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I. Biliunaite [a], M.A. Adriaanse [a,b], A.P.Y. Hoogendoorn [a], A. Montvila [c], M.R. Crone [d], L.C. van Gestel [b,*]

[a] Leiden University Medical Center, the Netherlands
[b] Leiden University, Institute of Psychology, Health, Medical and Neuropsychology Unit, the Netherlands
[c] Lithuanian University of Health Sciences Kaunas Clinics, Lithuania
[d] Maastricht University, Faculty of Health, Medicine and Life Sciences, the Netherlands

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ABSTRACT

Healthcare professionals (HCPs) commonly see the potential of health apps for their patients, but in practice do not actively recommend them during consultation. As quality concerns have been identified as a key barrier, a health and wellness app assessment framework and related quality label was previously developed. Yet, even when health apps are of high quality, recommendation behavior may not necessarily follow due to other factors that are yet to be identified and targeted. The main aim of this study was to explore a wide range of HCP behavioral determinants and identify the key determinants of HCP app recommendation behavior. We used the TDF-checklist, which is based on the Theoretical Domains Framework (TDF), an evidence-based framework for the systematic assessment of behavioral determinants of HCP behavior, and adapted it to the study context. 290 Catalan HCPs filled in the survey. For all determinants, room for improvement (deviation from the maximum), relevance (correlation with anticipated behavior), and the potential for change (based on combining room for improvement and relevance) were assessed. A large majority of HCPs indicated they would recommend high-quality apps to their patients. Overall, HCPs were motivated, but more room for improvement was found for capability and opportunity-related domains. Anticipated recommendation behavior correlated strongest with motivational factors like beliefs about consequences and beliefs about capabilities. The potential for change was highest for nature of the behaviors (habit), beliefs about capabilities and knowledge. When implementing the label, efforts should focus on promoting habit formation for recommending high-quality apps, boosting confidence of HCPs, and providing further knowledge regarding health apps.

1. Introduction

1.1. Healthcare professional willingness to recommend health apps

Health and wellness apps such as self-management apps have the potential to improve patients' health conditions while increasing autonomy and potentially limiting the burden on the healthcare system.[1–4] There is an increasing number of health apps available for patients and healthcare professionals (HCPs). Previous research has shown that patients are more likely to use health apps if they are recommended by their HCP.[5,6] For health and wellness apps to be useful in the clinical setting, HCPs must thus trust and be willing to recommend these apps to their patients when high-quality apps are available and appropriate to recommend to a particular individual patient.

While overall HCPs are positively disposed towards and see advantages of health and wellness apps for their patients, still studies show a significant number of HCPs have not engaged yet or not yet on a regular basis in recommending such apps to their patients.[7–9] Certainly, promoting app recommendation should not be considered a goal in and of itself, and its suitability depends on factors such as specific patient characteristics, medical complaints and other contextual factors. Yet, in situations where high-quality apps are available and believed to contribute to the quality of care, empowering HCPs to recommend high-quality apps to their patients to make use of the high-quality resources that are out there could benefit patients as well as HCPs and the wider healthcare system. This implies that it is crucial to better understand the determinants underlying HCPs decision to recommend apps.

* Corresponding author.
E-mail address: l.c.van.gestel@fsw.leidenuniv.nl (L.C. van Gestel).

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The decision to recommend a self-management health app to a patient is a complex decision depending on many different factors. Some of the reasons for this include, but are not limited to, having a lack of knowledge of apps suitable for recommendation or reliable sources via which such apps could be accessed,[10] having doubts regarding the security of the app-generated patient data,[11] or experiencing time pressure in an already busy work-routine.[10] Yet, probably the most commonly expressed reason for refraining from recommending apps relates to the health app quality and reliability,[10,12] that is whether the health apps are robust and safe to use for their patients.

HCPs' concerns regarding health and wellness app quality and reliability are not unfounded as health app quality can vary significantly.[13] Further, the multitude of existing and sometimes overlapping app assessment frameworks that presently exist are only of limited help to HCPs in efficiently selecting high-quality and appropriate health apps.[14] This indicates that there is a need for a harmonized and easy to use health and wellness app assessment framework with a full range of app assessment criteria.[15–17] In recognition of this need, at the request of the European Commission, the International Organization for Standardization (ISO) published a Technical Specification (ISO 82304-2) with quality requirements for health and wellness apps,[18] which offers such a health and wellness app assessment framework and related quality label (further referred to as 'the quality label').[19] Preliminary findings indicate that the quality label can act as an acceptable and effective tool to increase HCPs' willingness to recommend high-quality health apps.[20]

1.2. Other than quality-related barriers in recommending apps

The quality label is designed to assist HCPs in addressing app quality-related concerns, and has been found to increase the willingness to recommend health apps, and as such constitutes an important step forward to promoting app recommendation when appropriate. Still, however, it is unlikely that the label is sufficient to substantially change HCP recommendation behavior. That is, additional reasons unrelated to quality may still stand in the way of HCPs recommending high-quality health apps. Country-specific evidence for this originates for example from Germany, where HCPs have an opportunity to prescribe quality assessed health applications, referred to as DiGAs (Digitale Gesundheitsanwendungen; https://diga.bfarm.de). The implementation of DiGAs should eliminate app quality-related concerns for HCPs and hence, stimulate the recommendation of high-quality apps for patients. Yet, recent data indicates an overall recommendation rate of 12 % with some regional differences observed.[21] This indicates that other barriers beyond quality considerations need to be addressed to effectively promote HCPs to recommend apps to their patients.

Numerous barriers and facilitators for health and wellness app recommendation behavior, including those unrelated to quality concerns, have already been identified in the literature.[22,23] However, studies generally tend to focus on a limited set of factors such as (demographic) patient characteristics (patient age or education), (demographic) HCP characteristics (e.g., age or own technology use), work pressures or app features.[6] Crucially, social cognitive and behavioral determinants have been studied less. For example, few studies have explored how social or interpersonal factors (e.g., social norms, expected consequences, professional identity) may affect the willingness to recommend apps. Overall, there appears to be a lack of systematic and broad assessment of behavioral determinants of HCPs app recommending behavior, with previous studies zooming in on app quality, or relatively specific, but limited determinants such as HCP attitudes[11,22] or time constraints.[10] A recent interview study with French GPs for example revealed that some hold positive attitudes, while others worry about negative consequences for patients (e.g., data privacy) or HCPs (e.g., additional tasks or burden).[11] While such studies are insightful, and have helped to identify several barriers, they tend to put a spotlight on a few specific determinants and as such provide a limited understanding of the behavioral determinants that need addressing to impact recommendation behavior.

Thus, if the quality label is to be successfully implemented across the EU countries, a more thorough and broader understanding of the behavioral determinants of HCPs' recommendation behavior is necessary to allow for addressing key determinants and effectively supporting high-quality app recommendation in situations where it is appropriate and desirable. Now is the perfect time for exploring these barriers, as the quality label is soon to be implemented in practice. This should ideally be done while simultaneously addressing other relevant determinants in the implementation process.

1.3. Assessing behavioral determinants

Theoretical models or frameworks can offer a systematic way of assessing behavioral determinants of healthcare professional behavior. The Theoretical Domains Framework (TDF) is possibly the most widely used evidence-based framework for the systematic assessment of behavioral determinants of HCP behavior.[24] The TDF is a 14-domain framework that was developed in an attempt to integrate existing behavioral change theories in one, overall, user friendly, framework for identifying determinants of HCP behavior. The TDF is a refinement of the overarching COM-B (Capability, Opportunity, Motivation) model and lists various domains of determinants (e.g., 'beliefs about consequences', 'emotions', or 'knowledge') that each fall within one of the three larger COM-B domains. The TDF is widely used to assess relevant and changeable determinants of a large variety of HCP behaviors, and has been designed so that relevant determinants can subsequently be linked to specific behavior change techniques (BCTs).[25] Together, this (for all steps see the Behavior Change Wheel)[26] offers a systematic, step-by-step approach for not only assessing the behavioral determinants of specific HCP behaviors, but also for subsequently mapping out techniques for addressing them. Since its development, the TDF has been primarily used in qualitative studies,[27] but also in several quantitative studies.[28] To facilitate the use of the framework in quantitative studies, TDF based questionnaires, such as the TDF-checklist[29] and the Determinants of Implementation Behavior Questionnaire (DIBQ)[30] questionnaire have been developed.

1.4. The current study

The current study is an exploratory study with the main aim to assess the behavioral determinants of HCP anticipated behavior of recommending high-quality (as indicated by the label) health and wellness apps to their patients. In this study, we focus on self-management apps as a specific subtype of apps that are aimed at chronic disease (e.g., asthma) symptom management.[31] This focus was chosen as self-management apps have been shown beneficial for health outcomes across several chronic diseases,[1,2,32] and as willingness to recommend health apps is highest for self-management apps.[33] As the TDF-checklist is shorter than the DIBQ and has been suggested to be of specific relevance in assessing HCPs' behavioral determinants in preparation for intervention implementation,[29] we will use the TDF-checklist tailored to the target behavior of recommending high quality self-management apps in the present study. As this is an exploratory study, aims and analyses were preregistered (https://aspredicted.org/XM7_DK2), but no hypotheses were formulated.

To identify the most important determinants of health app recommendation behavior, we will assess room for improvement and relevance for all determinants in the checklist. That is, we will describe the univariate distributions of the behavioral determinants (room for improvement) and we will run correlations between the determinants and anticipated recommendation behavior (relevance). If scores on the scale are further away from the maximum, then numerically there is considered to be more room for improvement compared to when scores are closer to the maximum of the scale. Building on a newly developed methodology we will combine room for improvement with relevance into a combined potential for change index[34] from which we will distill the determinants with the highest potential for change. This number will allow us to pinpoint the behavioral determinants which should be the main targets of interventions to promote behavior change in HCP app recommending behavior when recommending apps is appropriate given the context. Consequently, the study's findings will bridge the existing knowledge gap by providing a more complete overview of barriers experienced by HCPs taking into account that the quality dimension is covered by the quality label.

2. Method

2.1. Participants and design

Recruitment took place in the Spanish region Catalonia and was coordinated by TIC Salut Social, an entity of the Catalan Department of Health that works to promote the digital transformation of healthcare services (www.ticsalutsocial.cat). Invitations to participate in the study were shared among four Catalan associations for nurses and physicians who were invited to take part in the study via email. To be eligible for participation, participants had to be HCPs practicing in the Catalan region, of adult age, and had to be able to fill in an online questionnaire individually. All these participants were entitled to recommend apps as part of their profession. Recruitment for the study lasted for 5.5 weeks, from September 19, to October 27, 2023.

We conducted an a priori power analysis using G*power to assess the minimum number of participants required to run two-tailed correlations for our smallest effect size of interest (medium effect size, r = 0.30) with 0.80 power and alpha set to 0.05. This medium effect size was chosen as the smallest effect size of interest for the primary aim of exploring correlations between the behavioral determinants and anticipated recommendation behavior. This analysis revealed that we had to include at least 82 participants. With this number in mind as our minimum sample size, we preregistered that we would recruit as many participants as possible within the predetermined recruitment period of 5.5 weeks. This resulted in 290 participants (M_{age} = 51.79, SD_{age} = 11.87; 159 female, 128 male, 3 other/prefer not to say) completing our survey. A post-hoc sensitivity analysis indicated that with 290 participants, significant correlations as low as r = 0.16 with 0.80 power and alpha 0.05 can be revealed.

2.2. Procedure

Participants were approached via an e-mail, which contained a link to the survey. After clicking on this link, participants were provided with information about the study and were asked to provide informed consent. After agreeing to take part in the study, participants were informed about the quality label by providing them with written information about the quality label followed by a visual depiction of three different quality label scores. After having read this information, participants were asked to imagine themselves in the hypothetical situation that the quality label has been implemented and that all health apps are always accompanied by a quality label. Having this situation in mind, we next asked participants to provide answers to 37 statements regarding recommending high-quality (as indicated by the label) self-management apps to their patients in the upcoming three months. These statements referred to potential TDF determinants of HCP behavior. This was followed by an open-ended question as well as a few questions regarding demographics and personal characteristics. HCPs could withdraw from the survey at any time by closing the browser. Participants were only able to submit their responses if they had answered all items.

The research protocol was assessed and approved by the Science Committee of the Public Health and Primary Care Department (PHEG) at Leiden University Medical Center (LUMC) (nr WSC-2023-20/PvN). In addition, a statement for non-Medical Research Involving Human Subjects research study was received (nr 23-3062).

2.3. Materials

All study materials were in Catalan. Please refer to the Supplementary File 1 for an English version of the complete study materials.

2.3.1. Behavioral determinants and implementation factors

The main study instrument was a questionnaire assessing behavioral determinants of HCPs' behavior of recommending high-quality, as indicated by the quality label, self-management apps to their patients. The instrument started with a question about HCPs' anticipated recommendation behavior (''I will recommend high-quality apps to my patients in the upcoming three months'') with answer options provided on 7-point Likert scales, ranging from 1 (Strongly disagree) to 7 (Strongly agree). The remaining 36 statements were based on the 16-domain TDF-checklist,[29] which includes a) items to assess the typical TDF domains (including nature of the behavior that was previously included in the TDF) organized according to the overarching Capability, Opportunity, and Motivation categorization, as well as b) items that assess broader implementation factors organized according to Innovation Strategy, Socio-political Context, Organization, Patients and Innovation. These domains were included alongside the TDF domains to capture broader factors relevant for implementation success beyond individual behavioral determinants. In line with previous approaches,[35] an interdisciplinary research team, including HCPs, behavioral scientists, e-health experts, and a co-author of the TDF-checklist (MC) was involved in reviewing the checklist to adapt it to the study's context and the overall research aim. As a result, while we retained all 16 TDF-checklist domains, eleven items (from Beliefs about consequences (1), Innovation (4), Socio-political context (3), and Organization (3)) were removed as these items were irrelevant to the goal of the study or the context of the behavior of interest. At the final stage of developing the instrument, the questionnaire was once again reviewed by a small convenience sample of HCPs. Based on their feedback, small amendments such as clarifications in the instructions were made. The final questionnaire consisted of 36 statements across 16 domains (see Supplementary File 2 for items, domains and their definitions). Domains were measured with one up to six items per domain, which could be answered on 7-point Likert scales ranging from 1 (Strongly disagree) to 7 (Strongly agree). Three items were reverse coded (See Supplementary File 2). Lastly, we included one additional open-ended question where participants could enter any other potential barriers which they might experience in recommending high-quality self-management apps to their patients (''Do you expect to experience

obstacles in recommending high-quality apps to your patients? Please share them below"). However, we decided not to report on these outcomes, given the brevity of most of the answers.

For domains from the TDF that were measured with at least two items, we first assessed the reliability of the scale. For domains consisting of two items, we used Spearman-Brown correlations, and for domains with more than two items, we used traditional reliability analysis with Cronbach's alpha. Domains with a Cronbach's alpha or correlation of at least 0.7 were averaged. This was done for Beliefs about consequences (α = 0.89), Behavioral Regulation (α = 0.85), and Beliefs about capabilities (ρ = 0.82). For the broader implementation factors, we deemed the individual items too different to conceptually form one construct and we will therefore report them separately.

2.3.2. Demographics, professional and eHealth experience

At the end of the questionnaire, participants were requested to add their demographic characteristics (gender, age), their professional characteristics and experience (location setting, occupation, years of practice, and current practice setting), and their experience in recommending health apps (whether they had recommended a health app previously and whether they received requests from their patients on health app recommendations).

2.4. Main analyses

First, descriptive statistics (median, interquartile range (IQR), and percentages) and horizontally stacked bar charts were used to summarize HCPs' anticipated recommendation behavior and the behavioral determinants. Based on this, we interpreted *room for improvement* on the behavioral determinants with low scores indicating high room for improvement. Second, Pearson's correlations were conducted to assess the association between the HCPs' anticipated recommendation behavior and the behavioral determinants (i.e., indicating the *relevance* of the determinant in predicting anticipated recommendation behavior). The final analysis step included combining the previous analyses by calculating the potential for change index using the behaviorchange package in R.[36] This score was calculated by subtracting the mean from its maximum and multiplying it with the correlation between that item and the main outcome of interest (anticipated recommendation behavior). This thus resulted in a combined potential for change score based on how much room for improvement there is for a specific determinant, and how much it relates to the outcome of interest, where higher scores represent higher potential for change.

3. Results

3.1. Preprocessing steps

As preregistered (https://aspredicted.org/XM7_DK2), outliers were defined as 3 *SD*s above or below the mean. Only few variables contained a few outliers (all towards the lower end of the scales): Beliefs about consequences 1 (4), socio-political context 2 (3), patients 1 (2), innovation strategy 1 (4), and innovation strategy 4 (8). Exclusion of these outliers did not affect any of the results. Therefore, as preregistered, we report on the entire sample with outliers included.

All data and analysis code are available on Zenodo [https://doi.org/10.5281/zenodo.13309620].

3.2. Sample characteristics

A large variety of different HCPs participated in the study. The majority of the participating HCPs practiced in an urban area (93.8 %). Most participants were physicians (92.8 %) followed by a considerably smaller minority of nurses (4.1 %). Within the group of physicians, most were specialized in family medicine (21.4 %), followed by internal medicine 7.2 %), obstetrics/gynecology (5.9 %), pediatrics (5.2 %) and psychiatry (5.2 %). Participants on average had 25.36 (*SD* = 12.20) years of experience. The most frequent practice setting was an inpatient hospital setting (22.4 %) followed by private practice (22.1 %). A majority of HCPs indicated to have experience in recommending apps (59.6 %). The majority of participants never received patient requests for health and wellness apps (44.1 %) or less than once a month (39.0 %). Only few participants indicated to receive patient requests about health apps at least monthly (16.9 %). For a complete overview of all sample characteristics, see Supplementary File 3 (Table 1).

The primary variable of interest, anticipated recommendation behavior, was not affected by or related to demographics or professional experience (all *ps* > 0.140). Yet, anticipated recommendation behavior was higher when HCPs had previously recommended apps to their patients, $F(2, 287) = 12.64$, $p < 0.001$, and when they received requests from patients more frequently, $F(4, 285) = 4.16$, $p = 0.003$.

3.3. Anticipated recommendation behavior

Within our sample, participants were generally quite positive regarding their anticipated app recommendation behavior (median = 5.00, IQR = 4.00, 7.00). Specifically, 65 % said that they would recommend high-quality apps as indicated by the label (i.e., scoring above the neutral point of 4 on the scale), 16 % scored neutrally, and only 19 % did not anticipate recommending high-quality apps (i.e., scoring below the midpoint of 4 on the scale). Below we present the descriptives per cluster of domains (Capability, Opportunity, and Motivation) and for the broader implementation factors.

3.4. Room for improvement

3.4.1. Capability

Participants indicated to possess relevant skills (median = 5.00, IQR = 4.00, 7.00), with only a quarter (25 %) disagreeing with this statement. On average, participants indicated to have sufficient knowledge (median = 4.00, IQR = 3.00, 6.00), although still about a third (34 %) of respondents reported insufficient knowledge. Participants indicated to remember what they had to do recommend apps (Memory, attention, and decision processes: median = 5.00, IQR = 4.00, 5.00), with only 23 % disagreeing with this statement. Behavioral regulation was scored around the midpoint of the scale (median = 4.00, IQR = 2.67, 5.00), but especially Behavioral Regulation 3 ("I check regularly whether I am doing everything necessary to recommend high-quality apps to my patients") was scored low by a considerable proportion of participants (58 %). See Fig. 1 for an overview of the scores on the capability items.

3.4.2. Opportunity

Within opportunity, we looked at social influence with two items, which were both scored relatively low (Social influence 1: median = 3.00, IQR = 2.00, 4.75; Social influence 2: median = 3.00, IQR = 2.00, 4.00). Only a small proportion of participants agreed that it was expected of them and that they receive support to recommend high-quality health apps to patients (25 % and 20 %, respectively). See Fig. 2 for an overview of the scores on the opportunity items.[1]

[1] Please note that while the Theoretical Domains Framework also includes Environmental Context and Resources under Opportunity, the TDF-checklist does not include this domain but instead includes related items that are reported under Socio-Political Context and Organization (see 3.4.5 Broader Implementation Factors).

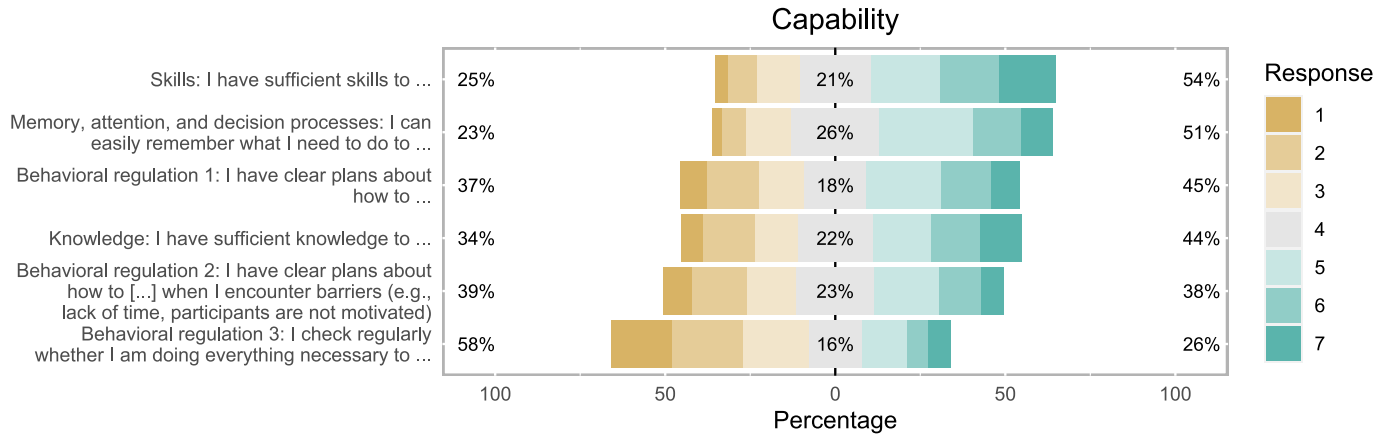

Fig. 1. HCPs' responses on the questions regarding capability. The response scale for all items ranges from 1 (Strongly disagree) to 7 (Strongly agree). Percentages on the left are the proportion of answers below the midpoint of the scale, percentages in the middle are at the midpoint, and percentages at the right are above the midpoint.

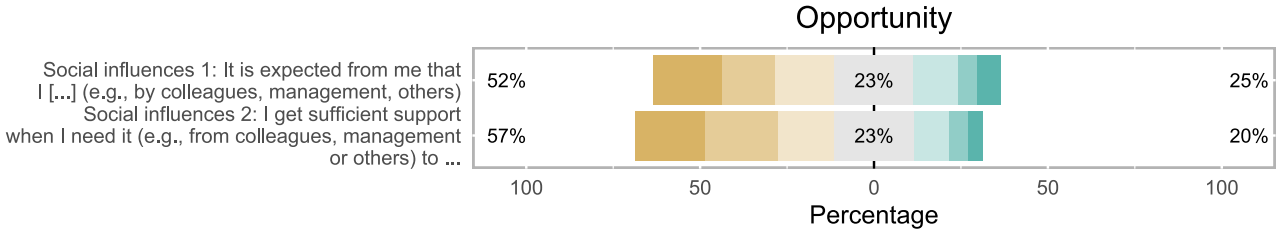

Fig. 2. HCPs' responses on the questions regarding opportunity. The response scale for all items ranges from 1 (Strongly disagree) to 7 (Strongly agree). Percentages on the left are the proportion of answers below the midpoint of the scale, percentages in the middle are at the midpoint, and percentages at the right are above the midpoint.

3.4.3. Motivation

The motivational domains were scored relatively high, but many participants also indicated to have other interfering tasks (median = 3.00, IQR = 2.00, 5.50; lower scores indicating more interfering tasks). Beliefs about consequences were relatively positive (median = 5.00, IQR = 4.00, 6.00). Participants were especially optimistic about improvements in patient experience and population health (with 77 % and 69 % agreeing to the statements) and were a little more conservative in their expectations for reducing healthcare costs and improving the work-life of HCPs (with 54 % and 46 % agreeing with such statements). Beliefs about capabilities also received relatively lower scores with approximately a third of participants indicating to lack the confidence to recommend high-quality apps (29 % and 34 %, respectively). Participants confirmed that recommending apps fitted their social/professional role and identity (median = 5.00, IQR = 4.00, 7.00), with only 17 % not seeing it as their role as a HCP to recommend high-quality apps. Finally, emotions and optimism were scored relatively high across two items (Emotions & optimism 1: median = 5.00, IQR = 4.00, 6.00; Emotions & optimism 2 (reverse coded): median = 6.00, IQR = 4.00, 7.00). See Fig. 3 for an overview of the scores on the motivation items.

3.4.4. Nature of the behaviors

Most HCPs (63 %) indicated that it is not a habit for them to recommend high-quality apps (median = 3.00, IQR = 1.00, 4.00; See Fig. 4).

3.4.5. Broader implementation factors

See Fig. 5 for an overview of the scores on the items measuring broader implementation factors.

3.4.5.1. Innovation strategy. HCPs reported a strong need for more information (median = 6.00, IQR = 5.00, 7.00), training (median = 6.00, IQR = 5.00, 7.00), and assistance (median = 6.00, IQR = 4.00, 7.00), as well as for continuous updating about developments of the quality label (median = 6.00, IQR = 5.00, 7.00). A majority of participants agreed with the statements about such needs (80 %, 77 %, 71 %, and 90 %, respectively). Most participants (61 %) also expressed a need for recognition from colleagues (median = 5.00, IQR = 4.00, 6.00). The need for financial compensation was scored low (median = 2.00, IQR = 1.00, 4.00), with only 21 % indicating such a need.

3.4.5.2. Socio-political context. HCPs indicated to be able to make free choices for whether to recommend high-quality apps (82 % scored above the midpoint of the scale; median = 6.00, IQR = 5.00, 7.00), but many participants expressed a lack of sufficient time (median = 4.00, IQR = 2.00, 5.00), with only 31 % expressing sufficient time.

3.4.5.3. Organization. A large majority of participants indicated to have no formal arrangements within their organization or clear guidelines for recommending high-quality health apps (64 % scored below the midpoint of the scale; median = 2.00, IQR = 1.00, 4.00). About half of the participants (49 %) also indicated to experience other changes in their organization that could interfere with recommending apps to their patients (median = 4.00, IQR = 2.00, 5.00).

3.4.5.4. Patients. Most HCPs (80 %) reported to see enough patients for whom they could recommend high-quality apps (median = 5.00, IQR = 4.00, 6.00). A small majority (52 %) expected that patients would appreciate it when they would recommend high-quality apps (median = 5.00, IQR = 4.00, 6.00). With regard to patient motivation for using such apps, participants were mixed (median = 4.00, IQR = 4.00, 5.00), with 42 % expecting patients to be motivated.

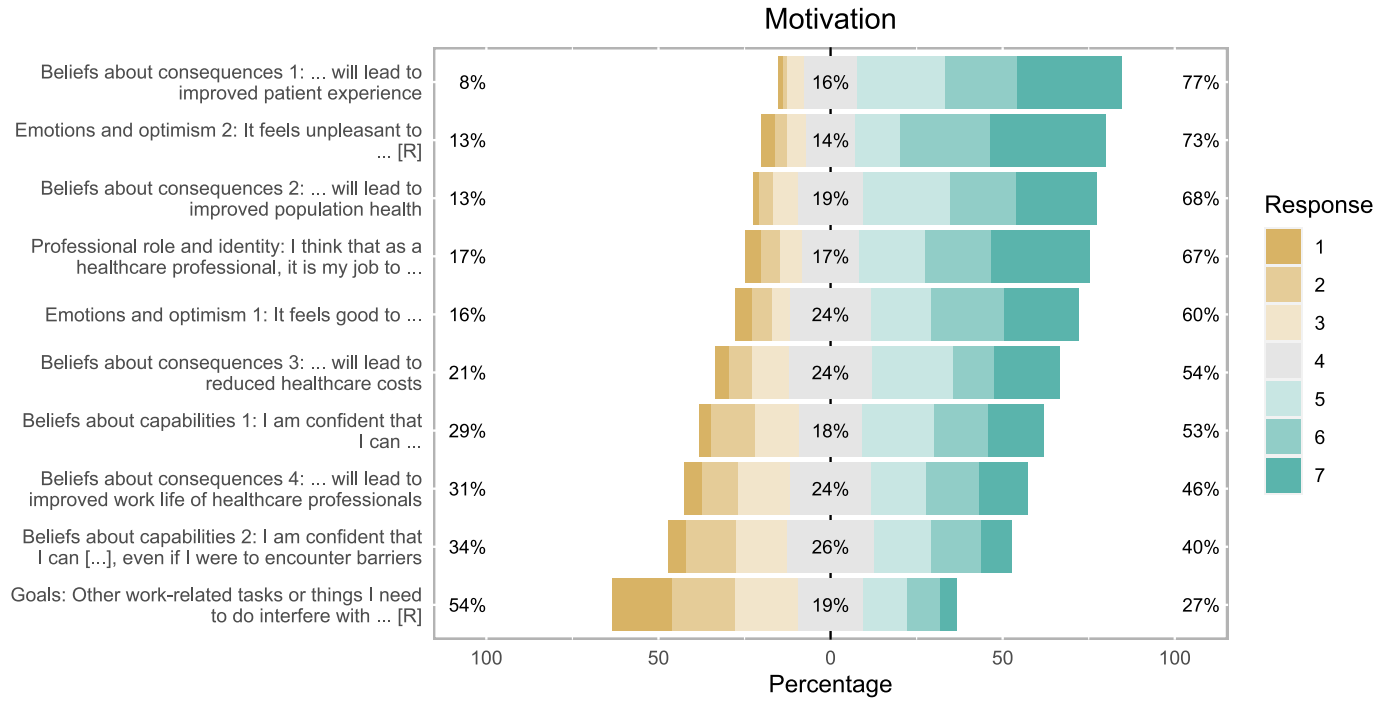

Fig. 3. HCPs' responses on the questions regarding opportunity. The response scale for all items ranges from 1 (Strongly disagree) to 7 (Strongly agree). Percentages on the left are the proportion of answers below the midpoint of the scale, percentages in the middle are at the midpoint, and percentages at the right are above the midpoint.

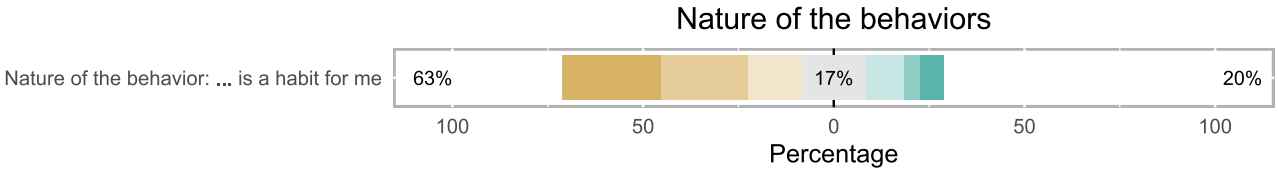

Fig. 4. HCPs' responses regarding nature of the behaviours. The response scale for all items ranges from 1 (Strongly disagree) to 7 (Strongly agree). Percentages on the left are the proportion of answers below the midpoint of the scale, percentages in the middle are at the midpoint, and percentages at the right are above the midpoint.

3.4.5.5. Innovation. The quality label itself was evaluated relatively positively by most HCPs. For example, 64 % indicated that the quality label is well-constructed while only 11 % disagreed to this statement (median = 5.00, IQR = 4.00, 6.00). Additionally, 56 % indicated that the quality label offers all information and materials needed to recommend high-quality apps (median = 5.00, IQR = 4.00, 6.00). 28 % scored on the midpoint of the scale, while 16 % did not find the information sufficient. Finally, 64 % indicated that recommending high-quality apps is compatible with their usual way of working (median = 5.00, IQR = 4.00, 6.00).

3.5. Relevance

Next to looking at the distributions of scores within each of the domains to assess room for improvement, we looked at correlations with our main outcome anticipated recommendation behavior to assess the relevance of determinants. Due to the large sample size, almost all correlations are significant. Therefore, we focus on correlations that can be considered large (i.e., $r \geq 0.50$; Cohen, 1992). The strongest positive correlations with anticipated recommendation behavior were found for beliefs about consequences ($r = 0.58$), followed by beliefs about capabilities ($r = 0.56$), professional role and identity ("I think that as a healthcare professional, it is my job to recommend high-quality apps to my patients", $r = 0.55$), innovation 2 ("Recommending high-quality apps to my patients is compatible with my usual way of working", $r = 0.53$), and emotions and optimism 1 ("It feels good to recommend high-quality apps to my patients", $r = 0.50$). See Supplementary materials 2 for a full overview of correlations between determinants and anticipated recommendation behavior, as well as all intercorrelations between the determinants.

3.5. Potential for change

The highest potential for change was found for Nature of Behavior (1.652), which was primarily driven by a relatively low mean ($M = 3.00$) indicating considerable room for improvement, and to a lesser extent by a medium correlation with anticipated behavior ($r = 0.41$). Beliefs about capabilities also had a high potential for change (1.489). Even though the mean for beliefs about capabilities was already above the midpoint of the scale ($M = 4.33$), the potential for change was especially found in the strong correlation with anticipated recommendation behavior ($r = 0.56$). Knowledge (1.373) was also found to have high potential for change, again driven by the combination of a mean slightly above the midpoint of the scale ($M = 4.21$) and a strong correlation ($r = 0.49$). See Supplementary File 3 (Table 2) for a complete overview of all potential for change scores accom-

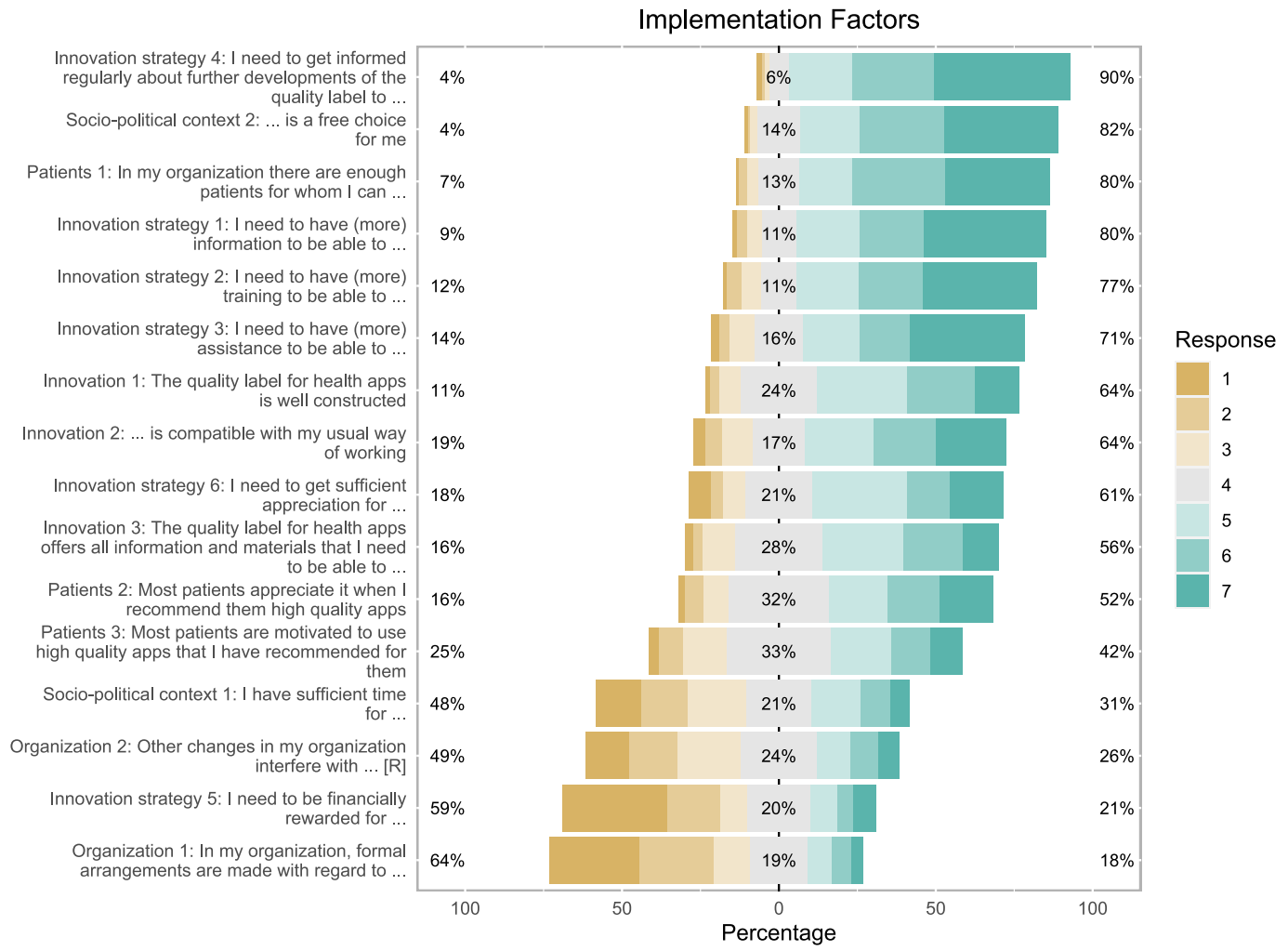

Fig. 5. HCPs' responses on the questions regarding implementation factors. The response scale for all items ranges from 1 (Strongly disagree) to 7 (Strongly agree). Percentages on the left are the proportion of answers below the midpoint of the scale, percentages in the middle are at the midpoint, and percentages at the right are above the midpoint.

panied by descriptives (means and SDs) and correlations with anticipated recommendation. See Fig. 6 for an overview of the scores of all determinants and their associations with anticipated recommendation behavior.

4. General discussion

4.1. Main findings

With this study, we aimed to identify key determinants of HCPs' anticipated recommendation behavior of high-quality (as indicated by the quality label) self-management apps. Previous research has identified quality concerns as a barrier to recommending health apps. With the present study we aimed to test which other factors influence recommending appropriate high-quality apps when quality concerns are alleviated using the newly developed health app quality label. This study aimed to identify these determinants using a version of the TDF-checklist that was adapted by an interdisciplinary research team to the context of our study to allow for identifying a wide range of barriers. For all determinants, we mapped the numerical room for improvement (based on descriptives), relevance (based on correlations), and combined these pieces of information to calculate a potential for change score.

Our results revealed that a large majority of Catalan HCPs responded positively towards the question of whether they would recommend high-quality apps to their patients in the upcoming three months, with only 19 % scoring below the neutral point of the scale. Further, looking into COM-B-related behavior determinants, HCPs were found to be overall motivated to recommend high-quality apps. In contrast, more room for improvement was identified for the capability and opportunity-related domains, as these were generally scored lower. Specifically, for capability, around a third of HCPs reported to have insufficient knowledge and less than half reported having plans for recommending high-quality apps. This is in line with previous research that identified insufficient knowledge or awareness of health apps as a potential barrier for recommending health apps.[8,37,38] For opportunity, HCPs did not feel supported to recommend apps and did not feel like this was expected of them. In addition, regarding the broader implementation factors it was found that most HCPs feel positive about the quality label and the information it provides, but that a considerable minority remains more reserved about its potential based

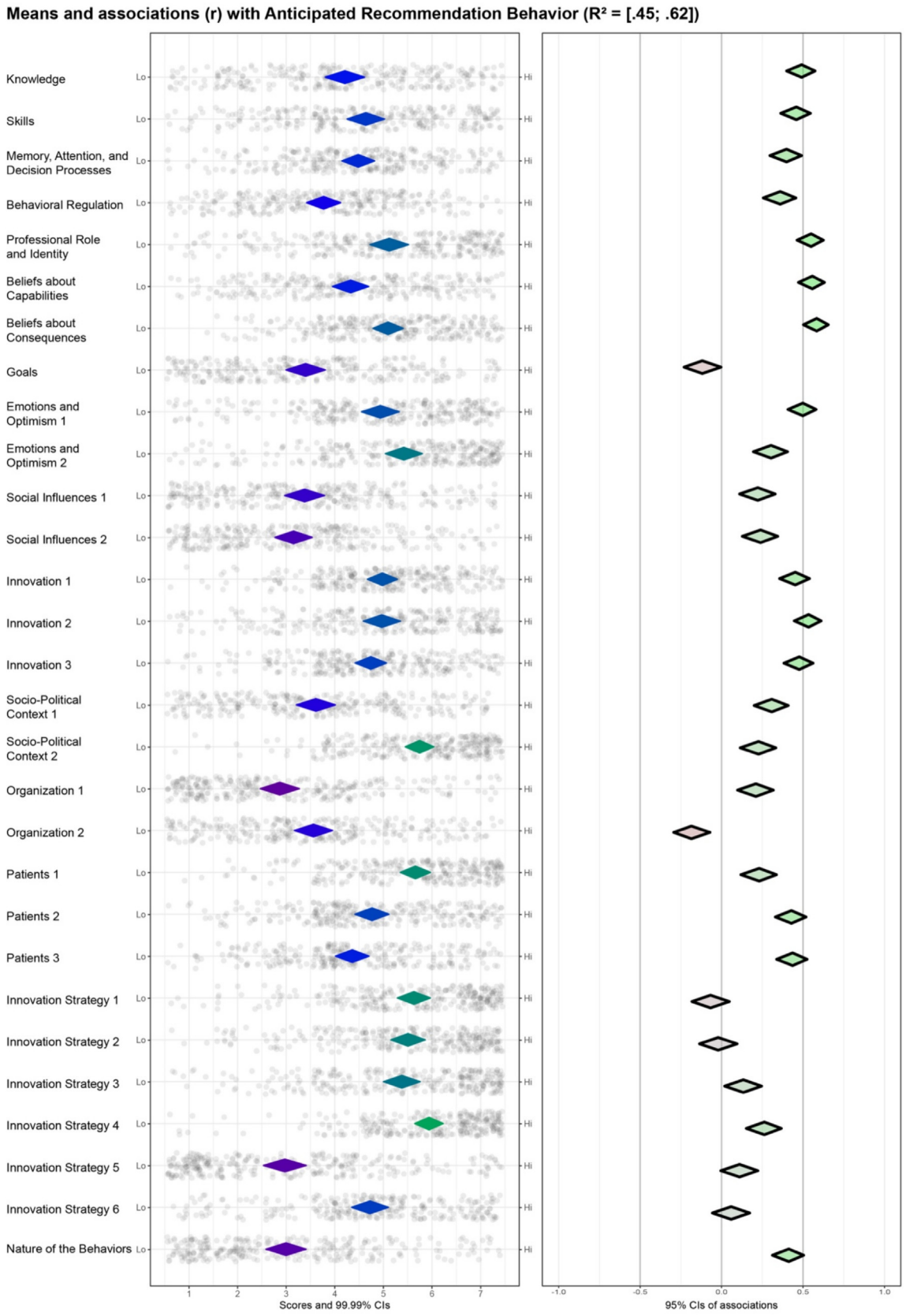

Fig. 6. Means (left panel) and associations (right panel) of all determinants with the main outcome of anticipated recommendation behavior. The response scale (presented in the left panel) for all items ranges from 1 (Strongly disagree) to 7 (Strongly agree).

on the information provided in our study. Finally, participants indicated to experience a lack of organizational support and a need for more information and training, which corresponds with earlier studies documenting organizational and structural barriers.[39]

To assess relevance of the explored factors we calculated correlations between behavioral determinants and anticipated recommendation behavior. The strongest associations with anticipated recommendation behavior were found for motivational factors, including beliefs about consequences, beliefs about capabilities, professional role and identity, and emotions and optimism. This indicates that the most relevant factors to predict anticipated recommendation behavior are related to responses or consequences anticipated for patients and whether recommending apps fits their role, rather than time constraints, knowledge or resources.

When calculating the potential for change by combining the relevance information (correlations) with room for improvement, the three determinants that were found to yield the highest potential for changing HCP behavior were: nature of the behaviors (habit), beliefs about capabilities, and knowledge. This indicates that if the quality label indicates availability of high-quality apps, interventions to stimulate HCP recommendation of such apps when appropriate should aim to promote habit formation for recommending high-quality health apps, boost the confidence of HCPs, and provide further knowledge regarding health apps.

4.2. Implications

4.2.1. Helping HCPs to build a habit of recommending apps

Nature of the behaviors was found to be the determinant with the highest potential for change, which is in line with recent findings indicating this to be the most important individual determinant to promote behavior change in general.[40] Meta-analytical evidence also points to the importance of habit as a determinant of HCP behavior,[41] which aligns with findings demonstrating that HCPs experience high work demands and time constraints.[42] In the present study nature of the behaviors was assessed by directly probing participants about the degree to which participants perceive the behavior as a habit, and our results pointed out that room for improvement is high (also in comparison to other determinants in our study). Habitual behavior in psychology refers to behavior that has been frequently performed in a stable context so that through associative learning a strong association has been formed.[43] As a result, when encountering the relevant context, the behavioral response is activated relatively automatically without the need for conscious deliberation. As such, habit is considered to promote behavioral maintenance by shielding behavior from temporary lapses in motivation or attention, or when under high load or stress, which is not unusual for HCPs. It thus makes sense to assume that, in specific contexts (i.e., with specific patients encountered in a specific clinical setting) where recommendation of a high-quality app is generally considered appropriate, forming strong cue-response associations, through stably and consistently linking a specific moment or question during consultation to recommendation behavior, could potentially increase actual execution of a HCPs intention to recommend a health app.

To promote the formation of such cue-response associations (i.e., habits), implementation of the novel quality label should be supplemented by habit interventions such as the formulation of implementation intentions. These are if-then action plans linking specific behaviors to specific contextual cues (e.g., "If I talk to a patient with a recent asthma diagnosis experiencing a symptom burden that can benefit from self-management, I will recommend them a high-quality app for this").[44] When adopting this strategy, it is important to keep in mind that recommending apps should not be considered a goal in and of itself and that therefore this strategy should be reserved for promoting health app recommendation in very specific situations (i.e., targeting relevant cues that reliably signal that app recommendation is appropriate). Moreover, when adopting this strategy, it is important to acknowledge that focusing on building a habit solely without addressing other existing barriers, such as lack of self-efficacy, might not be fully sufficient in changing HCPs recommending behavior.[45]

4.2.2. Boosting HCPs' confidence in their abilities

HCPs' beliefs in their capabilities to recommend high-quality apps as well as their abilities to deal with barriers were found to have a high potential for change, which seemed mostly driven by the strong correlation between beliefs about capabilities and anticipated recommendation behavior. Beliefs about capabilities to recommend high-quality apps, commonly referred to as self-efficacy in psychological theories,[46] can be boosted in various ways. For example, modeling can be used to learn from someone else performing the behavior.[47] This technique has been used frequently before to stimulate recommendation of health apps (see [48]). To boost self-efficacy for recommending high-quality apps, efforts to implement the quality label could for example be combined with short videos in which professionals show how they recommend apps to their patients. Once initial mastery of the ability to recommend high-quality apps has been obtained, setting graded tasks could be another technique to further stimulate self-efficacy.[49] In doing so, HCPs can decide to recommend apps to a small number of patients to start with (e.g., solely one particular app to one particular patient type), and gradually increase this over time (e.g., to other patients). This, again, could boost self-efficacy to recommend health apps in particular contexts that are deemed appropriate. Importantly, implementation intentions have also been shown to increase self-efficacy.[45]

4.2.3. Increasing knowledge

The third domain with high potential for change in our study was knowledge. This finding was corroborated by high scores on the need for more information. It goes without saying that knowledge is essential for performing behavior adequately, but in order to increase knowledge with the goal of stimulating health app recommendation behavior it is important to first know what kind of knowledge is currently lacking. For example, from our study it is not clear whether participants currently lack knowledge about when exactly apps are appropriate, about the yet to be implemented quality label, about what they ought to do themselves to recommend high-quality apps, or something else. When implemented, the quality label will be accompanied by a detailed health app quality report, which aims to ensure that HCPs, their institutions and medical societies can look up information regarding app quality that fits their needs. Whether this report indeed solves the need for information requires further exploration.

Luckily, many efforts already exist to increase HCP knowledge about health apps with some promising results in terms of increasing this knowledge.[48] However, given that healthcare professional behavior is to a large extent driven by more automatic processes,[41] it is questionable whether these increases in knowledge alone will lead to actual changes in app recommendation behavior, especially in the longer term. Efforts to increase success of implementing the label should thus not solely focus on increasing knowledge, but should also focus on habit formation and self-efficacy.

4.3. Strengths, limitations and suggestions for future research

Several limitations need to be mentioned. First, regarding generalizability, it should be noted that our sample included a large variety of physicians, but only few other HCPs. Besides, partici-

pants on average had a lot of experience and showed high motivation for recommending health apps, which might be higher than observed in the general HCP population. This may be due to the high proportion of urban HCPs, who were previously found to be more likely to recommend health apps and more often consider themselves capable to do so.[50,51] Second, in this study, we asked HCPs to place themselves in a hypothetical scenario of recommending high-quality (as indicated by the quality label) self-management apps to their patients. Even though the use of hypothetical scenarios is not uncommon in research with HCPs,[52] it does impose a limitation on the ecological validity of the study's findings. Yet, as the quality label has not been implemented yet, asking HCPs to place themselves in a hypothetical scenario was presently the only route towards addressing this issue and does present us with important information that can be most effectively used since implementation of the label is still ongoing. Third, while using the potential for change score is a novel and useful method for selecting relevant behavioral determinants, the quality of the output crucially depends on the operationalizations of the constructs in the questionnaire.[53] Therefore, in order to have a high-quality instrument, we used the TDF-checklist as the basis, which we further refined with input from an interdisciplinary team to fit the purposes of our study. Yet, it is well known that habits, for example, are difficult to assess and if one were to focus on habits more precisely, different measures would be more suitable.[54] Relatedly, our quantitative approach was useful for identifying relevance of a wide range of determinants of high-quality app recommendation behavior, but it does not provide us with in-depth information about these determinants. The open-ended question in our questionnaire also did not provide such in-depth answers. Qualitative research, therefore, should be performed as a second step to further explore the meaning and context of the barriers towards high-quality app recommendation behavior and to allow for subsequently designing suitable and appropriate interventions that aid HCPs in recommending apps when this is indeed appropriate. Finally, it should be mentioned that some of the results may be context-specific for the Catalan sample that we used. For example, we did not find a need for financial compensation, while studies in other countries did find such a need.[9]

4.4. Conclusion

With this study, we aimed to assess the behavioral determinants of HCP anticipated behavior of recommending high-quality (as indicated by the label) health and wellness apps to their patients. We identified several behavioral barriers to recommending apps, out of which nature of the behaviors (or habits), HCPs' beliefs in their capabilities (or self-efficacy), and knowledge stood out as the determinants with the highest potential for change. Hence, HCPs could be further supported by offering interventions to help them build their self-efficacy in recommending apps (including educating as well as practical components). In addition, HCPs could be assisted in helping them to build a habit of recommending apps, by allowing them to repetitively rehearse app recommending as part of their clinical routine. Finally, it is important to recognize the need for more information and to provide HCPs with the necessary knowledge. Addressing the determinants with the highest potential for change with the right Behavior Change Techniques could further increase the implementation success of the quality label.

Pre-registration

The aim, design, and main study analyses were preregistered at AsPredicted (https://aspredicted.org/XM7_DK2).

CRediT authorship contribution statement

I. Biliunaite: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **M.A. Adriaanse:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **A.P.Y. Hoogendoorn:** Writing – review & editing, Methodology. **A. Montvilla:** Writing – review & editing, Methodology. **M.R. Crone:** Writing – review & editing, Methodology. **L.C. van Gestel:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Formal analysis, Conceptualization.

Ethics approval

The research protocol was assessed and approved by the Science Committee of the Public Health and Primary Care Department (PHEG) at Leiden University Medical Center (LUMC) (nr WSC-2023-20/ PvN). Also, a non-Medical Research Involving Human Subjects statement was obtained (nr 23-3062).

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Data availability statement

All data and analysis code are available on Zenodo [https://doi.org/10.5281/zenodo.13309620].

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ceh.2025.10.001.

References

1. Kitsiou S, Paré G, Jaana M, Gerber B. Effectiveness of mHealth interventions for patients with diabetes: An overview of systematic reviews. Li D, ed. *Plos One*. 2017;12(3):e0173160. doi:10.1371/journal.pone.0173160.
2. Firth J, Torous J, Nicholas J, et al. The efficacy of smartphone-based mental health interventions for depressive symptoms: a meta-analysis of randomized controlled trials. *World Psychiatry*. 2017;16(3):287–298. https://doi.org/10.1002/wps.20472.

3. Zhang H, Jiang Y, Nguyen HD, Poo DCC, Wang W. The effect of a smartphone-based coronary heart disease prevention (SBCHDP) programme on awareness and knowledge of CHD, stress, and cardiac-related lifestyle behaviours among the working population in Singapore: a pilot randomised controlled trial. *Health Qual Life Outcomes*. 2017;15(1). https://doi.org/10.1186/s12955-017-0623-y.
4. WHO. The ongoing journey to commitment and transformation Digital health in the WHO European Region 2023. https://cdn.who.int/media/docs/librariesprovider2/data-and-evidence/english-ddh-260823_7amcet.pdf?sfvrsn=4c674522_2&download=true.
5. Rossmann C, Riesmeyer C, Brew-Sam N, et al. Appropriation of mobile health for diabetes self-management: lessons from two qualitative studies. *JMIR Diabetes*. 2019;4(1):e10271. https://doi.org/10.2196/10271.
6. Alaslawi H, Berrou I, Al Hamid A, Alhuwail D, Aslanpour Z. Diabetes self-management apps: systematic review of adoption determinants and future research agenda. *JMIR Diabetes*. 2022;7(3):e28153. https://doi.org/10.2196/28153.
7. Wangler J, Jansky M. How can primary care benefit from digital health applications? – a quantitative, explorative survey on attitudes and experiences of general practitioners in Germany. *BMC Digit Health*. 2024;2(1):14. https://doi.org/10.1186/s44247-024-00068-x.
8. Byambasuren O, Beller E, Glasziou P. Current knowledge and adoption of mobile health apps among australian general practitioners: survey study. *JMIR MHealth UHealth*. 2019;7(6):e13199. https://doi.org/10.2196/13199.
9. Dahlhausen F, Zinner M, Bieske L, Ehlers JP, Boehme P, Fehring L. There's an app for that, but nobody's using it: Insights on improving patient access and adherence to digital therapeutics in Germany. *Digit Health*. 2022;8:205520762211046. https://doi.org/10.1177/20552076221104672.
10. Byambasuren O, Beller E, Hoffmann T, Glasziou P. mHealth App prescription in Australian general practice: pre-post study. *JMIR MHealth UHealth*. 2020;8(6):e16497. https://doi.org/10.2196/16497.
11. Sarradon-Eck A, Bouchez T, Auroy L, Schuers M, Darmon D. Attitudes of general practitioners toward prescription of mobile health apps: qualitative study. *JMIR MHealth UHealth*. 2021;9(3):e21795. https://doi.org/10.2196/21795.
12. Wangler J, Jansky M. Two years of approved digital health applications in Germany – Perspectives and experiences of general practitioners with an affinity for their use. *Eur J Gen Pract*. 2023;29(1):2186396. https://doi.org/10.1080/13814788.2023.2186396.
13. Grundy Q. A review of the quality and impact of mobile health apps. *Annu Rev Public Health*. 2022;43(1):117–134. https://doi.org/10.1146/annurev-publhealth-052020-103738.
14. Caiani EG, Kemps H, Hoogendoorn P, et al. Standardized assessment of evidence supporting the adoption of mobile health solutions: a Clinical consensus statement of the ESC regulatory affairs committee. *Eur Heart J - Digit Health*. 2024;5(5):509–523. https://doi.org/10.1093/ehjdh/ztae042.
15. Hensher M, Cooper P, Dona SWA, et al. Scoping review: Development and assessment of evaluation frameworks of mobile health apps for recommendations to consumers. *J Am Med Inform Assoc*. 2021;28(6):1318–1329. https://doi.org/10.1093/jamia/ocab041.
16. Lagan S, Sandler L, Torous J. Evaluating evaluation frameworks: a scoping review of frameworks for assessing health apps. *BMJ Open*. 2021;11(3):e047001. https://doi.org/10.1136/bmjopen-2020-047001.
17. mHealthHUB. D2.1 Knowledge Tool 1. Health apps assessment frameworks. Published online 2021. https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5e1496716&appId=PPGMS.
18. International Organization for Standardization (ISO). ISO/TS 82304-2:2021 Health software - Part 2: Health and wellness apps - Quality and readability. Published online 2021.
19. Hoogendoorn P, Versluis A, Van Kampen S, et al. What makes a quality health app—developing a global research-based health app quality assessment framework for CEN-ISO/TS 82304-2: delphi study. *JMIR Form Res*. 2023;7:e43905. https://doi.org/10.2196/43905.
20. Biliunaite I, Van Gestel L, Hoogendoorn P, et al. Value of a quality label and European healthcare professionals' willingness to recommend health apps: An experimental vignette study. *J Health Psychol*. Published online August 2, 2024:13591053241258205. doi:10.1177/13591053241258205.
21. Die Techniker. DiGA-Report II: Preise für Apps auf Rezept sind um 50 prozent gestiegen. Published online 2024.
22. Dahlhausen F, Zinner M, Bieske L, Ehlers JP, Boehme P, Fehring L. Physicians' attitudes toward prescribable mHealth apps and implications for adoption in Germany: mixed methods study. *JMIR MHealth UHealth*. 2021;9(11):e33012. https://doi.org/10.2196/33012.
23. Richter JG, Chehab G, Stachwitz P, et al. One year of digital health applications (DiGA) in Germany – Rheumatologists' perspectives. *Front Med*. 2022;9:1000668. https://doi.org/10.3389/fmed.2022.1000668.
24. Cane J, O'Connor D, Michie S. Validation of the theoretical domains framework for use in behaviour change and implementation research. *Implement Sci*. 2012;7(1):37. https://doi.org/10.1186/1748-5908-7-37.
25. Michie S, Richardson M, Johnston M, et al. The Behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: building an international consensus for the reporting of behavior change interventions. *Ann Behav Med*. 2013;46(1):81–95. https://doi.org/10.1007/s12160-013-9486-6.
26. Michie S, van Stralen MM, West R. The behaviour change wheel: a new method for characterising and designing behaviour change interventions. *Implement Sci*. 2011;6(1):42. https://doi.org/10.1186/1748-5908-6-42.
27. Alhusein N, Scott J, Neale J, Chater A, Family H. Community pharmacists' views on providing a reproductive health service to women receiving opioid substitution treatment: a qualitative study using the TDF and COM-B. *Explor Res Clin Soc Pharm*. 2021;4:100071. https://doi.org/10.1016/j.rcsop.2021.100071.
28. McParlin C, Bell R, Robson SC, Muirhead CR, Araújo-Soares V. What helps or hinders midwives to implement physical activity guidelines for obese pregnant women? A questionnaire survey using the Theoretical Domains Framework. *Midwifery*. 2017;49:110–116. https://doi.org/10.1016/j.midw.2016.09.015.
29. Huijg JM. Towards the effective introduction of physical activity interventions in primary health care. Published online 2014. https://hdl.handle.net/1887/29082.
30. Huijg JM, Gebhardt WA, Dusseldorp E, et al. Measuring determinants of implementation behavior: psychometric properties of a questionnaire based on the theoretical domains framework. *Implement Sci*. 2014;9(1):33. https://doi.org/10.1186/1748-5908-9-33.
31. Agarwal P, Gordon D, Griffith J, et al. Assessing the quality of mobile applications in chronic disease management: a scoping review. *Npj Digit Med*. 2021;4(1):46. https://doi.org/10.1038/s41746-021-00410-x.
32. Greenwood DA, Gee PM, Fatkin KJ, et al. A systematic review of reviews evaluating technology-enabled diabetes self-management education and support. *J Diabetes Sci Technol*. 2017;11(5):1015–1027. https://doi.org/10.1177/1932296817713506.
33. Biliunaite I, Van Gestel L, Hoogendoorn P, Adriaanse M. Value of a quality label and European healthcare professionals' willingness to recommend health apps: an experimental vignette study. *J Health Psychol*. 2025;30(6):1278–1290. https://doi.org/10.1177/13591053241258205.
34. Crutzen R, Peters GJY. A lean method for selecting determinants when developing behavior change interventions. *Health Psychol Behav Med*. 2023;11(1):2167719. https://doi.org/10.1080/21642850.2023.2167719.
35. Talkhan H, Stewart D, McIntosh T, et al. Investigating clinicians' determinants of antimicrobial prescribing behaviour using the Theoretical Domains Framework. *J Hosp Infect*. 2022;122:72–83. https://doi.org/10.1016/j.jhin.2022.01.007.
36. Peters GJY, Crutzen R, Gruijters S. The behaviorchange Package: Tools for Behavior Change Researchers and Professionals. Published online 2023. https://behaviorchange.opens.science.
37. Cirkel L, Lechner F, Schlicker N, et al. Adoption and perception of prescribable digital health applications (DiGA) and the advancing digitalization among German internal medicine physicians: a cross-sectional survey study. *BMC Health Serv Res*. 2024;24(1):1353. https://doi.org/10.1186/s12913-024-11807-1.
38. May S, Seifert F, Bruch D, Heinze M, Spethmann S, Muehlensiepen F. Insights into how mHealth applications could Be introduced into standard hypertension care in Germany: qualitative study with German cardiologists and general practitioners. *JMIR MHealth UHealth*. 2025;13:e56666. https://doi.org/10.2196/56666.
39. Giebel GD, Speckemeier C, Abels C, et al. Problems and barriers related to the use of digital health applications: scoping review. *J Med Internet Res*. 2023;25:e43808. https://doi.org/10.2196/43808.
40. Albarracín D, Fayaz-Farkhad B, Granados Samayoa JA. Determinants of behaviour and their efficacy as targets of behavioural change interventions. *Nat Rev Psychol*. 2024;3(6):377–392. https://doi.org/10.1038/s44159-024-00305-0.
41. Potthoff S, Rasul O, Sniehotta FF, et al. The relationship between habit and healthcare professional behaviour in clinical practice: a systematic review and meta-analysis. *Health Psychol Rev*. 2019;13(1):73–90. https://doi.org/10.1080/17437199.2018.1547119.
42. Berkowitz CM, Zullig LL, Koontz BF, Smith SK. Prescribing an App? Oncology providers' views on mobile health apps for cancer care. *JCO Clin Cancer Inform*. 2017;1:1–7. https://doi.org/10.1200/CCI.17.00107.
43. Zhang C, Adriaanse MA, Potgieter R, et al. Habit formation of preventive behaviours during the COVID-19 pandemic: a longitudinal study of physical distancing and hand washing. *BMC Public Health*. 2022;22(1):1588. https://doi.org/10.1186/s12889-022-13977-1.
44. Gollwitzer PM. Implementation Intentions: Strong Effects of Simple Plans. *Am Psychol*. Published online 1999.
45. Lorig K, Laurent DD, Plant K, Krishnan E, Ritter PL. The components of action planning and their associations with behavior and health outcomes. *Chronic Illn.*. 2014;10(1):50–59. https://doi.org/10.1177/1742395313495572.
46. Bandura A. Self-Efficacy Mechanism in Human Agency.
47. Taylor PJ, Russ-Eft DF, Chan DWL. A meta-analytic review of behavior modeling training. *J Appl Psychol*. 2005;90(4):692–709. https://doi.org/10.1037/0021-9010.90.4.692.
48. Alkhaldi O, McMillan B, Maddah N, Ainsworth J. Interventions aimed at enhancing health care providers' behavior toward the prescription of mobile health apps: systematic review. *JMIR MHealth UHealth*. 2023;11:e43561. https://doi.org/10.2196/43561.
49. Johnston M, Carey RN, Connell Bohlen LE, et al. Development of an online tool for linking behavior change techniques and mechanisms of action based on triangulation of findings from literature synthesis and expert consensus. *Transl Behav Med*. 2021;11(5):1049–1065. https://doi.org/10.1093/tbm/ibaa050.
50. Wangler J, Jansky M. The use of health apps in primary care—results from a survey amongst general practitioners in Germany. *Wien Med Wochenschr*. 2021;171(7–8):148–156. https://doi.org/10.1007/s10354-021-00814-0.
51. Wangler J, Jansky M. Attitudes and experiences of registered diabetes specialists in using health apps for managing type 2 diabetes: results from a mixed-methods study in Germany 2021/2022. *Arch Public Health*. 2023;81(1):36. https://doi.org/10.1186/s13690-023-01051-0.

52. Wilson A, Ronnekleiv-Kelly SM, Pawlik TM. Regret in surgical decision making: a systematic review of patient and physician perspectives. *World J Surg*. 2017;41(6):1454–1465. https://doi.org/10.1007/s00268-017-3895-9.
53. Crutzen R, Peters GJY, Noijen J. Using confidence interval-based estimation of relevance to select social-cognitive determinants for behavior change interventions. *Front Public Health*. 2017;5:165. https://doi.org/10.3389/fpubh.2017.00165.
54. Gardner B, Abraham C, Lally P, De Bruijn GJ. Towards parsimony in habit measurement: Testing the convergent and predictive validity of an automaticity subscale of the Self-Report Habit Index. *Int J Behav Nutr Phys Act*. 2012;9(1):102. https://doi.org/10.1186/1479-5868-9-102.