those developed by governmental bodies to investigate whether portal design related features are considered less or more important than credibility and trust in apps listed on them. Experimental research is needed to assess whether there is a trade-off between credibility, social influences and perceived utility of the apps presented on curated health app portals. Furthermore, with a growing concern around widening inequalities (193), solutions should be focused on reducing the digital divide and health inequalities that may appear as a result of financial constraint of owning a smartphone and lack of sufficient app literacy skills.

3.6.5. Conclusion

Among factors mapped under capability, opportunity and motivation components of the COM-B model, social influences and the perceived utility of an app appear to be the core factors influencing uptake in general and on curated health app portals. Curated app portals are considered trustworthy and serve as a credible source for apps, however there is disappointment with their current implementation. Uptake on health app portals, as opposed to uptake in general, appears to help address people's concerns regarding data protection and accuracy of apps. Health organisations that develop app portals may consider targeting the factors identified across the COM-B and the TDF as part of additional experimental work as this could help to increase impact through better selection of appropriate health apps.

3.7. Next steps

Uptake and engagement with health and wellbeing apps are two linked behaviours. Engagement cannot take place without uptake and uptake without engagement is meaningless in terms of use of such products. Therefore, linking to the factors influencing the uptake of health and wellbeing apps presented in this chapter, the next chapter of the thesis (Chapter 4) continues to explore people's experiences and reasons for engaging and not engaging with health and wellbeing apps, complementing the findings identified in Chapter 2. The findings may inform future app development to improve user engagement and feeds into the second stage of this thesis, the development of the discrete choice experiment (Chapter 5).

Chapter 4. Perceptions of factors influencing engagement with health and wellbeing apps: a qualitative study using the COM-B model and Theoretical Domains Framework.

4.1. Dissemination

Findings of this chapter were presented together with findings of Chapter 3 at the UK Society of Behavioural Medicine's Annual Meeting (2020), at the Society of Behavioural Medicine (2020 – cancelled due to COVID, but disseminated virtually), at the UCL Centre for Behaviour Change Digital Health Virtual Conference (2020), at the European Health Psychology Society's Annual Virtual Conference (2021) and at the International Society of Physical Activity and Health Virtual Congress (2021).

A version of Chapter 4 was accepted for publication in the Journal of Medical Internet Research mHealth and uHealth and is currently in press (194).

4.2. Abstract

Background. Digital health devices, such as health and wellbeing smartphone apps, could offer an accessible and cost-effective way to deliver health and wellbeing interventions. A key component of the effectiveness of these apps is user engagement. However, engagement with health and wellbeing apps is typically poor. Previous studies have identified a list of factors that could influence engagement; however, most were conducted on a particular population or for an app targeting a particular behaviour. Understanding factors that influence engagement with a wide range of health and wellbeing apps can inform the design and the development of more engaging apps in general.

Objectives. The aim of this chapter was to explore users' experiences of and reasons for engaging and not engaging with a wide range of health and wellbeing apps.

Methods. A sample of adults in the UK (N=17) interested in using a health or wellbeing app took part in a semi-structured interview to explore experiences of engaging and reasons for not engaging with these apps. Participants were recruited via social media platforms. Data were analysed with the framework approach, informed by the

Capability, Opportunity, Motivation – Behaviour (COM-B) model and the Theoretical Domains Framework, two widely used frameworks that incorporate a comprehensive set of behavioural influences.

Results. Factors influencing the *capability* of participants included available user guidance, statistical and health information, reduced cognitive load, well-designed reminders, self-monitoring features, features that help to establish a routine, features that offer safety netting and stepping-stone app characteristics. Tailoring, peer support and embedded professional support were identified as important factors that enhance users' *opportunities* for engagement with health and wellbeing apps. Feedback, rewards, encouragement, goal setting, action planning, self-confidence and commitment were judged to be *motivation* factors that affect engagement with health and wellbeing apps.

Conclusion. Multiple factors were identified across all components of the COM-B model that may be valuable for the development of more engaging health and wellbeing apps. Engagement appears to be influenced primarily by features that provide user guidance, promote minimal cognitive load and support self-monitoring (*capability*), provide embedded social support (*opportunity*), and goal setting with action planning (*motivation*). This chapter provides recommendations for policy makers, industry, health care providers and app developers on how to increase effective engagement.

4.3. Introduction

4.3.1. Background

Smoking, physical inactivity, inadequate diet, and excessive alcohol consumption are the main risk factors for noncommunicable diseases, responsible for over 56.9 million deaths worldwide (195). People with mental health problems often have poorer physical health and vice versa (196, 197). To reduce the burden of ill health, a range of interventions have been developed. Integration of multimedia technologies within the healthcare domain has led to the development of interventions delivered digitally via mobile phones, wearable devices and smartphone applications ('apps'). Smartphone apps are constantly available to the user and therefore act as portable tools for the delivery of easily accessible health and wellbeing interventions (42). There is early evidence of effectiveness of apps for physical inactivity (29, 31, 32, 39), weight loss (34, 35, 39), alcohol reduction in non-dependent drinkers (36) and mental health promotion (169). Health apps are also considered a cost-effective solution (24, 39) and have the potential to increase access for hard-to-reach populations that are resistant or unable to seek face-to-face support, for instance due to stigma or geographical barriers (170).

Engagement is a necessary component for the effectiveness of a health or wellbeing app. Engagement with health and wellbeing apps can be defined as '(1) the extent (e.g. amount, frequency, duration, depth) of usage and (2) a subjective experience characterised by attention, interest and affect' (56).

However, it has been argued that measuring 'effective engagement' is more important than simply the time spent on an app and the frequency of use (19). Yardley and colleagues define 'effective engagement' with a smartphone app as involving two components: the first is the intensity of engagement that is necessary for achieving desired outcomes, with sustained app engagement over a period of weeks, months or even years (referred to as 'micro-engagement'). However, micro-engagement alone is not sufficient for behaviour change (19). Yardley's model also emphasises engagement with the broader behaviour change process and goal (i.e. 'macro-engagement'), which is considered separate from, although intimately linked with, micro-engagement. Based on this distinction of micro- and macro-engagement with health and wellbeing apps, some factors may relate more to the former or the latter, with micro-engagement influencing macro-engagement and vice-versa. For example, engagement may be affected by common contextual factors, such as personal (e.g., their interest), environmental (e.g., where the engagement occurs, individual's lifestyle) or social context (e.g., family or culture). Due to the complexity of engagement, researchers recognise that it is difficult to define what constitutes 'good' or 'sufficient' engagement. Some individuals may require a longer period of engagement with an app than others for the desired behaviour change to occur.

Despite the promise of health apps, engagement tends to be poor (55, 198). For example, a Mobile Consumer Report found that for medical, health and fitness apps, only 20% of users use the app one day after installation, and only 8% after seven days after installation (54). A panel-based analysis systematically examined usage patterns in 93 mental health apps and found that the median app retention rates at 15 and 30 days after installation were 3.9% and 3.3.%, respectively (55).

There is a growing literature on factors influencing engagement with health and wellbeing smartphone apps. In the review of 41 studies described in Chapter 2, 26 factors were identified as being important for the uptake of, and engagement with, such apps (44). In addition to a wide range of behaviour change techniques (e.g. self-monitoring, goal setting) (171, 199), several other factors were identified as influential, including the role of healthcare professionals in the promotion and recommendation of health apps (188) and embedded professional support (173). The latter was found to be particularly important for certain behaviours (i.e. alcohol reduction, suicide prevention, anxiety, self-harm), with stand-alone apps considered insufficient by users and clinicians (170). In an assessment of 93 mental health apps, daily minutes of engagement were higher for apps that included peer support (median=35.1, IQR=N/A, n=2) and coping strategies, such as mindfulness and meditation (median=21.5, IQR=15) compared with apps that incorporated self-monitoring or psychoeducational features (median range=3.53-8.32) (55).

Few qualitative studies have been undertaken to explore factors that affect engagement with health and wellbeing apps. Those undertaken have focused on specific populations or behaviours as described in Chapter 2. Available studies have focused on weight loss behaviours and alcohol reduction, and have found that health information provided (198, 199), personalisation of app content (136) and tailoring of content to the user's demographics (199) are some of the factors deemed to be important for engagement with weight loss and alcohol reduction apps. Most studies conducted to date investigate features of health apps that are desirable by a certain population, and little is known about factors deemed important for engagement with a wider range of health and wellbeing apps. These studies suggest that the context in which apps are developed and used might often be behaviour or population specific. Most studies conducted to date investigate features of health apps that are desirable by a certain population, and little is known about factors deemed important for engagement across a wider range of health and wellbeing apps (44). Therefore, this research intends to address this gap by exploring views of the 'big four' public health priority behaviours related to prevention (smoking, alcohol consumption, physical activity, diet) and mental health. The findings from this study may inform future app development to improve user engagement with apps that target health promotion. Findings may also be particularly useful for stakeholders in public health to inform the development of interventions to promote engagement with evidence-based health and wellbeing apps, for example directly contributing to the long-term plan of the NHS to become 'digital first'.

4.3.2. Theoretical framework

As described in Chapter 1, the COM-B and TDF together provide a detailed theoretical framework that facilitate the careful consideration of factors influencing engagement with health and wellbeing apps and the use of the BCW to develop interventions to improve engagement.

4.3.3. Aim

A theoretical framework informed by the COM-B model and the TDF was applied in this chapter as well to investigate people's experiences and reasons for engaging and not engaging with health and wellbeing apps. The findings may inform future app development to improve user engagement.

4.4. Methods

The methods of this study are described in Chapter 3. While Chapter 3 focused on the presentation of the findings of the uptake of health and wellbeing apps and participants views on curated health app portals, this chapter presents and focuses on the engagement aspects of the research.

4.5. Results

4.5.1. Participant characteristics

Eighteen adults (mean age = 43, range 21-68) were recruited, of whom 10 were females, 14 were White British, 13 were employed full time, 8 had college degree or higher. Eleven participants reported currently using at least one health or wellbeing app at the time of the interview. Three participants expressed their intention to change one behaviour, with most participants interested in changing more than one behaviour (e.g. losing weight, being more active, managing their mood). One participant had never used health apps before and did not wish to express their views on engagement; therefore, the findings of this study are based on the views and experiences of the remaining 17 participants about their engagement with health and wellbeing apps (see Chapter 3, Table 4.).

4.5.2. Factors influencing engagement with health and wellbeing apps

An overview of the factors mapped under the constructs of the TDF and components of the COM-B can be found in Table 7. All relevant data was coded under 10 out of 14 constructs of the TDF. There was no data that could not be coded under any of the constructs of the TDF.

Table 7. Perception of factors influencing engagement with health apps

COM-B component and *TDF construct*	Identified factor	Description
Psychological Capability		
TDF construct: Knowledge		
	User guidance	Instructions on how to effectively use a health app
	Statistical information	A visual or numerical summary of progress or quantification of the behaviour
	Health information	Educational information related to health and wellbeing aspects
TDF construct: Memory, attention Decision processes		
	Reduced cognitive load	The app is not too time consuming, easy to use and requires minimal input
	Reminders	Preferably customisable, notification-type messages
TDF construct: Behaviour regulation		
	Self-monitoring	The ability of the app to support self-regulation of the target behaviour
	Routines	The ability to support routine/habit formation
	Safety netting	Retaining the app for a potential precipitating event in the future
	'Stepping stone'	App as a first step in the behaviour change process
Physical Opportunity		
TDF construct: Environmental resources		
	Tailoring	Innovative features and adaptability, and an interactive, two-way communication between the app and user
Social Opportunity		
TDF construct: Social influences		
	Peer support	Including social interaction with users with similar needs within the app or within their community; a choice to connect to social media platforms, competitions and challenges with others or with themselves
	Social support (practical)	Possibility to contact health professionals and practitioners within the app

Table 7 (Continued). Perception of factors influencing engagement with health apps

COM-B component and *TDF construct*	Identified factor	Description
Reflective Motivation		
TDF construct: Beliefs about capabilities		
	Self-confidence	Perceived capability to change one's behaviour using an app
TDF construct: Goals		
	Goal setting	Establishing what the user would like to achieve
	Action planning	Establishing how the user would like to achieve set goals
TDF construct: Beliefs about consequences		
	Commitment	The level of commitment while engaging with an app to change the behaviour and achieve set goals.
Automatic Motivation		
TDF construct: Reinforcement		
	Feedback	Feedback regarding the user's performance
	Rewards	• Tangible (objects, discount, etc.) and intangible (badges, certificates, etc.) rewards in response to the user's effort Gamification elements
	Encouragement	Additional ways to provide reinforcement (e.g. encouraging messages)
TDF construct: Emotions		
	Positive emotions	Triggered by included user guidance, statistical information, additional health information, embedded professional support, community networking possibilities, tracking features and rewards
	Negative emotions	Triggered by lack of user guidance, invasive push-notifications, cognitive overload, unrevealed in-app costs
	Mixed emotions	Triggered by reminders

4.5.2.1. Capability to engage with health and wellbeing apps

4.5.2.1.1. Knowledge

Many participants perceived their knowledge on how to use an app, as well as embedded statistical and health information, as an important influence on their engagement with an app. We inferred this from the desire many people reported for clear user guidance and, in some cases, for help on how to increase their capability to perform a behaviour (e.g. demonstration of the behaviour). One participant explained that they had stopped using an app in the past due to there being "*insufficient guidance on how to use it*." (P8)

> *"So, this is where I start getting, well why are you asking me these questions if you're not going to let me carry on with it and that's where I start getting confused, going back, not really understanding where I need to go from here." (P15)*

Further, the necessity of statistical information about their progress and achievements was reported by most participants:

> *"It's nice to see your progress on a graph and it's just very clear. It's a single screen, you have icons for all the activities that you've done during the day." (P6)*

In addition, most participants expressed the need for relevant and comprehensive health information.

> *"Knowledge is key." (P14).*

Several participants stated that having educational articles embedded would help them to build knowledge, and to understand and to manage their behaviour better. Not getting enough health information was reported as the main reason for one participant to look for a different app.

> *"It's got to have the information that I want and have it easily accessible." (P2)*

4.5.2.1.2. Memory, attention, decision processes

Participants perceived reduced cognitive load and customisable, notification type reminders as factors that positively affect their capability to engage with an app. All participants described favouring apps with reduced cognitive load. This included apps with limited complexity, less data input, and a limited number of available features to choose from.

One participant suggested that an app should apply a multi-level approach with *"a light version of an app and then enhanced*" (P15). They described that an app might have a simple version for basic users with no registration and minimum data input and a more advanced version with all features available for power users.

Several participants expressed that a time-consuming app would be immediately deleted.

> *"A mood tracker is something I probably wouldn't use because it looks like it would require a lot of data of me putting in and typing it on to stuff." (P7)*

Although push notifications were considered more or less annoying, many participants described reminders as being particularly useful. One participant described that not being reminded to engage with an app led him to disengage.

> *"Because I wasn't reminded, I stopped using it. And I think that's really important." (P1)*

However, a few participants who reported not finding notifications useful stated that they would immediately turn reminders off or delete the app.

> *"I'm sure there are many apps I've deleted because of reminders." (P7)*

Others suggested that reminders might cause harm. For example, one participant described uninstalling a smoking cessation app as reminders were periodically reminding them about their addiction, thus serving as a prompt that induced cigarette cravings. Two participants proposed that opting in to receive reminders would be desirable instead of opting out. In addition, one participant suggested that human-like reminders in the form of text messages would be less likely ignored, and would create the perception of a human touch within the app.

> *"I think text messages would work better because I don't ignore my text messages and my WhatsApp messages because there's real people connected to those; you know? (…) if I could think of an ideal it would be a text message that kind of asked you a question and you replied, and it felt like it was a human being." (P6)*

4.5.2.1.3. Behaviour regulation

Participants perceived that self-monitoring, established routines, as well as safety netting and 'stepping-stone' characteristics of the app, would enhance their engagement with an app.

All described self-monitoring features as key in behaviour regulation, even when there is no particular goal set or when achieving the goal shows a delay.

> *"Monitoring, really because the goal is probably going to go a bit by the wayside because work has been too busy, and life has changed and lots of stuff has happened this year. So, I'm behind my goal but I still use it as a monitor." (P17)*

Some participants reported that a daily routine of using an app would make engagement with it more accessible and continuous. Two participants described how using a weight management app for a week was necessary for them to get into a routine and helped them staying engaged after that. However, one of them explained that it felt difficult using the app at the beginning, although after a few days it got easier.

A number of participants explained they perceived physical activity apps as stepping stones to physical activity services with the app acting as an intermediate tool in behaviour change. Two participants described that an app helped them to get enough experience and practice home-workouts that boosted their confidence to sign up for a gym membership eventually.

> *"You can just literally do it at home [fitness app] until you feel I suppose a bit more confident to go out and join [the gym]." (P10)*

Many of the participants described apps as a safety netting tool (e.g. relapse prevention). Several reported a tendency to re-engage with a weight management app periodically and when necessary to regulate their weight, for example before or after a holiday season, or an important upcoming event because the app had helped them achieve their goals in the past.

> *"I think I have periodically come back to it and thought 'no it worked before; it'll work again'." (P13)*

4.5.2.2. Opportunity to engage with health and wellbeing apps

4.5.2.2.1. Environmental resources

Participants perceived that tailoring the technology was a factor that would influence sustained engagement. Many participants expressed the need for features that would create a better physical opportunity to engage with an app, and a more personalised experience during the engagement. Many participants described seeking to engage with apps that provide two-way communication that can adapt to the person's needs based on how they interact with such tools. Several participants mentioned the inclusion of innovative features. These features consisted of embedded artificial intelligence to receive health-related advice and tailored content, facial recognition and recognition of non-verbal cues for better outcomes in physical activity, e.g. correcting posture, and using the phone's camera for providing nutritional data of cooked food.

“If it’s smart, as well. Has it got a little bit of artificial intelligence built into the background? Is it using my data? Is it saying “do you know what? Actually, you’ve done really well this week, you’ve used the app this amount of times. How are you feeling?” (P2)

One participant described that the lack of novelty of an app would lead them to disengage with it. In contrast, another reported the opposite: they would feel put off if they would need to learn new features.

“It’s no good downloading an app and then six months later looking at that app and it’s still the same, that would stop me.” (P14)

“If something’s working we want it to stay as it is, we don’t want it to change, and even if there are improvements to it, if it’s new it can kind of put people off in a way.” (P13)

Syncing with wearables or other additional devices was described as desirable by many.

4.5.2.2.2. Social influences

Peer support and social support (practical) were perceived by participants as factors that may sustain engagement with an app. Several participants perceived networking within an online community as necessary peer support. Some described that sharing and exchanging experiences with others would encourage and motivate them in their journey. Others suggested anonymity for users as well as a moderation of discussions to avoid “misinformation” (P12).

“I like the idea that it’s round the clock support, because so very often with mental health issues it’s kind of 2 o’clock in the morning that they are the worst, and that is when you need to talk to somebody, and the idea of having a community who you don’t have to explain how you’re feeling sounds really good.” (P11)

Embedded social media to share their progress with others was reported useful feature only by a few participants who were using physical activity or weight management apps. However, a couple of participants highlighted that this feature should be optional. Physical activity and weight management app users also described challenges and competitions as motivating and fun:

“There’s challenges, which will help you with your weight loss, your fruit and vegetable intake, the exercise challenges that you can do, either with yourself or your friends, which are good for motivation.” (P15)

All participants expressed their preference for an app that would offer built-in professional support, such as health practitioners, coaches and dieticians (social support, practical). One participant with an existing medical condition described the need for health practitioner support within an app. Additionally, two participants described that built-in support would help with accountability, and one participant indicated they would be willing to pay to access an app with in-built support. Another participant commented that the embedded professional support was the best feature of a mental health app they were using:

> *"Yeah, if you could sort of talk to a healthcare professional in that app I think that would be better, because then they would have the up to date I suppose treatments and methods so that you know you're not going on old information." (P10)*

> *"I: If you would need to say just one thing that is the best in the app, what would that be? P: The support." (P11)*

4.5.2.3. Motivation to engage with health and wellbeing apps

4.5.2.3.1. Beliefs about capabilities

Apps were perceived by several participants as useful tools to enhance their self-confidence in changing their behaviour. One participant described that the community networking opportunities further helped her self-confidence and motivated her to use the app:

> *"The app made me feel more confident in doing it, even it was just basic home exercises." (P7)*

4.5.2.3.2. Goals

Goal setting and action planning were perceived as key factors for sustained engagement and motivators of behaviour change. Goal setting was reported to be valuable by all to address behaviour change, but half of the participants described the need for action planning features to help them achieve their set goals:

> *"I'd want something which was a bit more than press one button every day to say you haven't smoked; it was great for the first 10 minutes of using the app because I got all this information about 'wow thousands of pounds and the health benefits', and then after that it was literally just press this button to say you haven't smoked, and that wasn't really enough for me." (P13)*

4.5.2.3.3. Beliefs about consequences

Several participants expressed that their level of commitment to achieve their goal shaped the level of engagement with the app they used:

> *"The app, the initial – the main reason you're on that app is to get your result of what you want to achieve, what you want to do to help you stay on track." (P9)*

4.5.2.3.4. Reinforcement

Many participants perceived feedback, rewards and encouragement automatic motivational factors that may sustain engagement with an app. A number of participants expressed that they needed continuous feedback to reinforce their continuous use:

> *"I think an app that might give you feedback, a notification, that would keep me entertained and would keep my level of focus and wanting to continue with it." (P3)*

Intangible rewards (i.e. badges, certificates) were described as another form of reinforcement by several participants, for motivating them and as "nice" (P14) or something to "show off" (P5). However, some other participants described intangible rewards as "irrelevant". They reported that the tangible rewards they received in the past including cinema tickets, lower insurance premiums, loyalty points that can be exchanged for objects or a free water bottle, provided better motivation to engage with the app than intangible ones. In addition, a few participants expressed the need for encouragement in the form of motivational messages:

> *"In this context, so badges, you earn nine of 24 badges so far. For me a little bit irrelevant actually, what are you going to do with it, there's other reasons why you're quitting, not to get the badges." (P16)*

4.5.2.3.5. Emotions

Participants expressed positive emotions regarding available user guidance, statistical information, additional health information, embedded professional support, the possibility for community networking, self-monitoring features and rewards. However, negative emotions were expressed by lack of user guidance, invasive push-notifications and cognitive overload. Finally, reminders were person dependent and triggered mixed feelings across participants.

4.6. Discussion

4.6.1. Principal findings

This chapter applied the COM-B and the TDF to explore users' views about factors that influence engagement with health and wellbeing apps. Based on the frequency that themes occurred, it was found that knowledge, such as user guidance and statistical information, memory, attention and decision processes, such as reduced cognitive load, environmental resources, expressed by the tailored technology, and social influences, referred as peer and professional support, are most important factors for these participants for engagement.

Many factors that were identified in this chapter are consistent with previous literature. Previous research found that engagement with health apps is greatly influenced by factors affecting users' capabilities including different types of knowledge (user guidance, statistical information, health information) (44, 200), reduced cognitive load, reminders and self-monitoring features (44, 59, 199). These factors could be targeted during app development updates of existing apps to improve user engagement. In line with previous findings, reminders were not found to be universally useful (44). One possible explanation is that reminders may be behaviour-dependent and person-dependent. Some participants reported that they had stopped engaging with a health app because they were not reminded to continue using it, while others tended to ignore or delete apps that sent reminders.

This chapter is the first to identify a novel factor, the perception of certain apps as 'stepping stones' to more intensive behaviour change. For example, a home-based workout app or a walking app could seek to provide enough self-efficacy and competence for an individual to join a gym or start using a running app. An explicit 'stepping stone' approach could be a useful addition for apps targeting behaviours that are harder to achieve because of negative emotions, such as embarrassment, shame or pressure, including those targeting sedentary behaviour. This novel finding shows that sustained engagement is not always necessary to support desired health and wellbeing outcomes through additional behaviour change activities.

Engagement is further influenced by users' physical opportunities, such as tailored technology, and social opportunities, peer support including community networking, embedded social media and social competitions, and professional support (44, 59, 136, 173). Some users would want the app to be based on machine learning opportunities and on two-way interaction with users. The adaptable nature of an app and the provision and level of artificial intelligence (AI) included may also play a key feature in engagement. These factors may be harder to include once an app is developed; therefore, it might be important to consider these aspects in the development process. Indeed, such tailored technology may be the most important aspect to consider. For example, while there may be financial considerations precluding the provision of personal professional support within an app, this service may be developed using AI. These forms of technological personalised models in health behaviours such as nutrition or smoking, including machine learning models, has been suggested to aid the process of making decisions about diet and food (201). However, AI was not yet found in diet monitoring apps (202). A randomised controlled trial found that participants allocated to an advanced version of a smoking cessation app with an AI chatbot had 107% higher engagement with the app, and over twice the odds of being abstinent at one month follow up, compared with participants using the standard version of the app (161). Furthermore, timely AI-based behaviour change support received just-in-time may further increase behaviour change. Although unguided interventions can be effective, having professional support within an app tends to increase effective engagement (19). Simple interventions that do not require professional support can be more widely disseminated and are more cost-effective than those with embedded professional support (19).

Users' reflective motivation, including beliefs in their capabilities (self-confidence) and consequences (commitment) as well as goals (goal setting and action planning), are essential for engagement. While the first two are harder to address because these are within-person factors, the latter could be easily implemented as features of the app. One possible way to increase self-confidence and commitment is perhaps to address these within the app by using quizzes or articles (203), (e.g. for commitment 'How to stay on track to achieve your goal?') or check-in messages using AI (161).

Emotions are considered automatic motivation factors and are a powerful driver of behaviour that affect adherence, for example engagement with a health app (190). It is noteworthy that this study did not identify emotions directly influencing engagement or failed to identify them. However, this study found evidence that the other factors affected participants' emotions. Appealing features, such as statistical and health information, embedded peer and professional support, and tracking features and rewards, triggered positive emotions. In contrast, lack of user guidance, invasive notifications and cognitive load triggered negative emotions. A better understanding of how the presence or absence of specific features affect participants' emotions may be useful for the development of new or refinement of existing apps, which, consequently, may lead to better engagement with health apps.

4.6.2. Strengths and Limitations

The broad strengths and limitations are described in Chapter 3. However, there are several additional elements of particular relevance to the work on engagement, and these are described below.

The recruitment of a sample of participants with more diverse demographics might have identified additional factors that are important for engagement. Several participants were not using health or wellbeing apps at the time of the interviews and had not downloaded any health and wellbeing apps in the past 6 months prior the interview. This may have led to limitations associated with the challenges of retrospective recall. Although the aim was to recruit heterogeneous sample to capture a wide with ‘big four’ public health priority behaviours related to prevention (smoking, alcohol consumption, physical activity, diet) and mental health apps, a homogeneous sample may have allowed for a more in-depth understanding of engagement with apps for specific behaviours.

The study only included participants who considered using a smartphone app to change their behaviour in the future. Including participants who have used health and wellbeing apps in the past, but are less receptive to using them now, may have provided additional perspectives on factors influencing app engagement. Findings may be influenced by the intention-behaviour gap, with participants reporting on factors perceived as important for changing their behaviour through an app; however, this does not mean that they would act on their intention. One example of this is the finding that many participants wanted access to an online community. Although, online communities typically suffer from the ’90-9-1 principle’, whereby the content in online communities is generated by 1% of the members with 9 percent editing or modifying it, while 90% are passive observers (204), this may not be the case with a closed community built to support behaviour change, where individuals are seeking support from each other.

Additionally, the meaning of the term engagement was not explicitly defined during the interview when individuals shared their experiences and views of engagement. Their interpretation of engagement is likely a mixture of micro-and macro-engagement and distinction between micro- and macro-engagement was not considered when interpreting findings.

4.6.3. Implications and future research

This chapter provides insight for stakeholders in public health, policymakers, and developers of apps that target disease prevention and health promotion. Findings may also be used to inform the development of interventions aiming to promote engagement with evidence-based health and wellbeing apps. In the UK, this aligns with the priorities of the NHS Long Term Plan (i.e. 'digital first').

The main finding of this chapter is centred around providing necessary support for increased engagement with health apps. This chapter found that embedded professional support may have a substantial impact on engagement, although it may not be beneficial for all health behaviours. Embedded social support may be particularly important for some behaviours that are more likely to be complex and require intensive support in order to maintain engagement. These behaviours are the ones that require reassurance, guidance or emotional support (19), such as apps targeting substance misuse, or the ones developed to improve mental health. While it is not always feasible to develop an app with embedded professional support, there might be different ways to address this need outside of the app. For instance, there may be a way to provide support within the community-based care to assist with the uptake of health apps and with the progress or potential barriers of engagement. Another way to mitigate the absence of embedded professional support is to investigate the potential efficacy of advanced computational techniques, such as AI, to mimic the support provided by healthcare professionals (e.g. in the form of chatbots or other types of conversational agents). There is an urgent need for more research on the optimal type (e.g. technology-mediated or 'blended') and timing of support needed within various health and wellbeing smartphone apps.

To better meet users' needs, the design of apps would ideally be informed by a user-centred and iterative development process, supported by mixed-methods research including in-depth interviews. As app engagement is generally greater in those with higher socioeconomic status (101), involving individuals with lower socioeconomic status is particularly important (19). Furthermore, people directly affected by the digital divide, or digital exclusion and who may struggle to benefit from health apps due to a lack of skills or low digital literacy, could be targeted by offering app-use tutoring. While this may require investment or relocation of resources within community health care settings, it may increase the reach of health apps and lead to a greater public health benefit. Furthermore, there may be a tension between users wanting the app to be easy to use (which may be facilitated by providing user guidance) but at the same time not too time-consuming. As the provision of user guidance helps individuals with limited technological skills, such features should still be prioritised. Undoubtedly, finding the balance between producing an app with all features necessary for behaviour change to occur and ensuring the app is intuitive enough will pose a challenge for app developers.

Additionally, more experimental research would help us to better understand the effects and potential interactions between the engagement factors identified in this study including usability (ease of use), reminders, embedded support, rewards and goal management. Table 8 provides a summary of recommendations to help app developers and commissioners design interventions to increase effective engagement. These factors are structured around the COM-B and TDF.

Table 8. Recommendations for policy makers, industry, healthcare providers and app developers for maximising engagement with health and wellbeing smartphone apps.

COM-B component	Recommendations for policy makers, health app portal providers, app developers
1. Capability	1.1. Provide user guidance on how to use an app, visual and/or numerical summary of progress and evidence-based additional health information related to the behaviour targeted by the app 1.2. Minimise time required to use app where possible 1.3. Provide customisable reminders that users could opt out 1.4. Provide the option of self-monitoring features 1.5. Promote safety-netting and relapse prevention features such as the possibility to restart or reengage with the app later 1.6. Promote a routine for engagement with an app e.g. highlighting the role that routine may play in effectiveness of an app
2. Opportunity	2.1. Collaborate with interaction design experts and end-users to enhance the aesthetics of apps 2.2. Provide the possibility for community networking within the app and linking to social media as an optional feature to share progress where appropriate 2.3. Offer the possibility for social competition and challenges where appropriate 2.4. Consider the provision of embedded professional support, and if this is not feasible, providing offline one-to-one support with the uptake of and the engagement with health apps. This may improve motivational factors, such as commitment, self-confidence and perceived competence of engaging with a health app 2.5. We advise that exploration should be made for where engagement enhancement could be made with appropriate and proportionate machine learning and artificial intelligence or other forms of learning system.
3. Motivation	3.1. Develop a time-efficient app that would require as much engagement as is required to achieve the desired outcome. This might be different for different behaviours 3.2. Include reinforcement in forms of feedback, encouraging messages and rewards 3.3. Offer intangible rewards, such as certificates or badges 3.4. Offer tangible rewards that can be converted as discount in other places (e.g. health insurance providers or pharmacies, sports parks) 3.5. Include goal setting as well as action planning features on how to achieve set goals (when applicable) 3.6. Take into account user's emotions about certain features by involving users in the development and update of health apps as lack of some features could provoke strong negative emotions such as disappointment and might lead to rapid disengagement

4.6.4. Conclusion

People perceive their capability to engage with an app as an important influence on their sustained engagement with it. This perception was inferred from people's desire for apps to contain clear user guidance, require less cognitive load and support easy self-monitoring. Tailored technology and peer and professional support may influence users' opportunity to engagement with an app and goal setting with action planning may play a key role in motivation to engage with an app.

4.7. Next steps

This chapter marks the end of the first stage of this thesis. Findings from studies reported in Chapters 2 and 3 suggest that social influences and the perceived utility of the app may be the core factors influencing the uptake of health and wellbeing apps. However, these studies relied on participants' perceptions and it was deemed to be important to investigate some of these factors through an experimental methodology. Therefore, the next stage of the thesis describes the development of a discrete choice experiment (Chapter 5) that aimed to elicit participants' preferences for the uptake of a smoking cessation app.

Chapter 5. Understanding uptake of digital health products: Discussion of the Methodology of a Discrete Choice Experiment using a Bayesian efficient design.

5.1. Dissemination

A version of this Chapter has been published as a tutorial in the Journal of Medical Internet Research (205). See Appendix 14 for the published peer reviewed journal article.

5.2. Abstract

Understanding the preferences of potential users of digital health products is beneficial for digital health policy and planning. Stated preference methods could help elicit individuals' preferences in the absence of observational data. A discrete choice experiment (DCE) is a commonly used stated preference method: a quantitative methodology that argues that individuals make trade-offs when engaging in a decision by choosing an alternative of a product or service that offers the greatest utility, or benefit. This methodology is widely used in health economics in situations where revealed preferences are difficult to collect but is much less used in the field of digital health. This chapter outlines the stages involved in developing a discrete choice experiment. As a case study, it uses the application of a DCE for revealing preferences in targeting the uptake of smoking cessation apps. It describes the establishment of attributes, the construction of choice tasks of two or more alternatives, and the development of the experimental design. This chapter offers a guide for researchers with no prior knowledge of this research technique.

5.3. Introduction

Understanding how the public value different aspects of digital health tools, such as smoking cessation or physical activity apps, can help providers of the tools to identify functionality that is important to users, which may improve uptake (i.e. selection, download and installation of apps) (206), which was described in Chapter 1 as being generally low. More information regarding the preferences of users when selecting a digital health tool, for example via an app store, may allow providers to present their products in such a way that may increase their uptake. However, pragmatic challenges, such as examining how each potentially modifiable aspect of a digital health product (e.g. presentation, design and features that it offers) or intervention design will impact preference or choice of uptake, often mean this is not feasible or practical (207). Therefore, increasing attention is being paid towards stated preference methods to understand preferences when designing digital health products and services, with examples including COVID tracing apps (208, 209), sun protection apps to prevent skin cancer (210), and the uptake of health apps in general (86).

Stated preference methods are survey-based methods aiming to elicit individuals' preferences on a specific behaviour, particularly those that are not well understood. The most widely used type of stated preference method is the discrete choice experiment (DCE) (211). Louviere and Hensher (1982) and Louviere and Woodworth (1983) originally developed DCEs to study the marketing and economics of transport, and the fields of psychology and economics have profoundly influenced the DCE methodology since it was developed (212). In recent years, DCEs have been increasingly employed in health and health care settings (213, 214), as well as in addiction research (215) and digital health (86, 209, 210). The increasing number of DCEs in digital health highlights their potential although they are currently underutilised.

DCEs differentiate from other stated preference methods in the way that responses are elicited (216). The DCE uses a survey-based experimental design where participants are presented with a series of hypothetical scenarios. In these scenarios, participants are shown situations, known as *choice tasks*. Attempting to mimic real-world decision-making, in each choice task participants then have to choose a product or a service from two or more options, known as *alternatives* (217). Each alternative consists of a set of characteristics, known as *attributes*, with at least two types, known as *attribute levels* (217). Participants are asked to choose a preferred alternative in each choice task, which allows researchers to quantify the relative strength of preferences for improvements in certain attributes (212, 218).

The outputs from statistical models developed using DCE data can be beneficial for estimating uptake of new products or services, including digital health tools, where observational data is not available or is difficult to obtain otherwise (219, 220). Lack of observational data often implies a requirement to seek scientific views and comments from experts, to generate predictions of a target behaviour (221). However, DCEs can provide an empirical alternative to expert opinions while accounting for possible interactions between attributes (e.g. design of a product and brand name), which are otherwise often ignored (222).

Findings of Chapter 3 suggested that individuals found curated health app portals promising, therefore this study wanted to understand how to present health apps on curated health app portals to increase their uptake. This chapter elaborates on the development of a DCE in digital health that aimed to elicit potential user preferences on smoking cessation app uptake. It explains how the attributes and their levels are selected and describes the construction of choice tasks and the experimental design. The study protocol of the research this study is based on is registered on the Open Science Framework (https://osf.io/5439x/).

5.4. The development of a discrete choice experiment

The development of the DCE should follow published recommendations, including the checklist for good research practices (213), guides on the development of a DCE (217, 223), recommendations on how to construct the experimental design (223-227), and which statistical methods can be used (228).

5.4.1. Establishing attributes

An important step in designing a DCE is the identification of the relevant attributes for the subject matter. Attributes in a DCE can be quantitative, such as cost, or qualitative, such as the design of a product (229). The identification of attributes is typically based on primary and secondary data collection to ensure that the DCE is tailored to the study setting (217). It should ideally commence with a literature review which will inform qualitative research to identify relevant attributes (230). Although there is no set limit on the number of attributes that can be included in a DCE, to ensure that the cognitive load of the participants is manageable, it should be less than ten (217) with a general expectation to include five to seven attributes (231).

This DCE was based on a comprehensive systematic review investigating factors influencing the uptake and engagement with health and wellbeing smartphone apps (44) described in Chapter 2, and a qualitative research component that consisted of a think-aloud and interview study to examine further the previously identified factors or attributes (165) described in Chapters 3 and 4. The importance of qualitative research lies in ensuring inclusion of attributes that are relevant to most participants (229). Of the 14 factors initially identified as being relevant for the uptake of health and wellbeing apps, only a few were retained and included in the DCE: *the monthly price of the app*, *who developed the app*, *the star ratings of the app, the description of the app* and *images shown*. These factors were chosen due to their perceived importance during a previous qualitative study described in Chapters 3 and 4 and for pragmatic reasons including how easily measurable and presentable they were within a DCE. See Appendix 15 the actions taken regarding the 14 factors relevant for uptake.

An important step in designing a DCE is in ensuring the content validity of the instrument: the identification of the relevant attributes for the subject matter. Following administration of the survey, methods are available for the measurement and assessment of the content validity of the instrument, although their use is not widely reported (232).

5.4.1.1. Establishing attribute levels

The next step is to establish the attribute levels. The level of an attribute must also be of a range that ensures a trade-off between attributes. A trade-off is defined as an exchange in which a participant gives up some amount of one attribute to gain more of another. It has been suggested that increasing the number of levels for an attribute increases the relative importance of that attribute (233), and that imbalance of numbers of levels across attributes raises the importance of the attributes with higher levels (234). Yang and colleagues have suggested a balance exists between simpler designs with lower numbers of levels, which reduce respondent burden (and consequently measurement error) and are useful for identifying attribute rankings; and more complex designs with higher levels (and higher statistical precision) and are more sensitive to identifying trade-offs between attributes (234). Based on this, and the commonly adopted practices in the research field, this study aimed to include at least three levels for each attribute.

If a range is not suitable, participants might consider the differences between levels unimportant (229). For example, the difference of the star ratings of 4.8 and 4.7 of a smoking cessation app are not as relevant as a difference of 4.8 and 4. In this DCE, to refine the attribute levels, a survey was conducted with 34 participants. In the survey, the levels of two attributes the authors involved were unsure of, the monthly price of the app and the ratings, were carefully considered so that the levels of these two attributes were specified at a sufficiently wide range that the difference between the levels would likely make a difference in response. When a range is not wide enough, there is a risk that participants could ignore the attributes because they judge the difference between levels to be insignificant (223). See Table 9. for the final list of attributes and levels included in the DCE.

Table 9. The attributes and attribute levels included in the DCE.

TDF construct	Attributes	Attribute levels
Environmental resources (cost)	1. The monthly price of the app	• £0 • £2.99 • £5.99 • £8.99
Social influence (credible source)	2. Who developed the app	• Does not say • 'Mhealth Essentials Ltd.' • 'NHS Digital'
Social influence (social proof)	3. The ratings of the app	• Does not show • 3.2 stars • 4 stars • 4.8 stars
Beliefs in consequences (perceived utility of the app)	4. App description	• Generic, to create a rough idea of what the app is about without getting into details of app features • Short with some details about app features • Long and detailed description of the app and its features
Beliefs in consequences (perceived utility of the app)	5. Images	• Shows the logo of the app • Shows the screenshot(s) of the app • Shows the logo and screenshot(s) of the app

5.4.2. Choice tasks

Once the attributes and their levels are identified, the decision to develop 'full-profile' or 'partial-profile' tasks with or without an opt-out option needs to be made. Full-profile refers to the display of all five attributes in both alternatives in each choice-set. A partial-profile DCE will not present certain attributes for certain alternatives. For example, if a DCE was used to investigate the trade-off between a higher number of attributes (e.g. a total of nine attributes), it could be beneficial to limit the number of attributes shown at one time (e.g. five attributes) to limit participant cognitive load. Five attributes is generally considered low enough to complete a full-profile choice task which consequently maximises information about trade-offs (235). Hence, in this study, a full profile DCE was applied.

A neutral option ('Neither of these two'), known as an opt-out alternative, was included in addition to selecting alternative apps. The opt-out option has the potential to make the choices more realistic (236) by simulating a real-world context where individuals can exercise their right not to take up an app, given the apps on offer (223). In this DCE, participants had the option to choose or reject the hypothetical uptake of a smoking cessation app. However, where a participant selects the opt-out option, no information is provided on how they trade-off attribute levels or alternatives (217). In some situations, a *forced-choice* scenario can be included, where participants who chose an opt-out option are prompted to make a choice regardless. An example of a scenario with an opt-out option is shown in Figure 6.

You wish to quit smoking, and you decide to select a smartphone app to do that. Please look at the options carefully, and decide on which app (App 1 or App 2) you think you would likely want to download and use to help you quit smoking.
You could also choose 'Neither of these two' if you do not like either option and would not choose to download either app.

Take your time to make a decision. Please, select an option and click on the arrow to continue.

	App 1	**App 2**
The monthly price of the app	£8.99	£0
Who developed the app	Mhealth Essentials Ltd.	NHS Digital
The ratings of the app	4.8 ★★★★★	4.0 ★★★★☆
App description	Generic, to create a rough idea of what the app is about without getting into details of app features	Short with some details about app features
Images shown	Logo and screenshot(s) of the app	Logo of the app

App 1

App 2

Neither of these two

Figure 6. An example of a scenario with an opt-out option used in the discrete choice experiment.

5.4.2. Experimental Design

An experimental design is a systematic method of generating the choice sets that are presented to respondents. This one enables the specification of the choice sets that respondents see, with the objective of obtaining a high quality data set (211). When creating the experimental design, there are several aspects that need to be taken into consideration including: 1) the analytical model specification, 2) whether the aim is to estimate main effects only or interaction effects as well, 3) whether the design is labelled or unlabelled, 4) the number of choice tasks and blocking options to be used, 5) which type of design of the choice matrix to use (e.g. full factorial or fractional factorial, orthogonal or efficient design), and 6) how the attribute level balance is achieved. These are now considered.

5.4.2.1. Analytical model specification

The first step in the generation of an experimental design is to specify the analytical model to estimate the parameters of the DCE. This step is an important component of choosing the type of choice matrix design, described later in this chapter. The approach selected here needs to be accounted for when generating the structure of the experimental design.

A discrete choice model describes the probability that an individual will choose a specific alternative. This probability is expressed as a function of measured attribute levels specific to the alternative and of characteristics of the individual making the choice. This probability is represented by the dependent variable (the *choice variable*), which indicates the choice made by participants (212). In this modelling framework the attributes are the independent variables (212, 217).

As part of the analytical model specification, knowing what type of statistical analysis will be used is key. Data analysis involves regression modelling in a random utility framework (212). The random utility model conventionally used is also based on Lancaster's theory of consumer demand (237) which together assume that individuals make trade-offs when making a decision, and would choose an option that offers the greatest utility (238), determined by how much importance the individual places on the attributes associated with the product (239).

The Multinomial Logit (MNL) model has been previously described as the ‘workhorse’ of DCE estimation (240, 241), and it typically serves as a starting point for basic model estimation (although alternative models, such as probit, may be used). It is important to note that MNL requires some important assumptions and limitations; for example independence of irrelevant alternatives, homogeneity of preferences, and independence of observed choices (242, 243). Extensions of MNL (e.g. nested logit, mixed logit, and latent class models) may be employed to account for these limitations (241, 242).

Based on the model specified in this DCE, the underlying utility function for alternative *j* (240) is shown in the Textbox 1 below.

Textbox 1. The utility function used in this DCE research.

$$U_j = (\beta_{cost} * X_{j\ cost}) + (\beta_{developer} * X_{j\ developer}) + (\beta_{ratings} * X_{j\ ratings}) + (\beta_{description} * X_{j\ description}) + (\beta_{images} * X_{nj\ images}) + \varepsilon$$

Note:

1) *U* the overall utility derived from alternative j
2) β is the coefficient attached to X_j estimated in analysis and represent the part-worth utility attached to each attribute level
3) ε is the random error of the model, in other words, the unmeasured factors influencing variation of preferences

5.4.2.2. Main effects or interaction effects

The next step in model specification is deciding whether main effects or interaction effects will be investigated. Main effects, the most commonly used, investigate the effect of each attribute level on the choice variable. The effect on the choice variable gained by combining two or more attribute levels (e.g. app developer and the app's monthly cost) refers to an interaction effect (217). In this DCE given the novel nature of the research in the uptake of health apps and the lack of empirical evidence to suggest the presence of potential interactions between attributes, a decision to only look at main effects was made.

5.4.2.3. Labelled or unlabelled

In a labelled experiment, the alternatives are specific and different (e.g. smartphone app-based smoking cessation intervention vs website-based smoking cessation intervention) and alternative specific attributes could be used (e.g. some attributes relevant only for apps and others for websites). This is in contrast to an unlabelled experimental design, where the alternatives are unspecified (e.g. smoking cessation app alternative 1 vs smoking cessation app alternative 2) and also must have the same attributes. Given a DCE model estimates parameter for each of the alternatives being considered, these alternative specific parameters must be included in the structure of the experimental design (described in the next section) in a labelled experiment; in an unlabelled experiment, because they are arbitrary, they are excluded (226, 244, 245). In health economics, the unlabelled approach is the most common. In this DCE, the unlabelled approach was deemed to be logical here as different presentations of the same app were compared. Therefore, this DCE design applied an unlabelled approach.

5.4.3. Generation of the structure of the experimental design

Once the model is specified, the structure of the experimental design can be generated. For this stage hypothetical alternatives are generated and combined to form choice tasks, based on the chosen attributes and their levels. Several different software packages may be used to generate the experimental design of a DCE, such as Ngene, SAS, SPEED, SPSS, Sawtooth. For this DCE, Ngene software was used (246).

5.4.3.1. The number of choice tasks and blocking

The next step in the generation of an experimental design is to decide on the choice task and blocking. In order to minimise respondent and cognitive burden, and the risk of participants losing interest during the DCE task, consideration must be paid to the target population, the number of tasks, and their complexity (217). The higher the number of attributes, alternatives and choice tasks, the higher the task complexity (223). The literature suggests that a feasible limit is 18 choice sets per participant (247, 248). In the review by Marshall and colleagues, most studies included between 7 and 16 choice sets (231). In this DCE 12 choice tasks per participant were administered, which were deemed to be a number low enough to avoid excessive cognitive load but high enough to establish sufficient statistical precision.

Forty-eight choice tasks were developed and blocked into four survey versions (12 choice tasks for each). Each block represented a separate survey and participants were randomly assigned to one of the four survey versions. Blocking is a technique widely used in DCEs to reduce cognitive burden, by partitioning large experimental designs into subsets of equal size, and thereby reducing the number of choice tasks that any one respondent is required to complete (249). Blocks were generated in Ngene software, which allows for the minimisation of the average correlation between the versions and attributes' levels (250). For the blocking to be successful, the number of choice tasks included in one block must be divisible by the number of the attribute levels; in this DCE, attributes had either three or four levels.

It is noteworthy that, in order to undertake the sample size calculation, it is crucial to know the number of alternatives per choice set, the largest number of levels of any attribute (for DCEs looking at main effects only) or the largest level of any two attributes (for DCS looking at interaction effects) and the number of blocks (240). Therefore, DCEs using blocking require a larger sample size (249).

5.4.3.2. Type of choice matrix design

Depending on the number of attributes and their levels, a full-factorial or fractional factorial design can be applied. A full factorial design would include all possible combinations of the attributes' levels and allow the estimation of all main effects and interaction effects independently of one another (223). However, this type of design is often considered impractical due to the high number of choice tasks required (223). To illustrate this, the formula of calculation of the possible unique choice alternatives for a full factorial design is: L^A, where L represent the number of levels and A the number of attributes (241). If the attributes in the DCE have a different number of levels these need to be calculated separately and multiplied together. In order to reduce response burden, a fractional factorial design in Ngene was generated (246), representing a sample of possible alternatives from the full factorial design. In this way the total 432 alternatives in the full design (given by $L^A = 4^2 \times 3^3$), was reduced to a fractional sample of 96 alternatives, arranged in 48 choice pairs.

Systematic approaches for generation of fractional factorial designs may further subset into orthogonal design and efficient design. An orthogonal design is a column-based design based on orthogonal arrays which present properties of orthogonality (attributes are statistically independent of one another) and level balance (levels of attributes appear an equal number of times), and does not introduce correlation between the attributes (240). An orthogonal array is an optimal design that is often used for DCEs examining main effects when the number of attributes and their levels are small.

For studies with five or more attributes with two or more levels, an orthogonal design may not be practical. There has therefore been a recent change in thinking toward a nonorthogonal and statistically more efficient design (240). When perfect orthogonality and balance cannot be achieved or are not desirable, an efficient design can be applied (223). In contrast to an orthogonal design, an efficient design aims to increase precision of parameter estimates for a given sample size (i.e. minimising the standard errors of the estimated coefficients), while allowing some limited correlation between attributes. The most widely used efficiency measure is *D-error* which may be easily estimated using various software packages such as Ngene, and refers to the efficiency of the experimental design in extracting information from respondents (225). Experimental designs generated using this approach are known as D-efficient designs. A D-efficient experimental design is also recommended to maximise statistical efficiency and minimise the variability of parameter estimates (211).

An efficient design requires that known prior information about the parameters (known as ‘priors’) are made available to the algorithm, and also requires the analyst to specify the analytical model specification, as described previously. Depending on what information is available, one of three types of D-efficient design can be generated (225).

1) *D_z-efficient* design (*z* stands for zero priors) - if no prior information about the magnitude or directions of the parameters are available (D_z-efficient design is an orthogonal design). This design assumes the parameters are zero.
2) *D_p-efficient* design (*p* stands for priors) - assumes a fixed, certain value and direction for the parameters
3) *D_b-efficient* design (*b* stands for Bayesian) – A Bayesian approach whereby the parameter is not known with certainty, but may be described by its probability distribution

Best practice is to pilot the DCE. For the pilot phase, there is limited information available and using D_z-efficient or D_p-efficient design is sensible. In this DCE a D*p*-efficient design was applied as the direction of priors of the app was known from the previously conducted survey to narrow down the attribute levels and to provide prior estimates of the parameters for the attribute levels. For example, it is known that a trusted organisation will likely positively influence uptake and cost estimated negatively so. The direction of priors was assumed to be a very small near zero negative or positive value for the design.

The pilot phase provided estimation that was used to generate a *D_b-efficient* design for the final DCE. It is noteworthy that when the parameter priors are different from zero, the efficient design generated produces smaller prediction errors than the orthogonal designs (225, 251, 252). Hence, a D-efficient design will outperform an orthogonal design, and, (given reliable priors) a D_p-efficient design will outperform a D_z-efficient design (225). Further, when reasonable assumptions about the distributions are made, a D_b-efficient design will outperform a D_p-efficient design. Therefore, it may be advisable to start piloting with a *D_p-efficient* design and to generate a *D_b-efficient* design for the final DCE. The DCE literature provides a detailed and more comprehensive description of the orthogonal and efficient designs (225), and approximation of Bayesian efficient design (227).

5.4.3.3. Attribute level balance in the model

The attribute level balance aims to ensure all attribute levels ideally appear an equal number of times in the experimental design. The allocation of the attribute levels within the experimental design can affect statistical power; if a certain level is under-represented in the choice sets generated, then the coefficient for that level cannot be easily estimated. How attributes levels are distributed is therefore an important consideration when designing the choice sets. Dominant alternatives, where all attribute levels of one alternative are more desirable than all attribute levels in the other, do not provide information of how trade-offs are made, as individuals usually would select the dominant alternative. Therefore, avoiding dominant alternatives in the experimental design is important and can be achieved by consulting the software manual to ensure the correct algorithm is used. The syntax used in Ngene to generate choice sets of the pilot phase and more information about the algorithm used can be accessed on the Open Science Framework (https://osf.io/5439x/) (253).

5.4.4. Piloting the DCE and generating the Bayesian design

As well as providing estimations for the choice matrix design described above, piloting offers an opportunity to ensure that the information is presented clearly, and that the choices are realistic and meaningful. It also provides insight into how cognitively demanding it is for respondents to complete. This can be achieved by gathering feedback on the survey completion process. The findings of the pilot may suggest that the DCE needs to be amended, such as reducing the number of choice sets or the number of attributes, so that the responses are a better reflection of participants' preferences and improve the precision in the parameter estimates (217). There is no formal guidance on how large the pilot sample should be, this is largely guided by budget and complexity of the experimental design. Accuracy of the priors will improve with increasing sample, but as few as 30 responses may be sufficient to generate useable data (246).

In the pilot study, feedback from participants suggested that with the initial order of the attributes there was a tendency to ignore the last two attributes, the app description and images, the most text heavy attributes. This may have compromised the examination of the relative importance of those two attributes (description and images of the app). Therefore, the decision to change the final order of the attributes from 1) *monthly price of the app*, 2) *the ratings of the app*, 3) *who developed the app*, 4) *the description* and 5) *images shown*, to the one listed in Figure 6, was made. The longest completion time for the survey was under 12 minutes. Thus, it was concluded that the number of choice tasks did not need to be reduced.

In this study, the data from the pilot phase was analysed using the freely available Apollo package in R (254). The coefficients and their standard errors from the output were used as priors to generate the final choice sets using the Bayesian efficient design following the steps described previously. The syntax used in R used to analyse the pilot data and that used to generate the Bayesian efficient design in Ngene can be accessed on the Open Science Framework (https://osf.io/5439x/) (253).

5.4.5. Internal validity

Assessing the internal validity of a DCE can help with understanding the consistency and trade-off assumptions made by participants (255). There are several ways to examine the internal validity of a DCE. For example, in the *stability validity test,* a choice task would be repeated later in the sequence to investigate the consistency of the participants' decision, whether the respondent would choose the same alternative (255). Another way to test internal validity is the *within-set dominated pairs* type of internal validity in which one alternative is a dominant alternative in which all attributes are of the most desirable. The choice sets designed to measure the internal validity are excluded from the analysis. There are several internal validity tests that are built in software packages such as MATLAB (255), although these can be produced manually as well.

In this research the stability validity test was used to check the internal validity by repeating a randomly generated choice set (in this case it was the fourth). Therefore, participants were shown 12 choice tasks, plus an additional 'hold-out' task. The data from the randomly generated hold-out task was excluded from the analysis. While internal validity checks provide some measure of data quality, it should be noted that answering a repeat choice inconsistently is not a violation of random utility theory (256). Furthermore, there is no consensus on what to do with the data from responses that 'fail' validity tests. Following the advice of Lancsar and Louviere (2006) participants who 'failed' the internal validity check were not excluded, as that may cause statistical bias or affect statistical efficiency (257). However, data on internal validity was reported to enable the reader to make a judgement on likely biases.

All additional study materials used in this example, including the full dataset and the results of the DCE, can be accessed on Open Science Framework (https://osf.io/5439x/) (253).

5.5. Discussion

This chapter describes the development of a DCE, following the stages required to establish attributes and their levels, construct choice-tasks, define the utility model, decide on labelled and unlabelled choices to apply, decide on the number of choice tasks that need to be generated, as well as make decisions on the structure of the experimental design, how to achieve attribute level balance, to assess the internal model validity, and to pilot test. In doing so, the intention is to advance methodological awareness of the application of stated preference methods in the field of digital health, as well as to provide researchers with an overview of their application using a case study of a DCE of smoking cessation app uptake.

Although DCEs are widely used to understand patient and provider choices in healthcare (212, 214, 219, 258), they have only recently started to gain popularity in digital health (86, 209, 210), and as such represent an underused approach in digital health. With the growing evidence of the benefit of digital health initiatives, there are clear benefits to widening the application of DCEs so that they may more routinely inform digital health development, digital tool presentation, and most importantly to predict uptake and engagement with digital products. Whilst several attempts have been made to measure engagement with digital tools using a wide range of methodologies (259-261), the insights that is available from them that can be translated to uptake are limited. One plausible explanation is that uptake of digital tools is difficult to empirically measure.

DCEs bring several benefits to help overcome the issue of measuring uptake in digital health or in other areas where the measurement of the predictors of uptake in a good or service is required. For example, as illustrated by the case study here, they enable the researcher to gain measurable insights into situations where quantitative measures are hard to otherwise obtain, such as the factors impacting the uptake of health apps on curated health app portals. A DCE also helps to quantify preferences to support more complex decisions (262). An example would be the consideration of how to plan the development of an app that would provide appealing looks or features that would promote uptake. The DCE methodology is also considered to be a convenient approach to investigate the uptake of new interventions, including digital health interventions (240), for example digital behaviour change interventions using health and wellbeing smartphone app. Therefore, DCEs can be used in hypothetical circumstances, enabling the measurement of preferences for a potential policy change or digital health system change before it is implemented (217), such as the recent investigation of the uptake of a COVID-19 test and trace health app (208, 209). The experimental nature of the DCE also means that participants' preferences can be recorded based on controlled experimental conditions where attributes are systematically varied by researchers to provide insight into the marginal effect of attribute changes on individuals' choices (263).

Despite their benefits, the application of DCEs present several challenges. As with all expressed preference methodologies, the hypothetical nature of the DCE choice-set raises concerns about external validity and the degree to which real-world decisions might equate to those made by study participants under experimental conditions, a phenomenon known as the intention-behaviour gap (264). As such, participants may believe they would choose a scenario presented and described in a choice task, but in real-life there might be other factors that would influence their behaviours, such as the aesthetics of the app (44). This limitation can at least partially be overcome by developing convincing and visually appealing choice tasks. Nevertheless, to date there has been limited progress in testing for external validity due to the difficulty in investigating preferences in the real world (240). Indeed, a recent systematic review of the literature on DCEs in health care reported that only 2% of the included studies (k=7) reported details of the investigation of external validity (249), whilst an earlier systematic review and meta-analysis (k=6) found DCEs have only a moderate level of accuracy in predicting behaviours of health choices (265). To date, no study has been published that investigates the external validity of a DCE developed in digital health. One potential opportunity to undertake some testing would be through a curated health app portal, where the same health app is presented in two or more different ways. With the help of website analytics actual user behaviour could be measured in this situation.

A final significant concern associated with the use of a DCE is that any single choice set is unlikely to be able to present the user with all relevant attributes, regardless of how well it has been developed (265). Choosing the most relevant attributes to test in a DCE, therefore, requires comprehensive preparatory research, which can lengthen the time required to undertake the development phase of any piece of work.

In summary, DCEs have significant potential in digital health research, and can serve as an important decision-making tool in a field where observational data is lacking.

5.6. Next steps

This chapter described the second stage of the thesis, the development of a discrete choice experiment informed by the findings of the first stage of the thesis, reported in Chapters 2 and 3. The next steps of the thesis and the final stage were to describe the findings of the discrete choice experiment and to report on a series of factors influencing the uptake of, and engagement with, smoking cessation apps informed by the findings of Chapters 2 to 4, to better understand to what extent are these facilitators or barriers.

Chapter 6. Eliciting preferences for the uptake of smoking cessation apps: A Discrete Choice Experiment

6.1. Dissemination

The abstract was accepted as an oral presentation at the Centre for Behaviour Change Virtual Digital Health Conference (2021 – but not presented due to personal circumstances). The abstract will be submitted as an oral presentation for the European Health Psychology Society's Annual Conference (2022).

A version of Chapter 6 has been submitted to Addiction and is currently under review.

6.2. Abstract

Background. If the most evidence-based and effective smoking cessation apps are not selected by smokers wanting to quit, their potential to support cessation is limited. This chapter sought to determine the attributes that influence smoking cessation app uptake and understand their relative importance, to support future efforts to design and present evidence-based apps more effectively to maximise uptake.

Methods. Adult smokers from the UK were invited to participate in a discrete choice experiment. Participants made 12 choices between two hypothetical smoking cessation app alternatives, with five predefined attributes: 1) star rating, 2) app developer, 3) monthly price of app, 4) images shown and 5) the app's description type; or opting out (choosing neither app). Preferences and the relative importance of attributes were estimated using mixed logit modelling. Willingness to pay (WTP) and predicted uptake of the most and least preferred app was also calculated.

Findings. A total of 337 adult smokers completed the survey (49.8% females; mean age 35, SD 11). 89.9% of participants selected a smoking cessation app rather than opting out. Relative to other attributes, a 4.8 star user rating was the strongest driver of app selection (mean preference weight 2.15; 95% confidence interval [CI] 1.90 to 2.40). Participants preferred an app developed by a healthcare-orientated trusted organisation over a hypothetical company (mean preference weight 0.92; 95% CI 0.74 to 1.10), with a logo and screenshots over logo only (mean preference weight 0.25, 95% CI 0.11 to 0.38), and with a lower monthly cost (mean preference weight -0.39; 95% CI -0.45 to -0.33). App description did not influence preferences. The uptake

estimate for the best hypothetical app was 93%, and for the worst 3%. Participants were willing to pay up to £9.48 for 4.8 star ratings, £3.91 for 4 star ratings, and £5.22 for app developed by a trusted organisation.

Conclusions. A range of app attributes influenced the smoking cessation app uptake preferences of smokers. An app's star rating was the most influential factor and was more important than the app being developed by a healthcare-orientated and trusted organisation, who may be most likely to provide evidence-based apps.

6.3. Introduction

Smoking is one of the leading risk factors of noncommunicable diseases worldwide (266). Supporting people to quit smoking is a primary concern for public health (167). One approach is the use of apps, which can be effective for smoking cessation (27). Many are available on commercial app stores like the Apple App Store and Google Play but, as described in Chapter 1, low uptake and sub-optimal engagement with effective health apps are common (198). Commercial app stores generally omit app quality measures and provide insufficient information about apps (267).

As suggested in Chapter 3, curated health app portals (PHE One you App website, NHS Apps Library in the UK, or the Digital Health Applications (DiGA) directory in Germany), showcasing high-quality apps developed by trusted organisations, could improve uptake of effective apps. This could increase the uptake of effective smoking cessation apps among smokers and decrease the risk that apps are installed primarily due to popularity, as opposed to potential effectiveness, from commercial app stores (268).

There is an extensive literature on engagement with health apps (44, 269, 270), but the evidence about factors influencing their uptake is limited. In Chapters 2, 3 and 4 several factors were identified that appear to influence the uptake and engagement of these apps and explored views on curated health app portals (44, 165). A common discrepancy between user needs and what an app offers was found, such as the perceived utility of the app, which refers to the way apps are presented, including the images shown and the description of the apps (44, 117, 165). App users have also expressed disappointment by the presentation of apps on app portals (165).

Uptake of health apps may also be primarily affected by social influences such as ratings of an app (49, 51, 165). However, highly rated apps do not necessarily mean evidence-based content and functionality (267). Although highly rated smoking cessation apps appear better tailored to individual needs (49), other evidence suggests that there is a weak association between the quality of a smoking cessation app and its popularity (51, 271).

There is limited evidence on which factors are likely to drive the uptake of apps and no studies investigating this for smoking cessation app uptake from a curated portal. Therefore, this chapter aimed to determine app attribute preferences for the uptake of a smoking cessation app when choosing from a curated app portal by applying a DCE (272). Such evidence can help policymakers, health app portal and health app developers to become more responsive to potential users' needs when presenting and developing apps, on curated health app portals in particular. The survey further assessed a series of factors influencing the uptake of, and engagement with, smoking cessation apps to better understand to what extent are these facilitators or barriers.

6.4. Methods

6.4.1. Discrete choice experiment development

The development of the DCE is described in Chapter 5. Therefore, this chapter provides a short summary of the development. The development of the DCE was informed by discussion with stakeholders, including patient and public involvement representatives. Ethical approval for the study was obtained from the University of East Anglia Faculty of Health Ethics Committee (2020/21-017, see Appendix 16). The study protocol was pre-registered on the Open Science Framework (https://osf.io/5439x/).

6.4.1.1. Attributes and levels

The two alternatives in each choice task described by a set of predefined attributes, with two or more levels are referred to as App 1 and App 2. The systematic review (44), and the interview and think-aloud study (165, 194) described in Chapters 2, 3 and 4, informed the selection of relevant factors mapped under the TDF that influence uptake of health apps, hereby attributes of this study. The authors internally assessed the relevancy and feasibility of the attributes identified in the previous stages and narrowed down the selection of potential attributes. The selected attributes were *the monthly price of the app*, *who developed the app*, *the star ratings of the app, the description of the app* and *images shown*, and their levels are shown in Table 9, Chapter 5. For the 'who developed the app' attribute the 'NHS Digital' was used, which is a widely trusted organisation in the UK, and 'Mhealth Essentials Ltd' as a hypothetical company.

6.4.1.2. Experimental design

Participant preferences were estimated using conditional logit regression to model their choices. A DCE model specifies the probability that an individual will choose a specific smoking cessation app. This probability is expressed as a function of measured attributes specific to the alternative. The (simplified) underlying utility function for alternative *j* is show in Equation 1 below:

Equation 1

$$U_j = (\beta_{cost} * X_{j\ cost}) + (\beta_{developer} * X_{j\ developer}) + (\beta_{ratings} * X_{j\ ratings}) + (\beta_{description} * X_{j\ description}) + (\beta_{images} * X_{j\ images}) + \varepsilon$$

In Equation 1, U represents the overall utility gained from choosing alternative j, β is the coefficient attached to X_j estimated by the mixed logit model and represents the part-worth utility attached to each attribute level, and ε is the random error of the model.

This DCE included three attributes (A) with three levels (L) and two attributes with four levels, which, following the formula L^A would have led to 432 possible choice alternatives in a full factorial design (241). To limit participant burden, a fractional factorial design was used. A total of 48 choice tasks applying Bayesian D-efficient design principles using Ngene software (246) were generated and blocked into four survey versions each containing 12 choice-tasks (see Appendix 17 for the 48 choice tasks blocked into four versions). Each participant was randomised to complete one survey. An additional repeat choice task was added to test choice consistency (the repeat task was excluded from the primary data analysis). This design aimed to estimate the main effects. Interactions between attributes were not considered.

The initial version of the DCE was piloted online with 49 participants. Based on the feedback received the wording of the survey and the order in which attributes were listed in the table were revised. Coefficients from the pilot phase were used as priors to estimate a Bayesian D-efficient design. Data from the pilot phase were not included in the final analysis.

To imitate real-world decisions regarding app uptake an opt-out option was included (‘Neither of these two’, see Figure 6, Chapter 5.). Participants who chose the opt-out option were prompted to repeat the decision and make a forced choice between the two alternatives. As the rate of the opt out was low, the complete dataset was used for analysis of choice data, including the opt out option.

6.4.2. Data collection

6.4.2.1. Participants and recruitment

The study was conducted online. Eligible participants were adults 1) aged 18 and over, 2) residents of the UK, 3) able to give consent, 4) owned or had primary use of a smartphone, 5) smoked cigarettes, and 6) interested in quitting smoking using a smartphone app. Recruitment took place between December 2020 and February 2021 on social media (Facebook, Twitter, LinkedIn), and on the 'Call for participants'(273) and 'Prolific' (274) websites. Participants recruited on Prolific were paid £1.50 for participation and those recruited on other platforms were invited to participate in a prize draw to win one of ten £20 shopping vouchers.

6.4.2.2. Sample size

The sample size calculation was based on a rule of thumb formula (Equation 2) (240).

Equation 2

$$N > 500c / (t \times a)$$

In Equation 2, 'N' represents the sample size, t the number of tasks (=12), 'a' the number of alternatives (=2), 'c' the number of analysis cells (=4, as this is the largest number of levels for any of the attributes). Equation 2 suggests a minimum sample size of 83. With four versions of the survey, the targeted sample size was of at least 332 (4x83) participants.

6.4.3. Procedure

The survey was administered using Qualtrics survey software. First participants' eligibility was assessed via a series of questions in line with the eligibility criteria. Eligible participants then accessed a welcome page, read the participant information sheet and provided consent. To encourage participants to pay attention to the choice task they were informed that authors are interested in their preferences to help develop more effective ways of designing and presenting health apps. Once consent was obtained participants were explained the purpose of the DCE and how to complete it, and were randomly assigned to one of the four DCE versions containing 13 choice tasks. After completion of the choice tasks, participants were asked to complete further measures relating to potential facilitators and barriers for the uptake and engagement with smoking cessation apps, previous use of smoking cessation apps and other health apps, user type, smoking behaviour and sociodemographics (see *Measures*).

6.4.4. Measures

6.4.4.1. Attributes that are likely to influence smoking cessation app preferences

The primary outcomes are the preference weights estimated for each attribute level, represented by the β coefficients in the equation above.

6.4.4.2. Factors perceived to influence the uptake and the engagement with smoking cessation app

The TDF was used to identify 13 potential facilitators and barriers of uptake and engagement with health apps based on factors identified as important in previous work (44, 165) described in Chapters 2 and 3. These were included in the survey as a set of statements with the level of agreement with the statements measured using a 5-point Likert type scale. For analysis, responses to these statements were dichotomised into *agree* ('strongly agree' and 'agree') versus *not* ('neither agree nor disagree, 'disagree' and 'strongly disagree'). See Appendix 18 for the potential facilitators and barriers of uptake of, and engagement with, smoking cessation apps and the survey statements to assess these.

6.4.4.3. Other variables

The survey included questions about previous use of smoking cessation apps and other health apps, as well as user type (power user or minimal user) based on the time spent exploring app features. Other measures consisted of smoking behaviour measures, including heaviness of smoking index (275), frequency of smoking, attempts to stop smoking, strategies used in attempt to quit smoking, intention to stop smoking, defined as whether the participant is planning to quit in the next six months, determination to stop smoking and the main reason for stopping smoking. Finally, socio-demographic characteristics were also measured, including age, gender, level of education, household income, ethnicity, sexuality, disability. See Appendix 19 for the complete questionnaire.

6.4.5. Statistical analysis

The pilot data were analysed using the Apollo package in R (254), and the final data using Stata 16.1. Participants' characteristics were summarised using descriptive statistics. Associations between attributes and uptake responses was estimated using mixed logit model (MIXL). This approach accommodated the existence of preference heterogeneity within the sample by allowing one or more model parameters to be specified as having a random distribution (276). In the model all attributes were dummy coded as categorical variables, except for cost, which was treated as continuous, and all were treated as random parameters. The TDF factors perceived to influence the engagement with smoking cessation apps were described using proportions and 95% confidence intervals. Only data from participants who completed the full survey was analysed. The overall likelihood of choosing an app (equating to uptake), was calculated from the distributional parameters of the constant for the opt out option as described by Hole (276). Additionally, the uptake of the most preferred and least preferred apps was investigated by calculating their utility values and the probabilities for selecting these hypothetical apps, using the approach described by Jonker *et al.* (209). The model was re-estimated in willingness-to-pay space, to derive marginal willingness-to-pay (mWTP) estimates for improvement in the individual product attributes (277). Finally, the choice data of participants who were consistent with the repeat choice task was analysed and compared to the results of the choice data including all participants.

6.5. Results

A total of 499 eligible participants were recruited, 469 consented, and 337 participants completed the experiment and measures. Data from 337 participants yielded 4,029 observations (15 choices were omitted by participants). Participants were aged between 19 and 65 years, with mean age 35 years (SD=11), 168 (49.8%) were females, 176 (52.2%) showed low dependency on the heaviness of smoking index and 107 (31.8%) had used smoking cessation apps before. Participants' characteristics are reported in Table 10.

Table 10. Participants' characteristics

Sociodemographic data	
Age (years)	
Range	19-65
Mean (SD)	35 (11)
Gender *n* (%)	
Female	168 (49.8)
Male	163 (48.4)
Non-binary/genderfluid	4 (1.2)
Prefer not to disclose	2 (0.6)
Ethnicity *n* (%)	
White	300 (89.0)
Black or African American	11 (3.2)
Arab	10 (3.0)
Asian	6 (1.8)
Mixed/multiple ethnic groups	8 (2.4)
Other	2 (0.6)
Education *n* (%)	
Postgraduate or equivalent	31 (9.2)
Degree or equivalent	127 (37.7)
A-levels or equivalent	113 (33.5)
GSCE or equivalent	63 (18.7)
Other	3 (0.9)
Monthly net household income *n* (%)	
£0 - £999	39 (11.6)
£1000 - £1999	112 (23.2)
£2000 - £2999	68 (20.2)
£3000 - £3999	48 (14.2)
£4000 - £4999	23 (6.9)
Over £5000	15 (4.4)
Prefer not to disclose	32 (9.5)
Sexual orientation *n* (%)	
Heterosexual	268 (79.5)
LGBTQ+	64 (19)
Prefer not to say	5 (1.5)
Disability *n* (%)	
Living with disability	88 (26.1)
No disability	232 (68.8)
Prefer not to disclose	17 (5.1)
Type of smartphone *n* (%)	
Android	163 (48.4)
Apple	164 (48.6)
Android and Apple	8 (2.4)
Windows	2 (0.6)
Prior use of health app *n* (%)	
Prior use of health app	226 (67.1)
No prior use of health app	111 (32.9)
Prior use of smoking cessation app	107 (31.8)
No prior use of smoking cessation app	230 (68.2)

Table 10. (Continued) Participants' characteristics

Sociodemographic data	
Health app uptake source* *n* (%)	
Google search	62 (25.7)
Commercial app stores	158 (65.6)
Health related website	51 (21.2)
Recommendations (friends, family)	58 (24.1)
Recommendations (health practitioners)	21 (8.7)
Other	6 (2.5)
User type* *n* (%)	
Power user	113 (46.9)
Minimal user	120 (49.8)
Unsure	8 (3.3)
Heaviness of smoking *n* (%)**	
Low dependence	176 (52.2)
Moderate dependence	139 (41.3)
High dependence	22 (6.5)
Last quit attempt *n* (%)	
In the last month	44 (13.1)
In the last 12 months	136 (40.3)
Longer than 12 months	113 (33.5)
None	44 (13.1)
Previous experience with smoking cessation strategies *n* (%)	
Nicotine replacement products	148 (43.9)
Zyban (buprorion)	9 (2.7)
Champix (varenicline)	26 (7.7)
E-cigarette or vaping device	195 (57.9)
Stop smoking group	28 (8.3)
Stop Smoking one-to-one counselling or support services	35 (10.4)
Smoking helpline	16 (4.8)
A book about quitting smoking	51 (15.1)
Smoking cessation website	54 (16.0)
Smoking cessation app	59 (17.5)
Other: hypnotherapy	2 (0.6)
None	66 (19.6)
Intention to quit in the next 6 months *n* (%)	
Likely	240 (71.3)
Unlikely	23 (6.8)
Unsure	74 (21.9)
Determination to quit *n* (%)	
High determination	216 (64.1)
Moderately or slightly determined	113 (33.5)
Low determination	8 (2.4)
Main reason to quit *n* (%)	
Health concerns	125 (37.1)
Health concerns related to COVID-19	28 (8.3)
To save money	112 (33.2)
To regain control	42 (12.5)
Pressure or encouragement from others	27 (8)
Other	3 (0.9)

Note. *Questions answered by those who have used smoking cessation or health apps before; **Computed from number of cigarettes smoked a day and the time the first cigarette is smoked in the morning.

On 89.9% of the choices, participants selected one of the two smoking cessation apps over ‘neither’. There was no participant who opted out of all choices. Most of the attributes influenced participants’ preferences, except for the description of the app (Table 11).

Relative to other attributes, the star rating of the app was the most important attribute. Relative to the referent app (developed by Mhealth Essentials, star rating not shown, generic app description, with a logo shown only), having a 4.8 star rating (mean preference weight 2.15; 95% CI 1.90 to 2.40) was around twice as important as the 4 star rating (mean preference weight 0.97; 95% CI 0.76 to 1.17), and twice as important as it being developed by the NHS Digital (mean preference weight 0.92; 95% CI 0.74 to 1.10). Participants marginally preferred an app that showed screenshots (mean preference weight 0.25; 95% CI 0.11 to 0.38) or both screenshot and logo (mean preference weight 0.33; 95% CI 0.17 to 0.49) over logo only. An app with a low monthly price was also preferred (mean preference weight -0.39; 95% CI -0.45 to -0.33). However, the wide standard deviations, relative to their coefficients for many attributes indicate a broad variation in attribute importance among participants. There was significant preference heterogeneity across all except two attribute levels (app ratings of 4 SD = -0.01, 95% CI -1.05 to 1.03, p=0.99; images screenshot SD = -0.05, 95% CI -0.39 to 0.31, p=0.82).

Table 11. Mixed logit estimation results

Attributes		Mean preference weight (SE)	95% CI	Willingness to pay (SE)	95% CI
Alternative specific constants					
Alternative 1	Mean	0.10 (0.06)	-0.01 to 0.22	-	-
	SD	0.31** (0.12)	-0.54 to -0.08	-	-
Alternative 2	Mean	Ref	N/A	-	-
	SD	Ref	N/A	-	-
Opt out option	Mean	-2.34** (0.20)	-2.74 to -1.94	-	-
	SD	1.80** (0.21)	1.40 to 2.21	-	-
Developer					
Does not say	Mean	-0.42** (0.08)	-0.58 to -0.27	-0.14 (0.37)	-0.86 to 0.58
	SD	0.44** (0.12)	0.20 to 0.69	3.81** (0.46)	2.91 to 4.71
Mhealth Essentials	Mean	Ref	N/A	Ref	N/A
	SD	Ref	N/A	Ref	N/A
NHS Digital	Mean	0.92** (0.09)	0.74 to 1.10	5.22** (0.44)	4.35 to 6.09
	SD	0.99** (0.10)	0.79 to 1.19	4.55** (0.47)	3.63 to 5.48
Rating of the app					
Does not show	Mean	Ref	N/A	Ref	N/A
	SD	Ref	N/A	Ref	N/A
4.8 stars	Mean	2.15** (0.12)	1.90 to 2.40	9.48** (0.57)	8.36 to 10.60
	SD	-0.69** (0.14)	-0.97 to -0.41	7.08** (0.61)	5.89 to 8.27
4 stars	Mean	0.97** (0.10)	0.76 to 1.17	3.91** (0.45)	3.03 to 4.79
	SD	-0.01 (0.53)	-1.05 to 1.03	4.93** (0.56)	3.83 to 6.03
3.2 stars	Mean	0.12 (0.13)	-0.13 to 0.37	3.06**(0.56)	1.95 to 4.16
	SD	1.57** (0.15)	1.27 to 1.87	7.41** (0.70)	6.04 to 8.79

Note. *denotes ‘p’ value of <0.05; **denotes ‘p’ value of <0.001; SD = standard deviation of the distribution around the mean preference estimates and is a measure of heterogeneity; SE = standard error; CI = confidence interval; Ref = reference category.

Table 11. (Continued) Mixed logit estimation results

Attributes		Mean preference weight (SE)	95% CI	Willingness to pay (SE)	95% CI
App description					
Generic	Mean	Ref	N/A	Ref	N/A
	SD	Ref	N/A	Ref	N/A
Short	Mean	-0.03 (0.07)	-0.17 to 0.11	1.37** (0.32)	0.74 to 2.01
	SD	-0.34** (0.02)	-0.66 to -0.02	2.46** (0.44)	1.59 to 3.33
Long	Mean	-0.09 (0.09)	-0.26 to 0.08	-0.42 (0.41)	-1.22 to 0.38
	SD	0.74** (0.12)	0.51 to 0.96	4.45** (0.44)	3.56 to 5.33
Images					
Logo	Mean	Ref	N/A	Ref	N/A
	SD	Ref	N/A	Ref	N/A
Screenshot	Mean	0.25** (0.07)	0.11 to 0.38	2.54** (0.30)	1.96 to 3.11
	SD	-0.04 (0.18)	-0.39 to 0.31	-0.10 (1.13)	-2.32 to 2.11
Both	Mean	0.33** (0.08)	0.17 to 0.49	2.50** (0.35)	1.81 to 3.19
	SD	0.57** (0.13)	0.32 to 0.83	2.57** (0.49)	1.61 to 3.53
Monthly price of the app					
	Mean	-0.39** (0.03)	-0.45 to -0.33	-	-
		0.33** (0.3)	0.28 to 0.38	-	-
AIC	7315.37			AIC	6948.01
BIC	7404.17			BIC	7096.00
Log-likelihood	-3454.01			Log likelihood	-3454.00

Note. *denotes 'p' value of <0.05; **denotes 'p' value of <0.001; SD = standard deviation of the distribution around the mean preference estimates and is a measure of heterogeneity; SE = standard error; CI = confidence interval; Ref = reference category. The monthly price of the app was coded as continuous variable presented at four levels: £0, £2.99 £5.99, £8.99; AIC = Akaike information criterion; BIC = Bayesian Information criterion; population mean = the estimated mean preference estimate.

The characteristics of the most preferred app was having a monthly cost of £0, a rating of 4.8 stars, developed by NHS Digital, having a generic description and presenting both type of images (app logo and screenshots). The least preferred app has a monthly price of £8.99, the developer is not shown, has ratings of 3.2 stars, a long description and shows the app logo only. The uptake level of the best app was estimated at 93%, and for the worst was estimated at 3%.

Table 11 also reports mWTP estimates for improvement in the attributes of the app, relative to the reference category. Participants were willing to pay £9.48 (95% CI £8.30 to £10.50), £3.91 (95% CI £3.03 to £4.79) and £3.06 (95% CI £1.95 to £4.16) for app with 4.8, 4 and 3.2 star ratings, respectively. Participants were willing to pay £5.22 (95% CI £4.35 to £6.09) for development by a trusted organisation (NHS Digital) compared to Mhealth Essentials Ltd.

A total of 71/337 (21%) individuals were inconsistent with their choices. The demographics of this group were similar to those who were consistent with their choices. The results of the MIXL model with and without the individual's response who gave an inconsistent response to the repeat choice task, returned comparable results (results not presented, but available on request from authors).

Table 12 shows the proportion of participants reporting factors that were perceived to influence the uptake of and the engagement with smoking cessation apps. Participants indicated that the strongest facilitators that might promote their engagement with a smoking cessation app were user guidance of how to use the app (72.4% agreement, CI 67.37% to 76.93), additional health information (75% agreement, CI 70.16% to 79.42%) and rewards (75.4% agreement, CI 70.47% to 79.69%). Key barriers were concerns around data protection (66.8% agreement, CI 61.54% to 71.61%), cognitive load (47.5% agreement, CI 42.16% to 52.87%), reminders as triggers for cravings (40.7% agreement, CI 35.51% to 46%), and peer support (46.9% agreement, CI 41.59% to 52.25%).

Table 12. Proportion of potential factors influencing smokers' uptake and engagement with smoking cessation apps

Barriers and facilitators mapped under the TDF	Percentage % (95% CI)
TDF construct: Skills	
App literacy (facilitator) *('In general, I can easily use a newly installed app on my phone.')*	
Agree	92.6 (89.2 – 94.9)
TDF construct: Knowledge	
App awareness (barrier) *('I was aware of the existence of smoking cessation apps prior to taking part in this study.')*	
Agree	55.5 (50.1 – 60.7)
User guidance (facilitator) *('A guide of how to use features would help me use the app more often.')*	
Agree	72.4 (67.4 – 76.9)
Health information (facilitator) *('Information in the app about how quitting smoking improves my health would make me use the app more often.')*	
Agree	75.0 (70.2 – 79.4)
TDF construct: Memory, attention, decision processes	
Cognitive load (barrier) *('In general, I don't want to use an app with features that would take some time to learn.')*	
Agree	47.5 (42.2 – 52.8)
Reminders (facilitator) *('It would be important that an app to help me quit smoking sends personalised reminders to me.')*	
Agree	68.3 (63.1 – 73.0)
Reminders (barrier) *('I wouldn't want to use an app that sent me reminders about quitting smoking in case it would trigger my cravings to smoke.')*	
Agree	40.7 (35.5 – 46.0)
TDF construct: Social influence	
Peer-support (facilitator) *('Being connected with other app users would motivate me to stay on track with my intention to stop smoking'.)*	
Agree	65.6 (60.3 – 70.5)
Peer-support (barrier) *('Being connected with other app users would make me feel ashamed or disappointed if I started smoking again after quitting.')*	
Agree	46.9 (41.6 – 52.2)
Professional support (facilitator) *('Being connected with online helpers (quit smoking advisors) within the app would make want to use the app more.')*	
Agree	69.5 (64.3 – 74.1)
TDF construct: Beliefs about capabilities	
Self Confidence (facilitator) *('I am confident I could quit smoking by using an app.')*	
Agree	50.7 (45.4 – 56.1)
TDF construct: Beliefs about consequences	
Data protection (barrier) *('I am concerned how my personal data is handled in apps.')*	
Agree	66.8 (61.5 – 71.6)
TDF construct: Goals	
Goal setting and action planning (facilitator) *('Receiving guidance of how to achieve goals is more important for me than just simply setting goals.')*	
Agree	84.3 (79.9 – 87.8)
TDF construct: Social identity	
Social identity (barrier) *('When using a smoking cessation app, I don't want to feel that I am being treated like a patient.')*	
Agree	61.4 (56.1 – 66.5)
TDF construct: Reinforcement	
Rewards (facilitator) *('Receiving badges or awards for achieving a set goal, would make me use the app more often.')*	
Agree	75.4 (70.5 – 79.7)

6.5. Discussion

This study investigated five potential attributes relevant to the likelihood of the uptake of a smoking cessation app. Participants preferred a smoking cessation app with high star ratings, developed by a trusted organisation, with images that include a screenshot of the app and the least expensive apps. The description of the app shown to participants did not influence preferences.

Relative to other attributes, a high star rating was the most important factor. People are likely familiar with highly rated apps as these are more likely to get to the top of the search list. Although some highly rated popular smoking cessation are better tailored to individual needs (49), not all high-quality evidence based smoking cessation apps have high star ratings (51, 271). This suggests that popularity indicators are likely more important to uptake than evidence-based content.

The preference for apps from trusted organisations, such as NHS Digital, aligns with existing evidence. Findings of this DCE are similar to a DCE that investigated the uptake of a COVID tracing app in the UK where participants were more likely to adopt a NHS contact tracing app (208). Similarly, users are increasingly concerned about whether apps come from reputable sources (278) and prefer smartphone apps developed by experts than those from unknown or less reputable sources (189).

Images showing both the logo and screenshots of the app relative to the other attributes were as important as the low price of the app. Surprisingly, descriptions, however, did not seem to influence the uptake of a smoking cessation app. One plausible explanation is that this attribute was not conceptualised to capture the participants' attention. To save space and avoid cognitive load, this DCE did not provide an example of a description. Instead, this DCE provided a verbal description, defined briefly what a generic, short or long description means in the context of this research. Hence, the presentation of this attribute may not have been salient enough to mirror how well app description may influence uptake.

In line with similar studies, this DCE found that participants most preferred an app at zero cost (44, 279). However, some individuals might consider paying for it if it offers certain features (e.g. professional support or developed by a trusted organisation) (165). Investigating the mWTP findings of this DCE suggest that individuals may be willing to pay a small fee for an app if other preferences are met, such as being highly rated (4.8 stars and 4 stars) and developed by a trusted organisation.

Only around half of the participants included in this DCE were aware of smoking cessation apps, which suggests that more work is needed to raise awareness of these tools. In line with previous findings, access to health information and a user guide of using the app would increase most participants' engagement (44, 165). The latter could be particularly important to those who reported having limited app literacy skills. Interestingly, less than half of the participants reported they would not want to use an app with complex features. Chapters 2 and 4 found mixed views on reminders, with some believing they may negatively influence behaviour change by triggering cravings (44, 165). This chapter found that less than 40% reported reminders were a barrier. In line with Chapters 2 and 4 (44, 165), potential users believed peer and professional support would further encourage engagement (44, 165), and less than half reported failing to quit would lead to feelings of disappointment. Only around half of the participants agreed with many of the hypothesised barriers. This shows the difficulty app developers may face when developing an app to suit most individuals' needs and the potential importance of guidance from organisations such as the UK National Institute for Health and Care Excellence on developing digital behaviour change tools.

6.5.1. Limitations

This DCE had several limitations. Although the recruitment was adjusted to include a wide range of participants, the sample may not be to be representative of smokers in general. Furthermore, some views may have been missed by recruiting exclusively online, including views of individuals experiencing homelessness, those living in deprived areas and those living in areas without a suitable internet coverage. Additionally, the non-response bias was greater for the sample recruited through social media, as opposed to the Prolific website.

The design of the study investigated main effects only, therefore possible interaction between attributes were not assessed. Furthermore, the sample size was inadequate to enable investigating stratifications of certain demographics. Moreover, the clarity and usability of the DCE were not explored. For example, prompting participants to make a forced choice when they chose the opt out option might have influenced their choice behaviour and in anticipation of the forced choice question, they may have chosen an alternative throughout the survey.

Lastly, this study investigated the uptake of a smoking cessation app based on stated preferences, which may be different from the uptake of a smoking cessation app in real life. For example, due to pragmatic reasons, this DCE could not consider all previously identified factors that may shape choice behaviour, such as the aesthetics of the app (44, 165).

The relative importance of the attributes may vary between genders and age groups. Therefore, future research applying DCE methods may want to consider recruiting a larger sample size to investigate the relative importance of the attributes stratified based on socio-demographical factors. To build on the limited conceptualisation of the perceived utility of the app, future DCEs could borrow ideas from interaction design and user research studies and apply a visual representation of apps, instead of textual description. In this case, participants are shown images of apps as opposed to a table. Lastly, the measured factors influencing the uptake and engagement with smoking cessation apps suggest that more empirical studies are needed to test the extent of facilitators and barriers.

6.5.2. Implications

Findings may help public health organisations to increase the uptake of evidence or theory-informed smoking apps that are likely to have the greatest public health benefit. This study's findings also inform health app providers and health app portal curators to better design the presentation of health apps to meet user preferences and increase their uptake, particularly on curated health app portals, such as the NHS Apps Library. The values from the willingness to pay could be used to predict how a potential smoking cessation app user will react to a given product and help determine which attributes are used when presenting the app. Furthermore, these could provide evidence which could inform future cost-benefit analysis of smoking cessation app. This would further increase access to smoking cessation, reducing costs associated with delivery and reducing patient burden.

6.5.3. Conclusion

This study found that uptake is more likely if smoking cessation apps have high star ratings, are developed by a trusted organisation, include screenshots, and are low cost. However, high app ratings outstrips the importance of any other attribute investigated.

6.6. Next steps

This was the final stage of the thesis. Chapter 7 summarises key findings from the systematic review, the think-aloud and interview study and the discrete choice experiment conducted as part of this thesis and provides a series of important considerations for policy and practice, as well as recommendations for future research.

Chapter 7. General discussion

This thesis describes the use of theoretical frameworks from the behavioural science literature and a diverse set of methods to investigate the problems relating to the sub-optimal uptake of, and engagement with, health and wellbeing smartphone apps. This thesis reports results from a systematic review (Chapter 2), a comprehensive qualitative study (Chapters 3 and 4) and a discrete choice experiment (Chapters 5 and 6) to address the following research objectives:

1. To gain a better understanding of the factors influencing the uptake of, and engagement with, health and wellbeing apps
2. To explore how and why individuals select a health and wellbeing app, including routes for identifying apps other than commercial smartphone app stores, as well as reasons for engagement and non-engagement with apps
3. To determine the factors likely to influence the uptake of smoking cessation apps and to identify factors which may potentially influence adults' engagement with health and wellbeing apps.

In this final chapter, the key findings obtained in relation to the research objectives are discussed through triangulation of the studies. The subsequent sections provide an overview of implications for policy and practice, considerations for future research, and a summary of strengths and limitations of the thesis. Finally, this chapter ends with personal reflections and concluding remarks.

7.1 Summary and interpretation of key findings

Findings reported in Chapters 2, 3 and 6 identified a total of forty factors mapped under the components of the COM-B model and constructs of the TDF that were identified to be relevant for the uptake of health and wellbeing apps, engagement with health apps or both. Seventeen out of these were identified to be relevant for the uptake of health and wellbeing apps and twenty-eight factors were found to be relevant for engagement, and with five factors overlapping and considered important for both. Main findings are discussed below.

7.1.1. Identifying which factors are influencing the uptake of health and wellbeing apps

Two factors were judged to be most important for uptake. One core factor was social influence, mapped under the social opportunity component of the COM-B model and is represented by ratings and reviews, and an identified credible source (i.e. trusted organisation). Although an app develop by a trusted organisation was found to be important for uptake, findings from the chapters presented in this thesis suggest that popularity may be more important than whether an app is evidence-based. This implies that commercial platforms alone may not be suitable to identify an effective health and wellbeing smartphone app without prior professional recommendation.

The other core factor found to be important was the perceived utility of an app, mapped under the reflective motivation component of the COM-B model, which includes relevant title, the description and pictures of apps. This can be interpreted through the lens of the Technology Acceptance Model (TAM) (280). One of the constructs of the TAM is perceived usefulness that contributes to the intention to use a piece of technology, which aligns closely to what in this thesis is conceptualised as the perceived utility of an app. It is of note that the finding that the perceived utility of an app is a key predictor of uptake was only partially supported in the DCE, where this factor was conceptualised by the images shown and the description of a smoking cessation app. The written presentation of the app's description did not affect the uptake of a hypothetical smoking cessation app, and images showing screenshots or screenshots and logo of the app, as opposed to logo only, only marginally informed the decision around uptake. The disparity in these findings may be due to the lack of visual representation of smoking cessation apps (i.e., lack of the use of an image in the DCE) such as a screenshot of how these are listed on a curated health app portal, including images and app description.

This work also found that individuals prefer apps at low cost or free. However, this research identified circumstances when individuals are willing to pay for an app. Some would be willing to pay for an app that contains valued extra features not available otherwise, such as professional support, while others would be more likely to pay if an app is listed on curated health app portals, if an app is developed by a trusted organisation, or for an app that has high star ratings of 4 or more. The conditions when individuals are willing to pay for an app suggest that, in general, factors under social influences (social opportunity factors, e.g., professional support) outweigh the environmental factors (physical opportunity factors) represented by the price of an app. Suggestions of how to use this understanding to increase uptake are described under the '*7.4. Implications for policy and practice'*.

7.1.2. Identifying which factors are influencing the engagement with health and wellbeing apps

The findings presented in this thesis suggest that engagement with health and wellbeing apps appears to be influenced primarily by features that improve users' capability, such as user guidance, the requirement of minimal cognitive load and support of self-monitoring, users' opportunity by providing embedded social support, and users' motivation by enabling goal setting with action planning. When specifically investigating smoking cessation apps, the strongest facilitators for engagement were user guidance, additional health information and rewards.

Out of these core factors found to be important for engagement with health and wellbeing apps in general, embedded professional support may be particularly important. The importance of embedded professional support may be interpreted through Mohr's supportive accountability model (160), which specifies that human support represented by a person seen as being a trustworthy expert increases engagement with eHealth interventions. The importance of rewards suggests that extrinsic motivation, as described by Self Determination Theory (4, 5), also plays a crucial role in changing certain behaviours, such as smoking cessation. Changing these health behaviours may be easier by increasing people's intrinsic motivation, which refers to engaging in an activity because of the satisfaction of the action, for example by simply being able to see the progress (e.g., losing weight, getting stronger, increasing stamina). Nevertheless, in addictive behaviours in which the unhealthy behaviour provides a level of reward (e.g., smoking, alcohol consumption, binge eating), intrinsic motivation may be harder to achieve. As an extrinsic motivator, rewards, such as loyalty points, could provide a starting point in incentivising behaviour change in similar circumstances for some individuals. Later, progression (e.g., fewer cigarettes smoked or having more smoke free days) may then enhance the user's intrinsic motivation.

Some factors were not universally identified as facilitators or barriers to engagement. These include cognitive load (represented by apps with complex features or apps deemed to be complicated to use), reminders, and peer support for smoking cessation apps in particular. The way that cognitive load is conceptualised in this thesis is similar to one of the other constructs of the TAM, the perceived ease of use, which refers to the perception of using a system without extra effort (280). Together with the perceived usefulness, this construct is expected to contribute to the intention to use technology.

Although cognitive load was initially found to negatively affect engagement, in the DCE only half of the participants reported not wanting to use an app with complex features.

All studies included in this thesis reported mixed findings with regards to reminders, which suggests that the importance of this factor might vary significantly between individuals. Receiving reminders could be a good strategy for many to prompt engagement with an app; however, some individuals found them intrusive. Indeed, more than one-third of smokers included in the studies reported in this thesis believed reminders could trigger cravings.

Peer support may be a useful addition to a health app. However, care should be taken for apps that target behaviours that can be coupled with stigma, such as smoking. Although many individuals believed that peer support would help with engagement and would motivate individuals to quit smoking, others believed that it could contribute to shame and disappointment in case of relapse. However, these could also be powerful forces that help relapse through avoidance behaviour (i.e., avoiding shame or regrets). Suggestions of how to improve engagement with health and wellbeing apps are described under the '*7.4. Implications for policy and practice*'.

7.2. Strengths

Key strengths of this thesis lie in applying open science principles, the use of robust methodology, use of a theoretical framework, use of PPI and a pre-specified sampling method. Following the principles of 'Open Science' by pre-registering all study protocols on either on PROSPERO (Chapter 2) or OSF (Chapters 3, 4, 5 and 6) and making data, results, and publications freely available to help advance scientific progress by providing transparency in science and discoverability. The transparent reporting of all steps of the DCE increases the credibility of the results and help with the reproducibility of the research, enabling other researchers to verify the findings or to conduct additional analysis. The data is freely available on the OSF (https://osf.io/szk96/), as well as the source code used to develop the DCE. The results and publications of all studies were made available in the form of open access journals for the accepted publications or in the form of preprints on 'Qeios' (https://www.qeios.com/), a website that has the purpose of distributing and receiving early feedback on, the newly generated knowledge.

In terms of methodology, a mix of qualitative and quantitative methods was used to address the linked research questions. This helped to mitigate well-known limitations associated with each method, as data sources were triangulated. Triangulation compares and integrates findings from different methods (279) and this thesis has triangulated findings from a systematic review, a qualitative study and a discrete choice experiment.

Moreover, the application of the same theoretical models, the COM-B model and the TDF allowed a behavioural analysis of factors influencing the uptake of, and engagement with, health and wellbeing apps, with findings translated to established behaviour change strategies, which it is hoped helps make the findings more tangible for app developers, commissioners, and digital health researchers. Furthermore, several of these factors could also be used to target an app-based intervention and could lead to the identification of important intervention components. In addition, the development of each stage of this project involved stakeholders' engagement, including PPI representatives and representatives of PHE and NHS digital. Their input ensured that the research was easy to understand from a participant perspective and the work generated with their input helped provide policymakers with meaningful insights to improve the uptake of, and engagement with, health and wellbeing apps. Finally, another strength of the thesis is the carefully applied purposive sampling technique that was used to increase the diversity of characteristics in the sample.

7.3. Limitations

Taken as a whole, the approach adopted in this thesis presents several limitations. First, this thesis applied a strong behaviour science perspective and did not account for other perspectives, such as those from the human-computer interaction literature. For example, this thesis did not differentiate between factors influencing engagement related to the human side, such as motivational factors, from those referring to the technology, such as feature-based factors or BCTs. Use of perspectives from the human-computer interaction literature could have potentially complemented findings mapped under the COM-B model and further help to understand mechanism through which strategies for engagement would be more effective.

Second, the first stage of the thesis investigated a wide range of health behaviours rather than focusing on a single health behaviour. Therefore, factors identified being important for a wide range of behaviours were applied to investigate the uptake of smoking cessation apps. This may have led to the failure of investigating factors specific to the uptake of, and engagement with, smoking cessation apps. Furthermore, limited knowledge was generated regarding the specific characteristics of the setting of use that may influence the uptake and engagement with apps for other behaviours.

Third, only some of the factors deemed to be important for uptake were feasible to assess in the experimental approach within the given timeframe and engagement features were not assessed. Additionally, the experimental approach applied in this thesis was only able to investigate hypothetical situations, and therefore the findings might not be replicated in real-world settings. The *'7.5. Consideration for future research*' section covers a few aspects that helps overcome some of the limitations of this thesis.

7.4. Implications for policy and practice

Use of a similar framework to the work reported in this thesis, i.e. use of the COM-B model and the TDF to interpret and organise the findings, could be helpful when developing interventions to increase the uptake of and improve the engagement with health and wellbeing smartphone apps, particularly when applied through the Behaviour Change Wheel (BCW) approach (described in Chapter 1). The BCW has been successfully used in digital health interventions in the past by applying behaviour change techniques (282, 283). This is vital, as many health and wellbeing smartphone apps listed in commercial platforms lack behaviour change techniques (60, 62-68). Further, apps that have used behaviour change techniques associated with effectiveness were found to provide better quality content to users (61), potentially improving engagement with them. Hence, factors relevant for the uptake and engagement with health and wellbeing apps, mapped under the core of the BCW (COM-B and TDF), provide a starting point in developing interventions to improve uptake and engagement with these.

There are additional ways to the use of the BCW, to improve the uptake of, and engagement with, health and wellbeing apps. This may be achieved by applying a multidisciplinary approach involving health care practitioners, app developers, user researchers and interaction designers to better meet individuals' needs. These are further discussed below, including suggestions to address potential digital health inequalities.

7.4.1. Increasing the uptake of health and wellbeing apps

In terms of the uptake of health apps, studies in this thesis showed that individuals lack awareness of certain health and wellbeing apps and health app portals, and they heavily rely on social opportunities when selecting apps, such as recommendations for use, ratings of the app and credible source, and on the perceived usefulness of these apps. Strategies of how to improve these are described below.

There is limited awareness about the existence of health and wellbeing apps for a wide range of behaviours and the general public may require better awareness on how to identify and where to select evidence-based health apps (173). Although most participants of the studies included in this thesis reported that they had previously selected a health app through a commercial app store, at least one-third chose different routes to select an app, such as health-related websites, Google searches, or sought recommendations from friends and family or health practitioners. This highlights that app selection often may not take place in the commercial app stores and that potential users may want to know more about the apps they select than is typically presented in these stores. One opportunity would be to increase the visibility of available curated health app portals by disseminating and recommending the use of them, which would provide an evidence-based, and, therefore, a safer option for an app (178). Curated health app portals were viewed by the participants of the studies included in this thesis as a good opportunity to ease the uptake process and address the unstructured way health apps are typically listed on the commercial app stores. Following the principles of transparency and trust, disclosing information about privacy and data protection, about the app development and feasibility data and benefits, may further increase uptake (176). This is important, because, unfortunately, there is still a lack of information about the accuracy of apps, such as how they were developed and tested (284, 285) and the lack of fairness in privacy policies and data protection (286, 287).

Although the above-mentioned aspects are necessary to provide high-quality tools to end-users, this thesis suggests that showing the star ratings, and disclosing app developers may be key factors to further improve uptake of health and wellbeing apps. However, this may only be useful when apps have a reasonably high star rating (i.e. 4 and higher), therefore, improving lower star ratings would require further attention. To achieve high ratings a collaboration with user experience researchers and interaction designers may be important to ensure that the apps' functionalities meet users' needs and, consequently, prompt better ratings (49). Some strategies to better meet users' needs are described under the '*7.4.2. Improving the engagement with health and wellbeing apps*' section of this chapter. Additionally, prompt responses to and acknowledgments of unsatisfactory reviews of apps left in the commercial app stores and addressing concerns regarding functionality of apps would ensure that the end-users' feedback is taken into consideration, which could potentially lead to improved popularity of apps, and better rating of them.

Another important aspect to consider for commissioners of health apps is to address the perceived utility of the app, such as the way apps are presented either through dissemination as a stand-alone tool (i.e., a specific app available for certain individuals, for example a smoking cessation app for patients with chronic obstructive pulmonary disease) or as part of a curated health app portal. Realistic and relevant titles and with pictures that show screenshots of the app, as opposed to media-promoted unrealistic body images for example, could affect the perceived utility of the app. The description should aim to answer the 'how' aspect of the app instead of having a generic presentation of the app that could fit several apps. Furthermore, improved transparency in the app description, including providing more relevant information, such as how that app can help them to achieve their goals, could further influence the perceived utility. All these aspects have the potential to strengthen potential end-users' decision-making process about the uptake of health apps which could involve steps such as accessing all relevant information about the apps, weighting up the available evidence presented with the apps, choosing an app, taking action (i.e. download) and review their decision. This could lead to an app usage decision (175), and, therefore, would not only increase uptake, but could potentially prompt initial engagement.

Finally, integrating mhealth into care does not often fit the context of 'care' (288). This may pose a barrier to increasing awareness or recommendation of apps amongst healthcare practitioners. One potential solution would be to enhance the incorporation of digital health into the curriculum of health care professionals. An additional solution could be to introduce formal referrals to curated health app portals and to evidence-based health and wellbeing apps, as part of the social prescribing services (289).

7.4.2. Improving the engagement with health and wellbeing apps

Studies in this thesis suggest that cognitive load may negatively affect engagement, apps are not tailored adequately to end-users' needs and that individuals seek embedded social support. A few key recommendations to improve these are presented below.

It is well known among app developers, user researchers and user experience designers that an interactive app can fight boredom and prompt engagement (290-292). However, the studies conducted for this thesis suggested that interactive apps that provide a personalised experience could increase cognitive load for some. This could be addressed if an app had two versions, a basic and a more advanced, similar to currently available free version versus 'pro' version (i.e. paid). However, instead of providing extra features for a one-off payment or monthly cost, an app could provide two versions based on the user type, minimal user versus power user. A basic version could be a simple version where the user is required to input minimal information, with the limitation of not receiving tailored content and without access to more advanced features. The advanced version would require initial user input for more personalised features and health and demographics-related content. This strategy could address the needs different user types may have such as minimal users, who do not want to interact with an app for long, versus power users who enjoy spending time on an app. However, minimal users would need to accept that the use of a basic version would not necessarily provide a personalised experience described below.

A personalised experience implies providing content or features relevant for individuals. Findings presented in this thesis suggest that potential users are willing to engage with health and wellbeing apps with multiple strategies to help change the behaviour (i.e. goal settings with action planning versus goal setting only). However, this may lead to a more difficult app development process as, in general, there is rarely a singular behaviour change strategy that works for everyone. This could be overcome by providing several different BCTs and strategies to support users in achieving their health goal. For example, in smoking, although the literature suggests that quitting smoking ‘cold turkey’ (i.e. abruptly) or quitting by smoking gradually smoking less are equally effective in achieving smoking cessation, when individuals are offered the opportunity to choose an approach it increases the effectiveness of quitting (293). Therefore, personal preferences for behaviour change should not be ignored.

Tailoring to sociodemographics was found as an important aspect of engagement. This may be easily achieved if users complete a profile, and the content is generated based on that. For example, health information shared in a smoking cessation app for females over 40 may contain also contain female-specific information, such as the link between perimenopause or menopause and weight gain, and quitting smoking and weight gain, and provide advice on how to prepare for this and how to keep a healthy weight. To complement findings of tailoring to sociodemographics, tailoring to the behaviour that a health app addresses and tailoring to the participants’ psychological constructs (e.g. beliefs in their capabilities) may be equally, if not more, important for engagement. Indeed it has been suggested that this could be more effective in behaviour change than tailoring to demographics (294).

Embedded professional support, as part of social influences, was found to be one of the core factors for engagement. Health and wellbeing apps with professional support have the potential to increase long-term engagement (295-298). However, many organisations seem reluctant to provide integrated professional support (299), perhaps, due to financial reasons or lack of perspective of integrating health apps into routine care. Professional support may however refer to artificial intelligence mimicking embedded support using machine learning techniques (300), which has been successfully implemented in smoking cessation apps in the forms of chatbot features (161, 301). However, smoking and other behaviours, such as excessive alcohol consumption (302), can carry a social stigma. Therefore, there is likely an interaction between behaviours and individuals regarding some other social influence features, such as peer support, social comparison and social competition, and the findings of this thesis that suggest that not everyone would appreciate these features. Practical considerations regarding integrating peer support into an app may require further work. One potential opportunity would be to link or invite app users to a peer support platform or a closed group on a social media channel. For example, Tweet2Quit offered such a closed group platform for a Twitter-delivered smoking cessation intervention where participants were able to access a private, self-help group to motivate members to quit and doubled sustained abstinence (303).

Additionally, some factors deemed to be important for engagement are not universally useful, such as reminders or peer support. Suggestion for clarification of the direction of these factors are described under '*7.5. Consideration for future research'*.

7.4.3. Addressing digital health inequalities

The findings of this thesis contribute to the ongoing narrative about digital health inequalities that may affect the uptake and engagement with digital health interventions, and some factors identified should be considered when promoting uptake and engagement. The World Health Organization mandates health equity, and this implies that everyone should have an equal opportunity to reach their full health potential, and no one should be disadvantaged from achieving this (304). Chapter 2 of this thesis found that the uptake of health and wellbeing apps is more common amongst women, except for apps targeting alcohol consumption. Younger age was also linked with both the uptake of and the engagement with health and wellbeing apps. Living in an urban area, having a higher level of education, and having a higher income was also linked to better engagement. These findings suggest that technology may contribute to differences in access to health resources for groups of people with limited resources. However, health and wellbeing apps could also have a positive impact on equity (305). For example, low socioeconomic status smokers, who have access to digital technologies, may be more inclined to turn towards digital smoking cessation interventions instead of face-to-face interventions or quit lines to quit smoking because the online mode of delivery could overcome barriers of guilt, shame and stigma associated with their identities as smokers (306, 307). Health apps could also provide content tailored to users' literacy and overcome barriers such as treatment engagement and financial and time factors, such as in usual smoking cessation services (308).

To address digital health inequalities, exploring ways for more rigorous content development may be required. Researchers and developers could work together with local communities when developing health apps to improve their health by developing these tools based on where people live and work (309). One potential solution is to integrate community engagement into the development of data-driven strategies, for example the community-based participatory research (CBPR) (310) or participatory design (311). CBPR refers to the collaboration with community members at every phase of the research process, from conceptualising the research to dissemination (310). For example, CBPR was successfully implemented in the US to develop an app to reduce the risk of developing cardiovascular disease among the black community (312, 313). This was particularly important as the cardiovascular disease mortality rate is twice as high in black individuals relative to white individuals (314). In this study, practising cultural appreciation, such as biblical scriptures and messaging, led to high app acceptability, usability and satisfaction rating (313). Similarly to CBPR, participatory design fosters collaboration with end users and researchers to increase the acceptability and engagement of target users (315). However, in participatory design end users have a more active role and could directly contribute to the design and content development (e.g., create app content), this way becoming a key group of stakeholders. Participatory design was successfully implemented in the development of patient-centred digital interventions to marginalised populations, including those with limited English language proficiency (316), low-income women (317), individuals living with HIV (318), and the LGBTQ+ population (319, 320).

It is hoped that the integration of community engagement using participatory methods into the development of data-driven strategies to address the digital divide could bring a number of benefits (such as addressing issues of functionality) and lead to better engagement with digital interventions that promote health behaviours. As highlighted in Chapter 1, high-quality apps would encourage behaviour change, hence improving app effectiveness (60).

Specific recommendations for policy and practice under the components of the COM-B model to improve the uptake and engagement with health and wellbeing apps can be found in Appendix 20. These recommendations were disseminated among policy makers, including the digital team at Public Health England, NHS Digital and NHSX. These recommendations have been considered during the development of a health promotion portal led by NHS Digital.

7.5. Considerations for future research

7.5.1. Uptake of health and wellbeing apps

Uptake of health apps currently is an under-researched area of digital health. Engagement without uptake is not possible and increasing uptake is one approach to increase engagement. Some suggestions for future research to provide more evidence to increase uptake are described below.

Perceived usefulness remains an important factor influencing the uptake and initial engagement with health apps. The extent to which this can be measured and conceptualised should be investigated in the future. For example, though A/B testing (321), often used in user experience research to test two versions of the same products, or factorial experimental designs (322). These could explore the uptake of smoking cessation apps through visual representations of how they are listed on a series of improved and mocked up versions of curated health app portals where apps could be presented with different images and descriptions. Another possibility is the development of additional DCEs, which could show a screenshot of apps listed, as opposed to the verbal description employed in Chapter 5. However, as each image would contain more information than a table describing the attributes, a larger sample size with fewer choice tasks per participant would be recommended to avoid cognitive load during the experiment.

Besides perceived usefulness, there are other uptake-related factors that could be investigated in the future. Different methods are required to identify what environmental factors may influence the uptake of, and engagement with, certain health and wellbeing smartphone apps. For example, eye-tracking research (323) could be used to investigate visual perception and decision making when selecting an app from a curated health app portal by exploring what potential user found most relevant on the portal (i.e., description of the app, or images), which could complement findings of this thesis. Furthermore, this type of research could test the usability of a mocked up and improved curated health app portal, that contains user guidance, additional health information and possibility the ability to filter for user demographics, that the think-aloud research found potentially relevant for the uptake of health apps on health app portals.

Finally, research methods, similar to those used in this thesis for smoking cessation, could be employed to test whether the findings can be generalised to health apps for other behaviours. A series of behaviour specific think-aloud studies (181) prompting participants to search for an app of their choice (e.g. for diet or physical activity) and additional DCEs that could target the uptake of apps developed would allow a deeper understanding of the differences in the uptake of different behaviour change or wellbeing apps

7.5.2. Engagement with health and wellbeing apps

More experimental work is required to address the challenge of maintaining engagement with health apps and to test the identified factors that influence engagement (295, 324, 325).

Personalisation to individual needs, as suggested in this thesis, may be crucial for engagement. However, how best to tailor content to support engagement requires additional investigation. Addressing changing needs of individuals can be achieved by using methods such as ecological momentary assessment (EMA) (326), which involves repeated measures of certain behaviours in real-time in a real-life setting (327), and N-of-1 studies which focus on within person variability over time (328). These can collect real-time data through sensors from wearables or through apps (191). These could be combined with machine-learning techniques, which could push content based on the user’s profile or interest shown when using an app, or features the individual interacts with while using the app. For example, in physical activity apps, the association between reward and social learning is stronger for females, and the association between reward and social competition is stronger for males (329). Therefore, in this case an app could push content containing social competition to those who show interest in these (i.e., interact with social competition features, such as step count challenge). Future research could also investigate using data driven-approach factors that are more important for certain groups or communities: for example, marginalised populations, such as ethnic minorities or LGBTQ+ communities, may need other health and wellbeing information.

Randomised factorial designs could be used to further investigate factors that the studies in this thesis did not find universally beneficial, including cognitive load (apps with complex features), reminders and peer support. The use of this design is particularly suitable for digital interventions to evaluate the extent to which features improve engagement, which otherwise would be difficult to carry out in a face-to-face setting (330). These are often guided by the Multiphase Optimization Strategy (MOST), a comprehensive framework for optimising and evaluating complex interventions efficiently which allows multiple variables (i.e., app features) and their interactions to be evaluated simultaneously (331, 332). Similar to a DCE, sample sizes are reduced as participants are assigned to multiple conditions, represented by two levels of the features of the app. For example, a minimal and an intensive level could test the difference in engagement for an app with simple or complex features, and different type and style of reminders, and apps with or without peer support. The most promising intervention components are then tested in a randomised control trial. Furthermore, other randomised factorial designs could also be applied to different health behaviours (e.g., smoking, alcohol consumption, physical activity, diet), to test whether the importance of these factors is different across these behaviours. Finally, to overcome the difficulties of the timing of reminders, there are promising developments in the use of using probabilistic models to learn individual’s behaviours and provide reminders based on user activity (333), which is worth exploring further in the future.

7.6. Personal reflections

This thesis initially constituted a development of web-based interventions to increase the uptake and engagement with health and wellbeing apps. The planned stages of the project were to conduct a comprehensive systematic literature review to understand better the factors influencing the uptake of, and engagement with, health and wellbeing apps, followed by a think-aloud and interview research for a deeper understanding. Finally, the development of web-based interventions was planned to be followed by a feasibility study. The development of the web-based intervention was planned to take place in close collaboration with the digital department of PHE. This explains why there was a card sorting task at the end of the qualitative research described in the topic guide (Appendix 13) which was initially part of the intervention development and aimed to shed light on the most preferred features of a prototype health app portal: the platform planned to use for the intervention. The development of the web-based intervention was ongoing when the COVID-19 pandemic started to threaten the public’s health in the UK. PHE’s priorities changed, and the original plan was no longer feasible, forcing the project to find a different methodological alternative to address its main objectives and the DCE methodology was chosen instead. The development of a DCE requires the same steps as the ones planned to develop web-based interventions. Therefore, the change of the last stage was incorporated efficiently.

As a first stage of this thesis, a systematic literature review with a potential meta-analysis was initially planned. However, while exploring the published literature, I found a lack of intervention studies that investigated the uptake or engagement with health and wellbeing apps. Hence, there was a need to expand the focus of the systematic review. A systematic review that applied an integrative approach including qualitative and quantitative studies was appealing because the quantitative results could be converted into text and coded together with the qualitative findings using thematic synthesis. This is not a novel approach but a less known and underused way of synthesising findings.

I believe that the think-aloud methodology is one of the best ways to gain a deeper understanding of how the uptake takes place. Uptake of apps is difficult to measure and even more challenging to understand the decision-making process for app selection. The think-aloud methodology provided a unique way of observing this. However, on reflection, features deemed important for engagement may have been more accurate to measure through data-driven approaches, such as EMA, N-of-1 study, or factorial experimental design, where the use of different features and frequency of engagement is measured in real-time. Nevertheless, the quantitative studies would not have explained how, why, and when disengagement happens or show what the most important aspects of engagement are. Additionally, quantitative studies would not have highlighted factors affecting engagement that are not related to app features, for example, the ones related to their social identity, hence, the importance of semi-structured interviews to answer these questions.

During the recruitment of participants, I applied purposive sampling for the qualitative research, and I aimed to be as rigorous as possible to include a wide range of participants in terms of age, gender, ethnicity and education. To promote diversity and inclusion, the recruitment also included a person who was deaf, for which I made all necessary adjustments, including additional resources and liaising with a British Sign Language interpreter. However, this participant later decided not to attend the session, and explanation was never given. When writing up the findings, the think-aloud methodology and semi-structured interviews generated such rich data that the decision to report the results based on the two behaviours (uptake and engagement) separately was made.

I found the use of the TDF to analyse and present the findings of the systematic review and the think-aloud and interview research challenging. It required an additional learning curve of accurately interpreting findings through the lenses of the chosen behavioural model. In some cases, there appeared to be an overlap between the factors mapped under the TDF constructs, and there was a constant discussion with co-authors with knowledge of applying the TDF on how the best interpret findings. However, the mapping exercise of findings under the TDF were disseminated with researchers with relevant experience in using these models to confirm the findings.

The DCE development was the most challenging part of the PhD. It was slow and extensive, and it relied on self-directed learning of the method. Due to the COVID-19 pandemic, training on conducting this type of research was cancelled or postponed to a year later. By the time institutions started to organise DCE methodology training online, it would have been too late for this project to be delivered in time. However, to ensure the accuracy of the self-learnt methodology, experts in health economics and in conducting DCEs were involved as advisors. During self-directed learning, I noticed that no single research article would advise a novice researcher on the initial steps in conducting a DCE. Therefore, the decision to write up the development chapter as a paper was made to help fellow authors, those with limited experience with DCEs in particular, to conduct a DCE. On reflection, although I have limited experience in writing research papers, I found writing a methodology paper the most challenging manuscript to write so far. It also required a more extended period to finalise it, partly because I had to ensure the language used was adequate for the readership and that I did not go into complex methodological details unsuitable for an introductory methodology paper.

The recruitment of participants for the DCE was achieved in three months due to a managed recruitment strategy to ensure a wide range of the sample will be included. This was achieved by constantly monitoring the recruitment process and adjusting the variables in the paid social media adverts. For example, when the DCE included a higher number of females and more individuals with a higher level of education, I adjusted the recruitment so that the advert was shown to males and from lower socioeconomic status.

The transformation of DCE data was another difficult task that required careful attention and additional quality checks. The data was collected in a survey format, providing the selection of one out of three alternatives (App 1, App 2 or neither) in each choice task. The dataset used to analyse in Stata requires a specific data structure in which the dataset has one row per alternative for each choice-task for each participant. For 337 participants, this meant 337x12x3 rows (with a few choices omitted, this yielded a total of 12,087 rows) and 20 columns (including the alternative specific constants). There is a guide on implementing DCEs in Qualtrics to automatise the data transformation process, which assumes HTML familiarity (334). However, I found this difficult to interpret. Additionally, to my knowledge, there is no automated method to be used for data transformation when visuals are used too (star ratings, in this case). Therefore, the data transformation was undertaken manually. To limit the human error associated with data entry (335), I conducted a series of quality checks once the dataset was ready by comparing the transformed dataset against the raw data. Additionally, I requested a co-author of the DCE research manuscript (Rory Cameron) to randomly check the data transformation and check the underlying data, and there were no errors found.

The DCE, as opposed to a feasibility study of a web-based intervention that was initially planned, may have been a better choice to investigate the uptake of a smoking cessation app. The DCE, due to its repeated choice sets, requires a smaller sample size to have sufficient power to detect the probability of the uptake based on the attributes used in the study.

7.7. Concluding remarks

The uptake and engagement of health apps is generally low and improving this is needed to increase their impact on health and wellbeing outcomes at the population level. The research presented in this thesis was undertaken to better understand the factors that influence the uptake of, and engagement with, health and wellbeing apps. This was achieved through the triangulation of findings of qualitative and quantitative methods. One of the key findings was that social influences (i.e. the popularity of apps and the credible source), seem to play a crucial role in the uptake of health and wellbeing apps in general. The importance of different factors found to be associated with engagement is likely to be behaviour dependent. Nevertheless, in general, factors that improve users' capability, including knowledge (i.e. user guidance, health information), memory attention (i.e. minimal cognitive load) and behaviour regulation (i.e. self-monitoring), were found to be the key drivers of engagement.

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Appendix 1. The constructs of the Theoretical Domains Framework

The Refined Theoretical Domains Framework

Reproduced from Cane, Connor & Michie, *Implementation Science*, 2012

Domain/Definition*	Constructs
Knowledge *An awareness of the existence of something*	- Knowledge (including knowledge of condition/ scientific rationale) - Procedural knowledge - Knowledge of task environment
Skills *An ability or proficiency acquired through practice*	- Skills - Skills development - Competence - Ability - Interpersonal skills - Practice - Skill assessment
Social/Professional Role and Identity *A coherent set of behaviours and displayed personal qualities of an individual in a social or work setting*	- Professional identity - Professional role - Social identity - Identity - Professional boundaries - Professional confidence - Group identity - Leadership - Organisational commitment
Beliefs about Capabilities *Acceptance of the truth, reality, or validity about an ability, talent, or facility that a person can put to constructive use*	- Self-confidence - Perceived competence - Self-efficacy - Perceived behavioural control - Beliefs - Self-esteem - Empowerment - Professional confidence
Optimism *The confidence that things will happen for the best or that desired goals will be attained*	- Optimism - Pessimism - Unrealistic optimism - Identity
Beliefs about Consequences *Acceptance of the truth, reality, or validity about outcomes of a behaviour in a given situation*	- Beliefs - Outcome expectancies - Characteristic of outcome expectancies - Anticipated regret - Consequents
Reinforcement *Increasing the probability of a response by arranging a dependent relationship, or contingency, between the response and a given stimulus*	- Rewards (proximal/distal, valued/not valued, probably/improbable) - Incentives - Punishment - Consequents - Reinforcement - Contingencies - Sanctions
Intentions *A conscious decision to perform a behaviour or a resolve to act in a certain way*	- Stability of intentions - Stages of change model - Transtheoretical model and stages of change
Goals *Mental representations of outcomes or end states that an individual wants to achieve*	- Goals (distal/proximal) - Goal priority - Goal/target setting - Goals (autonomous/controlled) - Action planning - Implementation intention
Memory, Attention and Decision Processes *The ability to retain information, focus selectively on aspects of the environment and choose between two or more alternatives*	- Memory - Attention - Attention control - Decision making - Cognitive overload/tiredness
Environmental Context and Resources *Any circumstance of a persons' situation or environment that discourages or encourages the development of skills and abilities, independence, social competence, and adaptive behaviour*	- Environmental stressors - Resources/material resources - Organisational culture/climate - Salient events/critical incidents - Person x environment interaction - Barriers and facilitators
Social Influences *Those interpersonal processes that can cause individuals to change their thoughts, feelings, or behaviours*	- Social pressure - Social norms - Group conformity - Social comparisons - Group norms - Social support - Power - Intergroup conflict - Alienation - Group identity - Modelling
Emotion *A complex reaction pattern, involving experiential, behavioural, and physiological elements, by which the individual attempts to deal with a personally significant matter or event*	- Fear - Anxiety - Affect - Stress - Depression - Positive/negative affect - Burn-out
Behavioural Regulation *Anything aimed at managing or changing objectively observed or measured actions*	- Self-monitoring - Breaking habit - Action planning

*All definitions are based on definitions from the American Psychological Associations' Dictionary of Psychology (Washington: 2007)

Appendix 2. Publication of systematic review

Review

Influences on the Uptake of and Engagement With Health and Well-Being Smartphone Apps: Systematic Review

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Abstract

Background: The public health impact of health and well-being digital interventions is dependent upon sufficient real-world uptake and engagement. Uptake is currently largely dependent on popularity indicators (eg, ranking and user ratings on app stores), which may not correspond with effectiveness, and rapid disengagement is common. Therefore, there is an urgent need to identify factors that influence uptake and engagement with health and well-being apps to inform new approaches that promote the effective use of such tools.

Objective: This review aimed to understand what is known about influences on the uptake of and engagement with health and well-being smartphone apps among adults.

Methods: We conducted a systematic review of quantitative, qualitative, and mixed methods studies. Studies conducted on adults were included if they focused on health and well-being smartphone apps reporting on uptake and engagement behavior. Studies identified through a systematic search in Medical Literature Analysis and Retrieval System Online, or MEDLARS Online (MEDLINE), EMBASE, Cumulative Index to Nursing and Allied Health Literature (CINAHL), PsychINFO, Scopus, Cochrane library databases, DataBase systems and Logic Programming (DBLP), and Association for Computing Machinery (ACM) Digital library were screened, with a proportion screened independently by 2 authors. Data synthesis and interpretation were undertaken using a deductive iterative process. External validity checking was undertaken by an independent researcher. A narrative synthesis of the findings was structured around the components of the capability, opportunity, motivation, behavior change model and the theoretical domains framework (TDF).

Results: Of the 7640 identified studies, 41 were included in the review. Factors related to uptake (U), engagement (E), or both (B) were identified. Under *capability*, the main factors identified were app literacy skills (B), app awareness (U), available user guidance (B), health information (E), statistical information on progress (E), well-designed reminders (E), features to reduce cognitive load (E), and self-monitoring features (E). Availability at low cost (U), positive tone, and personalization (E) were identified as physical *opportunity* factors, whereas recommendations for health and well-being apps (U), embedded health professional support (E), and social networking (E) possibilities were social *opportunity* factors. Finally, the *motivation* factors included positive feedback (E), available rewards (E), goal setting (E), and the perceived utility of the app (E).

Conclusions: Across a wide range of populations and behaviors, 26 factors relating to capability, opportunity, and motivation appear to influence the uptake of and engagement with health and well-being smartphone apps. Our recommendations may help app developers, health app portal developers, and policy makers in the optimization of health and well-being apps.

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KEYWORDS

mHealth; health app; engagement; uptake; systematic review; COM-B; TDF; digital health; mobile phone; smartphone; smartphone app

Introduction

Background

Digital behavior change interventions, such as smartphone apps, can be effective and cost-effective tools to change a range of health-related behaviors [1,2]. For example, there have been promising studies of apps, including (1) delivering health prevention messages for men who have sex with men [3], (2) self-managing diabetes [4] and cardiovascular diseases [5], (3) weight management [6-8], (4) alcohol reduction [9-11], (5) mental health interventions [12], and (6) managing long-term conditions [13]. For certain behaviors such as reduction of alcohol consumption, they could also address the barriers experienced by health professionals when delivering brief interventions in person, such as lack of necessary training [11] and to reduce the stigma associated with alcohol consumption [2]. The public health implications are substantial because of their potential to have a low incremental cost and broad reach.

Despite their promise, effect sizes reported in evaluations of app-based interventions are often small. One potential explanation is the level of uptake and engagement. Uptake refers to the act of downloading and installing a smartphone app. Engagement has been defined as "(1) the extent (e.g. amount, frequency, duration, depth) of usage and (2) a subjective experience characterized by attention, interest and affect" [14]. To date, low uptake and poor engagement are commonly observed with digital interventions, which are often insufficient to sustain behavior change [15,16]. However, there is a lack of evidence regarding the main factors contributing to this problem.

Systematic reviews that focused on one specific behavior or a certain type of health or well-being app suggest that the effectiveness of evidence-based smartphone apps can be improved by targeting the design and engagement features, such as user-friendly design, individualized and culturally tailored content, or health professional support [17-19]. A review based on experiential and behavioral perspectives conceptualized key factors that might affect engagement with digital behavior change interventions: the content (eg, behavior change techniques, social support, and reminders) and how the content is delivered (eg, professional support, personalization, and aesthetic features) [14].

To our knowledge, no systematic review that primarily seeks to identify factors that influence the uptake of and engagement with a wide range of health and well-being smartphone apps has yet been conducted. To narrow the focus of this review, the four public health priority behaviors related to prevention (smoking, alcohol consumption, physical activity, and diet) along with mental health and well-being were targeted.

Theoretical Framework

The capability, opportunity, motivation, behavior (COM-B) model is a comprehensive framework that posits that individuals, to perform or change a behavior, need the capability to undertake it, the opportunity to take part in, and the motivation to engage with that behavior [20]. COM-B is increasingly being applied to inform the development of digital behavior change interventions [21-23]. The theoretical domains framework (TDF) [24] has previously been successfully applied for systematic reviews in other contexts [25,26]. The 14 domains of the TDF, described elsewhere [24], offer a concise coding framework that can be usefully conceptualized as possible targets for behavior change interventions. The TDF, being linked to the COM-B model [24], can be used as subthemes under the components of the COM-B model (see Multimedia Appendix 1).

Objectives

This systematic review aimed to synthesize factors identified in studies that influence the uptake of and engagement with health and well-being smartphone apps among adults targeting public health priority behaviors (smoking, alcohol consumption, physical activity, and diet) and mental health and well-being, and mapped these factors under the components of the COM-B model and constructs of the TDF. This could help inform stakeholders in public health and policy makers, digital behavior change intervention developers, and providers of health and well-being smartphone app portals to better target uptake and engagement.

Methods

Systematic Review

The review was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA; Multimedia Appendix 2) [27], and the protocol was registered on the International Prospective Register of Systematic Reviews (CRD42019120312). The review used a mixed methods approach to generate different but complementary knowledge about users' views from qualitative findings and predictors and patterns of behavior from quantitative findings.

Eligibility Criteria

Eligible studies had to explore factors that influence uptake or engagement with health and well-being smartphone apps among adults. Table 1 summarizes the inclusion and exclusion criteria using the Population, Intervention, Comparison or Context, Outcomes, and Study Type tool.

Table 1. List of inclusion/exclusion criteria.

PICOS[a] component	Inclusion criteria	Exclusion criteria
Participants	• Adults ≥18 years. Studies including individuals ≥16 years were included if at least 70% of the participants were ≥18 years	Apps targeting health professionals
Intervention and context	• Studies investigating digital interventions using smartphone health and well-being behavior change apps on the following behaviors and outcomes: smoking, alcohol consumption, physical activity, diet and mental health, and well-being	Studies where the smartphone was not the primary intervention component
Outcomes	• Qualitative: findings described as facilitators, barriers, determinants of uptake, or engagement with health or well-being apps (either already existing or planned to be developed), including perceptions, beliefs, experiences, and interest of the participants. • Quantitative: uptake, measured as number of downloads, and engagement measured as number of logins, frequency of use, or any other relevant measure that tracks user engagement	Usability and user-testing studies, where functionality and app design were exclusively investigated for specific apps
Study design	• All study designs were included	None

[a]PICOS: Population, Intervention, Comparison or Context, Outcomes, and Study Type.

Search Strategy

Electronic Search

A systematic literature search was developed in consultation with a specialist librarian from the University of East Anglia and a senior information scientist from Public Health England (PHE). An iterative process helped to define the final search terms while ensuring a balance between sensitivity and specificity. A systematic literature search was performed in 8 electronic databases: Medical Literature Analysis and Retrieval System Online, or MEDLARS Online (MEDLINE), EMBASE, Cumulative Index to Nursing and Allied Health Literature (CINAHL), PsycINFO, Scopus, Cochrane library database, DataBase systems and Logic Programming (DBLP), and Association for Computing Machinery (ACM) Digital library. The databases were searched with no data limit, no publication or geographical restriction, but limited to the English language. Synonyms of 3 concepts were searched: (mhealth) AND (behavior change) AND (uptake or engagement; Multimedia Appendix 3 shows the MEDLINE search strategy). The electronic search was initially performed in November 2018 and was updated in August 2019.

Searching for Other Resources

Additionally, the search also included a manual search in key journals, such as *Journal of Medical Internet Research* and *Computers in Human Behavior*, and in *Google Scholar*. Reference lists of all included studies were hand-searched for additional studies. The search for gray literature included dissertations and theses, and unpublished research data and material were sought from government bodies and policy makers during stakeholder communication (PHE, National Health Service [NHS] in England).

Identification of Studies

All records identified by the search strategy were exported to Endnote X9 and deduplicated. To reduce the likelihood of reviewer selection bias and to assess how reliably the study eligibility criteria were applied, a subsample (10%) of records was additionally screened by a second reviewer (FN) during the title and abstract screening. Interrater reliability based on the number of eligible and ineligible studies was tested using Cohen's kappa statistics [28], with the following cut-offs being used: 0.41-0.60 to indicate moderate agreement, 0.61-0.80 substantial agreement, and 0.81-0.99 almost perfect agreement [28]. The full texts of potentially eligible studies were independently screened by DS, with 20% randomly selected and double-screened by FN. The exclusions of the studies were justified and recorded.

Data Extraction

A data extraction proforma was developed by the first author following the existing Cochrane guidelines [29], and the subsequent data were extracted: study characteristics (author, date of publication, sample size and type, location of the study, type of app investigated in the study, aim of the study, methodological characteristics such as design, data collection, and participants), main findings related to the research question of this systematic review (including participants' quotations and authors' interpretations in the qualitative studies and reported results of the quantitative studies), and conclusions of each study. The data extraction was performed by 1 reviewer (DS) and was checked for accuracy by a second reviewer (FN).

Quality Assessment

To assess the quality of the studies, critical appraisal was conducted using the latest version of the mixed methods appraisal tool (MMAT) [30]. MMAT is a unique tool [30] that was developed by pooling together the core relevant methodological criteria found in different well-known and widely used qualitative and quantitative critical appraisal tools [31-33].

The quality of all studies was assessed by the first reviewer (DS) and checked for accuracy by 2 other authors (FN and AJ). The tool is not intended to score the studies or to exclude papers but to offer a guide for interpreting findings [30].

Data Synthesis and Analysis

Integrative synthesis was applied to analyze the data [34,35]. The focus of the synthesis was on interpreting the data using specific concepts of the TDF as a deductive coding framework, which, for ease of interpretation, is summarized under the components of the COM-B model. Using the integrated approach, the data were pooled together by findings viewed as answering the same research questions, rather than by methods (eg, quantitative vs qualitative) [34,35].

Deductive thematic synthesis, a methodology designed to enhance the transparency of synthesizing qualitative data [36], was used to conduct the data synthesis of the findings of the qualitative studies and the qualitative component of the mixed methods studies. Using line-by-line coding, the findings were coded deductively into the domains of the TDF. The coding was conducted by the first author, and a randomly selected 10% of the coding was checked for accuracy by another author (FN). Regular coding meetings were conducted to maintain consistency. The expert opinion of an independent researcher with extensive experience in systematic reviewing was sought for data synthesis. The integrative approach includes interpretation of the quantitative findings by *qualitizing* [35], which refers to the textual interpretation of the findings of the quantitative studies (regardless of the interpretation of the author) so they can be combined narratively with qualitative data [35].

Results

Included Studies

A total of 7633 studies were initially retrieved, with a further 6 identified through manual search and reference check. An additional unpublished research report was received from stakeholders as part of the gray literature search process. No non-English papers were identified. A total of 2138 duplicates were removed. A total of 5429 studies were excluded based on the review of their titles and abstracts. Figure 1 illustrates the inclusion and exclusion of the studies following the guidance of the PRISMA flowchart [27].

During title and abstract screening, *substantial* agreement was achieved between the 2 independent reviewers (κ=0.63) [28]. Two types of disagreements were identified (one reviewer included studies that targeted app used in conjunction with a connected device and purely user-research studies) that limited agreement between the reviewers during the selection process, which were resolved through discussion and consultation with another author (AJ). After disagreements were resolved and the eligibility criteria were updated accordingly, 73 studies were identified as potentially meeting the inclusion criteria. All remaining titles and abstracts of records were assessed by 1 reviewer (DS). Of these, 41 studies were included in the review [37-77], out of which 13 were quantitative [41-44,49,53,55,63-65,68,76,77], 7 were mixed methods [38,47,59,62,73,74,78], and 21 were qualitative studies [37,39,40,45-47,50-52,54,56-58,60,61,66,67,70-72,75].

Description of the Included Studies

The end users of the studies were described as the general public [37,39,42,44,46,47,50-54,56-59,65,71,72,75,76], college students [48], existing app users [38,43,46,49,55,63,67,77,78], male workers in the male-dominated industry [60], lesbian, gay, bisexual, transgender, queer, and other spectrum of sexuality and gender (LGBTQ+) communities [40], rural communities [57], Asian ethnic minorities [41], pregnant women [73], patients in primary care [45,61,74], adult cancer survivors [62], adults with diabetes [57], those infected with HIV [64], those with chronic disease [68], and those with a bipolar disorder [69]. The focus of some studies was very specific and targeted a certain health behavior or condition, including alcohol reduction [38,46,54,58,59,64], smoking cessation [40,58,67,72,77], increasing physical activity [39,45,48,49,53,62,65,68], weight management [47,48,51,53,63,65,66,71,78], depression [52,61], mindfulness [50], diabetes management [57], and health management in pregnancy [73]. Other studies were less specific and targeted a more general mental health app [43,60,70] and a more general health app [37,41,42,44,55,56,74-76]. In all, 15 studies investigated factors influencing one particular app [38,39,43,45,46,49,50,54,55,63,65,67,70,72,77]. The remaining 27 studies examined users' perceptions of a wide range of apps or of a hypothetical app not yet developed.

The studies were published between 2011 and 2019 and were carried out in Australia [37,49,60,61,70], Belgium [69], Canada [40,51,55,67], China [68,73,76], Czech Republic [65], Ireland [45], Italy [39], New Zealand [47], Norway [75], Sweden [52], the United Kingdom [38,46,50,54,58,59,62,66,71,72,74], and the United States [41-44,48,53,56,57,63,64,77]. The study characteristics are summarized in Multimedia Appendix 4.

Quality Assessment of the Studies Included

On the basis of MMAT [30], the majority of the studies employing qualitative methodology were deemed to be of high quality. Concerns related to the sample were identified across many quantitative studies. This included issues around sampling and lack of clarity as to whether the groups were comparable at baseline or whether the sample was representative of the general population. In 4 nonrandomized studies, confounders were not accounted for by the design and analysis. Out of 7 mixed methods studies, 2 were judged to be of low quality, out of which one is an unpublished report (gray literature) and the other one is a published short report. See Multimedia Appendix 5 for details of the quality assessment for each study.

Data Analysis and Thematic Synthesis

Although not all the studies presented data for all aspects of this review, all studies presented some data that could be included in the synthesis. Evidence that was considered weakly explained or was judged to be unclear was not included in the summary of findings. An overview of the identified factors and the level of influence (uptake, engagement, or both) along with a brief description of each factor can be found in Table 2. Examples of supporting evidence are provided in the Textboxes 1-10.

Figure 1. Preferred Reporting Items for Systematic Reviews and Meta-Analyses flowchart illustrating the inclusion and exclusion of studies.

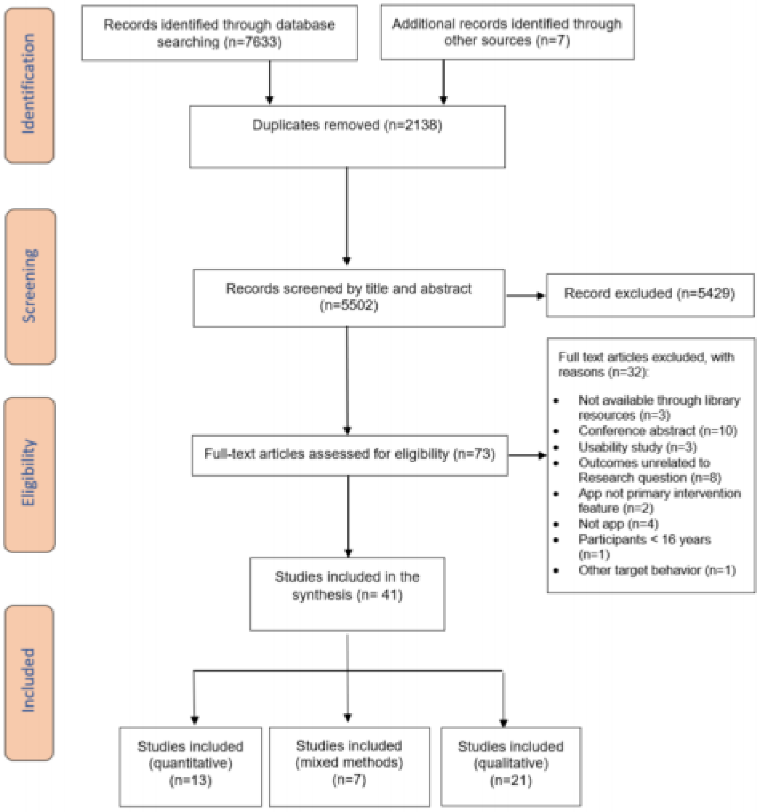

Table 2. Factors identified in the systematic review.

COM-B[a] component, TDF[b] construct, and identified factor (source)[c]	Uptake, engagement, or both	Short description of the factor
Physical capability		
Skills		
App literacy [46,50,57,61,65]	Both	Technological competency
Psychological capability		
Knowledge		
App awareness [54,56,57,61,75]	Uptake	Knowledge of the existence of health and well-being apps
User guidance [37,39,46,50,59,72]	Both	Instructions on how to effectively use the app
Health information [47,51,53,54,56-58,62,69,72,75,78]	Engagement	Educational information related to health and well-being aspects
Statistical information [37-39,46,52,54,57,66,67,71,72,75]	Engagement	A visual or numerical summary of progress
Memory, attention, and decision processes		
Well-designed reminders [37-40,43,46,48,51,52,54,56-58,62,66-69,71,78]	Engagement	The ability to customize reminders
Less cognitive load [37,39,46,48,50,51,54,56-58,60,66,69,71,72,75]	Engagement	The app is not too time consuming, easy to use, and requires minimal input
Coping games [40,60,67,72]	Engagement	Distraction activities within the app
Behavioral regulation		
Self-monitoring [36,38-40,45,48,51,52,55,57,59,60]	Engagement	The ability of the app to help self-regulation of the target behavior
Established routines [38,48,50,54,66]	Engagement	Regularity in using the app
Safety netting [37,61,66,73]	Engagement	Retaining the app for a potential precipitating event in the future
Physical opportunity		
Environmental context and resources		
Availability and accessibility [37,40,45,49,52,57,72,78]	Uptake	The ability to use a smartphone anytime anywhere
Low cost [37,40,47,48,56,68,72,74]	Uptake	The price of the app
Interactive and positive tone [46,51,57-60,69,71,72]	Engagement	Encouraging communication style
Personalization to needs [37,38,40,47,50,52,56,57,60-62,69,71,72,75,78]	Engagement	The possibility to use an app that is tailored to a user's needs
Social opportunity		
Social influences		
Recommendations [56-58,61,74]	Uptake	Suggestions received from other users
Health practitioner support [37,40,51,52,57,59,62,67,69,72,73]	Engagement	Possibility to get in touch with health professionals and practitioners within the app
Community networking [37,39,40,47,56,59,62,66-73,75]	Engagement	Social interaction with users with similar needs within the app or within their community
Social media [39,40,48,54,56,58,61,66,67,71,72,75,78]	Engagement	A choice to connect to social media platforms
Social competition [37,39,48,56,59,66,67]	Engagement	Competitive nature of the app with others or with themselves

COM-B[a] component, TDF[b] construct, and identified factor (source)[c]	Uptake, engagement, or both	Short description of the factor
Personification of the app [39,45,47,48,50,56]	Engagement	Applying human attributes to the app
Automatic motivation		
Reinforcement		
Feedback [37,39,45-48,51,52,54,56,58,62,67,72]	Engagement	Feedback regarding the user's performance
Rewards [37,40,45,46,56-59,66,69,71,75]	Engagement	Tangible and intangible reward in response to the user's effort
Emotions		
Curiosity [38,52,54,61]	Uptake	Desire to acquire knowledge and skills to use a behavior change tool
Reflective motivation		
Goals		
Goal setting [38,39,45,48,51,54,56,58,59,66,71,74]	Engagement	Establishing what the user would like to accomplish
Beliefs about consequences		
Perceived utility of the app [37,46,52,59,61,74]	Engagement	Discrepancy of what the users are looking for and what the app offers

[a]COM-B: capability, opportunity, motivation, behavior model.

[b]TDF: theoretical domains framework.

[c]Studies where the factors were identified.

Physical Capability

Theoretical Domains Framework: Skills

Skills refer to one's ability to perform an action and include constructs such as competencies, interpersonal skills, skill development, and practice (Textbox 1). App literacy [46,50,57,61,65], defined as technological competency to use a smartphone app, was reported by participants as being of high importance for both uptake and engagement. A basic level of app literacy is required to be able to download and initiate engagement with an app (see quote 1, Q1), whereas adequate app literacy skills would enhance users' intentions to engage with an app (Q2) [46,50]. In a cross-sectional study, advanced app literacy was associated with increased use of the social functions of an app, such as networking, but not with the functions that target action planning and goal management [65]. This suggests that app literacy might be an important aspect for successful uptake, but this alone might not be enough to maintain engagement. In contrast, users have reported that lack of app literacy skills could trigger negative emotions toward themselves (eg, self-blame and disappointment of not being able to use an app) [46,50,61] and could contribute to their perceived low self-confidence in using technology [61].

Textbox 1. Illustrative quotes (Q1 and Q2) for factors mapped onto the physical capability subcomponent of the capability, opportunity, motivation, behavior model and coded under the theoretical domains framework: skills.

Uptake and engagement

App literacy

- Quote 1: "I'd be happy to do it if I knew how to do it [but] I don't know how to download apps...I need help with technology. Like, I'm 58 and I didn't grow up in a technological age and so do find that I lack confidence with technology." [61]
- Quote 2: "I've never used it [these apps] because I never got it to work the way I wanted it to." [57]

Psychological Capability

Theoretical Domains Framework: Knowledge

Multiple factors were identified under the TDF domain that covers rational, procedural, and other types of knowledge; information; and awareness of the existence of something (Textbox 2). App awareness [54,56,57,61,75], such as information on the existence of health and well-being apps, would positively influence the uptake of health and well-being smartphone apps (Q3). It was suggested that many participants were not aware of the availability of such tools, and some found the disorganized nature of the commercial app stores confusing and represented a barrier for uptake [61].

Textbox 2. Illustrative quotes (Q3-Q13) for factors mapped onto the psychological capability subcomponent of the capability, opportunity, motivation, behavior model and coded under the theoretical domains framework: knowledge.

Uptake

App awareness

- Quote 3: "I didn't realize that they had an app." [57]

Engagement

User guidance

- Quote 4: "I want something to tell me 'Do number 1 first, then number 2. When you've done this go here' so I don't have to think too much about it. Once I've got it up and running I'm fine." [46]
- Quote 5: "Just at the beginning of the app, when you've downloaded it and you're using it for the first time, it should tell you what to do. But not every time. You don't need guidance how to use it and where things are, because I think it would just be annoying." [59]

Health information

- Quote 6: "[It is] important and really helps me to learn about bipolar disorder and read about stuff." [67]
- Quote 7: "I... enjoy learning something new. It's quite informative and makes you think about what you're doing. [QG] helps you to understand a bit more about what's going on...what could go wrong by continuing [to smoke]." [72]
- Quote 8: "I personally am scared of getting lymphedema, and still don't know sometimes what exercises are good to prevent it, so I think that maybe educating people about [...] consequences of not exercising from a really good NHS source would be helpful." [62]
- Quote 9: "I think everyone has heard that information many times. It's actually quite patronizing...shallow stuff, not hard-hitting useful facts. It obviously isn't a tailored app to each person, but it gives enough information that each person can relate to it in a tailored way. I find it really engaging, I suppose that's why I stuck with it." [72]

Statistical information

- Quote 10: "I like the numbers. I like to track stuff and have some figures behind it rather than just like, oh, I'll go for a run today. I'll be like, well, I'll go for a run today but what's my time from last time and how can I beat it? And I think that's why this kind of app appeals to me. If I just put the drinks in and it just said you're drinking too much but didn't give any numbers behind it, I'd probably delete it within a few days." [38]
- Quote 11: "It was like a visual of my day of smoking. And every day, you'd look at it, it went down and down and down, like it got better every day. So it was like a motivational thing to just look, like positive reinforcement." [67]
- Quote 12: "I couldn't find any graph that's reflected the mood so therefore I didn't see the point of having to fill that part out and I stopped filling it out." [46]
- Quote 13: "If you're having a bad day or a couple of bad days, seeing it on [the app] as a reflection [of your bad days] just like kicks you in the face even more, you know?" [67]

User guidance [37,39,46,50,59,72], namely, instructions on how to effectively use an app, such as how to create achievable goals, influenced uptake and initial engagement. It was proposed that having a guide on how to use an app could positively affect the users' intention to engage with it, and hence, users might be able to better regulate their behavior (Q4) [46,59]. However, the presence of a guide was reported off-putting and unnecessary for long-term engagement by producing negative emotions (eg, annoyance) once the knowledge regarding app functionality has been gathered (Q5) [59].

Available health information within the app was perceived by users as beneficial and positively influenced their engagement in several studies (Q6 and Q7) [47,51,53,54,56-58, 62,69,72,75,78]. Depending on the target behavior, end users wished to (1) access advice on exercise routines [39,56,62,66]; (2) seek nutritional education [39,51,56,57,66,70]; (3) widen their knowledge of health consequences [58,67,72]; (4) find out more about healthy living while living with a medical condition [62,73]; (5) know more about the conditions they are living with [69,73,75]; (6) improve their health literacy [75]; (7) demystify myths [72]; (8) receive health news updates, such as on smoking taxes and bans [72]; and (9) better understand alcohol units in the UK [54].

However, the quality of information was identified as potentially affecting engagement [72]. Some users wanted a credible source, a trustworthy and evidence-based guide with references to the information they receive (Q8) [62,70,73]. Health information that focuses on negative aspects of past behavior that cannot be modified (eg, smoking or alcohol consumption) would trigger negative emotions (eg, regrets) [58]. It was suggested that better quality of information would increase the likelihood of maintaining users' engagement with an app, and consequently, they would better self-monitor their behavior [56,67]. This could be achieved by providing a wide range of information that everyone could relate to rather than facts that are already known (Q9) [72]. For example, 1 qualitative study suggested the use of health quizzes to promote engagement [75]. Health quizzes were also found promising by a large study that evaluated the uptake of a loyalty points–based health app conducted in Canada [55]. One of the intermediate objectives of that study was to improve the Canadian population's health literacy by using health information related to quizzes. The app usage data included quiz completion rates, and the results showed that 60% of the users were highly engaged with the app by having more than 75% of health quizzes completed. Furthermore, better health literacy might enhance beliefs about consequences (eg, health outcome expectancies) [67,72] and the users' intention to stay engaged with an app and subsequently with the behavior they target to change [72,75]. Mackert et al [53] also found that adequate heath literacy was associated with increased engagement with fitness and nutrition apps.

Users valued available statistical information [37-39,46,52,54,57,66,67,71,72,75], which was a visual or numerical summary of progress or a trend in their behavior. This included features such as step counting [71,75], the number of calories consumed [54,71], number of days spent abstaining from smoking [67], the amount of money saved by quitting smoking [72] or by reducing drinking [54], a trend in their alcohol consumption and how it changes over time [38,46,54], as well as a way to allow analysis of user data [37,75]. Being able to check their progress helped users better monitor their behavior (Q10) [37-39,71,72], and for some individuals, a positive trajectory acted as a behavioral reinforcement (Q11) [46,67]. In 2 studies, participants reported that a lack of visual representation of progress led to disengagement with the alcohol reduction app (Q12) [38,46], and 1 study on smoking cessation reported negative emotions associated with progress viewing during *a few bad days*, suggesting discouragement (Q13) [67].

Theoretical Domains Framework Domain: Memory, Attention, and Decision Processes

This domain focuses on the ability to retain and select information, including aspects of attention, memory, decision making, and cognitive overload (Textbox 3). Reminders [37-40,43,46,48,51,52,54,56-58,62,66,67,69-71] to engage with an app were reported to be useful for people with busy schedules and for those who tend to forget engaging with the app and, therefore, with the target behavior [37,39,43,56,67]. Individuals described being inclined to check their phones when receiving a notification [37,38,40]. Reminders positively affected behavioral regulation by prompting engagement with self-monitoring and the tracking features of the app (Q14) [37,39,40,51,54,62,67,69-71] as well as reinforcing the users by reminding them about their positive progress [40,48,51]. A microrandomized trial found that a push notification that contained a tailored health message resulted in a small increase in the engagement with a health app [43]. A large study conducted on engagement with a weight loss app found that 16% of the most engaged group used reminders, compared with 1% of the least engaged group [64]. However, not all users found reminders useful [37,39,51,56-58,66]. In the case of behaviors that are associated with stigma (eg, alcohol consumption), reminders would threaten the users' social identity when they are received at an inappropriate time or wrong place (Q15) [38,46,54]. Therefore, the timing of when the reminders were sent as well as the language used appeared to be important conditions. If these conditions were not met, users were more likely to turn the notifications off [37,38,69] or ignore them (Q16) [56,66,67].

Textbox 3. Illustrative quotes (Q14-Q20) for factors mapped onto the psychological capability subcomponent of the capability, opportunity, motivation, behavior model and coded under the theoretical domains framework: memory, attention, and decision processes.

Engagement

Well-designed reminders

- Quote 14: "I found it was almost like having my girlfriend there, in a good way. So you're like, oh I haven't done this in two days, I didn't even realize, but my phone just reminded me. Better keep it going." [67]
- Quote 15: "I think because they were just pinging... and I was just thinking, I don't really want to read this right now. Obviously, and I don't know whether they do but I guess most people check their phone when something pings in and you can be with your friends and actually maybe you wouldn't want to be saying to your friends, I've just got a notification from Drinkaware." [38]
- Quote 16: "I completely ignored them [notifications]. Actually, I'm pretty sure I had the notifications that were from the app all turned off. It just felt like a pop up, like another thing for me to click close on throughout the day. I completely paid no attention to it." [67]

Less cognitive load

- Quote 17: "I really loved it [Couch to 5K], there was no excessive login, it was really easy you just downloaded and start you have to have your email, no password, no nothing like that, they don't send you a bunch emails that annoy the crap out of me. Nothing." [48]
- Quote 18: "What I'm thinking is, this better be easy, because otherwise I'm probably not going to do it. If there are too many obstacles in the way I won't. Even though I know I need to do this, I probably won't." [46]

Coping games

- Quote 19: "If there was a bunch of games on the app that were there to distract you from smoking, (you could) go play 5 mins of a quick game instead of smoking." [40]
- Quote 20: "Maybe if they had prior to like some type of like a mini game or something in there that would keep the mind occupied rather than telling you, "Don't smoke." [72]

Regarding attention and decision processes, the findings of the studies included in the review proposed that cognitive overload should be avoided to maintain engagement with an app. An app that is less time consuming, requires minimal input, and is easy to use and log into was preferred (Q17) [37,39,46,48,50,51,54,56-58,60,66,69,71,72,75]. Additional functions that decrease the time spent on a task using an app were highly appreciated [37,39,48,50,54,56,71,72,75]. The automatization of data collection, for example, by linking apps to wearables [37] or by using the camera function to scan the barcodes to input calories [71] was found to be particularly useful in physical activity and weight management apps. An app that is easy to use and does not require extra effort would increase the intention to engage with it [39,46,48,54,56,57,74] and would improve users' self-monitoring and self-management strategies [48,51,66,75]. Conversely, using a difficult and time-consuming app would affect the users' perceived competence in engaging with it (Q18) [50]. Such an app often would be deleted or replaced with another app that is perceived to be easier to use [46,48,56,66,71]. Only 1 study found that users who are highly committed to change behavior (in this case, to reduce alcohol consumption) would be willing to overcome this barrier [54].

Including coping games [40,60,67,72] as distraction activities has been suggested as a helpful way to cope with cravings (smoking) [40,67,72] or with distress [60]. Some users indicated that by using their hands and minds, they expected to be preoccupied, instead of engaging with the undesirable behavior, while keeping them engaged with the app itself (Q19-Q20).

Theoretical Domains Framework Domain: Behavioral Regulation

Behavioral regulation refers to managing, monitoring, or changing actions or behavior (Textbox 4). Self-monitoring, the ability of an app to help monitor and regulate the target behavior [36,38-40,45,48,51,52,55,57,59,60], was found to be important in supporting behavior change. A self-monitoring feature was able to raise awareness about the number of cigarettes smoked [40,58], the amount of alcohol consumed [58], the number of steps taken [45], the mood they have [60], or users calorie intake (Q21) [48,56]. It also enhanced users' intention to engage with an app [51,52,58], provided *self-reinforcement* [52], helped increase self-efficacy (Q22) [56,61,71], and evoked feelings of *control, security, health, empowerment, and autonomy* [54].

An established routine or regularly using an app [38,48,50,54,66] positively affected the intention to engage with an app [50] and to maintain engagement (Q23). Furthermore, safety netting [37,61,66,73], defined as the ability of an app to provide *aftercare* [66] and an option to retain an app for a potential precipitating event in the future and for relapse prevention, was found to be useful to maintain the behavior, even when the target behavior has been achieved (Q24).

Textbox 4. Illustrative quotes (Q21-Q24) for factors mapped onto the psychological capability subcomponent of the capability, opportunity, motivation, behavior model and coded under the theoretical domains framework: behavioral regulation.

Engagement

Self-monitoring

- Quote 21: "You get a chance to see what you do on a daily basis, something you're probably not aware of." [56]
- Quote 22: "Because I can see I'm getting better, I use the app now, but I can see myself in the future not having to use it. Kind of like a stepping stone I guess." [71]

Routines

- Quote 23: "Because, I've got a couple of other little apps that I look at on a daily, not all apps, but a little regime of four or five, you know, I check the weather and I look at my drink app, and various things like that, a little routine, so pretty much daily." [38]

Safety netting

- Quote 24: "I think the migraine one's probably outlived its usefulness for me, but the back pain one, I could still go back to that at any time. If I started to need to monitor my pain again in a systematic way, I'd still go back to it." [37]

Physical Opportunity

Theoretical Domains Framework: Environmental Context and Resources

This domain refers to the circumstances of an individual's situation or environment that positively or negatively affects the uptake of or engagement with health and well-being smartphone apps (Textbox 5). The availability and accessibility of a smartphone [37,40,45,49,52,57,72,78] facilitate both uptake and engagement by having a behavior change device in close proximity (Q25). Although smartphones or tablets enhance the portability and accessibility of health apps, the development of an accompanying website was suggested to reduce inequality for those who might not have the opportunity to own a smartphone (Q26) [40]. Furthermore, the results of a digital behavior change intervention study examining engagement and nonusage attrition with a physical activity program suggest that when the app was used together with the accompanying website, a higher engagement rate was observed compared with those who used the app-only or the web-only versions [49].

The low cost of an app was found to be an influential factor for uptake [37,40,47,48,56,68,72,74] so that low-income individuals would be able to afford them (Q27) [47]. In a questionnaire study in China, 1 of the top barriers to using a health app was the extra cost, having a total of 83% of patients reporting that they would not be willing to pay for a health app [68]. Nevertheless, a few participants expressed their willingness to pay a small extra fee (ie, under US $5) if, this way, they could unlock unique features otherwise not available with the free version (Q28) [37,48,56,74].

Textbox 5. Illustrative quotes (Q25-Q34) for factors mapped onto the physical opportunity subcomponent of the capability, opportunity, motivation, behavior model and coded under the theoretical domains framework: environmental context and resources.

Uptake

Availability

- Quote 25: "It was real easy you just put it in your pocket and off you go and... you could do it at your own pace." [45]
- Quote 26: "I feel like there would need to be a website equivalent with it (for) people who don't have access to smartphones but do have access to public libraries. A lot of smokers are LGBTQ and a lot of LGBTQ are in poverty and homeless. The people that you want to access might not be able to access the program." [40]

Low cost

- Quote 27: "I wouldn't pay money for an app. I think that's kinda stupid." [48]
- Quote 28: "I'm prepared to pay for applications. As well as being in the software industry, I understand that it's people's livelihoods are attached to this. I use some free applications, but I often will pay for the upgraded or the purchased option." [37]

Engagement

Positive tone

- Quote 29: "I had a chocolate bar today and It would say, this chocolate bar contained this much saturated fat and... I just feel really guilty now." [71]
- Quote 30: "I think I'm more likely to listen to practical advice rather than finger wagging..." [58]
- Quote 31: "I just see it as a way to help me monitor what I'm doing and maybe give me a little kick in the pants every now again to be like, 'By the way, that donut had five hundred calories in it. Maybe make a better choice at dinner'." [51]

Personalization

- Quote 32: "The more I would be able to manipulate the app to be and do what I wanted or needed, for my own circumstances, the more likely I am to use it." [59]
- Quote 33: "It must be very personalized, it's easy to find things on the Internet, but it's mostly for normal people." [75]
- Quote 34: "Assuming that it's customised to LGBTQ (and) it incorporates the kinds of struggles that we've lived through, it wouldn't be any average quit-smoking app. The fact that it's specific to a community... the fact that it's LGBTQ-specific, that would help us more than if it was just a general quit-smoking app." [40]

Numerous studies have found that interactivity and positivity of tone may be efficacious for engagement, especially when attempting to change behaviors associated with self-blame (eg, weight management) (Q29) [46,51,57-60,69,71,72]. In total, 3 studies provided evidence that an encouraging tone rather than a condescending tone was important [46,58,69]. Evidence from 1 study suggested that apps should use praise but avoid shame [51], and another study provided evidence that a relaxed tone may be beneficial and may include jokes [46]. Several studies suggested that demanding or annoying language would be ignored (Q30) [57-59], although a study of nutrition apps reported the occasional need for a tougher attitude to achieve goals (Q31) [51]. Nevertheless, careful selection of the terminology used to understand the app and what it does, such as using simple and clear language, was suggested to make a noteworthy difference in the effectiveness of the content [60,72]. Terminology around certain behaviors might make a difference. For example, it was reported that using a *nonsmoker* label as opposed to an *ex-smoker* label would increase people's self-confidence [72]. It was suggested that unsupportive language would evoke negative emotions (eg, guilt and regret), which would affect the intention to engage with an app [46,59,71].

A personalized app was highly valued for engagement [37,38,40,47,50,52,56,57,60-62,69-72,75]. Users would want to have control over the app (Q32) [59,66,69]. They would like to be able to switch off features they do not use [37], and to use external incentives, such as uploaded photos or quotes [66,67], and to personalize their goal and how to achieve it [40]. Users would also like to choose a level where to start using a particular app. For example, a more experienced user would want to have the possibility to start a mindfulness practice at the intermediate level rather than at the beginner level [50]. Users were seeking to receive more personalized information about their current behavioral habits, demographic characteristics, long-term effects of the current behavior [38,56,60,78], and recommendations based on their tracked data [57]. Personalization can also be extended to their identity (Q33). Participants were looking for an app that is tailored to their cultural and social identities, such as LGBTQ+ people, cancer survivors, or other patients who are predisposed to have other struggles and mental health issues (Q34) [40]. Personalization to users' needs and preferences suggested better engagement [58,59,61], whereas lack of flexibility in content was found to be a reason to stop engagement [52], and in some cases, it created frustration [71]. Furthermore, a large study found that 30% of the most frequently engaged group customized the app more, for example, uploaded pictures, than the least engaged group (2%) [63].

Social Opportunity

Theoretical Domains Framework: Social Influences

Social influences are interpersonal influences (received from other individuals) that could impact an individual's behaviors, decisions, thoughts, and feelings (Textbox 6). In 5 studies, recommendations to use an app [56-58,61,74], received from health care practitioners or trusted providers [57,61,74], friends and families [56,60,74], or by reading user reviews [56,58,74], positively affected the uptake of health and well-being apps (Q35-Q37).

Connections between an app and health practitioner support were highly valued [37,40,51,52,57,59,62,67,69,72,73]. Participants reported that counseling services should be linked to an app [40,67,69], such as an *emergency button* feature [69], whereas others have emphasized the importance of linking an app to their health care provider (Q38-Q40) [37,62]. Health practitioner support could help overcome potential barriers caused by lack of skills, such as app literacy [52]; enhance self-monitoring [52,62]; and act as reinforcement [52], having the potential to enhance intentions to engage with the app (Q40) [52,62,72].

The possibility of community networking within apps with other users or other people with similar needs has been identified in multiple studies [37,39,40,47,56,59,62,66,67,69-73,75]. It was considered an important social support by reinforcing behavior change [47,56,59,62,69,72,73] and by sharing knowledge and experiences [37,69,73,75]. This was found to increase their intention to engage with the app and, subsequently, the behavior (Q41-Q42) [62]. A large study found that the most engaged group had a mean number of 24 friends within the app, as opposed to the least engaged group (1 friend) [64]. Users' potential social roles or group identities and personal preferences should be taken into consideration. For instance, individuals from the LGBTQ+ community [40] and cancer survivors [62] would wish to interact with people who face similar challenges (Q41). In addition, some users would not want to share information with strangers due to fear of social comparison [39,59] or social stigma [54], whereas others were more open to connecting with strangers rather than with friends or family (Q42-Q44) [56].

Evidence for the importance of embedded social media for engagement has been mixed [39,40,48,54,56,58,61,66,67,70-72,75]. It largely depends on the individual's attitude toward these channels and on the target behavior. Some users found this reinforcing (Q46) [40,61,71,75], whereas others did not want to engage with such features due to social stigma (eg, smoking, alcohol consumption, or weight management; Q46-Q47) [39,48,54,56,58,67,72].

Social competition [37,39,48,56,59,66,67] includes the possibility for individuals to compete with themselves (ie, their previous achievements or breaking their own records) or with other app users (Q48-Q49). A total of 5 studies suggest that the reinforcing nature of social competitions might increase the intention to engage with an app [37,48,56,59,66]. The increased engagement was anticipated when the competition is based on support by receiving encouragement from others [39,67], rather than on defeating each other, which might prompt discouragement to use the app (Q50) [67].

Several studies described that some participants felt that apps can impersonate a little person [39,45,47,48,50,56], which increased the intention to use the app (Q51-52) [45,48,50]. It was also suggested that if the app is too impersonal, it would not offer the social support the users' need [47]. In contrast, in 2 studies, the participants were concerned about having a machine telling them what to do (Q53) [47,56].

Moreover, personal experience related to noncommunicable diseases might increase the chances of the uptake of apps. One study conducted on Latino and Asian subgroups in the United States found that the odds of downloading a health app was twice as high for those who had a family history of heart attack (odds ratio 2.02, 95% CI 1.16-3.51), compared with those who did not [41].

Automatic Motivation

Theoretical Domains Framework: Reinforcement

Reinforcement is a process or action of encouraging a pattern of behavior (Textbox 7). Users reported better engagement when positive feedback was received (Q54) [37,39,45-48,51,52,54,56,58,62,67,72]. Visual feedback of progress made users aware of their advancement in reaching their goal (Q55) [37,45,46], whereas auditory feedback was seen as encouraging during physical activity (eg, running) [37,48]. For some, instant feedback on their progress, even if it is of a positive nature, was perceived to cause pressure and potential disappointment if they were not able to reach their goal (Q56) [45,56].

Offering rewards [37,40,45,46,56-59,66,69,71,75] was found to be a useful way to increase engagement. Participants suggested including gamification elements in apps to enhance engagement [37,56,69,71,75]. Some users found intangible rewards (eg, badges) motivating (Q57) [46,56,58,59,66,71], whereas others would want to receive tangible rewards instead (eg, free t-shirt, gift cards, cash, reduction in health insurance, or vouchers provided by hospitals or doctor's office; Q58-Q59) [40,56,58,66]. This has been partly supported by 2 quantitative studies. In 1 study, having a health insurance was associated with uptake of, but not with engagement with, health apps [42]. Another study found that when offering loyalty points, engagement increased for at least three months [55].

Textbox 6. Illustrative quotes (Q35-Q53) for factors mapped onto the social opportunity subcomponent of the capability, opportunity, motivation, behavior model and coded under the theoretical domains framework: social influences.

Uptake

Recommendations

- Quote 35: "I'd rather ask a counselor or a doctor what they would recommend." [61]
- Quote 36: "Most of mine [my apps] are friend recommendations, people with similar activities." [56]
- Quote 37: "...if an app has a good rating, despite the one or two people who are not satisfied, I think it would mean that it works for the majority of people." [58]

Engagement

Health practitioner support

- Quote 38: "It would help in times of crisis to be able to be in touch with a professional, or if I needed to ask health questions related to alcoholism." [59]
- Quote 39: "I want to let others know when I'm not well, the app would help me." [69]
- Quote 40: "The therapist helped me to find my motivation every now and then, and then I was on top of it for about a week or so, and eventually the application sort of became a part of my everyday life. Then it was pretty obvious that I would use it and then I didn't even think about whether it was hard to use it, I just did it." [52]

Community networking

- Quote 41: "It is so important to get in touch with people who went through the same thing as you have. [...] I think that if an app for cancer survivors had a forum on it as a part of the application to motivate each other, that would be amazing." [62]
- Quote 42: "I don't think I would share on the social media, but within the app community I think it is important to like inspire and be motivated by others." [66]
- Quote 43: "So having some sort of platform where everyone can just say, 'This is how I stopped' or 'This is how I'm trying to stop' and then other people giving feedback saying, 'This is good' or, 'This is not'." [72]
- Quote 44: "Being able to exchange feedback with strangers with the same goal could be supportive but non-judgemental as you will probably not know the other users." [59]

Embedded social media

- Quote 45: "Integrating it with the social media is definitely a great thing to do because they can always fall back to Facebook, Twitter, etc. And through this, people can get to share their experiences and keep an update and tell whatever experiences they may have to share. So it's like ongoing support." [40]
- Quote 46: "Yeah you can share on Facebook and stuff, but I hate that. I hate when apps sync to like every form of social media. I'm like really weird about social media, so, no I don't want to share it." [48]
- Quote 47: "Don't want to share progress on social media in case you fail." [72]

Social competition

- Quote 48: "Whenever we do a weekend challenge, you always have a look at what the other person's doing and [their] competitive side. I just want to beat the other people I see on there, so [using the app] is quite a good motivator." [37]
- Quote 49: "It made me want to exercise more just, as like, kinda like, a competition to see how many calories because it takes your calories off whenever you exercise so I'm like let's see how many I can get off this time." [48]
- Quote 50: "Someone whose successful and quit smoking isn't any better than someone that's struggling with it. Like, no, I didn't-I don't like that aspect...it just makes someone feel bad." [67]

Impersonated app

- Quote 51: "It's like a 'little boss in my pocket'... that's sort of saying 'you know you need to get out and do this'." [45]
- Quote 52: "It's like your own little motivator, in a way. And it definitely, it's like, okay it's like a little person, but it doesn't talk, but it's like, you shouldn't eat that, or it's like you should. So I don't know it's, I like it—I mean, I think it's cool. It's like my own little motivation." [48]
- Quote 53: "I don't want an electronic device telling me what to do." [56]

Textbox 7. Illustrative quotes (Q54-Q59) for factors mapped onto automatic motivation subcomponents of the capability, opportunity, motivation, behavior model and coded under the theoretical domains framework: reinforcement and emotions.

Engagement

Feedback

- Quote 54: "I liked how it gave notifications, like every day I've got a notification saying; You're on day four of your smoking quitting history. You could do this, don't give up. Stay loyal and stuff like that. That was quite impressive." [72]
- Quote 55: "The big green continue at the bottom and when it moves on to the next thing I feel great, I've achieved something, I've filled something in correctly. I like that. And a nice little noise which made me think, Oh, I'm not an idiot." [46]
- Quote 56: "The progress I didn't make—it shows [and thus is demotivating]." [56]

Rewards

- Quote 57: "Earning badges [was] important when I was doing it...We learned as a kid, to consider [it] as [an] accomplishment." [56]
- Quote 58: "Each time you try, you get the points. And if these points can be converted to something else. Because you know, you're not really working for the badge but if the virtual badge can turn into something tangible, I would want that." [57]
- Quote 59: "Well, both of them are a kind of 'well done for doing this', they're both a reward, they both make you feel a bit better. But a badge, it's a cool fact, but it's not the same as having vouchers, where you can go and treat yourself to something you want." [59]

Theoretical Domains Framework Domain: Emotions

Emotions, based on previous experiences and behavior, are a complex reaction by which people tend to respond to a personally important event or matter (Textbox 8). Curiosity [38,52,54,61] positively influences the uptake of health and well-being smartphone apps (Q60). However, in 2 studies, both targeting alcohol consumption reduction, this factor was only relevant for a specific user type: for those who were characterized as *low-risk* drinkers [38] and *noncommitters* (ie, users who did not commit to engage with the app and, thus, did not gain any benefit from it) of the app [54].

Textbox 8. Illustrative quote (Q60) for factors mapped onto the automatic motivation subcomponent of the capability, opportunity, motivation, behavior model and coded under the theoretical domains framework: emotion.

Uptake

Curiosity

- Quote 60: "It was more like seeing an ad and just, okay I should try this — and then I found it on the internet and signed up. It was more like a fun thing. We'll see if it works. More like that." [52]

Reflective Motivation

Theoretical Domains Framework: Goals

Goals are outcomes that an individual would like to achieve to change a certain behavior (Textbox 9). Goal setting [38,39,45,48,51,54,56,58,59,66,71,74] was related to sustained engagement with health and well-being apps (Q61). Some users chose to set a goal, and mostly, this was only 1 goal at a time, so their focus would remain on 1 single aspect of change of the behavior (Q62), whereas others were more reluctant to use this feature because of fears of not being able to achieve their set goal and to avoid disappointing themselves (Q63) [38]. In general, the studies suggest that users were more determined to engage in behavior change when they had set goals [45] and believed they had successfully achieved or could achieve their goals with the help of an app by increasing their intention to use the app and by better monitoring the target behavior (Q64-Q65) [48,54,56,58,59].

Textbox 9. Illustrative quotes (Q61-Q65) for factors mapped onto the reflective motivation subcomponent of the capability, opportunity, motivation, behavior model and coded under the theoretical domains framework: goals.

Engagement

Goal setting

- Quote 61: "I'm not good at self-discipline and exercise, so maybe this [goal setting in the app] can help me get to my goal." [56]
- Quote 62: "I only set one goal because I was very keen to kind of remain focused on one thing. I didn't want to come and get lost in the app using it like a game. You know, I wanted to use it for one very specific thing... I think I set it to drink probably within guidelines." [38]
- Quote 63: "No, it didn't appeal - probably because I thought if I put some goals in I'm probably not going to stick to it, which probably makes me sound a bit naughty." [38]
- Quote 64: "If you set those manageable goals, so you could achieve it, if you feel like you're actually progressing, getting something, then you're more likely to go back." [58]
- Quote 65: "It would encourage me to open the app on a daily basis." [59]

Theoretical Domains Framework Domain: Beliefs About Consequences

This domain includes aspects related to outcome expectancies (Textbox 10). Perceived utility of the app [37,46,52,59,61,74] refers to where there is a discrepancy between what the users are looking for and what an app actually offers. It was suggested that the unmet expectations of an app would lead to disengagement and frustration with the app (Q66-Q68).

Textbox 10. Illustrative quotes (Q66-Q68) for factors mapped onto the reflective motivation subcomponent of the capability, opportunity, motivation, behavior model and coded under the theoretical domains framework: beliefs about consequences.

Engagement

Perceived utility of the app

- Quote 66: "I do have some apps I don't use often, mainly because they've kind of bored me in a way. I'll just do an example: one fitness app shows you how to lose weight, but the way it's describing it, it's not what I'm after. It's one of those free apps I bought that—I thought [the fitness app] would be great, but when you actually use it, it's not the same." [37]
- Quote 67: "I think that's where it let itself down for me. Once I'd played with it, once I tried the game, done the identity and whatnot, there wasn't much else there for me." [46]
- Quote 68: "It [mindfulness app] didn't add anything...I guess it didn't detract, it didn't make anything worse, but it didn't add anything to my armoury, I guess, my tool kit, as keeping myself sane, I suppose, it didn't add." [61]

Other Factors

There were a number of sociodemographic factors that did not fit clearly under the components of the COM-B model.

Sociodemographic Factors

Apps were more frequently downloaded by women than men, with the percentage ranging from 59% to 74% [38,41,49,53,55,63], although 1 study found that being male was associated with using an app to manage alcohol consumption [65]. Being younger than 44 years was associated with a higher level of uptake and engagement [38,41,42,44,49,53,55,63,64] than older adults. Living in an urban area [42,44,55]; having a better education level, such as having high school education or higher [41,42,44,64] and college degree or higher [41,53]; and having a higher income [44] were also associated with better engagement with health and well-being apps.

Discussion

Principal Findings

This is the first systematic review to conduct a theoretical analysis using the COM-B model of factors influencing the uptake of and engagement with health and well-being apps. The findings from this review suggest that there are 26 key factors across the constructs of capability, opportunity, and motivation that influence the uptake of and engagement with these types of apps, which were found to be important for a wide range of populations and behaviors.

Our review replicates previous findings in the wider literature on digital behavior change interventions. The core findings of our review suggest that attention should be perhaps shifted mainly to the support and guidance offered to new and existing users of health and well-being apps. We found that support and guidance of uptake can be targeted by increasing their awareness of health apps through, for example, recommendations received from health practitioners. In line with the findings of previous reviews, help with initial engagement could be achieved by improving the users' app literacy skills and by providing knowledge [14,17]. We present knowledge in a novel way by breaking it down to instructions on how to use it (ie, user guidance), advice related to the target behavior or condition (ie, health information), and information on their progress or data (ie, statistical information). This suggests that allowing access to users to different information that serves different purposes (eg, health benefits vs progress data) would enhance their engagement through different channels, such as guidance, support, and education.

Potentially, one of the most important factors for engagement identified in this review is health practitioner support. In line with the emerging evidence from the human-computer interaction (HCI) literature, we found that an app coupled with human support [14,17] was likely to be more effective by increasing the intervention effectiveness and engagement [78,79]. Alternatively, human support can be impersonated by embedded artificial intelligence (AI) features. A recent experimental study found that a supportive AI-powered chatbot doubled the engagement with a smoking cessation app and increased its effectiveness [80]. This suggests that embedded human support or features that mimic human support might lead to greater engagement with digital behavior change tools.

Behavior change techniques, widely reported by others previously [14,17-19], were also identified as important factors to sustain engagement, including self-monitoring, feedback, goal setting, reminders, rewards, and social support. However, we found that not all of these have a positive effect. Reminders and social support factors (embedded social media and social competition) are not universally useful and might cause disengagement or even harm by triggering negative emotions. One plausible explanation is that the participants of the studies included may or may not have real-life experience with health and well-being apps. Some of the included studies examined participants' perceptions about a hypothetical app or an app that was planned to be developed. These studies relied on the participants' opinion of what they think would be important for them in terms of uptake of and engagement with health and well-being apps, rather than sharing their lived experiences with such tools. For example, reminders were found useful in all the studies targeting a hypothetical app, as opposed to those that were researching engagement with an app that had been used by the participants, where opinions about reminders were mixed, with some users finding them annoying. Another explanation is that the importance of these factors might be dependent on the target behavior. For example, people using apps that target mental health might not want to engage with social competition features or to share their progress or experiences on social media. This suggests that some of the identified factors in this review might be behavior dependent.

Another interesting finding, not identified in previous literature, is the safety netting characteristic of an app. This characteristic could promote long-term engagement rather than short goal-oriented engagement. The user could disengage at any time and reengage at a later stage when needed. This feature might be particularly useful for addiction research targeting relapse prevention strategies.

No factors were coded directly under 4 out of the 14 TDF domains (optimism, social identity, beliefs about capabilities, and intentions). However, 2 of these were highlighted in this review. We described how several factors coded under different domains affect intentions (eg, having adequate app literacy skills or user guidance provided to the user), in a manner similar to how emotions, other than curiosity, affect engagement with an app (eg, lack of app literacy skills triggers negative emotions, some found reminders annoying, or some fear of social comparison related to sharing on social media). We also found that aspects of the factor *personalization to needs* also include social identity aspects. Some communities (LGBTQ+ and cancer patients) prefer an app that is personalized to their social identity. Although social identity, in this case, was judged to be a weak factor to list it independently. In terms of the other two absent domains, factors under beliefs in their capabilities and optimism might be less relevant for uptake and engagement with health apps, or the studies may have missed them out, or, potentially, we failed to identify them from the included studies.

The importance of promoting equality and embracing cultural diversity has been partially identified previously [18]. Several studies in this review reported that apps should be provided at a low cost to users. It was suggested that multiculturalism should be embraced, and regional languages should be added. The concern of inequality for those who do not own a smartphone was also raised in this review [40]. An accompanying website was suggested as an alternative for homeless people who would not have access to a smartphone but may have access to the internet through nonprofit organizations, charities, or community libraries.

Strengths and Limitations

One major strength of this paper is that it adhered to the best practice processes for undertaking reviews by following the PRISMA guidance and Cochrane handbook [27,29]. By including all study designs, we were able to pool together and triangulate evidence and provide a novel and powerful synthesis of different study designs.

The use of theoretical frameworks is another strength. Other theoretical models were considered for this review, including the technology acceptance model [81] and the HCI models and theories [82]. However, the COM-B and TDF present advantages owing to their dynamic nature and by explaining the influences between components as they were developed from, and to represent, all theoretical components in behavior change–related models and theories. COM-B was explicitly developed to inform behavior change interventions through its connection to the Behavior Change Wheel [83], a tool that provides guidance on designing behavior change interventions. The factors identified under the components of the COM-B model allow easy identification of the intervention functions to target increased uptake of and engagement with health and well-being smartphone apps.

This review has several limitations. The review focused on 4 major behaviors related to prevention (smoking, alcohol consumption, physical activity, and diet) and mental health and well-being and could not capture other prevention type behaviors (eg, fall prevention). Factors relating to the uptake and engagement of apps focusing on other behaviors or conditions may differ from those found in this review and warrant further investigation.

Although we captured a wide range of populations, most of the included studies were carried out in high-income countries. Therefore, the findings might not be transferable to low- and middle-income countries or to other cultures. The quality of the studies was mixed. In some qualitative studies, the authors provided interpretations of their findings without an explicit quotation to support them. These interpretations were handled with care and were often ignored when no further explanation was provided about a concept. This might have led to losing some potentially important factors, not identified otherwise.

Policy and Practice: Recommendations and Implications

The findings of this review can inform app developers and researchers on how to develop health and well-being smartphone apps to better support behavior change and manage and monitor different physical and mental health conditions in adults.

This review may also have implications for policies that target prevention using digital technologies. Apps are an easy way to provide health-promoting behaviors and may play an important role in prevention strategies. For example, the UK government has recently published a Green Paper entitled *Advancing our health: prevention in the 2020s*, which shifted their focus from *cure to prevention*, committing to encourage the population to live a healthier life [84]. Additionally, the *Long Term Plan* policy document of the NHS in the United Kingdom dedicates an entire chapter to prevention programs and includes plans on digitally delivered methods to improve access to information, education, and intervention [85].

As part of prevention and health management strategies, the NHS and partners have created a pool of health and well-being apps for the individuals to access (NHS Apps Library). This research could help people access effective apps that people will remain engaged with, although the extent to which the population is open to use these portals for uptake is yet unknown and something worth investigating in the future.

A number of important themes are described in the projects and policy documents mentioned above. Some relate to digital health, for example, with an aim to reduce health inequalities [84] or to improve population health with personalized content and tailored lifestyle advice [85]. Our review suggests that app literacy skills are important for uptake. Enhancing app literacy skills for the elderly (eg, drop-in sessions in community settings) might be a feasible way to reduce health inequalities. Furthermore, some of the engagement-related factors might suggest the use of tailored lifestyle advice to address health behaviors, for example, by receiving personalized content within the app and web-based or offline help or advice from health practitioners as well as receiving recommendations for use of health apps from their health care professionals and general practitioner practices.

Therefore, our findings could inform stakeholders in public health, policy makers, and providers of health and well-being smartphone app portals to provide additional support for the uptake of and engagement with these digital interventions for adults.

Recommendations for stakeholders in public health, policy makers, and health and well-being app developers derived from the findings of this review can be found in Table 3.

Table 3. Recommendations for stakeholders in public health, policy, industry, health care, and health and well-being app development.

Component	Policy makers/industry/health care providers might want to consider	App developers might want to consider
Capability	• Improving app literacy skills • Increasing awareness of effective health and well-being apps, by advertising offline (eg, general practitioner practices) and web-based (eg, social media)	• Promoting less cognitive load by enabling automatization of data collection • Including user guidance that can be deactivated once the functionality of the app has been achieved (eg, help button) • Including content that targets education, health prevention, and health consequences related to the behavior that is targeted to change • Including statistical information (eg, graphs, percentages, and numbers) about the user's progress • Including well-designed reminders where the user can choose the time and frequency of receiving it • Including the self-monitoring feature that enables users to create routines • Including a *safety netting* feature that allows users to fall back on, even when the target behavior has been achieved
Opportunity	• Providing web-based or offline health practitioner support • Providing recommendations for health and well-being apps by health care professionals • Offering apps for free or at a low cost	• Allowing the provision of health professional support within the app • Allowing community networking within the app with other users • Organizing competition and challenges for users to opt in to • Avoiding automatic synching with the embedded social media (when applicable) • Personification of the app, by designing human-type attributes • Offering apps for free or at a low cost • Offering personalization of the app according to their demographics and individual and cultural needs
Motivation	• Offering tangible rewards, such as points that could be used as a discount in pharmacies or at other health- and well-being–related domains or health insurance providers • Providing a meaningful title and clear description of what the app does and what can offer, and how can help the user	• Providing positive, nonjudgmental, constructive, and informative feedback • Include gamification elements and offering rewards • Including goal-setting features (when applicable) • Providing a meaningful title and clear description of what the app does and what can offer, and how can help the user

Future Research

Although some of the factors identified and presented in the Results section appear to have a positive influence on uptake and engagement, there are mixed findings that might benefit from further investigation, such as reminders, embedded social media, and social competition. In the studies included in the review, descriptions of notification-type messages, such as reminders, feedback, push notifications, and other notifications, were used interchangeably, and it was not always clear which notifications were being referred to. Consistent terminology would help eliminate doubt around these concepts in the future. Issues around equality and diversity were highlighted in a few studies as something future research should address. Further work is also needed to aid our understanding of how to avoid digital health widening inequalities through the exclusion of individuals who face a financial barrier to owning a smartphone or to purchasing an app, or who do not possess the skills to use one.

Conclusions

This is the first systematic review to investigate factors that influence the uptake of and engagement with health and well-being smartphone apps. We identified 26 factors that are relevant to a wide range of populations and different behaviors. These have clear implications for improving population health and targeting health inequalities. We provide a list of recommendations built on the identified factors to guide app developers, health app portal developers, and policy makers when commissioning, developing, and optimizing health and well-being smartphone apps. These can help address the issues of suboptimal uptake and engagement, which currently constrain the public health benefit of apps.

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Authors' Contributions

The initial concept was developed by DS, TC, and FN. DS wrote the study protocol with contributions from FN, AJ, TC, and JB. DS undertook data collection (literature search, screening, data extraction, and quality appraisal), data analysis, interpretation, and report writing. FN double checked the study selection, data extraction, and data coding. FN and AJ double assessed the quality of the included studies. DS prepared the paper. All authors read, commented, and contributed to the final paper.

Conflicts of Interest

None declared.

Multimedia Appendix 1

A visual representation of mapping the capability, opportunity, motivation, behavior model onto the Theoretical Domains Framework.
[PDF File (Adobe PDF File), 82 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Preferred Reporting Items for Systematic Reviews and Meta-Analyses checklist.
[PDF File (Adobe PDF File), 95 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Medical Literature Analysis and Retrieval System Online, or MEDLARS Online search strategy.
[PDF File (Adobe PDF File), 29 KB-Multimedia Appendix 3]

Multimedia Appendix 4

Characteristics of the studies included in the review.
[PDF File (Adobe PDF File), 179 KB-Multimedia Appendix 4]

Multimedia Appendix 5

Quality assessment of the studies included in the review.
[PDF File (Adobe PDF File), 168 KB-Multimedia Appendix 5]

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Abbreviations

COM-B model: capability, opportunity, motivation, behavior model
TDF: theoretical domains framework
HCI: human-computer Interaction
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
MMAT: mixed methods appraisal tool
LGBTQ+: lesbian, gay, bisexual, transgender, queer, and other spectrum of sexuality and gender
MEDLINE: Medical Literature Analysis and Retrieval System Online, or MEDLARS Online

NHS: National Health Service
PHE: Public Health England

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Appendix 3. PRISMA 2009 checklist

PRISMA 2009 Checklist

Section/topic	#	Checklist item	Reported on page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	1
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	2
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	4
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).	5
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	5
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	5,6
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	6
Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.	6, MMFile 2
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	7, Table 1.
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	7
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	7
Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.	n/a
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means).	n/a
Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis.	7

PRISMA 2009 Checklist

Section/topic	#	Checklist item	Reported on page #
Risk of bias across studies	15	Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).	n/a
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.	n/a
RESULTS			
Study selection	17	Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.	8, Fig. 1
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.	10, Table 2
Risk of bias within studies	19	Present data on risk of bias of each study and, if available, any outcome level assessment (see item 12).	16, MMFile 4.
Results of individual studies	20	For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group (b) effect estimates and confidence intervals, ideally with a forest plot.	n/a
Synthesis of results	21	Present results of each meta-analysis done, including confidence intervals and measures of consistency.	16-35, Textboxes 1-10
Risk of bias across studies	22	Present results of any assessment of risk of bias across studies (see Item 15).	n/a
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).	n/a
DISCUSSION			
Summary of evidence	24	Summarize the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., healthcare providers, users, and policy makers).	35-41, Table 4
Limitations	25	Discuss limitations at study and outcome level (e.g., risk of bias), and at review-level (e.g., incomplete retrieval of identified research, reporting bias).	37
Conclusions	26	Provide a general interpretation of the results in the context of other evidence, and implications for future research.	41
FUNDING			
Funding	27	Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.	42

From: Moher D, Liberati A, Tetzlaff J, Altman DG, The PRISMA Group (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. PLoS Med 6(7): e1000097. doi:10.1371/journal.pmed1000097

For more information, visit: www.prisma-statement.org.

Appendix 4. Electronic search strategy applied in MEDLINE.

1. MeSH: health promotion, health behaviour, health education (/explode), smoking cessation OR

((Behaviour adj2 change) OR (Behavior adj2 change) OR (behaviour adj2 change adj2 technique*) OR (behavior adj2 change adj2 technique*) OR (behaviour change strategy*) OR (behavior change strateg*) OR health behaviour OR health behavior OR health education OR health promotion OR health prevent* OR BCT* OR behaviour* intervention* OR behaviour* modification* OR (health adj2 campaign*) OR diet* OR nutrition* OR (healthy adj2 eating*) OR exercise* OR (physical adj2 activit*) OR (physical adj2 inactivit*) OR (alcohol adj2 misuse) OR drink* OR (smok* adj2 cessation) OR (stop adj2 smok*)OR tobacco* OR mood OR depress* OR anxi* OR wellbeing).ti,ab,kw.

2. MeSH: Mobile application (/explode) OR

(Smartphone* OR (mobile adj phone) (Smartphone* adj2 app*) OR (mobile adj2 app*) OR mhealth OR (mobile adj2 technolog*) OR (mobile adj2 tablet*) OR (mobile adj2 health*)).ti,ab,kw.

3. (uptake* OR engage* OR use* OR adher* OR enrol* OR participat* OR commitment OR connect* OR download* OR disconnect* OR discontinue* OR abandon* OR disrupt* OR interrupt* OR quit* OR terminate OR disengage* OR detach* OR withdraw* OR usage* OR pageview* OR screenview* OR login* OR log-in*).ti,ab,kw.
4. 1 AND 2 AND 3

Appendix 5. Characteristics of the studies included in the systematic review.

Studies	Location	Study aim	App used (name if applicable)	Participants	Methods or design and analytic approach
Anderson et al 2016	Australia	To explore experiences of health app users	Nonspecific health apps	Adults in the general population; N=22; female n=15; age groups: 18-25 years, n=4; 26-35 years, n=13; 46-55 years, n=2; and ≥55 years, n=1	Semistructured interviews; thematic analysis
Attwood et al 2017	United Kingdom	To examine patterns of app usage over time and to explore app users' views of the app	Alcohol reduction (Drinkaware)	Existing app users; N=119,713, (interview participants N =21); female (%): 59.3, (interview part: 12); age groups: 31%, 35-44 years	Mixed methods approach (secondary data analysis of Drinkaware database and semistructured interviews); ANOVA[a], regression, *t* test, framework analysis
Baretta et al. 2019	Italy	To examine users' need and preferences regarding their engagement with physical activity apps	Physical activity (Runtastik, Edumondo, Runkeeper)	Adults in the general population; N=20; female (%): 45; mean age 39.8 years (SD 7)	Longitudinal, single-arm design with think-aloud methodology and interview techniques; thematic analysis
Baskerville et al 2016	Canada	To explore LGBTQ+[b] communities' perception of a smoking cessation app	Smoking cessation	LGBTQ+ youth and adults; N focus groups=204; female (%): 39, male (%) 26.6, trans female (%): 3.7, trans male (%): 6.9, two spirit (%): 4.1, queer (%): 14.7, 0.5% intersex (%): 0.5, 4.6% other (%): 4.6; age groups: 8.8%, 16-18 years; 91.2%, 18-29 years	Focus groups (n=24); framework analysis

Bender et al 2014	United States	To examine factors predicting uptake with health apps among ethnic minorities	Nonspecific health apps	Ethnic minorities in the United States (Caucasians, Latinos, and Koreans); N=904; female (%): 64.3; mean age 44 years (SD 16.1)	Cross-sectional survey; descriptives, regression
Bhuyan et al 2016	United States	To explore the use of mHealth[c] apps for health seeking behavior among US adults	Nonspecific health apps	Adults in the general population; N=3677; female (%): 51.7; age groups: 30.8%, under 35 years; 17.2%, 35-44 years; 18.9%, 45-54 years; 15.8%, 55-64 years; 17.4 >65 years	Secondary data analysis of a nationally representative sample (Health Information National Trends Survey—cycle 4); descriptives, regression
Bidargaddi et al 2018	United States	To assess the effectiveness of push notifications on engagement	Wellbeing app (JOOL)	Existing app users; N=1255; female (%): 63.97; age groups: 28.86%, < 30 years; 42.44%, 30-50 years; 28.70%, > 50 years	Microrandomized trial; regression
Carroll et al 2017	United States	To describe sociodemographic characteristics with health app use, predictors of health app use	Nonspecific health apps	Adults in the general population; N=3519; female (%): 51.62; age groups: 65.62%, 18-44 years; 34.38%, > 45 years	Secondary data analysis of a nationally representative sample (Health Information National Trends Survey—cycle 4); regression
Casey et al 2014	Ireland	To explore patients views of using a smartphone app to promote physical activity in primary care	Physical activity (SMART MOVE)	Adult patients in primary care; N=1255; female (%): 75%; mean age 42 years (age range 17-62)	Semistructured interviews; framework analysis
Crane et al 2017	United Kingdom	To understand the usability of the app	Alcohol reduction (Drink Less)	Adult excessive drinkers and users of the Drink Less app; N=24; female (%): 50; mean age (think-aloud) 42	Think-aloud and semistructured interviews; thematic analysis

				years; mean age (interviews) 40 years	
Gorton et al 2011	New Zealand	To explore a potential weight loss management intervention on smartphone	Weight management	Adults in the general population; N=306 (focus groups N=54); % female (% survey): 77 (% focus group: 76); age groups (survey): 20%, 16-30 years; 51%, 31-50 years; 28%, ≥51 years; age groups (focus group): 35%, 16-30 years; 50%, 31-50 years; 15%, ≥51 years	Mixed methods approach (cross-sectional survey and focus groups [n=10]); descriptives, thematic analysis
Gowin et al 2015	United States	To describe the use of health apps among students	Weight management and physical activity	College students; N=27; female (%): 78; age groups: 70%, 18-20 years; 22%, 21-23 years; 8%, 24-26 years	Semistructured interviews; grounded theory
Guertler et al 2015	Australia	To examine the engagement with physical activity promotion app and identify sociodemographic factors of nonengagement	Physical activity (10,000 steps)	App users, N=1451; female (%): 7 2.43; mean age 38.3 years (SD 11.1)	Secondary data analysis of the *10,000 Steps* database; ANOVA, chi-square, regression
Laurie and Blandford 2016	United Kingdom	To understand users' experiences with mindfulness app	Mindfulness (Headspace)	Adults in the general population; N=16; % female (%): 68.75; mean age, 32.5 years (age range 25-38)	Semistructured interviews; grounded theory
Lieffers et al 2018	Canada	To understand the experiences of adults who have used a nutrition app previously	Weight management	Adults in the general population; N=24; % female (%), 79; age groups: 63%, 18-30 years; 25%, 31-50 years; 13%, 51-70 years	Semistructured interviews; content analysis
Ly et al 2014	Sweden	To explore participants' views of a	Depression	Adults with major depression; N=12; female (%): 50; mean age 37.9 years (age range 21-59)	In-depth interviews; thematic analysis

		mental health app			
Mackert et al 2016	United States	To determine the association between health literacy and app engagement	Fitness and weight management	Adults in the general population; N=4974; female (%): 57.74; mean age 43.5 years (SD=16.7)	Cross-sectional survey; cross-tabulation analysis, regression
Milward et al 2018	United Kingdom	To understand why and how participants engaged with the app, to understand facilitators and barriers to engagement with the app, to understand how the app impacted drinking behavior, and to identify typologies of users (engagement)	Alcohol reduction (BRANCH)	Participants of a randomized controlled trial; N=20, female (%): 80; mean age 24 years (SD=3)	Semistructured interviews; framework analysis
Mitchell et al 2017	Canada	To evaluate uptake with a loyalty points–based health app and to describe sociodemograph ic characteristics of the users	Multipurpose health app (Carrot Rewards)	App users; N=57,885; % female, 62.96%; age groups: 2.4%, 13-17 years; 20.65%, 18-24 years; 33.69%, 25-34 years; 20.11%, 35-44 years; 13.17%, 45-54 years; 7.22%, 55-64 years; 2.74% >65 years	Process evaluation; descriptives
Peng et al 2016a	United States	To better understand a more diverse pool of users' perception of health apps	Nonspecific health apps	Adults in the general population; N=44; female (%): 65; mean age 37.2 years (SD 15.7)	Focus groups (n=6) and interviews (n=5); thematic analysis

Peng et al 2016b	United States	To explore the perception of rural adults with diabetes regarding apps to manage their condition	Nonspecific health apps	Adults with diabetes; N=18; female (%): 72.2; mean age 54 years (SD 12.7)	Focus groups (n=4); thematic analysis
Perski et al 2017	United Kingdom	To explore participants' choices of health apps and to identify important features of engagement	Smoking cessation and alcohol reduction	Adults in the general population; N=20; % female (%): 60; mean age (SD), 29.7 (SD 9.2) years	Think-aloud and semistructured interviews; thematic analysis
Perski et al 2018	United Kingdom	To explore the more important features of engagement	Alcohol reduction	Adults in the general population; N=132 (focus group: n=9); female (%): 49.2 (focus group %: 77.8); age groups (survey): 10.6%, 18-24 years; 24.2%, 25-34 years; 34.1%, 35-44 years; 21.2%, 45-54 years; 6.8%, 55-64 years; 3%, ≥65 years; age groups (focus group): 44.4%, 18-24 years; 33.3%, 25-34 years; 22.2%, 45-54 years	Mixed methods approach (Web-based survey and focus groups, n=3); interclass correlation coefficient, thematic analysis
Peters et al 2018	Australia	To explore participants' preferences of a mental health app	Wellbeing	Adult workers of male-dominated industry; N=60; female (%): 8%; Mean age 47 years (age range 26-65)	Participatory study: workshops (n=6); thematic analysis
Pung et al 2018	Australia	To explore mobile app use among patients with depressive symptoms	Depression	Patients of primary care presenting depressive symptoms; N=16; % female (%): 58; age groups: 19%, <25 years; 44%, 25-44 years; 38%, 45-65 years	Semistructured interviews; thematic analysis

Puszkiewitz et al 2016	United Kingdom	To assess cancer survivors' attitudes toward a physical activity app, to understand how the app could be adapted to their needs, to understand how to increase their physical activity level using the app	Physical activity	Adult cancer survivors; N=11; female (%): 89; mean age 45 years (SD=9.4)	Mixed methods approach (1-arm pre-post design and semistructured interviews); Wilcoxon sign rank test; thematic analysis
Serrano et al 2017	United States	To explore features of the app that influence engagement and to describe the characteristics of the users	Weight loss app (Lose it!)	App users; N=1,011,008	Secondary data analysis of a cross-sectional data; Classification and Regresion Tree analysis, descriptives, regression
Sharpe et al 2018	United States	To determine factors associated with uptake of an alcohol reduction app among persons living with HIV	Alcohol reduction	Adult population living with HIV; N=757; female (%): 35; age groups: 18%, 18-34 years; 20%, 35-44 years; 41%, 45-54 years; 21%, ≥55 years	Secondary data analysis of a cross-sectional survey data of a longitudinal cohort study (Florida cohort study); descriptives, regression
Smahel et al 2017	Czech Republic	To reveal characteristics regarding use of health apps	Fitness and weight management	Adults of the general population; N=406; female (%): 86.9; mean age 23.8 years (SD=5.3)	Cross-sectional survey; descriptives, regression
Solbrig et al 2016	United Kingdom	To explore experiences and wishes regarding weight management using apps	Weight management (FIT)	Adults of the general population; N=24; female (%): 79.2; mean age 30 years (age range 19-70)	Focus groups (n=6); thematic analysis

Struik et al 2018	Canada	To understand the interaction and experiences with the app	Smoking cessation (Crush the Crave)	App users; N=31; female (%): 42; mean age 24 years (SD=2.72)	Semistructured interviews; framework analysis
Sun et al 2017	China	To investigate the current usage, willingness to use, and barriers to use a physical activity app	Physical activity	Adult patients with chronic disease; N=218; female (%): 61; mean age 44.6 years (age range 20-69)	Cross-sectional survey; descriptives, chi-square
Switsers et al 2018	Belgium	To examine the needs of adults with bipolar disorder regarding apps	Mental health	Adults with bipolar disorder; N=16; female (%): 56.3; mean age 41.8 years (age range 21-69)	Focus groups (n=7); thematic analysis
Taki et al 2019	Australia	To examine how app characteristics influence engagement	Weight management (GH[d])	Female app users; N=18, mean age 30.9 years (age range 21-38)	Semistructured interviews; thematic analysis
Tang et al 2015	United Kingdom	To explore young adults' experiences of using apps	Weight management	Adults of the general population; N=19; female (%): 47.37; age range 19-33 years	Semistructured interviews; thematic analysis
Tudor-Sfetea et al 2018	United Kingdom	To explore individuals' perceptions of different smoking cessation apps	Smoking cessation (Quit Genius and NHS[e] Smokefree)	App users; N=15 (Quit Genius) and N=14 (NHS Smokefree); female (%): 13.3 (Quit Genius) and 14.3 (NHS Smokefree); mean age 25.07 years (Quit Genius) and 24.21 years (Quit Genius)	Semistructured interviews; thematic analysis
Wang et al 2018	China	To explore app engagement and to understand people's views about app containing health information	Pregnancy health apps	Pregnant women from secondary care; focus groups N=28, mean age 29.6 years (SD=3.1); survey N=535, mean age 30.6 years (SD=3.6)	Survey and focus groups (n=4); descriptives, logistic regression, thematic analysis

Webcredible Report, 2016 (unknown authors)	United Kingdom	To understand why people use health apps, how they choose them, what factors influences their choice and engagement	Nonspecific health apps	Adults in the general population; N=300 (focus group: n=12); female (%): 42; age range 33-60 years	Mixed methods approach. (Web-based survey and focus groups [n=2]); analysis used unreported
Woldaregay et al 2018	Norway	To explore motivational factors of user engagement with health apps	Nonspecific health apps	Adults of the general population; N=16; female (%): 50; Age range 21-55 years	Semistructured interviews; thematic analysis
Xie et al 2018	China	To examine the prevalence, extent, and demographics of health app use	Nonspecific health apps	Adults of the general population; N=633; female (%): 48.5; age groups: 24.6%, 18-29 years; 25%, 30-44 years; 24.6%, 45-59 years; 25%, ≥60 years	Cross-sectional survey; descriptives, regression
Zeng et al 2015	United States	To examine demographical, psychological, and behavioral predictors of the use of app	Smoking cessation (SmartQuit)	App users; N=98; female (%): 53; mean age 41.5 years (SD=12)	Secondary data analysis of the SmartQuit trial's data (intervention arm); descriptives, regression

[a]ANOVA: analysis of variance.

[b]LGBTQ+: lesbian, gay, bisexual, transgender, queer, and other spectrum of sexuality and gender.

[c]mHealth: mobile health.

[d]GH: Growing Healthy.

[e]NHS: National Health Service.

Appendix 6. Critical appraisal of the studies included in the systematic review.

1. Qualitative studies

First author	Year	Q 1.1	Q 1.2.	Q 1.3.	Q 1.4.	Q 1.5.
Anderson	2016	Yes	Yes	Yes	Yes	Yes
Attwood*	2016	Yes	Yes	Yes	Yes	Yes
Baretta	2019	Yes	Yes	Yes	Yes	Yes
Baskerville	2016	Yes	Yes	Yes	Yes	Yes
Casey	2014	Yes	Yes	Yes	Yes	Can't tell
Crane	2017	Yes	Yes	Yes	Yes	Yes
Gorton*	2011	Yes	Yes	Can't tell	No	Yes
Gowin	2015	Yes	Yes	Yes	Yes	Yes
Laurie	2016	Yes	Yes	Yes	Yes	Yes
Lieffers	2018	Yes	Yes	Yes	Can't tell	Yes
Ly	2014	Yes	Yes	Yes	Yes	Yes
Milward	2018	Yes	Yes	Yes	Yes	Yes
Peng	2016a	Yes	Yes	Yes	Yes	Yes
Peng	2016b	Yes	Yes	Yes	Yes	Yes
Perski	2017	Yes	Yes	Yes	Yes	Yes
Perski*	2018	Yes	Yes	Yes	Yes	Yes
Peters	2018	Yes	Yes	Yes	Can't tell	Yes
Pung	2018	Yes	Yes	Yes	Yes	Yes
Puszkiewitz*	2016	Yes	Yes	Yes	Yes	Yes
Solbrig	2016	Yes	Yes	Yes	Yes	Yes
Struik	2018	Yes	Yes	Yes	Yes	Yes
Sun	2017					
Switsers	2018	Yes	Yes	Yes	Yes	Yes
Taki*	2019	Yes	Yes	Yes	Yes	Yes
Tang	2015	Yes	Yes	Yes	Yes	Yes
Tudor-Sfetea	2018	Yes	Yes	Yes	Yes	Yes
Wang*	2018	Yes	Yes	Yes	Yes	Yes
Webcredible*	2016	Yes	Yes	Can't tell	Can't tell	Yes
Woldaregay	2018	Yes	Yes	Yes	Can't tell	Yes

Q 1.1. Is the qualitative approach appropriate to answer the research question?
Q 1.2. Are the qualitative data collection methods adequate to address the research question?
Q 1.3. Are the findings adequately derived from the data?
Q 1.4. Is the interpretation of results sufficiently substantiated by data?
Q 1.5. Is there coherence between qualitative data sources, collection, analysis and interpretation?

2. Randomised controlled trials						
First author	Year	Q 2.1.	Q 2.2.	Q 2.3.	Q 2.4.	Q 2.5.
Bidergaddi	2018	Yes	Can't tell	Yes	Yes	Yes

Q 2.1. Is randomization appropriately performed?
Q 2.2. Are the groups comparable at baseline?
Q 2.3. Are there complete outcome data?
Q 2.4. Are outcome assessors blinded to the intervention provided?
Q 2.5 Did the participants adhere to the assigned intervention?

3. Non-randomised studies						
First author	Year	Q 3.1.	Q 3.2.	Q 3.3.	Q 3.4.	Q 3.5.
Attwood*	2016	Yes	Yes	Yes	Can't tell	Yes
Bhuyan	2016	Yes	No	Yes	Can't tell	Can't tell
Carroll	2017	Yes	Yes	Yes	Yes	Yes
Guertler	2015	Yes	Yes	Yes	Can't tell	Yes
Puszkiewitz*	2016	Yes	Yes	Yes	Yes	Yes
Serrano	2017	Yes	Yes	Yes	Yes	Yes
Sharpe	2018	Can't tell	Yes	Yes	Can't tell	Yes
Zeng	2015	Yes	Yes	Yes	Yes	Yes

Q 3.1. Are the participants representative of the target population?
Q 3.2. Are measurements appropriate regarding both the outcome and intervention (or exposure)?
Q 3.3. Are there complete outcome data?
Q 3.4. Are the confounders accounted for in the design and analysis?
Q 3.5. During the study period, is the intervention administered (or exposure occurred) as intended?

4. Quantitative descriptive studies						
First author	Year	Q 4.1.	Q 4.2.	Q 4.3.	Q 4.4.	Q 4.5.
Bender	2014	Yes	Yes	Can't tell	Yes	Yes
Gorton*	2011	Yes	Can't tell	Yes	Can't tell	Yes
Mackert	2016	Can't tell	No	Yes	Yes	Yes
Mitchell	2017	Yes	Yes	Yes	Yes	Yes
Perski*	2018	Yes	Can't tell	Yes	Yes	Yes
Smahel	2017	Can't tell	Can't tell	Yes	Can't tell	Yes
Sun	2017	Yes	Yes	Yes	Yes	Yes
Taki*	2019	Yes	Yes	Yes	Can't tell	Can't tell
Wang*	2018	Yes	Yes	Yes	Yes	Yes
Webcredible*	2016	Yes	Yes	Yes	Can't tell	Can't tell
Xie	2018	Can't tell	Yes	Yes	Yes	Yes

Q 4.1. Is the sampling strategy relevant to address the research question?
Q 4.2. Is the sample representative of the target population?
Q 4.3. Are the measurements appropriate?
Q 4.4. Is the risk of nonresponse bias low?
Q 4.5. Is the statistical analysis appropriate to answer the research question?

5. Mixed methods studies						
First author	Year	Q 5.1.	Q 5.2.	Q 5.3.	Q 5.4.	Q 5.5.

Attwood*	2016	Yes	Yes	Yes	Yes	Yes
Gorton*	2011	No	Can't tell	Can't tell	Can't tell	Can't tell
Perski*	2018	Yes	Yes	Yes	Yes	Yes
Puszkiewitz*	2016	Yes	Yes	Yes	Yes	Yes
Taki*	2019	Yes	Yes	Can't tell	Can't tell	Can't tell
Wang*	2018	Yes	Yes	Yes	Yes	Yes
Webcredible*	2016	No	No	Can't tell	Can't tell	Can't tell

Q 5.1. Is there an adequate rationale for using a mixed methods design to address the research question?

Q 5.2. Are the different components of the study effectively integrated to answer the research question?

Q 5.3. Are the outputs of the integration of qualitative and quantitative components adequately interpreted?

Q 5.4. Are divergences and inconsistencies between quantitative and qualitative results adequately addressed?

Q 5.5. Do the different components of the study adhere to the quality criteria of each tradition of the methods involved?

*****mixed methods studies. Following the instruction of the MMAT guidance the mixed-methods studies first were assessed on their qualitative and quantitative components independently, and finally using the questions 5.1. – 5.5. on their mixed-methods methodology.

Note: all studies answered 'yes' to the first two screening questions of the MMAT:
S.1. Are there clear research questions?
S.2. Do the collected data allow to address the research questions?

Appendix 7. Publication of the think-aloud and interview study (uptake findings)

Original Paper

Influences on the Uptake of Health and Well-being Apps and Curated App Portals: Think-Aloud and Interview Study

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Abstract

Background: Health and well-being smartphone apps can provide a cost-effective solution to addressing unhealthy behaviors. The selection of these apps tends to occur in commercial app stores, where thousands of health apps are available. Their uptake is often influenced by popularity indicators. However, these indicators are not necessarily associated with app effectiveness or evidence-based content. Alternative routes to app selection are increasingly available, such as via curated app portals, but little is known about people's experiences of them.

Objective: The aim of this study is to explore how people select health apps on the internet and their views on curated app portals.

Methods: A total of 18 UK-based adults were recruited through social media and asked during an in-person meeting to verbalize their thoughts while searching for a health or well-being app on the internet on a platform of their choice. The search was then repeated on 2 curated health app portals: the *National Health Service Apps Library* and the Public Health England *One You* App portal. This was followed by semistructured interviews. Data were analyzed using framework analysis, informed by the Capability, Opportunity, Motivation-Behavior model and the Theoretical Domains Framework.

Results: Searching for health and well-being apps on the internet was described as a *minefield*. App uptake appeared to be influenced by participants' capabilities such as app literacy skills and health and app awareness, and opportunities including the availability of apps, app esthetics, the price of an app, and social influences. Motivation factors that seemed to affect the uptake were perceived competence, time efficiency, perceived utility and accuracy of an app, transparency about data protection, commitment and social identity, and a wide range of emotions. Social influences and the perceived utility of an app were highlighted as particularly important. Participants were not previously aware of curated portals but found the concept appealing. Curated health app portals appeared to engender trust and alleviate data protection concerns. Although apps listed on these were perceived as more trustworthy, their presentation was considered disappointing. This disappointment seemed to stem from the functionality of the portals, lack of user guidance, and lack of tailored content to an individual's needs.

Conclusions: The uptake of health and well-being apps appears to be primarily affected by social influences and the perceived utility of an app. App uptake via curated health app portals perceived as credible may mitigate concerns related to data protection and accuracy, but their implementation must better meet user needs and expectations.

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KEYWORDS

behavior change; health apps; mHealth; smartphone app; framework analysis; Capability, Opportunity, Motivation-Behavior model; Theoretical Domains Framework; think aloud; mobile phone

Introduction

Background

Noncommunicable diseases (eg, diabetes, heart disease and cancer as well as poor mental health) are considered key threats to global health [1] and are driven by factors such as physical inactivity, poor diet, tobacco smoking, and excessive alcohol consumption. A key global public health policy priority is to enact policies to ensure that the best possible health care is available for all [2]. In the United Kingdom, aims of the National Health Service (NHS) long-term plan [3] and priorities of UK government executive agencies such as Public Health England (PHE) are to provide a smoke-free society, to encourage healthier diets, and to improve mental health [4]. Encouraging the use of digital health interventions, such as smartphone apps, may be a cost-effective way of contributing.

Health and well-being smartphone apps can be cost-effective solutions for changing health behaviors [5,6]. Such tools can act as ideal platforms to deliver behavior change interventions [7] because of their availability, portability, and easy access [8]. Research has demonstrated early evidence of effectiveness of smartphone apps for smoking cessation [9], healthy dietary and physical activity promotion [5,10-12], weight loss [5,13,14], alcohol reduction among nondependent drinkers [15], and mental health promotion [16]. In addition, health apps can reach those resistant to seeking help in person (because of stigma) by improving access to behavior change interventions [17]. However, low uptake and poor engagement over time compromise the potential of health and well-being apps.

Uptake refers to the decision to select and install a health app [18]. The search for and selection of health apps tend to take place in commercial app stores such as Google Play for Android operating systems and the Apple App Store for iOS [10,19]. Thousands of health and well-being smartphone apps are available in the major app stores, a number that continues to grow [7], and the uptake of apps from commercial app stores tends to be influenced by indicators of popularity such as the app's rank order, ratings and reviews, and the total number of downloads [19]. However, such popularity indicators are not necessarily positively associated with the effectiveness of an app [20] and may even be negatively related [21]. An associated problem with app uptake is that the vast majority of apps listed in commercial stores lack evidence about their efficacy [22] or effectiveness [23]. The need for quality marks in commercial app stores [24] and regulation of health apps and evidence for their effectiveness has been raised [16]. Better transparency in an app's description to help people make an informed choice, including how the user's data are handled, how the app was developed, benefits explained in lay terms, and descriptions of the app content, has been recommended [25-27].

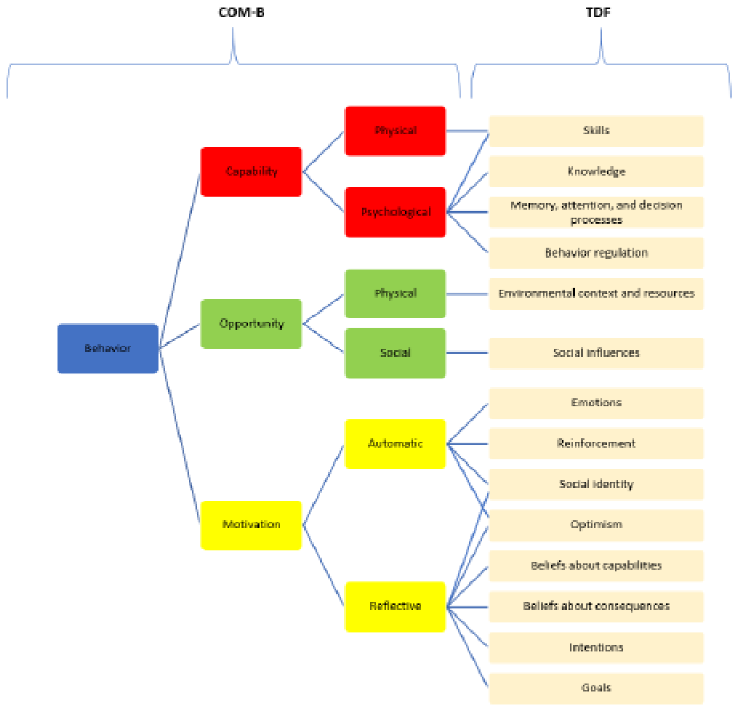
A barrier to the uptake of evidence-informed apps is that not all apps are available to the public, or prominently displayed, via commercial app stores [22,24]. Therefore, fewer people may benefit from the high-quality tools available. Evidence-informed apps tend to be promoted within community or health care settings (often targeting a specific geographic region or country) or on curated health app *portals*. These portals are websites that present a list of selected health apps [28]. Health app portals can be government funded, such as the UK NHS's *Apps Library* or PHE's *One You Apps* portal, or curated by private organizations, such as *App Script* by IQVIA in the United States, the United Kingdom, and the United Arab Emirates; the *MyHealthApps* by PatientView's in Europe and the United Kingdom; or *ORCHA* Health in the United Kingdom. These organizations can lend credibility to and have the potential to promote the uptake of selected health apps [29] by providing a list of safe; evidence-informed; tested; and, where possible, clinically effective health apps for the general public to choose from.

Research has focused on the identification of factors that influence the uptake of health apps in commercial app stores. There is an urgent need to explore whether the general public would be willing to use curated health app portals, which could improve the uptake of evidence-informed health and well-being apps [18]. Despite this need, little is known about the views on curated health app portals. This study aims to explore potential users' views on factors influencing the uptake of health apps in general and on curated health app portals in particular using think-aloud and interview methodology.

Theoretical Framework

The Capability, Opportunity, Motivation-Behavior (COM-B) model [30] offers a comprehensive framework for understanding behaviors. In the context of this study, the behavior of interest is the uptake of health and well-being apps. The model proposes that behavior arises because of the interaction of three components: capability (physical and psychological), opportunity (physical and social), and motivation (automatic and reflective). The Theoretical Domains Framework (TDF) [31], which contains 14 domains that can be mapped onto the components of the COM-B model, was also used. Together, the COM-B model and the TDF allow for a detailed analysis of data and identification of key factors influencing uptake in general and on curated health app portals in particular (Figure 1) [18].

Figure 1. A visual representation of mapping the TDF onto the COM-B model. COM-B model: Capability, Opportunity, Motivation-Behavior model; TDF: Theoretical Domains Framework.



Aims

This qualitative study applied a theoretical framework informed by the COM-B model and TDF to explore (1) factors influencing potential users' uptake of health and well-being smartphone apps through searching on the internet and (2) their views on available curated health app portals.

Methods

Study Design

This study elicited views and preferences of a sample of members of the public. The Consolidated Criteria for Reporting Qualitative Research checklist guided the design of the study [32] (checklist given in Multimedia Appendix 1). The think-aloud methodology [33] was applied to collect real-time data about health app selection on the internet and involved asking participants to verbalize their thoughts and impressions throughout the selection process. The researcher intervened only when a prompt was considered necessary (eg, during silent moments, asking questions such as "What are you thinking now?"). Following the think-aloud tasks, follow-up questions were asked to better understand the statements or utterances made during the tasks. Finally, semistructured interviews were conducted. The think-aloud tasks and the topic guide were informed by stakeholder consultation, which included views and opinions of lay persons (patient and public involvement representatives) and expert opinions of policy makers of this study. The study protocol was preregistered on the Open Science Framework [34]. The Faculty of Medicine and Health Sciences Ethics Committee at the University of East Anglia approved this study (reference number: 201819-089). The collected data are stored following the European Union General Data Protection Regulation and the University of East Anglia Research Data Management Policy. The data were anonymized, and all personal identifiers were removed. All participants read the participant information sheet and provided consent before participating in the study.

Participants and Recruitment

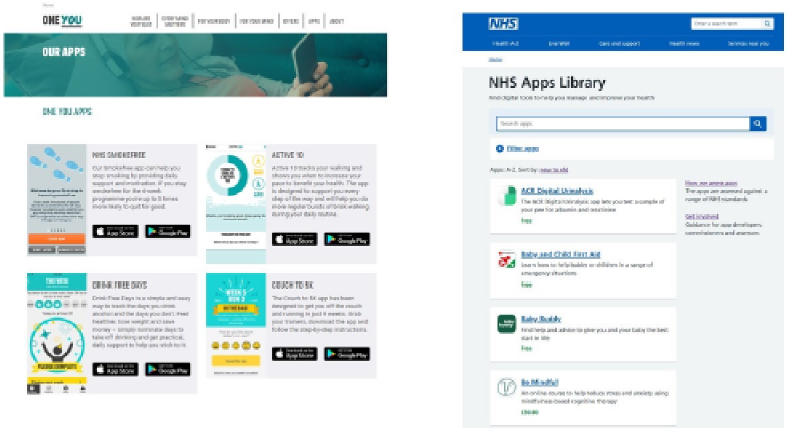
Participants were recruited through paid advertisements on Facebook. Adults in the general population were eligible if they were 18 years or older; were able to provide consent; owned a smartphone; would consider using a smartphone app to change their behavior in the future; and were able to attend an interview in Norwich, England, where the work took place. As a standard practice in qualitative research, the aim of this study is to gain a better understanding of the phenomenon of interest and to increase the coverage of perspectives rather than to recruit a population-representative sample [35]. Therefore, purposive sampling was used to promote the diversity of the sample (ie, age, gender, ethnicity, educational level, and employment) [36]. This included targeted advertisements on Facebook and the selection of participants to ensure the diversity of the sample. A total of 114 individuals responded to the Facebook advertisements and read a brief participant information sheet and completed the screening questionnaire. Of the 38 participants invited to an interview, 14 did not respond and 24 agreed to participate. Of these 24 participants, 6 were canceled for various reasons.

Procedure

Before completing the online screening survey, participants were asked to read a brief participant information sheet describing the study. After reading and agreeing to participate, participants were asked to complete an online questionnaire to assess their eligibility and to collect descriptive data (Multimedia Appendix 2). Data were collected on age; gender; ethnicity, measured using the Office for National Statistics' index; level of education; employment status; whether they had ever used health or well-being apps; whether they currently use a health or well-being app; last time they had downloaded an app; and frequency of app use. Participants who met the inclusion criteria were sent an email with a comprehensive participant information sheet and invited to participate in the interview. On the day of the interview, the interviewees received a printed copy of the participant information sheet, and written consent was obtained.

Face-to-face interviews were conducted between July and August 2019 and took place at the University of East Anglia (n=17) or participants' homes in Norwich (n=1). The interviews were conducted by a single female researcher (DS), and no one else was present during the sessions. Each session started with a think-aloud exercise, with participants being instructed on how to verbalize their thoughts. First, they were asked to perform a search for an app they would potentially use to change the health behavior of their choice. They had a choice of using either a study laptop or their smartphone. Second, the researcher asked them if they were familiar with curated app portals. If they were not, DS briefly explained the principle and asked them to repeat the search using the *NHS Apps Library* and the PHE's *One You Apps* curated health app portals (Figure 2). During the think-aloud sessions, positive reinforcement using verbal (eg, "You are doing great" and "Right") and nonverbal (eg, nodding) communication was used to encourage participants to continue to express their views. In quiet moments, prompts were used (eg, "What are you thinking now?" and "Tell me what is on your mind"). Following the think-aloud task, questions regarding their experience with the uptake of and engagement with apps were asked (the topic guide is given in Multimedia Appendix 3). The sessions lasted between 26 and 63 minutes. Participants received a US $27.50 (UK £20) gift voucher as compensation for their time.

Figure 2. Screenshot of the Public Health England's 'One You Apps' portal and the 'NHS Apps Library'.



Data Analysis

The sessions were audio recorded and transcribed verbatim by an external company. The transcriptions were checked for accuracy by the researcher undertaking the interviews. The data were analyzed using framework analysis following the stages of familiarization, identification of thematic framework, indexing, charting, mapping, and interpretation [37]. To ensure rigor, trustworthiness, and consistency, a percentage of randomly selected transcripts (2/18,15%) were independently coded by the second author (OP). The deductive thematic framework based on TDF was refined iteratively through repeated discussions with the second author (OP), and any discrepancies were resolved through discussion with the senior author (FN). Indexing was completed by the first author (DS) using QSR NVivo 12. The data were charted, and the responses were grouped according to the finalized thematic framework. During mapping and interpretation, the grouped data were examined by DS to identify patterns. During mapping, identified factors were classified according to their organic position rather than what they affect (eg, an opportunity factor may indirectly influence the behavior by increasing the motivation for uptake of a health app and influencing it directly). To aid comprehension of the findings for uptake in general and on health app portals in particular, data were analyzed and presented separately for these 2 topics.

External Validity

To enhance the credibility and trustworthiness of the results [38], 30% (6/18) of participants were randomly selected and requested via email to provide feedback on a document with a summary of the findings and conclusions (*member checking*). They were asked whether they recognized their opinions and whether they agreed with the interpretation of the findings. A total of 2 participants responded to our request and confirmed that their opinions had been captured. In one case, our email was not delivered.

Reflexivity

The researchers involved in this study are mixed methods researchers with experience applying the COM-B model and TDF to qualitative data. She disclosed her research interest to participants on the day of the interview, and no previous relationship was established between her and participants. The interviews were conducted by the lead author, a PhD candidate who has undertaken extensive training in the collection and analysis of qualitative data. Participants were encouraged to share their thoughts (both positive and negative) and to be honest. The interviewer felt that good rapport was built with the interviewees, and most participants (n=16) expressed their interest in learning more about the findings of the research. Field notes and a research journal were kept during data collection.

Results

Participant Characteristics

A total of 18 participants completed the interview. The average age of participants was 43 (SD 14) years, 50% (n=9) were female, 78% (n=14) were of White British ethnicity, 72% (n=13) were employed full time, 11% (n=2) had postgraduate qualifications, 94% (n=17) had used health apps before, and 61% (n=11) were using health apps at the time of the interviews, out of which 73% (n=8) reported daily health app use. Most participants were interested in changing more than one behavior (eg, losing weight, getting more active, and managing mood), and only 16% (n=2) of participants expressed a desire to change only one behavior. Participants' characteristics are presented in Multimedia Appendix 4.

A total of 2 participants were satisfied with the app they were already using and did not wish to take part in the think-aloud exercise to look for a different app. The remaining 16 participants searched for apps targeting physical activity (n=6), weight management (n=4), mood and mental well-being (n=3), smoking cessation (n=1), alcohol reduction (n=1), and sleep (n=1).

The findings pertaining to factors relevant for both the uptake of health apps and views on curated health app portals are presented under the components of the COM-B model. Higher order themes and subthemes informed by the COM-B model and TDF are reported in Table 1.

Table 1. Factors influencing uptake of health apps in general and on health app portals mapped onto the components of the Capability, Opportunity, Motivation-Behavior model and Theoretical Domains Framework constructs.

COM-B[a] component and TDF[b] construct and identified factor	Uptake in general	Uptake on health app portals
Physical capability		
Skills		
App literacy	• Technological competency	—[c]
Psychological capability		
Knowledge		
Health awareness	• General health consciousness or having family members diagnosed with a condition or disease or concerns regarding a behavior or health outcome	—
App awareness	• Knowledge of the existence of health and well-being apps	• Knowledge of the existence of health and well-being apps listed on health app portals
User guidance	—	• Instructions on how to effectively use a health app portal
Health information	—	• Educational information related to health and well-being
Memory, attention, and decision processes		
Cognitive load	—	• The manner in which apps are presented on the portal • The complexity of the search or to access a relevant health app
Physical opportunity		
Environmental resources		
Availability	• The ability to use a smartphone anytime, anywhere • Availability of an app on all major commercial app stores	—
Portal tailored to individuals' needs	—	• Personalized listing of apps targeting age, gender, and health condition
Cost of an app	• Low cost and apps that are free for users	• Low cost and apps that are free for users
Esthetics	• The look and design of an app	• User-friendly and design-related characteristics of the portal
Social opportunity		
Social influences		
Social influences	• The importance of reviews and ratings in the commercial app stores and apps promoted as "editor's choice" • Identified credible sources: apps developed or endorsed by trusted app developers, organizations, or universities or promoted by respected celebrities (eg, athletes) • Recommendations received from health practitioners or from friends and family	• Health app portals perceived as credible sources • Recommendations of health app portals needed mainly in primary care • Clarity about the recommended apps on health app portals • Explanations about any required GP[d] referral
Reflective motivation		
Beliefs about capabilities		
Perceived competence	• Apps preferred over face-to-face intervention when the user feels that they can engage with the app on their own	—

COM-B[a] component and TDF[b] construct and identified factor	Uptake in general	Uptake on health app portals
Beliefs about consequences		
Time efficiency	• The ability of a health app to be interacted with a minimum amount of time	—
The perceived utility of the app	• Discrepancies between what users are looking for and what the app offers, characterized by a relevant title, description, pictures, adaptation to individual characteristics, and users' previous experience with health apps	• Discrepancies between what users are looking for and what the app listed on health app portal offers, characterized by a relevant title, description, and pictures
Perceived accuracy	• The perceived effectiveness of apps before the selection of an app	• Potential app users' perceived effectiveness of apps listed on health app portals
Data protection	• Concerns regarding the handling of personal data	• Concerns over the handling of personal data
Intentions		
Commitment	• The level of commitment when deciding to download a health app	—
Social identity		
Social identity	• Identity related to app use (eg, trends and gender specificity)	• Identity related to app use (eg, feeling like a "patient")
Automatic motivation		
Emotions		
Positive	• Triggered by curiosity in trying a health app, and by the time efficiency characteristic of an app as opposed to face-to-face interventions, and being provided by a credible source	• Triggered by curiosity in choosing a behavior change tool from a curated health app portal and from a credible source
Negative	• Triggered by lack of availability on all major app stores • Preferred over a face-to-face intervention if feeling anxiety (eg, caused by an unhealthy behavior or unhealthy state) and pressurized (to succeed or show progress)	• Triggered by lack of search features on the portal or when the search yields irrelevant results; when an app requires GP referral without further explanation or when an app is only available in one major app store
Mixed	• Triggered by the esthetics (design) of the apps and by adaptation to individual characteristics (judged by the title, description, pictures, and gender specificity)	• Triggered by the esthetics and features of the portal and the perceived utility of the apps

[a]COM-B: Capability, Opportunity, Motivation-Behavior.
[b]TDF: Theoretical Domains Framework.
[c]Not available.
[d]GP: general practitioner.

Factors Influencing the Uptake of Health and Well-being Apps

Half of the participants who agreed to search for a health app (n=8) used Google Search as their first choice to find a suitable app, whereas the other half opened a commercial app store. The latter search among hundreds of available apps was described by most participants as difficult or a "minefield" (P2, P4, and P6). One participant described this task as being "far more complicated than I thought it would be" (P2). By the end of this exercise, only 3 participants found an app that they were willing to download and engage with further to change their behavior.

Capability Factors Related to the Uptake of Health and Well-being Apps in General

Participants who presented a higher level of technological competency were able to better navigate on their phones, thus highlighting that app literacy skills are necessary when selecting a health app. One participant, who had never used a health app before, showed signs of technical difficulties (ie, lack of skills) during the think-aloud exercise while searching for an alcohol reduction app in a commercial app store:

> *I wouldn't know how to do that [refining the search to find a suitable app].* [P12]

In addition, 2 participants expressed their concern toward the older generation and stated that training should be provided for those with insufficient technological and app literacy skills:

> *My nanny is diabetic and if there was an app to help her with her diabetes, then I'm sure she would be happy to use it but it's just someone would need to explain it to her.* [P18]

All participants expressed their decision to look for an app for health reasons, such as getting healthier or preventing illness. This included reasons of being diagnosed, or having a family member diagnosed, with a medical condition (eg, diabetes and high blood pressure) or concerns of the negative effect a current behavior may have (eg, smoking and alcohol consumption) to better manage or improve their mental health (eg, anxiety and self-confidence) and general well-being (eg, sleep quality):

> *I'm trying to avoid having type 2 diabetes, or getting it, so there's a background, my mother, in my family, there's a heart conditions background, which is why I'm really wanting to do something about my health.* [P3]

Although most participants were aware of the existence of some apps, 3 participants were surprised by the existence of health apps for smoking cessation and mental health issues:

> *It didn't cross my mind that I could use an app for stopping smoking, so it is new.* [P16]

Opportunity Factors Related to the Uptake of Health and Well-being Apps in General

Some participants expressed their preference to look for a health app as a digital behavior change intervention instead of a face-to-face intervention because of the availability and low cost of an app. However, concerns around widening inequalities were raised by one participant who showed signs of worry about the limited access to digital aids for individuals living in deprived areas:

> *So if they [people living in deprived areas] do not have the smart phone, they won't be able to use it, so it's not going to work, is it? It's what happened with the Universal Credit, so it's not going to work. I mean issue everyone a smart phone.* [P16]

A few participants highlighted the importance of the availability of health apps in both major commercial app stores (Apple App Store and Google Play), not just one or the other.

Most participants stated that apps should be available at no cost. Only 6 participants expressed their willingness to pay a small fee for an app if, for example, it would be "almost life-changing" (P4) or if it would include online professional support.

The specific design and color scheme preferred by participants appeared to be unique and dependent on the individual's taste. However, the majority were looking for a *simple* looking app.

Social influences appeared to be one of the core factors that shaped the selection of apps for all participants during the think-aloud exercise. This includes ratings and reviews of the app, the credibility of the source of the app, and recommendations of apps received from others. Within app stores, most participants described looking at the star ratings and the number of downloads of each app and whether the apps were listed as an *editor's choice*. A total of 3 participants acknowledged that reviews were subjective, and they still reported feeling influenced by the ratings of the app. In addition, 2 participants reported that they were skeptical of the reviews, which they believed may have been paid for, and that reviews are not enough, as more information is necessary to make an informed choice:

> *You know, so you're having to make all these judgements about people's reviews and then you know deep down that the reviews might be paid for and, you know, it's a bit of a minefield which is why I would only take a free sample and then see if it works for me.* [P6]

A credible source was also important. Apps developed or recommended by trusted organizations or respected celebrities seemed more appealing to all participants. Participants who used Google Search to find an app aimed to look for websites they were familiar with or had used before or for websites that would post "Top 10 apps for..." type of articles. In addition, word of mouth was another source of social influence:

> *I see two different specialists, I have a lung problem as well and I see a lung specialist at a hospital near me and she said to me, the best thing that I could do, which was downloading the Couch to 5k app.* [P14]

Motivational Factors Related to the Uptake of Health and Well-being Apps in General

Health or well-being apps were preferred over face-to-face options because participants reported feeling competent by changing their behavior through the use of an app, requiring less time commitment and avoiding the anxiety and pressure of interacting with others. Time appeared to be a particularly valuable resource for all participants, and they believed apps to have this advantage.

Another core factor in the selection of an app was the way users perceived its utility. This was based on 2 aspects. First, they appeared to judge how the app is adapted to the individual by reading the title and description of the app and by looking at pictures (ie, screenshots). A total of 12 participants reported the need for sufficient information about an app to make an informed choice:

> *I would definitely judge more from the pictures more than anything and I think that just nowadays everyone does, is you get an idea of the app from the pictures. (...) I mean I think when you see an older person on a picture and you're a lot younger, it makes you think, I mean it's the wrong think to think but it makes you think maybe it's not for me.* [P7]

Second, it seemed that 12 participants relied on their past experiences with health apps. Whether those experiences were positive or negative may have shaped their beliefs about health apps in general:

> *So that's why My Fitness Pal is the first app that I've ever had that's actually worked.* [P9]

In addition, 7 participants expressed skepticism about the accuracy and effectiveness of some apps (eg, mental health apps), and concerns about data protection were mixed:

> *These mindful ones, I've never downloaded one and I'm sceptical.* [P17]

Participants mentioned that commitment to the behavior change would influence uptake and future engagement:

> *So I think the committed ones seek out the ones that are the right ones for them, the best ones, rather than necessarily the trendy ones.* [P4]

Participants' social identities also shaped their selections. Many reported that they did not wish to select apps that promoted groups they did not seem to fit in with (eg, athletic body image or individuals of the hipster subculture):

> *They've got a kind of hipster bloke and now they've got a kind of sexy female image with tattoos down her arm, sexy, trendy, female image. Okay, so they are obviously aiming at younger, sort of people in their twenties and thirties, yeah, another sexy female image. It's quite interesting isn't it, I'm looking at the images and not the words and getting a sense, is this for me, middle aged, well older woman?!* [P6]

Curiosity, defined here as a desire to learn something, was the only stand-alone positive emotion and appeared to positively influence the uptake of health apps for many participants:

> *I thought out of curiosity I'd have a look, so I just typed in quit smoking in Google play store and there's hundreds of apps from various people with varying degrees of credibility, and they all were pretty similar to be honest.* [P13]

Apps linked to a credible source were important, with people unimpressed when an app was not available on all major app stores.

Views on Curated Health App Portals

None of the participants spontaneously used a curated portal. Curated portals were then introduced to the participants, but none were previously aware of them. Curated health app portals were appealing to all participants, and they believed the portals would be likely to engender trust. However, searching for a health app on the NHS Apps Library and the One You App portal was a generally disappointing experience. Only 2 participants chose a health app from a health app portal (One You Apps), whereas the rest of the participants decided to continue the search in commercial app stores.

Capability Factors Related to the Uptake of Health and Well-being Apps on Health Portals

All participants had heard of widely advertised apps (eg, Couch to 5k), but none were aware of the existence of curated health app portals before participating in this study:

> *I think they're brilliant [apps on health app portals]; I didn't know they existed.* [P11]

Navigating on the NHS Apps Library seemed easy for some. However, a few participants mentioned that a user guide or help section would be a useful added feature of the portal. Two participants reported that they did not find it easy to use the filter features, and in many cases, they felt the search yielded irrelevant results (eg, while searching for a physical activity app, the results also listed apps for mental health). A few participants reported that navigating on curated app portals was difficult, characterized as "cumbersome" (P4, P12):

> *It's not clear, it's suggests that they are independent apps but maybe they should have some guidelines about design, you know, of their sort of landing pages.* [P6]

Opportunity Factors Related to Uptake of Health and Well-being Apps on Health Portals

All participants indicated that they would want a portal tailored to their needs, with categories related to their gender, age group, and medical conditions they may have:

> *So something like that, this is suitable if you're over 65, this would be more suitable for you if you're under 40 or with these ones that you don't have to go and see your GP, that you can pay for, if you have any concerns, visit your GP or speak to a health professional because some people don't have that common sense.* [P14]

Participants had different opinions about the layout of these portals. Some liked the NHS Apps Library design better, with simple colors, whereas others enjoyed the more colorful One You App portal. Most participants felt that a fusion between these 2 designs (the searchability and filters of the NHS Apps Library and the look and presentation of the One You App portal) and a better functionality would create the ideal curated health app portal:

> *Why they are not combined?* [P8]

Although many participants expressed their wish to access apps for free, a few participants were more open to pay for an app that was listed on a curated health app portal:

> *This is fabulous, and I'd be much more inclined to pay money. This is really, really good.* [P6]

Participants found the NHS and PHE trustworthy and believed that these portals would provide safe and effective digital aids. Some indicated a desire to receive further recommendations for using these portals from their primary care physicians:

> *If GPs knew that they could say "well this could help you" I'm sure that they would recommend it to people.* [P11]

However, they also wanted to avoid putting unnecessary pressure on general practitioner (GP) practices:

> *You've got "free but requires GP referral" and when you're thinking the NHS is under so much financial strain and pressure at the moment, why do I need a GP referral to obtain an app?* [P2]

In addition, the One You App portal lists a few apps that are recommended, but participants expressed their confusion and lack of clarity regarding why some apps are *recommended* and by whom.

Motivation Factors Related to Uptake of Health and Well-being Apps on Health Portals

While searching on curated health app portals, none of the participants expressed signs of concern about data protection and accuracy of apps, although 2 participants reported that they would want to read more about how these apps were developed and tested:

> *How long it takes, how many sessions and the fact that it's been tested in clinical trials and evaluated by NICE which, to me, is probably quite an important thing.* [P1]

Social identity was also important. Some participants had identified themselves as individuals living with a medical condition. These participants were keen to look for an app that targets the behavioral change of individuals with preexisting medical conditions. Others stated that they do not wish to feel "like a patient" (P7) and seemed reluctant to continue the search on a curated health app portal:

> *So it would be nice to have one specific for maybe people with medical problems or age-related problems, etc.* [P15]

Discussion

Principal Findings

Online searches for health and well-being apps were found to be difficult. Factors influencing the uptake of health apps were mapped using the COM-B model and TDF. We found that social influences and participants' beliefs about consequences (the perceived utility of the app) are key factors influencing the uptake of health apps. This conclusion was based on the frequency and salience of the themes that occurred during the interview. Curated health portals were found to be appealing despite the lack of awareness of their existence. However, the way apps are currently presented on these portals did not meet users' needs because of a lack of certain features, such as lack of tailoring to the user's requirements.

In line with previous research, the findings revealed the importance of the capability and opportunity factors, such as app literacy skills; health awareness and app awareness; esthetics of an app; low cost of an app; reading reviews and checking ratings; credible sources; and recommendations of apps from others, including health professionals [18,22,39,40]. Interestingly, the perception of the cost of an app appeared to be related to the perceived utility and credibility of the source. Although at the start, some participants were against paying for apps, the more useful an app was perceived, the more inclined participants felt to pay a fee. This phenomenon was observed for apps listed on health app portals, which were considered a credible source. More importantly, unlike apps listed on commercial app stores, there was implied trust in apps listed on curated health app portals by participants. In addition, some health apps are not available for downloading in both commercial app stores. Participants found it disappointing that some apps were only available for iPhone users. This is in line with previous research that found that out of 18 investigated health apps, only one-third were available to download on both major commercial app stores [28].

In terms of motivational factors, we found that perceived utility included aspects related to individuals' perceptions about the presentation of an app and their previous experiences with health apps. Together, these shaped the way participants judged the usefulness of an app. This characterization underlines the need expressed by others previously for a better way to present health apps through a description that would lead to an informed choice (eg, the content of the app) [25-27] and potentially positively affect other motivational factors, such as the accuracy of an app and data protection [41]. Notably, concern about data protection and the accuracy of a health app was minimal when participants navigated on health app portals as opposed to commercial app stores.

There is a need to understand what design aspects generate positive or negative emotions and for whom. Emotions are powerful drivers of a behavior, which affects decision making (eg, app uptake) [42]. A key emotion identified in this study directly influencing the uptake was curiosity. However, this study emphasized the importance of positive emotions triggered by, for example, the credible source of an app and negative emotions triggered by restriction of information (eg, lack of understanding of the necessity of GP referral to download an app). Taking these factors into consideration may lead to better uptake with such tools.

Uptake and engagement are connected. Engagement without uptake is not possible, and uptake without taking into consideration the factors that are important for engagement is impractical. Some factors might influence both uptake and engagement; for example, our research suggests that the perceived utility of an app is one of the main factors for uptake. However, a previous study found that perceived utility was a predictor of engagement with an alcohol reduction app [43]. Therefore, where possible, uptake and engagement should be considered together as 2 linked constructs.

Strengths and Limitations

The main strength of this study lies in its methodology. Given that the aim of this study is to explore uptake with health apps and by applying a user-centered approach, the think-aloud methodology was the appropriate technique to use [33,44] as it will minimize recall bias. Involving stakeholders—patient and public engagement representatives and policy makers—in the design of the research enhances scientific rigor. The purposive sampling technique adopted enabled the recruitment of a wide range of participants that included the same number of females and males and having different levels of education and employment status, and the sample overrepresented ethnicity relative to local rates. The use of the COM-B and TDF to guide the data analysis is another strength of this study.

This study had several limitations. First, asking participants to perform the think-aloud task under observation may not be fully analogous to how they would perform a search when on their own. Second, some identified factors were difficult to define and describe because of the lack of specificity of the description provided by participants. These include esthetics of apps, often described vaguely (*nice* and *elegant*) and the cognitive load associated with engagement with these (*easy to use*). Third, for a qualitative research study exploring such a broad topic, we felt that information saturation was reached; however, it is possible that additional participants with more varied characteristics would have allowed us to identify additional concepts. Finally, during external validation, a randomly selected subsample of participants was asked via email to provide feedback on the summary of the findings. A total of 50% (3/6) of participants did not reply, and it is unclear whether these participants ignored our request or did not agree with the interpretation of the results.

Implications for Research, Policy, and Practice

This study has important implications for stakeholders in public health and policy makers who target prevention and health promotion using digital technologies and governmental bodies and trusted health organizations that provide curated health app portals. Low awareness, low app literacy skills, lack of availability on all major app stores, and lack of recommendation in primary care were identified as factors limiting the uptake of health apps in general and on curated app portals. These factors are important for improving the uptake of health apps. Selection was described as difficult. Therefore, there is a need for public guidance on how to identify evidence-based tools [18,22] and for health practitioners to promote and advise their patients on how to select appropriate health and well-being apps [40]. Raising awareness of such tools through both online and offline promotion channels might provide better access to effective apps.

Our findings could also help developers to reconsider the ways in which apps are currently presented on commercial app stores and app portals, which might, in turn, increase the uptake of evidence-informed health apps. The idea of selecting an app from a health app portal was appealing to all participants, although individuals' needs were not met. These findings describe essential barriers and facilitators related to participants' capability, opportunity, and motivation to take up health and well-being apps. For example, app descriptions and presentations that better align with individuals' needs may increase the uptake of health apps on health app portals. These findings can also be used to inform the development of interventions that specifically aim to promote the uptake of and engagement with evidence-informed health and well-being apps, a priority within the NHS long-term plan (ie, *digital first*). By targeting the identified psychological influences on app uptake through further interventional work, organizations that provide app portals (eg, the NHS and PHE) should be able to increase their impact by helping people to better select appropriate apps. A summary of the recommendations for policy makers, providers, and developers is presented in Textbox 1.

Textbox 1. Recommendations for policy makers, industry, health care providers, and app developers based on the Capability, Opportunity, Motivation-Behavior model for a better uptake of health and well-being apps.

Capability

- Improve app literacy skills, with a focus on older and marginalized populations, and continue working toward reducing the digital divide (eg, through the use of an outreach approach to target older, migrant, and homeless populations).
- Increase awareness of effective health apps and curated health app portals through promotion online and offline in primary care, mass media, and public spaces.
- Provide guidance on how to use a health app portal (eg, through incorporating an extensive help section) and additional physical and mental health–related evidence-based papers.
- Promote reduced cognitive load on curated health app portals (eg, through the use of images and short app descriptions).

Opportunity

- Ensure evidence-informed apps are available for free or at a low cost to everyone.
- Make apps available on all major app stores simultaneously.
- Offer the possibility to tailor the health app portal to target certain demographics (eg, apps for physical activity for women aged 60 years or more).
- Offer apps at low cost and provide explanation for those that require referrals and justifications for the cost of paid apps on curated health app portals.
- Collaborate with interaction design experts and end users to enhance the esthetics of health app portals.
- Promote evidence-informed apps via trusted organizations and provide information on how the apps were developed and tested.
- Encourage health professionals and practitioners of promotion of evidence-informed health apps and health app portals.

Motivation

- Provide relevant and realistic titles and avoid general app descriptions. Descriptions should be short but must contain details of what the app offers and how it is able to help the user.
- Provide pictures of the app (eg, screenshots) and avoid pictures that promote an unrealistic body image.
- Provide information about the accuracy and effectiveness of the app (eg, details about development and developers) and how users' data are handled.
- Take into account users' emotions about certain features by constantly involving the users in the development of health apps.

Future Research

Future research is needed to minimize factors limiting uptake, such as low awareness, low app literacy skills, and a lack of recommendations in primary care. Our results suggest that there is a need to better tailor the design and content of health app portals to better meet individuals' needs. However, the mixed views on specific app designs indicate that more research is needed to investigate whether there are general design principles that are missed and could be followed to accommodate the majority of people or whether better tailoring and/or adaptive interventions should be considered instead. Future research may also want to consider comparing curated health app portals developed by private organizations with those developed by governmental bodies to investigate whether portal design–related features are considered less or more important than credibility and trust in apps listed on them. Experimental research is needed to assess whether there is a trade-off between credibility, social influences, and perceived utility of the apps presented on curated health app portals. Furthermore, with a growing concern around widening inequalities [45], solutions should be focused on reducing the digital divide and health inequalities that may appear as a result of the financial constraint of owning a smartphone and lack of sufficient app literacy skills.

Conclusions

Among the factors mapped under capability, opportunity, and motivation components of the COM-B model, social influences and the perceived utility of an app appear to be the core factors influencing uptake in general and on curated health app portals. Curated app portals are considered trustworthy and serve as a credible source for apps; however, there is disappointment with their current implementation of these portals. Uptake of health and well-being apps on health app portals, as opposed to uptake in general, appears to help address people's concerns regarding data protection and the accuracy of apps. Health organizations that develop app portals may consider targeting the factors identified across the COM-B and TDF as part of additional experimental work, as this could help to increase impact through better selection of appropriate health apps.

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Authors' Contributions

DS, FN, AJ, TC, and JB conceptualized the study design. DS wrote the study protocol with contributions from FN, AJ, TC, and JB. All authors commented on the topic guide. DS undertook recruitment of participants, data collection, data analysis, interpretation, and report writing. OP double-coded a proportion of the transcripts. DS, OP, and FN finalized the final thematic framework. DS prepared the manuscript. All authors read, commented on, and contributed to the final manuscript.

Conflicts of Interest

JB has received unrestricted research funding to study smoking cessation from pharmaceutical companies that manufacture smoking cessation medications. JB, FN, OP, and DS are unpaid members of the scientific committee for the Smoke Free app and have no financial interest in the app.

Multimedia Appendix 1

Consolidated criteria for reporting qualitative studies: 32-item checklist.
[PDF File (Adobe PDF File), 150 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Screening questionnaire.
[PDF File (Adobe PDF File), 45 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Topic guide for the interviews.
[PDF File (Adobe PDF File), 137 KB-Multimedia Appendix 3]

Multimedia Appendix 4

Study participants' characteristics.
[PDF File (Adobe PDF File), 105 KB-Multimedia Appendix 4]

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Abbreviations

COM-B: Capability, Opportunity, Motivation-Behavior
GP: general practitioner
NHS: National Health Service
PHE: Public Health England
TDF: Theoretical Domains Framework

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Appendix 8. Consolidated criteria for reporting qualitative studies (COREQ): 32-item checklist

No. Item	Guide questions/description	Reported on Page #
Domain 1: Research team and reflexivity		
Personal Characteristics		
1. Inter viewer/facilitator	Which author/s conducted the inter view or focus group?	Pg. 5
2. Credentials	What were the researcher's credentials? E.g. PhD, MD	Pg. 1 (title page, list of authors), Pg. 6
3. Occupation	What was their occupation at the time of the study?	Pg. 16
4. Gender	Was the researcher male or female?	Pg. 5
5. Experience and training	What experience or training did the researcher have?	Pg. 6
Relationship with participants		
6. Relationship established	Was a relationship established prior to study commencement?	
7. Participant knowledge of the interviewer	What did the participants know about the researcher? e.g. personal goals, reasons for doing the research	Pg. 6
8. Interviewer characteristics	What characteristics were reported about the inter viewer/facilitator? e.g. Bias, assumptions, reasons and interests in the research topic	Pg. 6
Domain 2: study design		
Theoretical framework		
9. Methodological orientation and Theory	What methodological orientation was stated to underpin the study? e.g. grounded theory, discourse analysis, ethnography, phenomenology, content analysis	Pg. 5
Participant selection		
10. Sampling	How were participants selected? e.g. purposive, convenience, consecutive, snowball	Pg. 5
11. Method of approach	How were participants approached? e.g. face-to-face, telephone, mail, email	Pg. 5
12. Sample size	How many participants were in the study?	Pg. 5
13. Non-participation	How many people refused to participate or dropped out? Reasons?	Pg. 5
Setting		

14. Setting of data collection	Where was the data collected? e.g. home, clinic, workplace	Pg. 5
15. Presence of non-participants	Was anyone else present besides the participants and researchers?	Pg. 5
16. Description of sample	What are the important characteristics of the sample? e.g. demographic data, date	Pg. 7; Multimedia appendix 1
Data collection		
17. Interview guide	Were questions, prompts, guides provided by the authors? Was it pilot tested?	Multimedia appendix 4
18. Repeat interviews	Were repeat inter views carried out? If yes, how many?	N/A
19. Audio/visual recording	Did the research use audio or visual recording to collect the data?	Pg. 6
20. Field notes	Were field notes made during and/or after the inter view or focus group?	Pg. 7
21. Duration	What was the duration of the inter views or focus group?	Pg. 6
22. Data saturation	Was data saturation discussed?	Pg. 15
23. Transcripts returned	Were transcripts returned to participants for comment and/or correction?	Pg. 6
Domain 3: analysis and findings		
Data analysis		
24. Number of data coders	How many data coders coded the data?	Pg. 6
25. Description of the coding tree	Did authors provide a description of the coding tree?	Table 2.
26. Derivation of themes	Were themes identified in advance or derived from the data?	Pg. 6
27. Software	What software, if applicable, was used to manage the data?	Pg. 6
28. Participant checking	Did participants provide feedback on the findings?	Pg. 6
Reporting		
29. Quotations presented	Were participant quotations presented to illustrate the themes/findings? Was each quotation identified? e.g. participant number	Pg. 10-13
30. Data and findings consistent	Was there consistency between the data presented and the findings?	Pg. 8 -13
31. Clarity of major themes	Were major themes clearly presented in the findings?	Table 1.
32. Clarity of minor themes	Is there a description of diverse cases or discussion of minor themes?	Table 1.

Appendix 9. Ethical approval of the think-aloud and interview study

Faculty of Medicine and Health Sciences Research Ethics Committee

University of East Anglia

Dorothy Szinay
HSC

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Norwich Research Park
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27 March 2019

Dear Dorothy

Project Title: A qualitative study exploring people's perception of factors influencing the uptake and use of health and wellbeing smartphone apps.

Reference: 201819 - 089

Thank you for your response to the recommendations from the FMH Ethics Committee to your proposal. I have considered your amendments and can now confirm that your proposal has been approved.

Please can you ensure that any further amendments to either the protocol or documents submitted are notified to us in advance, and also that any adverse events which occur during your project are reported to the Committee.

Approval by the FMH Research Committee should not be taken as evidence that your study is compliant with GDPR and the Data Protection Act 2018. If you need guidance on how to make your study GDPR compliant, please contact your institution's Data Protection Officer.

Please can you also arrange to send us a report once your project is completed.

Yours sincerely

Professor M J Wilkinson
Chair, FMH Research Ethics Committee

Appendix 10. Screening questionnaire for the think-aloud and interview study

Question	Response Options
How old are you?	Enter free text
Are you able to travel to Norwich for the interview?	(1) Yes (2) No
Do you own a smartphone with Internet access and capable of running apps?	(1) Yes (2) No
Which of the following best describes you?	(1) I would like to stop smoking (2) I would like to drink less or stop drinking (3) I would like to lose weight to get healthier (4) I would like to do more physical activity (5) I sometimes feel down or depressed, and I would like to feel better (6) I sometimes have anxiety, and I would like to feel better (7) I would like to improve my mood (8) Other: [Enter Free Text] (7) None of these describes me
Have you used a health or wellbeing smartphone app to help you become healthier or to feel better? *(Examples of health or wellbeing smartphone apps: apps that can help you quit smoking, drink less, being more active, losing weight, become less depressed, become less anxious, improve your mood)*	(1) Yes (2) No
If yes, what was the name of the health or wellbeing smartphone app(s) that you have used?	Enter free text
Are you currently using a smartphone app to help you become healthier or to feel better?	(1) Yes (2) No
If yes, what was the name of the health or wellbeing smartphone app that you are currently using (if different from [earlier question]?	Enter free text
Would you consider using a smartphone app in the future to help you become healthier or to feel better?	(1) Yes (2) No

Baseline questionnaire

Question	Response Options
What is your gender?	(1) Female (2) Male (3) Other [free text]
What is the highest level of education you have completed?	(1) Primary School (2) GCSEs or equivalent (3) A level or equivalent (4) University undergraduate programme (5) University post-graduate programme (6) Doctoral degree
What is your employment status?	(1) Employed full-time (2) Employed part time

	(3) Self-employed full-time (4) Self-employed part-time (5) Unemployed (6) Unemployed and on state benefits (7) Unemployed - still in education
What is your ethnic group?	(1) English/Welsh/Scottish/Northern Irish/British (2) Irish (3) Gypsy or Irish Traveller (4) Any other White background (5) White and Black Caribbean (6) White and Black African (7) White and Asian (8) Any other Mixed/Multiple ethnic background (9) Indian (10) Pakistani (11) Bangladeshi (12) Chinese (13) Any other Asian background (14) African (15) Caribbean (16) Any other Black/African/Caribbean background (17) Arab (18) Any other ethnic group
When was the last time you downloaded an app, if ever?	(1) Today or yesterday (2) In the last week (3) In the last month (4) In the last 3 months (5) In the last 6 months (6) More than 6 months ago
How frequently do you use the apps on your smartphone, if at all?	(1) Daily (2) Weekly (3) Monthly (4) Never
Have your friends or family recommended any smartphone health or wellbeing app for you to use?	(1) Yes (2) No
Have you recommended any smartphone health or wellbeing app to your friends or family?	(1) Yes (2) No
How do you use your smartphone?	(1) Check your e-mail (2) For social media (e.g. Facebook, Twitter, Instagram, etc.) (4) Navigate using Google Maps or similar tools (5) Read the news (6) Research things to purchase (7) Download and play games (8) Download and use health/wellbeing apps (9) Other [free text]

Appendix 11. Participant information sheet for the think-aloud and interview study

Participant information sheet (interviews)

Title of the study: **A qualitative study exploring people's perception of factors influencing the uptake and use of health and wellbeing smartphone apps.**

Researchers involved: Dorottya Szinay, Dr Felix Naughton, Professor Andy Jones, Dr Tim Chadborn, Dr Jamie Brown

Before you decide we would like you to understand why the research is being done and what it would involve for you. This Participant Information Statement will give you more information about the research. Knowing what is involved will help you decide if you want to take part in the study. Please take time to read it carefully and ask questions you may have and about anything that you don't understand.

Purpose of the study

You are invited to take part in a research study that aims to better understand how people choose and use health and wellbeing smartphone applications. The findings will help to develop more effective digital intervention that supports health behaviour and lifestyle change.

Why have I been invited?

This study is open to adults who would like to be healthier and feel better. You have been invited to participate as you expressed interest in doing so.

Do I have to take part?

Being in this study is completely voluntary and you do not have to take part.

If you do decide to take part, you will be required to give consent.

What if I change my mind?

If you decide to take part in the study and then change your mind later, you are free to withdraw at any time (during or after the interview) and without giving a reason and without your legal rights being affected. Your information will be removed from our records and will not be included in any results, up to the point we have analysed and published the results.

What will the study involve for me?

Your participation will involve an interview with Dorothy Szinay in a quiet room at University of East Anglia or somewhere that you choose. The interview will take place at a time that is convenient to you and should last about 60 minutes. The discussion will be audio recorded.

You will be asked questions regarding choice and use of health and wellbeing smartphone apps and your experiences with them. You might be shown websites with different smartphone apps and be asked what you think of them.

Are there any risks or costs associated with being in the study?

Aside from giving up your time, we do not expect that there will be any risks associated with taking part in this study.

Are there any benefits associated with being in the study?

We cannot promise the study will help you, but the findings may help to provide better digital support in the future for people who want to get better and healthier.

What will I receive as a compensation for my time?

You will receive £20 worth voucher as a thank you for taking part.

What will happen to information about me that is collected during the study?

We will follow ethical and legal practice, and all information about you will be handled in confidence. Therefore, your information will be kept strictly confidential, will be looked at and stored by authorised persons on a password protected database at the University of East Anglia. To safeguard your rights, we will use the minimum personally-identifiable information possible and the data will be anonymised. Your personal data will be destroyed at the end of the project and the research data will be kept for 10 years and then disposed of securely.

If you are concerned about how your personal data is being processed, or if you would like to contact us about your rights, please contact University of East Anglia in the first instance at *dataprotection@uea.ac.uk*.

What if I would like further information about the study?

When you have read this information, Dorottya Szinay will be available to discuss it with you further and answer any questions you may have. If you would like to know more at any stage during the study, please feel free to contact Dorottya Szinay on d.szinay@uea.ac.uk

Will I be told the results of the study?

If you would like to know the results of the study, it can be emailed to you using the email address provided.

What will happen with the result of the study?

The results of the study may be presented to other researchers, at conferences and through publication in scientific and medical journals. No names will be used in the results and individuals will not be identifiable in any written reports or presentations. It is also intended that the findings will be used to design new techniques that support digital health and wellbeing behaviour change.

Who is carrying out the study?

This study is a postgraduate student research study which is jointly funded by Public Health England and University of East Anglia. The lead researcher of this study is the postgraduate researcher Dorottya Szinay.

Who has reviewed the study?

This research has been reviewed and approved under the regulations of the University of East Anglia's Faculty of Medicine and Health Sciences Research Ethics Committee.

Who can I contact about the study?

If you have quires or there is a concern about any aspect of this study, you should contact Dorothy Szinay, who is the lead researcher and will do her best to answer your questions:

Dorottya Szinay

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If you would like to speak to someone else, you can contact the primary supervisor of the project:

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If you are concerned about the way this study is being conducted or you wish to make a complaint to someone independent from the study, please contact the Head of the School of Health Science:

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+44 (0)1603 59 3940

Thank you for reading this information sheet and for considering taking part in this research study. Please click next to proceed to the consent form if you wish to take part.

Appendix 12. Consent form for the think-aloud and interview study

PARTICIPANT CONSENT FORM

Participant ID: ……………………

Title of Project: A qualitative study exploring people's perception of factors influencing the uptake and use of health and wellbeing smartphone apps.

Name of Researcher: Dorothy Szinay, Postgraduate researcher, University of East Anglia (d.szinay@uea.ac.uk)

The study has been approved by the **Faculty of Medicine and Health Sciences Research Ethics Committee at University of East Anglia** [*Project ID:R205853HSC*]

Thank you for your interest in taking part in this research. Before you agree to take part, please ensure you understand the project (through the participant information sheet) and ask any questions you may have. If you wish to take part, then please make sure you are happy with the statements below in order to join the study.

Please initial box

1. I have read the information sheet (version 1 – dated 06.02.2019) for the above study. I have been giving the opportunity ask questions and discuss the study. ☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time without giving any reason and without my legal rights being affected. ☐
3. I understand that I may stop the interview at any time if I do not wish to continue, and that I may refuse to answer any questions I don't wish to answer. ☐
4. I understand that the information collected about me will be anonymised and used to support other research in the future. I also understand that the results of this study may be published, and that publications will not contain my name or any identifiable information about me. ☐
5. I understand that personal information about me that is collected over the course of this project will be stored securely and will only be used for purposes that I have agreed to. ☐
6. I agree to be audiotaped during the interview. ☐
7. I consent to take part in the above study. ☐

____________________	____________________	____________________
Name of Participant	Date	Signature
Dorothy Szinay	____________________	____________________
Name of Person taking consent	Date	Signature

Appendix 13. Topic guide for the think-aloud and interview study

Think aloud exercise:

*'In the questionnaire you have mentioned that you would like to [**change a behaviour**]. Imagine that you are now looking for an app for that. Imagine that you are at home and have decided to use an app for that. Please look for an app. You can use your own phone or this laptop if you wish.* ***[Waiting to see where the participant would look for the app. Use of prompts to think-aloud.]****'*

'I would like to show you a different app pool on this laptop. Please repeat the first exercise but this time use this portal to find an app.'

'You have mentioned that […]. Can you elaborate on that? '

*'How did it feel to search for an app on this portal, instead of [**where they have searched for the first time**]?*

Why?'

Follow up questions:

'You have mentioned that [**…**]. Can you elaborate on that?'

'In your view, is there anything missing from this portal? '

Further questions:

'How do you think other people select an app?'

'Why would anyone choose to use an app to change their behaviour?'

'You have mentioned in the questionnaire that you have used/are using [***name of the app***]. How did you find that app?'

'Why have you used it?' **OR** 'What makes you to continue using it?'

OR 'Why have you stopped using it?' **AND** 'Is there anything that would have made you continue to have used it?'

'If it would be your decision, what would you do to promote the use of health apps?'

'I would like to show you a few cards. Imagine that we are going to improve the app portal. Out of these cards, which one would you implement and why?'

(Cards with: 'Short and simple description of the app listed on the portal';' Long and detailed description of the app listed on the portal'; 'It is possible to set up and manage your own goals on the portal and perhaps target more than one behaviour'; 'Portal where you can filter what features the app has'; 'Check in features')**. ***

Additional/final question

Is there anything else you wish to add or anything we haven't covered, and you feel it would important to share?

**The card sorting task was relevant for the development of web-based interventions and was not included in the reporting of the qualitative research.*

Appendix 14. Publication of the discrete choice experiment methodology

JOURNAL OF MEDICAL INTERNET RESEARCH Szinay et al

Tutorial

Understanding Uptake of Digital Health Products: Methodology Tutorial for a Discrete Choice Experiment Using the Bayesian Efficient Design

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Abstract

Understanding the preferences of potential users of digital health products is beneficial for digital health policy and planning. Stated preference methods could help elicit individuals' preferences in the absence of observational data. A discrete choice experiment (DCE) is a commonly used stated preference method—a quantitative methodology that argues that individuals make trade-offs when engaging in a decision by choosing an alternative of a product or a service that offers the greatest utility, or benefit. This methodology is widely used in health economics in situations in which revealed preferences are difficult to collect but is much less used in the field of digital health. This paper outlines the stages involved in developing a DCE. As a case study, it uses the application of a DCE to reveal preferences in targeting the uptake of smoking cessation apps. It describes the establishment of attributes, the construction of choice tasks of 2 or more alternatives, and the development of the experimental design. This tutorial offers a guide for researchers with no prior knowledge of this research technique.

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KEYWORDS

discrete choice experiment; stated preference methods; mHealth; digital health; quantitative methodology; uptake; engagement; methodology; preference; Bayesian; design; tutorial; qualitative; user preference

Introduction

Understanding how the public values different aspects of digital health tools, such as smoking cessation or physical activity apps, can help providers of the tools to identify functionality that is important to users, which may improve uptake (ie, selection, download, and installation of apps) [1]. This is important because uptake of digital tools is generally low. More information regarding the preferences of users when selecting a digital health tool, for example via an app store, may allow providers to present their products in such a way that may increase their uptake. However, pragmatic challenges, such as examining how each potentially modifiable aspect of a digital health product (eg, presentation, design, and features that it offers) or intervention design will impact preference or the choice of uptake, often mean this is not feasible or practical [2]. Therefore, increasing attention is being paid toward stated preference methods to understand preferences when designing digital health products and services, with examples including

COVID-tracing apps [3,4], sun protection apps to prevent skin cancer [5], and the uptake of health apps in general [6].

Stated preference methods are survey-based methods aiming to elicit individuals' preferences toward a specific behavior, particularly those that are not well understood. The most widely used type of stated preference method is the discrete choice experiment (DCE) [7]. According to Spinks et al [8], Louviere and Hensher (1982) and Louviere and Woodworth (1983) originally developed DCEs to study the marketing and economics of transport, and the fields of psychology and economics have profoundly influenced the DCE methodology since it was developed. In recent years, DCEs have been increasingly used in health and health care settings [9,10], as well as in addiction research [11] and digital health [4-6]. The increasing number of DCEs in digital health highlights their potential, although they are currently underused.

Discrete choice differentiates from other stated preference methods in the way that responses are elicited [12]. The DCE uses a survey-based experimental design, where participants are presented with a series of hypothetical scenarios. In these scenarios, participants are shown situations, known as *choice tasks*. Attempting to mimic real-world decision making, in each choice task, participants then have to choose a product or a service from two or more options, known as *alternatives* [13]. Each alternative consists of a set of characteristics, known as *attributes*, with at least two types, known as *attribute levels* [13]. Participants are asked to choose a preferred alternative in each choice task, which allows researchers to quantify the relative strength of preferences for improvements in certain attributes [8,14].

The outputs from statistical models developed using DCE data can be beneficial for estimating uptake of new products or services, including digital health tools, where observational data are not available or are difficult to obtain otherwise [15,16]. Lack of observational data often implies a requirement to seek scientific views and comments from experts in order to generate predictions of a target behavior [17]. However, DCEs can provide an empirical alternative to expert opinions, while accounting for possible interactions between attributes (eg, design of a product and brand name), which are otherwise often ignored [18].

In our research, we wanted to understand how to present health apps on curated health app portals to increase their uptake. This paper describes the development of a DCE in digital health that aims to elicit potential user preferences on smoking cessation app uptake. It explains how the attributes and their levels are selected and describes the construction of choice tasks and the experimental design. The study protocol of the research this paper is based on is registered on the Open Science Framework [19].

Development of a DCE

The development of a DCE should follow published recommendations, including the checklist for good research practices [9], guides on the development of a DCE [13,20], recommendations on how to construct the experimental design [7,20-23], and which statistical methods can be used [24].

Establishing Attributes

An important step in designing a DCE is the identification of the relevant attributes for the subject matter. Attributes in a DCE can be quantitative, such as cost, or qualitative, such as the design of a product [25]. The identification of attributes is typically based on primary and secondary data collection to ensure that the DCE is tailored to the study setting [13]. It should ideally commence with a literature review that will inform qualitative research to identify relevant attributes [26]. Although there is no set limit on the number of attributes that can be included in a DCE, to ensure that the cognitive load of the participants is manageable, it should be less than 10 [13], with a general expectation to include 5-7 attributes [27].

Our DCE was based on a comprehensive systematic review investigating factors influencing the uptake and engagement with health and well-being smartphone apps [28] and a qualitative research component that consisted of a think-aloud and interview study to examine further the previously identified factors or attributes [29]. The importance of qualitative research lies in ensuring inclusion of attributes that are relevant to most participants [25]. Of the 14 factors initially identified as being relevant for the uptake of health and well-being apps, 5 were retained and included in the DCE: the monthly price of the app, who developed the app, the star ratings of the app, the description of the app, and images shown. These factors were chosen due to their perceived importance during our previous qualitative research and for pragmatic reasons, including how easily measurable and presentable they were within the DCE.

An important step in designing a DCE is in ensuring the content validity of the instrument: the identification of relevant attributes for the subject matter. Following administration of the survey, methods are available for the measurement and assessment of the content validity of the instrument, although their use is not widely reported [30].

Establishing Attribute Levels

The next step is to establish attribute levels. The level of an attribute must also be of a range that ensures a trade-off between attributes. A trade-off is defined as an exchange in which a participant gives up some amount of one attribute to gain more of another. It has been suggested that increasing the number of levels for an attribute increases the relative importance of that attribute [31] and that imbalance in the numbers of levels across attributes raises the importance of the attributes with higher levels [32]. Yang et al [32] suggested that a balance exists between simpler designs with lower numbers of levels, which reduce the respondent burden (and consequently measurement error) and are useful for identifying attribute rankings, and more complex designs with higher levels (and higher statistical precision) and is more sensitive to identifying trade-offs between attributes. Based on this, and the commonly adopted practices in the research field, we aimed to include at least three levels for each attribute.

If a range is not suitable, participants might consider the differences between levels unimportant [25]. For example, the difference between the star ratings of 4.8 and 4.7 for a smoking cessation app is not as relevant as the difference between 4.8 and 4. In our research, to refine attribute levels, a survey was conducted with 34 participants. In the survey, the levels of two attributes we were unsure of (the monthly price of the app and the ratings) were carefully considered in order to specify at a sufficiently wide range so that the difference between the levels would likely make a difference in response. When a range is not wide enough, there is a risk that participants could ignore the attributes because they judge the difference between levels to be insignificant [20]. See Figure 1 for the final list of attributes and levels included in our DCE.

Figure 1. Attributes and attribute levels in our DCE. DCE: discrete choice experiment.

Attributes	Attribute levels
1. The monthly price of the app	• £0 • £2.99 • £5.99 • £8.99
2. Who developed the app	• Doesn't say • Mhealth Essentials Ltd. • NHS Digital
3. The ratings of the app	• Doesn't show • 3.2 ★★★ • 4.0 ★★★★ • 4.8 ★★★★★
4. App description	• **Generic**, to create a rough idea of what the app is about without getting into details of app features • **Short**, with some details about app features • **Long**, with a detailed description of the app and its features
5. Images	• Shows the logo of the app • Shows the screenshot(s) of the app • Shows the logo and screenshot(s) of the app

Choice Tasks

Once the attributes and their levels are identified, the decision to develop full- or partial-profile tasks with or without an opt-out option needs to be made. A full profile refers to the display of all five attributes in both alternatives in each choice set. A partial profile DCE will not present certain attributes for certain alternatives. For example, if a DCE is used to investigate the trade-off between a higher number of attributes (eg, a total of nine attributes), it could be beneficial to limit the number of attributes shown at one time (eg, five attributes) to limit participant cognitive load. Five attributes are generally considered low enough to complete a full-profile choice task, which consequently maximizes the information about trade-offs [33]. Hence, in our research, we applied a full-profile DCE.

A neutral option ("Neither of these 2"), known as an opt-out alternative, was included, in addition to selecting alternative apps. The opt-out option has the potential to make the choices more realistic [34] by simulating a real-world context where individuals can exercise their right not to take up an app, given the apps on offer [20]. In our DCE, a participant had the option to choose or reject the hypothetical uptake of a smoking cessation app. However, when a participant selects the opt-out option, no information is provided on how they trade-off attribute levels or alternatives [13]. In some situations, a *forced-choice* scenario can be included, where participants who chose the opt-out option are prompted to make a choice regardless. An example of a scenario with an opt-out option is shown in Figure 2.

Figure 2. An example of a scenario with an opt-out option used in our DCE. DCE: discrete choice experiment.

You wish to quit smoking, and you decide to select a smartphone app to do that. Please look at the options carefully and decide which app (App 1 or App 2) you think you would likely want to download and use to help you quit smoking. You could also choose "Neither of these two" if you do not like either option and would not choose to download either app.

Take your time to make a decision. Please select an option and click on the arrow to continue.

	App 1	**App 2**
The monthly price of the app	£8.99	£0
Who developed the app	Mhealth Essentials Ltd.	NHS Digital
The ratings of the app	4.8 ★★★★★	4.0 ★★★★☆
App description	Generic, to create a rough idea of what the app is about without getting into details of app features	Short, with some details about app features
Images shown	Logo and screenshot(s) of the app	Logo of the app

Experimental Design

An experimental design is a systematic method of generating choice sets that are presented to respondents. This enables the specification of the choice sets that respondents see, with the objective of obtaining a high-quality data set [7]. When creating the experimental design, there are several aspects that need to be taken into consideration, including (1) the analytical model specification, (2) whether the aim is to estimate main effects only or interaction effects as well, (3) whether the design is labeled or unlabeled, (4) the number of choice tasks and blocking options to be used, (5) which type of design of the choice matrix to use (eg, full factorial or fractional factorial, orthogonal or efficient), and (6) how the attribute-level balance will be achieved. These are now considered.

Analytical Model Specification

The first step in the generation of an experimental design is to specify the analytical model to estimate the parameters of the DCE. This step is an important component of choosing the type of choice matrix design, described later in this paper. The approach selected here needs to be accounted for when generating the structure of the experimental design.

A discrete choice model describes the probability that an individual will choose a specific alternative. This probability is expressed as a function of measured attribute levels specific to the alternative and of characteristics of the individual making the choice. This probability is represented by the dependent variable (the *choice variable*), which indicates the choice made by participants [8]. In this modeling framework, the attributes are the independent variables [8,13].

As part of the analytical model specification, knowing what type of statistical analysis will be used is key. Data analysis involves regression modeling in a random utility framework [8]. The random utility model conventionally used is also based on the Lancaster theory of consumer demand [35], which together assume that individuals make trade-offs when making a decision and would choose an option that offers the greatest utility [36], determined by how much importance they place on the attributes associated with the product [37].

The multinomial logit (MNL) model has been previously described as the "workhorse" of DCE estimation [38,39], and it typically serves as a starting point for basic model estimation (although alternative models, such as probit, may be used). It is important to note that MNL requires some important assumptions and limitations—for example, independence of irrelevant alternatives, homogeneity of preferences, and independence of observed choices [40,41]. Extensions of MNL (eg, nested logit, mixed logit, and latent class models) may be used to account for these limitations [39,40].

Based on the model specified in our DCE, the underlying utility function for alternative *j* [38] is shown in Textbox 1.

Textbox 1. The utility function used in our DCE research. DCE: discrete choice experiment.

$U_j = (\beta_{cost} \times X_{jcost}) + (\beta_{developer} \times X_{jdeveloper}) + (\beta_{ratings} \times X_{j\ ratings}) + (\beta_{description} \times X_{jdescription}) + (\beta_{images} \times X_{njimages}) + \varepsilon$

Note:

1) U is the overall utility derived from alternative j.

2) β is the coefficient attached to X_j estimated in the analysis and represents the part-worth utility attached to each attribute level.

3) ε is the random error of the model—in other words, the unmeasured factors influencing the variation of preferences.

Main Effects or Interaction Effects

The next step in model specification is deciding whether main effects or interaction effects will be investigated. The main effects, the most commonly used, investigate the effect of each attribute level on the choice variable. The effect on the choice variable gained by combining two or more attribute levels (eg, app developer and the app's monthly cost) refers to an interaction effect [13]. In our DCE, given the novel nature of the research on the uptake of health apps and the lack of empirical evidence to suggest the presence of potential interactions between attributes, we decided to only look at main effects.

Labeled or Unlabeled Experiment

In a labeled experiment, the alternatives are specific and different (eg, smartphone app-based smoking cessation intervention vs website-based smoking cessation intervention) and alternative specific attributes could be used (eg, some attributes relevant only for apps and others for websites). This is in contrast to an unlabeled experimental design, where the alternatives are unspecified (eg, smoking cessation app alternative 1 vs smoking cessation app alternative 2) and also must have the same attributes. Given that a DCE model estimates parameters for each of the alternatives being considered, these alternative specific parameters must be included in the structure of the experimental design (described in the next section) in a labeled experiment; in an unlabeled experiment, because alternative specific parameters are arbitrary, they are excluded [22,42,43]. In health economics, the unlabeled approach is the most common. In our DCE, the unlabeled approach was deemed logical here as we were comparing different presentations of the same app. Therefore, our DCE design applied an unlabeled approach.

Generation of the Structure of the Experimental Design

Once the model is specified, the structure of the experimental design can be generated. For this stage, hypothetical alternatives are generated and combined to form choice tasks, based on the chosen attributes and their levels. Several different software packages may be used to generate the experimental design of a DCE, such as Ngene, SAS, SPEED, SPSS, and Sawtooth. For our DCE, Ngene software was used [44].

Number of Choice Tasks and Blocking

The next step in the generation of an experimental design is to decide on the choice task and blocking. To minimize respondent and cognitive burden, and the risk of participants losing interest during the DCE task, consideration must be paid to the target population, the number of tasks, and their complexity [13]. The higher the number of attributes, alternatives, and choice tasks, the higher the task complexity [20]. The literature suggests that a feasible limit is 18 choice sets per participant [45,46]. In the review by Marshall et al [27], most studies included between 7 and 16 choice sets. In our DCE, we administered 12 choice tasks per participant, which were deemed a number low enough to avoid excessive cognitive load but high enough to establish sufficient statistical precision.

We developed 48 choice tasks and blocked them into 4 survey versions (12 choice tasks for each). Each block represented a separate survey, and participants were randomly assigned to one of the four survey versions. Blocking is a technique widely used in DCEs to reduce cognitive burden by partitioning large experimental designs into subsets of equal size, thereby reducing the number of choice tasks that any one respondent is required to complete [47]. Blocks were generated in Ngene software, which allows for the minimization of the average correlation between the versions and attributes' levels [48]. For the blocking to be successful, the number of choice tasks included in one block must be divisible by the number of attribute levels; in our DCE, attributes had either three or four levels.

It is noteworthy that to undertake the sample size calculation, it is crucial to know the number of alternatives per choice set, the largest number of levels of any attribute (for DCEs looking at main effects only) or the largest level of any two attributes (for a DCE looking at interaction effects), and the number of blocks [38]. Therefore, DCEs using blocking require a larger sample size [47].

Type of Choice Matrix Design

Depending on the number of attributes and their levels, a full- or fractional-factorial design can be applied. A full-factorial design would include all possible combinations of the attributes' levels and allow the estimation of all main effects and interaction effects independent of one another [20]. However, this type of design is often considered impractical due to the high number of choice tasks required [20]. To illustrate this, the formula of calculation of the possible unique choice alternatives for a full-factorial design is L^A, where L represents the number of levels and A the number of attributes [39]. If the attributes in the DCE have a different number of levels, these need to be calculated separately and multiplied together. To reduce response burden, in our DCE, we generated a fractional-factorial design in Ngene [44], representing a sample of possible alternatives from the full-factorial design. This way, we were able to reduce the total 432 alternatives in the full design (given by $L^A = 4^2 \times 3^3$) to a fractional sample of 96 alternatives, arranged in 48 choice pairs.

Systematic approaches for generation of fractional-factorial designs may be further categorized into orthogonal design and efficient design. An orthogonal design is a column-based design based on orthogonal arrays that present properties of orthogonality (attributes are statistically independent of one another) and level balance (levels of attributes appear an equal number of times) and does not introduce correlation between the attributes [38]. An orthogonal array is an optimal design that is often used for DCEs examining main effects when the number of attributes and their levels is small.

For studies with five or more attributes with two or more levels, an orthogonal design may not be practical. There has therefore been a recent change in thinking toward a nonorthogonal and statistically more efficient design [38]. When perfect orthogonality and balance cannot be achieved or are not desirable, an efficient design can be applied [20]. In contrast to an orthogonal design, an efficient design aims to increase the precision of parameter estimates for a given sample size (ie, minimizing the standard errors of the estimated coefficients), while allowing some limited correlation between attributes. The most widely used efficiency measure is the D-error, which may be easily estimated using various software packages, such as Ngene, and refers to the efficiency of the experimental design in extracting information from respondents [21]. Experimental designs generated using this approach are known as D-efficient designs. A D-efficient experimental design is also recommended to maximize statistical efficiency and minimize the variability of parameter estimates [7].

An efficient design requires that known prior information about the parameters (known as priors) be made available to the algorithm and also requires the analyst to specify the analytical model specification, as described previously. Depending on what information is available, one of three types of D-efficient design can be generated [21]:

1. *D_z-efficient* design (*z* stands for zero priors): If no prior information about the magnitude or directions of the parameters is available. D_z-efficient design is an orthogonal design. This design assumes the parameters are zero.
2. *D_p-efficient* design (*p* stands for priors): This assumes a fixed, certain value and direction for the parameters.
3. *D_b-efficient* design (*b* stands for Bayesian): A Bayesian approach is whereby the parameter is not known with certainty but may be described by its probability distribution.

The best practice is to pilot the DCE. For the pilot phase, there is limited information available and using the D_z-efficient or D_p-efficient design is sensible. In our DCE, we chose to apply a D_p-efficient design, as the direction of priors of the app was known from the previously conducted survey, to narrow down the attribute levels and to provide prior estimates of the parameters for the attribute levels. For example, we knew that a trusted organization will likely positively influence uptake and cost estimated negatively so. The direction of priors was assumed to be a small near-zero negative or a positive value for the design.

The pilot phase provided the estimation that we used to generate a D_b-efficient design for the final DCE. It is noteworthy that when the parameter priors are different from zero, the efficient design generated produces smaller prediction errors than orthogonal designs [21,49,50]. Hence, a D-efficient design will outperform an orthogonal design, and (given reliable priors), a D_p-efficient design will outperform a D_z-efficient design [21]. Further, when reasonable assumptions about the distributions are made, a D_b-efficient design will outperform a D_p-efficient design. Therefore, it may be advisable to start piloting with a D_p-efficient design and to generate a D_b-efficient design for the final DCE. The DCE literature provides a detailed and more comprehensive description of orthogonal and efficient designs [21] and the approximation of the Bayesian efficient design [23].

Attribute-Level Balance in the Model

The attribute-level balance aims to ensure all attribute levels ideally appear an equal number of times in the experimental design. The allocation of the attribute levels within the experimental design can affect statistical power; if a certain level is underrepresented in the choice sets generated, then the coefficient for that level cannot be easily estimated. How attributes levels are distributed is therefore an important consideration when designing the choice sets. Dominant alternatives, where all attribute levels of one alternative are more desirable than all attribute levels in the others, do not provide information about how trade-offs are made, as individuals usually would select the dominant alternatives. Therefore, avoiding dominant alternatives in the experimental design is important and can be achieved by consulting the software manual to ensure the correct algorithm is used. The syntax used in Ngene to generate choice sets of the pilot phase and more information about the algorithm used can be accessed on the Open Science Framework [19].

Piloting the DCE and Generating the Bayesian Design

In addition to providing estimations for the choice matrix design described above, piloting offers an opportunity to ensure that the information is presented clearly and that the choices are realistic and meaningful. It also provides insight into how cognitively demanding it is for respondents to complete. This can be achieved by gathering feedback on the survey completion process. The findings of the pilot may suggest that the DCE needs to be amended, such as reducing the number of choice sets or the number of attributes, so that the responses are a better reflection of the participants' preferences and improve the precision in the parameter estimates [13].

There is no formal guidance on how large the pilot sample should be, and this is largely guided by the budget and complexity of the experimental design. Accuracy of the priors will improve with increasing sample size, but as few as 30 responses may be sufficient to generate useable data [44]. In our pilot study conducted with 49 individuals, feedback from the participants suggested that with the initial order of the attributes, there was a tendency to ignore the last two attributes, app description and images of the app, the most text-heavy attributes. This may have compromised the examination of the relative importance of those two attributes (app description and images of the app). Therefore, we decided to change the final order of the attributes from (1) *monthly price of the app*, (2) *the* *ratings of the app*, (3) *who developed the app*, (4) *the description*, and (5) *images shown* to the one listed in Figures 1 and 2. The longest completion time for the survey was under 12 min. Thus, we concluded that the number of choice tasks did not need to be reduced.

In our research, the data from the pilot phase were analyzed using the freely available Apollo package in R software [51]. The coefficients and their standard errors from the output were used as priors to generate the final choice sets using the Bayesian efficient design following the steps described previously. The syntax used in R used to analyze the pilot data and that used to generate the Bayesian efficient design in Ngene can be accessed on the Open Science Framework [19].

Internal Validity

Assessing the internal validity of a DCE can help with understanding the consistency and trade-off assumptions made by participants [52]. There are several ways to examine the internal validity of a DCE. For example, in the *stability validity test,* a choice task would be repeated later in the sequence to investigate the consistency of the participants' decision, whether they would choose the same alternative [52]. Another way to test internal validity is the *within-set dominated pairs* type of internal validity, in which one alternative is a dominant alternative in which all attributes are the most desirable ones. The choice sets designed to measure internal validity are excluded from the analysis. There are several internal validity tests that are built into software packages such as MATLAB [52], although these can be produced manually as well. In our research, we used the stability validity test to check the internal validity by repeating a randomly generated choice task (in our case, it was the fourth). Therefore, participants were shown 12 choice tasks, plus an additional hold-out task. The data from the randomly generated hold-out task were excluded from the analysis.

Although internal validity checks provide some measure of data quality, it should be noted that answering a repeat choice inconsistently is not a violation of random utility theory [53]. Furthermore, there is no consensus on what to do with the data from responses that fail validity tests. Following the advice of Lancsar and Louviere [54], we did not exclude participants who failed the internal validity check, as that might have caused statistical bias or affected statistical efficiency. However, we reported data on internal validity to enable the reader to make a judgement on likely biases.

All additional study materials used in our example, including the full data set and the results of the DCE, can be accessed on Open Science Framework [19].

Discussion

Summary

This paper describes the development of a DCE, following the stages required to establish attributes and their levels, construct choice tasks, define the utility model, decide on labeled and unlabeled choices to apply, decide on the number of choice tasks that need to be generated, and make decisions on the structure of the experimental design, how to achieve attribute-level balance, how to assess the internal model validity, and how to pilot-test. In doing so, the intention is to advance methodological awareness of the application of stated preference methods in the field of digital health, as well as to provide researchers with an overview of their application using a case study of a DCE of smoking cessation app uptake.

Although DCEs are widely used to understand patient and provider choices in health care [8,10,15,55], they have only recently started to gain popularity in digital health [4-6] and as such represent an underused approach in digital health. With the growing evidence of the benefit of digital health initiatives, there are clear benefits to widening the application of DCEs so that they may more routinely inform digital health development, inform digital tool presentation, and, most importantly, predict uptake and engagement with digital products. Although several attempts have been made to measure engagement with digital tools using a wide range of methodologies [56-58], the insights we have from them that can be translated to uptake are limited. One plausible explanation is that uptake of digital tools is difficult to empirically measure.

Benefits and Limitations of DCEs

DCEs bring several benefits to help overcome the issue of measuring uptake in digital health or in other areas where the measurement of the predictors of uptake in a good or service is required. For example, as illustrated by the case study here, they enable the researcher to gain measurable insights into situations in which quantitative measures are hard to otherwise obtain, such as the factors impacting the uptake of health apps on curated health app portals. A DCE also helps to quantify preferences to support more complex decisions [59]. An example would be the consideration of how to plan the development of an app that would provide appealing looks or features that would promote uptake. The DCE methodology is also considered a convenient approach to investigate the uptake of new interventions, including digital health interventions [38], for example, digital behavior change interventions using a health and well-being smartphone app. Therefore, DCEs can be used in hypothetical circumstances, enabling the measurement of preferences for a potential policy change or digital health system change before it is implemented [13], such as the recent investigation of the uptake of a COVID-19 test-and-trace health app [3,4]. The experimental nature of the DCE also means that participants' preferences can be recorded based on controlled experimental conditions, where attributes are systematically varied by researchers to obtain insight into the marginal effect of attribute changes on individuals' choices [7].

Despite their benefits, the application of DCEs presents several challenges. As with all expressed preference methodologies, the hypothetical nature of the DCE choice set raises concerns about external validity and the degree to which real-world decisions might equate to those made by study participants under experimental conditions, a phenomenon known as the intention-behavior gap [60]. As such, participants may believe they would choose a scenario presented and described in a choice task, but in real life, there might be other factors that would influence their behaviors, such as the aesthetics of the app [28]. This limitation can at least partially be overcome by developing convincing and visually appealing choice tasks. Nevertheless, to date, there has been limited progress in testing for external validity due to the difficulty in investigating preferences in the real world [38]. Indeed, a recent systematic review of the literature on DCEs in health care reported that only 2% of the included studies (k=7) report details of the investigation of external validity [47], while an earlier systematic review and meta-analysis (k=6) found that DCEs have only a moderate level of accuracy in predicting behaviors of health choices [61]. To our knowledge, no study has been published that investigates the external validity of a DCE developed in digital health. One potential opportunity to undertake some testing would be through a curated health app portal, where the same health app is presented in two or more different ways. With the help of website analytics, actual user behavior could be measured in this situation.

A final significant concern associated with the use of a DCE is that any single choice set is unlikely to be able to present the user with all relevant attributes, regardless of how well it has been developed [61]. Choosing the most relevant attributes to test in a DCE, therefore, requires comprehensive preparatory research, which can lengthen the time required to undertake the development phase of any piece of work.

Conclusion

In summary, DCEs have significant potential in digital health research and can serve as an important decision-making tool in a field where observational data are lacking. We hope that the content of this paper provides a useful introduction and guide to those interested in developing such experiments in digital health.

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Authors' Contributions

DS prepared the manuscript. All authors have reviewed the draft for important intellectual content and approved the final version.

Conflicts of Interest

JB has received unrestricted funding to study smoking cessation from Pfizer and J&J, who manufacture smoking cessation medications.

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Abbreviations

DCE: discrete choice experiment
MNL: multinomial logit

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Appendix 15. Attributes relevant for uptake of health and wellbeing apps

1. TDF constructs	2. Identified attributes	3. Description of attributes	4. Action taken	5. Wording of the attributes in the DCE
Skills	1. App literacy	Technological competency	Included in the survey	*NA*
Knowledge	2. App awareness	Knowledge of the existence of health and wellbeing apps	Included in the survey	*NA*
	3. Health awareness	Health consciousness or by having family members diagnosed with a condition or disease, or concerns regarding a behaviour or health outcome	*Excluded*	*NA*
Environmental context and resources	4. Availability	The ability to use a smartphone anytime, anywhere; and availability of an app on all major commercial app stores	*Excluded*	*NA*
	5. Cost of an app	Cost of an app	Included in the DCE	'The monthly price of the app'
	6. Aesthetics	The look and design of an app and user-friendly and design related characteristics of the portal	*Excluded*	*NA*
Social influences	7. Social influences	The importance of reviews and ratings in the commercial app stores	Included in the DCE	'The ratings of the app'
		Identified credible sources: apps developed or endorsed by trusted app developers, organisations, universities	Included in the DCE	'Who developed the app'
Beliefs about capabilities	8. Perceived competence	App preferred over face-to-face intervention when an app is felt that can be engaged with on their own	Included in the survey	*NA*
Beliefs about consequences	9. Time efficiency	The ability of a health app to be interacted with a minimum expenditure of time	*Excluded*	*NA*
	10. The perceived utility of the app	Discrepancy between what the users are looking for and what the app offers, characterised by a relevant title, description, pictures, adaptation to individual characteristics and users previous lived experience with health apps	Included in the DCE	'Images shown'
				'App description'
	11. Perceived Accuracy	The perceived effectiveness of apps before selection of an app	*Excluded*	*NA*

	12. Data protection	Concern regarding the handling of personal data	Included in the survey	*NA*
	13. Commitment	The level of commitment when deciding on uptake with a health app	*Excluded*	*NA*
	14. Social identity	Identity related to app use (e.g. trends and gender specificity, feeling like a 'patient')	Included in the survey	*NA*

Appendix 16. Ethical approval of the discrete choice experiment

Faculty of Medicine and Health Sciences Research Ethics Committee

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Dorottya Szinay
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12th October 2020

Dear Dorottya

Title: Eliciting adult smokers' preferences for the uptake of smoking cessation apps: A Discrete Choice Experiment

Reference: 2020/21-017

Thank you for your email of 8th October 2020 notifying us of the amendments you would like to make to your above proposal. These have been considered and I can confirm that your amendments have been approved.

Please can you ensure that any further amendments to either the protocol or documents submitted are notified to us in advance, and that any adverse events which occur during your project are reported to the Committee.

Approval by the FMH Research Ethics Committee should not be taken as evidence that your study is compliant with GDPR and the Data Protection Act 2018. If you need guidance on how to make your study GDPR compliant, please contact your institution's Data Protection Officer.

Please can you arrange to send us a report once your project is completed.

Yours sincerely

Dr Jackie Buck
Chair
FMH Research Ethics Committee

Appendix 17. The 48 choice tasks of the discrete choice experiment

Block 1

Choice situations: 4, 9, 10, 15, 18, 22, 29, 32, 33, 34, 38, 47

Scenario 4 Block 1

	App 1	App 2
App description	**Long** and detailed description of the app and its features	**Short** with some details about app features
The ratings of the app	3.2	Does not show
Images shown	Screenshot(s) of the app	Logo and screenshot(s) of the app
Who developed the app	Does not show	Mhealth Essentials Ltd.
The monthly price of the app	£0	£0

Scenario 9 Block 1

	App 1	App 2
App description	**Long** and detailed description of the app and its features	**Short** with some details about app features
The ratings of the app	3.2	4.0
Images shown	Logo of the app	Screenshot(s) of the app
Who developed the app	Does not show	NHS Digital
The monthly price of the app	£2.99	£5.99

Scenario 10 Block 1

	App 1	App 2
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Long** and detailed description of the app and its features
The ratings of the app	3.2	Does not show
Images shown	Logo and screenshot(s) of the app	Screenshot(s) of the app
Who developed the app	Does not show	Mhealth Essentials Ltd.
The monthly price of the app	£5.99	£8.99

Scenario 15 Block 1

	App 1	App 2
App description	**Long** and detailed description of the app and its features	**Generic**, to create a rough idea of what the app is about without getting into details of app features
The ratings of the app	Does not show	3.2
Images shown	Logo of the app	Logo and screenshot(s) of the app
Who developed the app	Does not show	NHS Digital
The monthly price of the app	£8.99	£8.99

Scenario 18 Block 1

	App 1	App 2
App description	**Short** with some details about app features	**Generic**, to create a rough idea of what the app is about without getting into details of app features
The ratings of the app	3.2	4.8
Images shown	Logo of the app	Screenshot(s) of the app
Who developed the app	NHS Digital	Does not show
The monthly price of the app	£0	£2.99

Scenario 22 Block 1

	App 1	App 2
App description	**Short** with some details about app features	**Long** and detailed description of the app and its features
The ratings of the app	4.8	3.2
Images shown	Screenshot(s) of the app	Logo and screenshot(s) of the app
Who developed the app	NHS Digital	Mhealth Essentials Ltd.
The monthly price of the app	£2.99	£0

Scenario 29 Block 1

	App 1	App 2

App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Long** and detailed description of the app and its features
The ratings of the app	4.8 ★★★★★	3.2 ★★★☆☆
Images shown	Logo of the app	Screenshot(s) of the app
Who developed the app	Mhealth Essentials Ltd.	NHS Digital
The monthly price of the app	£2.99	£0

Scenario 32 Block 1

	App 1	**App 2**
App description	**Short** with some details about app features	**Long** and detailed description of the app and its features
The ratings of the app	4.0 ★★★★☆	4.8 ★★★★★
Images shown	Screenshot(s) of the app	Logo of the app
Who developed the app	Does not show	Mhealth Essentials Ltd.
The monthly price of the app	£2.99	£8.99

Scenario 33 Block 1

	App 1	**App 2**
App description	**Long** and detailed description of the app and its features	**Generic**, to create a rough idea of what the app is about without getting into details of app features
The ratings of the app	4.0 ★★★★☆	Does not show
Images shown	Logo of the app	Logo and screenshot(s) of the app
Who developed the app	NHS Digital	Does not show
The monthly price of the app	£5.99	£0

Scenario 34 Block 1

	App 1	**App 2**
App description	**Short** with some details about app features	**Short** with some details about app features
The ratings of the app	3.2 ★★★☆☆	3.2 ★★★☆☆

Images shown	Logo of the app	Screenshot(s) of the app
Who developed the app	Does not show	Mhealth Essentials Ltd.
The monthly price of the app	£8.99	£8.99

Scenario 38 Block 1

	App 1	**App 2**
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Short** with some details about app features
The ratings of the app	4.8	3.2
Images shown	Logo and screenshot(s) of the app	Screenshot(s) of the app
Who developed the app	NHS Digital	Does not show
The monthly price of the app	£5.99	£0

Scenario 47 Block 1

	App 1	**App 2**
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Short** with some details about app features
The ratings of the app	Does not show	3.2
Images shown	Screenshot(s) of the app	Logo and screenshot(s) of the app
Who developed the app	Mhealth Essentials Ltd.	NHS Digital
The monthly price of the app	£8.99	£8.99

Block 2

Choice situations: 1, 2, 13, 14, 16, 17, 19, 24, 26, 30, 36, 48

Scenario 1 Block 2

	App 1	**App 2**
App description	**Long** and detailed description of the app and its features	**Generic**, to create a rough idea of what the app is about without getting into details of app features

The ratings of the app	Does not show	4.8 ★★★★★
Images shown	Logo of the app	Screenshot(s) of the app
Who developed the app	NHS Digital	Mhealth Essentials Ltd.
The monthly price of the app	£0	£2.99

Scenario 2 Block 2

	App 1	**App 2**
App description	**Short** with some details about app features	**Long** and detailed description of the app and its features
The ratings of the app	3.2 ★★★☆☆	Does not show
Images shown	Screenshot(s) of the app	Logo and screenshot(s) of the app
Who developed the app	Mhealth Essentials Ltd.	Does not show
The monthly price of the app	£0	£2.99

Scenario 13 Block 2

	App 1	**App 2**
App description	**Short** with some details about app features	**Long** and detailed description of the app and its features
The ratings of the app	Does not show	4.8 ★★★★★
Images shown	Logo and screenshot(s) of the app	Screenshot(s) of the app
Who developed the app	Does not show	NHS Digital
The monthly price of the app	£0	£5.99

Scenario 14 Block 2

	App 1	**App 2**
App description	**Long** and detailed description of the app and its features	**Generic**, to create a rough idea of what the app is about without getting into details of app features
The ratings of the app	4.8 ★★★★★	Does not show
Images shown	Logo and screenshot(s) of the app	Logo of the app

Who developed the app	Mhealth Essentials Ltd.	NHS Digital
The monthly price of the app	£5.99	£0

Scenario 16 Block 2

	App 1	App 2
App description	**Short** with some details about app features	**Generic**, to create a rough idea of what the app is about without getting into details of app features
The ratings of the app	4.8 ★★★★★	Does not show
Images shown	Logo and screenshot(s) of the app	Logo of the app
Who developed the app	Does not show	NHS Digital
The monthly price of the app	£0	£0

Scenario 17 Block 2

	App 1	App 2
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Long** and detailed description of the app and its features
The ratings of the app	4.0 ★★★★☆	Does not show
Images shown	Logo of the app	Screenshot(s) of the app
Who developed the app	NHS Digital	Mhealth Essentials Ltd.
The monthly price of the app	£8.99	£5.99

Scenario 19 Block 2

	App 1	App 2
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Long** and detailed description of the app and its features
The ratings of the app	3.2 ★★★☆☆	4.8 ★★★★★
Images shown	Logo and screenshot(s) of the app	Logo of the app
Who developed the app	Mhealth Essentials Ltd.	Does not show
The monthly price of the app	£0	£5.99

Scenario 24 Block 2

	App 1	App 2
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Long** and detailed description of the app and its features
The ratings of the app	4.8	4.0
Images shown	Logo and screenshot(s) of the app	Logo of the app
Who developed the app	NHS Digital	Mhealth Essentials Ltd.
The monthly price of the app	£2.99	£5.99

Scenario 26 Block 2

	App 1	App 2
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Short** with some details about app features
The ratings of the app	Does not show	4.0
Images shown	Screenshot(s) of the app	Logo of the app
Who developed the app	Does not show	NHS Digital
The monthly price of the app	£0	£2.99

Scenario 30 Block 2

	App 1	App 2
App description	**Short** with some details about app features	**Generic**, to create a rough idea of what the app is about without getting into details of app features
The ratings of the app	4.0	3.2
Images shown	Logo and screenshot(s) of the app	Screenshot(s) of the app
Who developed the app	NHS Digital	Mhealth Essentials Ltd.
The monthly price of the app	£8.99	£2.99

Scenario 36 Block 2

	App 1	App 2

App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Long** and detailed description of the app and its features
The ratings of the app	4.8	Does not show
Images shown	Screenshot(s) of the app	Logo and screenshot(s) of the app
Who developed the app	Does not show	Mhealth Essentials Ltd.
The monthly price of the app	£2.99	£2.99

Scenario 48 Block 2

	App 1	**App 2**
App description	**Long** and detailed description of the app and its features	**Short** with some details about app features
The ratings of the app	4.0	4.8
Images shown	Screenshot(s) of the app	Logo of the app
Who developed the app	Does not show	Mhealth Essentials Ltd.
The monthly price of the app	£8.99	£8.99

Block 3

Choice situations: 3, 7, 11, 12, 20, 25, 28, 31, 39, 43, 44, 45

Scenario 3 Block 3

	App 1	**App 2**
App description	**Short** with some details about app features	**Generic**, to create a rough idea of what the app is about without getting into details of app features
The ratings of the app	4.8	4.0
Images shown	Screenshot(s) of the app	Logo of the app
Who developed the app	Mhealth Essentials Ltd.	NHS Digital
The monthly price of the app	£0	£2.99

Scenario 7 Block 3

	App 1	**App 2**

App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Long** and detailed description of the app and its features
The ratings of the app	3.2 ★★★☆☆	4.8 ★★★★★
Images shown	Logo and screenshot(s) of the app	Screenshot(s) of the app
Who developed the app	NHS Digital	Does not show
The monthly price of the app	£0	£2.99

Scenario 11 Block 3

	App 1	**App 2**
App description	**Short** with some details about app features	**Long** and detailed description of the app and its features
The ratings of the app	4.8 ★★★★★	Does not show
Images shown	Logo of the app	Screenshot(s) of the app
Who developed the app	Does not show	NHS Digital
The monthly price of the app	£2.99	£2.99

Scenario 12 Block 3

	App 1	**App 2**
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Short** with some details about app features
The ratings of the app	Does not show	3.2 ★★★☆☆
Images shown	Screenshot(s) of the app	Logo and screenshot(s) of the app
Who developed the app	Mhealth Essentials Ltd.	Does not show
The monthly price of the app	£2.99	£0

Scenario 20 Block 3

	App 1	**App 2**
App description	**Long** and detailed description of the app and its features	**Short** with some details about app features
The ratings of the app	Does not show	4.0 ★★★★☆

Images shown	Logo and screenshot(s) of the app	Logo of the app
Who developed the app	NHS Digital	Mhealth Essentials Ltd.
The monthly price of the app	£2.99	£2.99

Scenario 25 Block 3

	App 1	**App 2**
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Short** with some details about app features
The ratings of the app	4.0 ★★★★☆	4.8 ★★★★★
Images shown	Screenshot(s) of the app	Logo of the app
Who developed the app	Does not show	NHS Digital
The monthly price of the app	£0	£2.99

Scenario 28 Block 3

	App 1	**App 2**
App description	**Short** with some details about app features	**Generic**, to create a rough idea of what the app is about without getting into details of app features
The ratings of the app	4.0 ★★★★☆	3.2 ★★★☆☆
Images shown	Logo and screenshot(s) of the app	Logo of the app
Who developed the app	Mhealth Essentials Ltd.	Does not show
The monthly price of the app	£8.99	£5.99

Scenario 31 Block 3

	App 1	**App 2**
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Short** with some details about app features
The ratings of the app	4.0 ★★★★☆	3.2 ★★★☆☆
Images shown	Logo of the app	Screenshot(s) of the app
Who developed the app	Does not show	NHS Digital
The monthly price of the app	£2.99	£0

Scenario 39 Block 3

	App 1	App 2
App description	**Short** with some details about app features	**Long** and detailed description of the app and its features
The ratings of the app	4.8 ★★★★★	4.0 ★★★★☆
Images shown	Logo of the app	Logo and screenshot(s) of the app
Who developed the app	Mhealth Essentials Ltd.	NHS Digital
The monthly price of the app	£0	£0

Scenario 43 Block 3

	App 1	App 2
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Short** with some details about app features
The ratings of the app	4.0 ★★★★☆	3.2 ★★★☆☆
Images shown	Screenshot(s) of the app	Logo of the app
Who developed the app	NHS Digital	Mhealth Essentials Ltd.
The monthly price of the app	£5.99	£0

Scenario 44 Block 3

	App 1	App 2
App description	**Short** with some details about app features	**Long** and detailed description of the app and its features
The ratings of the app	4.8 ★★★★★	4.0 ★★★★☆
Images shown	Screenshot(s) of the app	Logo and screenshot(s) of the app
Who developed the app	NHS Digital	Does not show
The monthly price of the app	£8.99	£8.99

Scenario 45 Block 3

	App 1	App 2
App description	**Generic**, to create a rough idea of what the app is about without	**Long** and detailed description of the app and its features

	getting into details of app features	
The ratings of the app	4.0 ★★★★☆	4.8 ★★★★★
Images shown	Logo of the app	Logo and screenshot(s) of the app
Who developed the app	Does not show	NHS Digital
The monthly price of the app	£5.99	£5.99

Block 4

Choice situations: 5, 6, 8, 21, 23, 27, 35, 37, 40, 41, 42, 46

Scenario 5 Block 4

	App 1	**App 2**
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Long** and detailed description of the app and its features
The ratings of the app	4.0 ★★★★☆	Does not show
Images shown	Logo of the app	Logo and screenshot(s) of the app
Who developed the app	Mhealth Essentials Ltd.	NHS Digital
The monthly price of the app	£0	£0

Scenario 6 Block 4

	App 1	**App 2**
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Short** with some details about app features
The ratings of the app	3.2 ★★★☆☆	4.0 ★★★★☆
Images shown	Logo of the app	Logo and screenshot(s) of the app
Who developed the app	Does not show	Mhealth Essentials Ltd.
The monthly price of the app	£2.99	£5.99

Scenario 8 Block 4

	App 1	**App 2**

App description	**Short** with some details about app features	**Long** and detailed description of the app and its features
The ratings of the app	4.8 ★★★★★	4.0 ★★★★☆
Images shown	Logo and screenshot(s) of the app	Logo of the app
Who developed the app	NHS Digital	Mhealth Essentials Ltd.
The monthly price of the app	£2.99	£2.99

Scenario 21 Block 4

	App 1	**App 2**
App description	**Short** with some details about app features	**Long** and detailed description of the app and its features
The ratings of the app	Does not show	4.8 ★★★★★
Images shown	Logo of the app	Logo and screenshot(s) of the app
Who developed the app	NHS Digital	Mhealth Essentials Ltd.
The monthly price of the app	£2.99	£5.99

Scenario 23 Block 4

	App 1	**App 2**
App description	**Long** and detailed description of the app and its features	**Short** with some details about app features
The ratings of the app	4.8 ★★★★★	Does not show
Images shown	Screenshot(s) of the app	Logo and screenshot(s) of the app
Who developed the app	Mhealth Essentials Ltd.	Does not show
The monthly price of the app	£8.99	£5.99

Scenario 27 Block 4

	App 1	**App 2**
App description	**Short** with some details about app features	**Generic**, to create a rough idea of what the app is about without getting into details of app features
The ratings of the app	Does not show	4.0 ★★★★☆

Images shown	Logo of the app	Logo and screenshot(s) of the app
Who developed the app	Does not show	NHS Digital
The monthly price of the app	£0	£2.99

Scenario 35 Block 4

	App 1	**App 2**
App description	**Long** and detailed description of the app and its features	**Generic**, to create a rough idea of what the app is about without getting into details of app features
The ratings of the app	4.8 ★★★★★	Does not show
Images shown	Logo and screenshot(s) of the app	Screenshot(s) of the app
Who developed the app	Does not show	Mhealth Essentials Ltd.
The monthly price of the app	£5.99	£0

Scenario 37 Block 4

	App 1	**App 2**
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Long** and detailed description of the app and its features
The ratings of the app	4.8 ★★★★★	4.0 ★★★★☆
Images shown	Logo of the app	Screenshot(s) of the app
Who developed the app	NHS Digital	Does not show
The monthly price of the app	£8.99	£8.99

Scenario 40 Block 4

	App 1	**App 2**
App description	**Short** with some details about app features	**Long** and detailed description of the app and its features
The ratings of the app	4.0 ★★★★☆	3.2 ★★★☆☆
Images shown	Logo and screenshot(s) of the app	Logo of the app
Who developed the app	Mhealth Essentials Ltd.	NHS Digital
The monthly price of the app	£5.99	£2.99

Scenario 41 Block 4

	App 1	App 2
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Short** with some details about app features
The ratings of the app	4.0 ★★★★☆	Does not show
Images shown	Logo of the app	Screenshot(s) of the app
Who developed the app	Does not show	NHS Digital
The monthly price of the app	£2.99	£0

Scenario 42 Block 4

	App 1	App 2
App description	**Short** with some details about app features	**Generic**, to create a rough idea of what the app is about without getting into details of app features
The ratings of the app	3.2 ★★★☆☆	Does not show
Images shown	Screenshot(s) of the app	Logo of the app
Who developed the app	Does not show	Mhealth Essentials Ltd.
The monthly price of the app	£5.99	£8.99

Scenario 46 Block 4

	App 1	App 2
App description	**Generic**, to create a rough idea of what the app is about without getting into details of app features	**Short** with some details about app features
The ratings of the app	3.2 ★★★☆☆	Does not show
Images shown	Logo and screenshot(s) of the app	Screenshot(s) of the app
Who developed the app	Mhealth Essentials Ltd.	Does not show
The monthly price of the app	£5.99	£8.99

Appendix 18. Potential facilitators and barriers of the uptake of, and engagement with, smoking cessation apps

Potential facilitators and barriers of uptake of, and engagement with, smoking cessation apps and the survey statements to assess these.

TDF Domain	Factor	U/E/B *	Hypothesised facilitator	Hypothesised barrier	Item in the survey
Skills	App literacy	B	Having the ability to use apps confidently.	-	In general, I can easily use a newly installed app on my phone.
Knowledge	App awareness	U	-	Lack of awareness of smoking cessation apps.	I was aware of the existence of smoking cessation apps prior to taking part in this study.
Knowledge	User guidance	E	Providing knowledge of how to use an app.	-	A guide of how to use features would help me use the app more often.
Knowledge	Health information	E	Improves knowledge of own health.	-	Information in the app about how quitting smoking improves my health would make me use the app more often.
Memory, attention, decision processes	Cognitive load	E	-	Complicated and time-consuming features.	In general, I don't want to use an app with features that would take some time to learn.
Memory, attention, decision processes	Reminders	E	Help individuals to pay attention on quitting smoking.		It would be important that an app to help me quit smoking sends personalised reminders to me.
Memory, attention, decision processes	Reminders			Drawing individuals' attention on smoking triggering cravings.	I wouldn't want to use an app that sent me reminders about quitting smoking in case it would trigger my cravings to smoke.
Social influence	Peer support	E	Social interaction that promotes quitting.		Being connected with other app users would motivate me to stay on track with my intention to stop smoking.
Social influence	Peer support			Social interaction triggers shame or disappointment when one is failing to quit.	Being connected with other app users would make me feel ashamed or disappointed if I started smoking again after quitting.
Social influence	Profession al support	E	Improves quitting.	-	Being connected with online helpers (quit smoking advisors) within the app would make want to use the app more.
Beliefs about capabilities	Self-confidence	E	Promotes quitting smoking by using the app.	-	I am confident I could quit smoking by using an app.
Beliefs about consequenc es	Data protection	B	-	Concern of how the personal data is handled.	I am concerned how my personal data is handled in apps.

Goals	Goal setting and action planning	E	-	Goal setting without action planning.	Receiving guidance of how to achieve goals is more important for me than just simply setting goals.
Social identity	Social identity	E	-	Using a health app and feeling like a patient.	When using a smoking cessation app, I don’t want to feel that I am being treated like a patient.
Reinforcement	Rewards	E	Receiving reward in forms of badges and certificates.	-	Receiving badges or awards for achieving a set goal, would make me use the app more often.

*U - uptake, E – engagement, B – both uptake and engagement

Appendix 19. The discrete choice experiment and the additional survey questions

Eligibility questions

Thank you for your interest in participating in the Health and Wellbeing Smartphone App Research Study. We would like to ask you a few questions to check your eligibility for this study.'*

Question	Possible answers	Eligible if the answer is the following
Are you aged 18 or over?	(1) Yes (2) No	1
Do you live in the UK?	(1) Yes (2) No	1
Do you currently smoke cigarettes?	(1) Yes (2) No	1
Do you own or have regular access to a smartphone?	(1) Yes (2) No	1
Would you ever consider using a smartphone app to quit smoking cigarettes?	(1) yes (2) no	1

The survey questions

The Discrete Choice Experiment

Welcome!

In this section of the survey, you will be asked to choose between a few options. The options represent different hypothetical apps to help a smoker quit smoking.

How to complete this survey

Please consider the following scenario. You wish to quit smoking, and you decide to select a smartphone app to do that. You will need to make a series of choices about which app to select based on the description. In each set of choices, we will present you two options, each of which describes a set of characteristics of smoking apps you might potentially choose. Imagine that these apps are listed on a website that presents information only about health and wellbeing apps as opposed to how these are presented in an app store (e.g. the Apple app store or Google play). The presentation of the apps will describe five characteristics which will be different in each pair. These apps do not actually exist but please answer as if they were real.

Let's have a look at the characteristics.

1. ***The cost of the app per month*** – this can be any of the following:
- £0
- £2.99
- £5.99
- £8.99

2. ***Who developed the app*** – in some cases you will see the company who developed the app, while in other cases it will not say:
- Doesn't say
- NHS Digital
- Mhealth Essentials Ltd.

3. ***The user ratings of the app*** – in some cases you will see the ratings of the app, while in other cases it will not say:
- Doesn't say
- App rated with 3.2 stars
- App rated with 4 stars
- App rated with 4.8 stars

4. ***The app description*** – there are different ways of describing an app, these are the options you will be presented:
- Generic, to create a rough idea of what the app is about without getting into details of app features
- Short with some details about app features
- Long and detailed description of the app and its features

5. ***Images of the app*** – when presenting an app on a website dedicated for health apps can have any of the following picture:
- Logo of the app
- Screenshot(s) of the app
- Logo and screenshot of the app

When you make a choice between the two apps each time, all you need to do is to read the characteristics and choose the option that corresponds to the app you would select. We will remind you about the scenario with each series of choices. Please, take your time when making a decision.

In the next page we will show you a test choice set. Click on the arrow when you are ready to start.

<Test choice set shown – this will not be included in the data analysis>

'You wish to quit smoking, and you decide to select a smartphone app to do that. Please look at the options carefully, and decide on which app (App 1 or App 2) do you think you would likely want to download and use to help you quit smoking. You could also choose 'None of these two' if you do not like either option and would not choose to download either app. Take your time to make a decision.

Which app would you choose?'

<Insert test image>

My answer is:

- App 1 ☐
- App 2 ☐
- None of these two ☐

Once the choice test is done:

“You will now need to make several choices using the same scenario. Click on the arrow when you are ready to start.”

'Please, select an option and click on the arrow to continue.'

	App 1	App 2
The monthly price of the app	£2.99	£8.99
Who developed the app	NHS Digital	Mhealth Essentials Ltd.
The ratings of the app	Does not show	4.0 ★★★★☆
App description	Short with some details about app features	Generic, to create a rough idea of what the app is about without getting into details of app features
Images shown	Screenshot(s) of the app	Logo of the app

My answer is:

- App 1 ☐
- App 2 ☐
- None of these two ☐

[If the answer is 'None of these two']

'We understand that you did not like either option. But imagine that you would have to make a choice. Which one would you prefer?'

My answer is:

- App 1 ☐
- App 2 ☐

Uptake and engagement questions

'Thank you for completing the choice tasks! Now, we would like to know more about your previous experience in using health apps and your views about them. Please, answer the following questions.'

Question	**Your answer to the question is:**
What type of smartphone do you have or have access to for personal use?	(1) An Android phone (2) An Apple iPhone (3) Other type of phone
Have you ever used an app designed to help you stop or quit smoking (smoking cessation app)?	(1) Yes (2) No
Have you used any other type of health or wellbeing smartphone app to help you become healthier or to feel better in the last 12 months?	(1) Yes (2) No

(For example, apps that can help you drink less alcohol, being more active, losing weight, become less depressed, become less anxious, improve your mood, etc.)	
How did you discover the health app(s) you used (i.e. learn about the app's existence, not where you downloaded it from)? Select all that apply. **[Those who answered yes to 'Have you ever used a smoking cessation app?' or 'Have you ever used another health or wellbeing smartphone app to help you become healthier or to feel better?']**	(1) Found via Google search (2) Found in app store (3) Found on a health-related website (2) Recommended by friends or family (3) Recommended by health practitioners (4) Other: (free text)
When using a health app which of these statements best applies **[Those who answered yes to 'Have you ever used a smoking cessation app?' or 'Have you ever used another health or wellbeing smartphone app to help you become healthier or to feel better?']**	(1) I enjoy spending time exploring all the features an app has (2) I prefer to spend less time on the app, so I would prefer simple features (3) not sure

Please, click the box that most closely corresponds to your feeling regarding each of the statements.

Statements	**Your answer to the statement is:**
In general, I can easily use a newly installed app on my phone.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree
I was aware of the existence of smoking cessation apps prior to taking part in this study.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree
A guide on how to use features will help me use an app more often.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree
Information in an app about how quitting smoking improves my health would make me use the app more often.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree
In general, I don't want to use an app with features that would take some time to learn.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree
It would be important that an app to help me quit smoking sends personalised reminders to me.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree
I wouldn't want to use an app that sends me reminders about quitting smoking in case it would trigger my cravings to smoke.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree

	○ Strongly disagree
Being connected with other app users would motivate me to stay on track with my intention to stop smoking.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree
Being connected with other app users would make me feel ashamed or disappointed if I started smoking again after quitting.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree
Being connected with online helpers (e.g. quit smoking advisers) within the app would make me to use the app more.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree
I am confident I could quit smoking by using an app.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree
I am concerned how my personal data is handled in apps.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree
Receiving guidance on how to achieve goals is more important for me than just simply setting goals.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree
When using a smoking cessation app, I don’t want to feel that I am being treated like a patient.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree
Receiving badges or awards for achieving a set goal would make me use the app more often.	○ Strongly agree ○ Somewhat agree ○ Neither agree nor disagree ○ Somewhat disagree ○ Strongly disagree

Smoking and Sociodemographics

‘You are nearly done! We will now ask you a few more questions so we know more about your background. Remember, the information you provide will be anonymised.’

Question	**Your answer to the question is:**
How many cigarettes per day do you usually smoke?	[free text]

How soon do you smoke your first cigarette after you wake-up?	(1) Within 5 minutes (2) 6 – 30 minutes (3) 31 – 60 minutes (4) More than 60 minutes
When was the last time you made a serious quit attempt that lasted at least 24 hours?	(1) In the last month (2) In the last 12 months (3) Longer than 12 months ago (4) I haven't made an attempt to quit smoking before
Have you ever used any of the following to help you stop smoking? (Tick all that apply)	(1) Nicotine replacement product (e.g. patches, gum, inhalator) (2) Zyban (buprorion) (3) Champix (varenicline) (4) E-cigarette or vaping device (5) Attended a stop smoking group (6) Attended Stop Smoking one-to-one counselling or support services (7) Phoned a smoking helpline (8) A book about quitting smoking (9) Visited a smoking cessation website (10) Used a smoking cessation app installed on smartphone, tablet or PDA (11) None of these (12) Other (free text)
How likely are you planning to quit smoking within the next 6 months?	(1) Very unlikely (2) Unlikely (3) Maybe, maybe not (4) Likely (5) Very likely
How determined are you to quit for good?	(1) Not at all (2) Slightly (3) Moderately (4) Very much (5) Extremely
What would be your main reason for quitting smoking?	(1) Health concerns related to COVID-19 (2) Health concerns not related to COVID-19 (3) Pressure or encouragement from others (4) To save money (5) To regain control (6) Other (free text)

Demographics:

Question	Your answer to the question is:
What year were you born?	(free text)
What gender do you identify with?	(1) Female (2) Male (3) Non binary/ Gender fluid (4) Prefer not to say
What is your highest educational qualification?	(1) GSCE or equivalent (2) A levels or equivalent (3) Degree or equivalent (4) Postgraduate or equivalent (5) Other (free text)
What was your net (after tax) household income last month? Please include any benefits your household members received. If you are a single person living a shared house or lodging, please, base this on your individual income.	(1) £0 - £999 (2) £1000 - £1499 (3) £1500 - £1999 (4) £2000 - £2499 (5) £2500 - £2999 (6) £3000 - £3499 (7) £3500 - £3999 (8) £4000 - £4499 (9) £4500 - £4999 (10) over £5000 (11) prefer not to say
What is your ethnic group?	(1) White (2) Black (3) Asian (4) Arabic (5) Mixed/multiple ethnic groups (6) Other ethnic group (free text)
What is your sexual orientation?	(1) Heterosexual or straight (2) Lesbian (3) Gay man (4) Bisexual (5) Queer (6) Other (free text) (7) Prefer not to say
Do you have any long-standing illness, disability or infirmity? (Long-standing means anything that has troubled you over a period of time or that is likely to affect you over a period of time)?	(1) No (2) Yes (3) Prefer not to say

Appendix 20. Policy recommendations

Understanding factors influencing the uptake of, and engagement with, health and wellbeing apps

Findings of the PhD project jointly funded by the Public Health England and the University of East Anglia (thesis submission date: 30 November 2021)

PhD student: Dorothy Szinay (University of East Anglia)

Supervisors: Dr Felix Naughton (University of East Anglia), Prof Andy Jones (University of East Anglia), Dr Tim Chadborn (Public Health England), Prof Jamie Brown (University College London)

Multiple factors were identified across all components of the COM-B model and the constructs of the Theoretical Domains Framework that may be valuable for the uptake of helath and wellbeing apps and for the development of more engaging health and wellbeing apps. **Recommendations based on the findings may help app developers, health app portal developers, and policy makers in the optimization of health and wellbeing apps.**

Recommendations (based on the findings of the studies described in more detail below)

1. Increasing uptake

COM-B component	Recommendations for policy makers, health app portal providers, app developers to increase ***uptake***
1. Capability	1.1. Improve app literacy skills, with a focus on older and marginalized populations, and continue working toward reducing the digital divide (eg, through the use of an outreach approach to target older, migrant, and homeless populations). 1.2. Increase awareness of effective health apps and curated health app portals through promotion online and offline in primary care, mass media, and public spaces. 1.3. Provide guidance on how to use a health app portal (eg, through incorporating an extensive help section) and additional physical and mental health–related evidence-based papers. 1.4. Promote reduced cognitive load on curated health app portals (eg, through the use of images and short app descriptions)
2. Opportunity	2.1. Ensure evidence-informed apps are available for free or at a low cost to everyone. 2.2. Make apps available on all major app stores simultaneously. 2.3. Offer the possibility to tailor the health app portal to target certain demographics (eg, apps for physical activity for women aged 60 years or more). 2.4. Offer apps at low cost and provide explanation for those that require referrals and justifications for the cost of paid apps on curated health app portals. 2.5. Collaborate with interaction design experts and end users to enhance the esthetics of health app portals. 2.6. Promote evidence-informed apps via trusted organizations and provide information on how the apps were developed and tested.

	2.7. Encourage health professionals and practitioners of promotion of evidence-informed health apps and health app portals.
3. Motivation	3.1. Provide relevant and realistic titles and avoid general app descriptions. Descriptions should be short but must contain details of what the app offers and how it is able to help the user. 3.2. Provide pictures of the app (eg, screenshots) and avoid pictures that promote an unrealistic body image. 3.3. Provide information about the accuracy and effectiveness of the app (eg, details about development and developers) and how users' data are handled. 3.4. Take into account users' emotions about certain features by constantly involving the users in the development of health apps.

2. Improving engagement

COM-B component	Recommendations for policy makers, health app portal providers, app developers to improve ***engagement***
4. Capability	4.1. Provide user guidance on how to use an app, visual and/or numerical summary of progress and evidence-based additional health information related to the behaviour targeted by the app 4.2. Minimise time required to use app where possible 4.3. Provide customisable reminders that users could opt out 4.4. Provide the option of self-monitoring features 4.5. Promote safety-netting and relapse prevention features such as the possibility to restart or reengage with the app later 4.6. Promote a routine for engagement with an app e.g. highlighting the role that routine may play in effectiveness of an app
5. Opportunity	5.1. Collaborate with interaction design experts and end-users to enhance the aesthetics of apps 5.2. Provide the possibility for community networking within the app and linking to social media as an optional feature to share progress where appropriate 5.3. Offer the possibility for social competition and challenges where appropriate 5.4. Consider the provision of embedded professional support, and if this is not feasible, providing offline one-to-one support with the uptake of and the engagement with health apps. This may improve motivational factors, such as commitment, self-confidence and perceived competence of engaging with a health app 5.5. We advise that exploration should be made for where engagement enhancement could be made with appropriate and proportionate machine learning and artificial intelligence or other forms of learning system.
6. Motivation	6.1. Develop a time-efficient app that would require as much engagement as is required to achieve the desired outcome. This might be different for different behaviours 6.2. Include reinforcement in forms of feedback, encouraging messages and rewards 6.3. Offer intangible rewards, such as certificates or badges 6.4. Offer tangible rewards that can be converted as discount in other places (e.g. health insurance providers or pharmacies, sports parks) 6.5. Include goal setting as well as action planning features on how to achieve set goals (when applicable) 6.6. Take into account user's emotions about certain features by involving users in the development and update of health apps as lack of some features could provoke strong negative emotions such as disappointment and might lead to rapid disengagement

1. **Study 1. Systematic literature review of factors influencing the uptake of, and engagement with, health and wellbeing apps**

Summary

Across a wide range of populations and behaviours, 26 factors relating to capability, opportunity, and motivation appear to influence the uptake of, and engagement with, health and wellbeing smartphone apps.

Factors influencing both the uptake of and the engagement with health apps:

- App literacy - Technological competency
- User guidance - Instructions on how to effectively use the app

Factors influencing the uptake of health apps:

- App awareness - Knowledge of the existence of health and wellbeing apps
- Availability and accessibility - The ability to use a smartphone anytime anywhere
- Low cost - The price of the app
- Recommendations - Suggestions received from other users
- Curiosity - Desire to acquire knowledge and skills to use a behaviour change tool

Factors influencing the engagement with health apps:

- Health information - Educational information related to health and wellbeing aspects
- Statistical information - A visual or numerical summary of progress
- Well-designed reminders - The ability to customize reminders
- Less cognitive load - The app is not too time consuming, easy to use, and requires minimal input
- Coping games - Distraction activities within the app
- Self-monitoring - The ability of the app to help self-regulation of the target behaviour
- Established routines - Regularity in using the app
- Safety netting - Safety netting
- Interactive and positive tone - Encouraging communication style
- Personalization to needs - The possibility to use an app that is tailored to a user’s needs
- Health practitioner support - Possibility to get in touch with health professionals and practitioners within the app
- Community networking - Social interaction with users with similar needs within the app or within their community
- Social media - A choice to connect to social media platforms
- Social competition - Competitive nature of the app with others or with themselves
- Personification of the app - Applying human attributes to the app
- Feedback - Feedback regarding the user’s performance
- Rewards - Tangible and intangible reward in response to the user’s effort
- Goal setting - Establishing what the user would like to accomplish
- Perceived utility of the app - Discrepancy of what the users are looking for and what the app offers

Citation for this research:

Szinay D, Jones A, Chadborn T, Brown J, Naughton F. Influences on the Uptake of, and engagement with, Health and Wellbeing Smartphone Apps: Systematic Review. J Med Internet Res. 2020. Available at: https://www.jmir.org/2020/5/e17572/

2. Study 2. Think aloud and interview study about the uptake of health apps in general and on curated health app portals (PHE One You and the NHS Apps Library)

Summary

The uptake of health and wellbeing apps appears to be primarily affected by social influences and the perceived utility of an app. App uptake via curated health app portals perceived as credible may mitigate concerns related to data protection and accuracy, but their implementation must better meet user needs and expectations.

Factors influencing the uptake of health apps in general (unguided search for a health app)

- App literacy - Technological competency
- Health awareness - General health consciousness or having family members diagnosed with a condition or disease or concerns regarding a behavior or health outcome
- App awareness - Knowledge of the existence of health and wellbeing apps
- Availability – The ability to use a smartphone anytime, anywhere; Availability of an app on all major commercial app stores
- Cost of an app - Low cost and apps that are free for users
- Aesthetics - The look and design of an app
- Social influences (found as CORE factor) – The importance of reviews and ratings in the commercial app stores and apps promoted as ”editor’s choice”; Identifiable credible sources: apps developed or endorsed by trusted app developers, organizations, or universities or promoted by respected celebrities (eg, athletes); Recommendations received from health practitioners or from friends and family
- Perceived competence - Apps preferred over face-to-face intervention when the user feels that they can engage with the app on their own
- Time efficiency - The ability of a health app to be interacted with a minimum amount of time
- The perceived utility of the app (found as CORE factor) – Discrepancies between what users are looking for and what the app offers, characterized by a relevant title, description, pictures, adaptation to individual characteristics, and users’ previous experience with health apps
- Perceived accuracy – The perceived effectiveness of apps before the selection of an app
- Data protection - Concerns regarding the handling of personal data
- Commitment - The level of commitment when deciding to download a health app
- Social identity - Identity related to app use (eg, trends and gender specificity)
- Positive emotions - Triggered by curiosity in trying a health app, and by the time efficiency characteristic of an app as opposed to face-to-face interventions, and being provided by a credible source

- Negative emotions – Triggered by lack of availability on all major app stores; Preferred over over a face-to-face intervention if feeling anxiety (eg, caused by an unhealthy behavior or unhealthy state) and pressurized (to succeed or show progress)
- Mixed emotions – Triggered by the aesthetics (design) of the apps and by adaptation to individual characteristics (judged by the title, description, pictures, and gender specificity)

Factors influencing the uptake of health apps on curated health app portals (both PHE's One you Apps portal and the NHS Apps Library)

- App awareness - Knowledge of the existence of health and wellbeing apps listed on health app portals
- User guidance - Instructions on how to effectively use a health app portal
- Health information - Educational information related to health and wellbeing
- Cognitive load – The manner in which apps are presented on the portal; The complexity of the search or to access a relevant health app
- Portal tailored to individuals' needs - Personalized listing of apps targeting age, gender, and health condition
- Cost of an app - Low cost and apps listed on curated health app portals that are free for users
- Aesthetics - User-friendly and design-related characteristics of the portal
- Social influences – Health app portals perceived as credible sources; Recommendations of health app portals needed mainly in primary care; Clarity about the recommended apps on health app portals; Explanations about any required GP referral
- The perceived utility of the app – Discrepancies between what users are looking for and what the app listed on health app portal offers, characterized by a relevant title, description, and pictures
- Perceived accuracy - Potential app users' perceived effectiveness of apps listed on health app portals
- Data protection - Concerns over the handling of personal data
- Social identity - Identity related to app use (eg, feeling like a "patient")
- Positive amotions - Triggered by curiosity in choosing a behaviour change tool from a curated health app portal and from a credible source
- Negative emotions - Triggered by lack of search features on the portal or when the search yields irrelevant results; when an app requires GP referral without further explanation or when an app is only available in one major app store
- Mixed emotions - Triggered by the aesthetics and features of the portal and the perceived utility of the apps

Citation for this research:

Szinay D, Perski O, Jones A, Chadborn T, Brown J, Naughton F. Influences on the Uptake of Health and Wellbeing Apps and Curated App Portals: Think-Aloud and Interview Study. JMIR Mhealth Uhealth. 2021;9(4):e27173. Available at: https://mhealth.jmir.org/2021/4/e27173

3. Study 3. Interview research about the engagement with health apps

Summary

Engagement appears to be influenced primarily by features that provide user guidance, promote minimal cognitive load and support self-monitoring (capability), provide embedded social support (opportunity), and goal setting with action planning (motivation).

Factors influencing the engagement with health apps:

- User guidance - Instructions on how to effectively use a health app
- Statistical information - A visual or numerical summary of progress or quantification of the behaviour
- Health information - Educational information related to health and wellbeing aspects
- Reduced cognitive load - The app is not too time consuming, easy to use and requires minimal input
- Reminders - Preferably customisable, notification-type messages
- Self-monitoring - The ability of the app to support self-regulation of the target behaviour
- Routines - The ability to support routine/habit formation
- Safety netting - Retaining the app for a potential precipitating event in the future
- 'Stepping stone' - App as a first step in the behaviour change process
- Tailoring - Innovative features and adaptability, and an interactive, two-way communication between the app and user
- Peer support - including social interaction with users with similar needs within the app or within their community; a choice to connect to social media platforms, competitions and challenges with others or with themselves
- Social support - Possibility to contact health professionals and practitioners within the app
- Self-confidence - Perceived capability to change one's behaviour using an app
- Goal setting - Establishing what the user would like to achieve
- Action planning - Establishing how the user would like to achieve set goals
- Commitment - The level of commitment while engaging with an app to change the behaviour and achieve set goals.
- Feedback - Feedback regarding the user's performance
- Rewards - Tangible (objects, discount, etc.) and intangible (badges, certificates, etc.) rewards in response to the user's effort; Gamification elements
- Encouragement - Additional ways to provide reinforcement (e.g. encouraging messages)
- Positive emotions - Triggered by included user guidance, statistical information, additional health information, embedded professional support, community networking possibilities, tracking features and rewards
- Negative emotions - Triggered by lack of user guidance, invasive push-notifications, cognitive overload, unrevealed in-app costs
- Mixed emotions - Triggered by reminders (not universally found beneficial)

Citation for this research:

Szinay D, Perski O, Jones A, Chadborn T, Brown J, Naughton F. Perceptions of factors influencing engagement with health and wellbeing apps: a qualitative study using the COM-B model and Theoretical Domains Framework. Preprint. JMIR Preprints. 2021. Available at: https://preprints.jmir.org/preprint/29098

4. Study 4. Discrete Choice experiment investigating the uptake of smoking cessation apps

Summary

This study found that uptake is more likely if smoking cessation apps have high star ratings, are developed by a trusted organisation, includes screenshots, and is low cost.

Factors influencing the uptake of smoking cessation apps and their relative importance

- Relative to other attributes, a 4.8 star rating was the strongest driver of app uptake (mean preference weight 2.18; 95% confidence interval [CI] 1.94 to 2.43).
- Participants preferred an app developed by a trusted organisation (mean 0.90; 95% CI 0.73 to 1.07) over a hypothetical company, that shows logo and screenshots (mean 0.30, 95% CI 0.15 to 0.45) over logo only, and with a lower monthly cost (mean -0.4; 95% CI -0.44 to -0.37). App description did not influence preferences.

Factors influencing the engagement with smoking cessation apps (descriptive data only):

- Only around half of our participants were aware of smoking cessation apps, which suggests that more work is needed to raise awareness of existing smoking cessation tools.
- Access to health information and a user guide of using the app would increase most participants' engagement. The latter could be particularly important to those who reported having limited app literacy skills.
- Less than half of the participants believed they would not want to use an app with complex features.
- We previously found that reminders are mixed and could negatively influence behaviour change by triggering cravings. However, in this study, we found that less than 40% on average reported this being the case.
- Peer and professional support would further encourage engagement, although less than half reported that failing to quit would lead to feelings of disappointment.
- Goal setting with action planning and rewards would facilitate engagement.

Citation for this research:

Szinay D, Rory, C., Jones, A., Whitty, J., Chadborn, T., Jamie, B., Naughton, F. Eliciting adult smokers' preferences for the uptake of smoking cessation apps: A Discrete Choice Experiment (manuscript in prep).