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GENERAL INTRODUCTION

“The months after my heart attack, there has been a consecutive stream of professionals who were helping me in my recovery. Them telling me what to do and how to improve my health has been a great support. But now rehabilitation has ended and I feel like I’m completely on my own. I know my health is my own responsibility, but if I’m honest, I don’t know where to start.”

The story above is not an exception. Within the Netherlands, one out of ten adults suffer from cardiovascular diseases (CVD) (Koop et al., 2021). This does not only lead to a higher burden on the healthcare system and rising costs due to an increased need for care provision and productivity loss (Wilkins et al., 2017), but also has serious consequences for patients themselves. Apart from the negative health consequences, CVD patients often experience a deteriorated quality of life, meaning that their condition impacts their social, physical, or psychological functioning (De Smedt et al., 2013). Cardiac rehabilitation programmes in the Netherlands therefore also focus on psychological and social well-being (e.g. improving mental health, going back to work), next to improving physical fitness (e.g. exercise capacity; Multidisciplinaire Richtlijn Hartrevalidatie, Hartstichting, 2011).

The impact of a healthy lifestyle

A major part of rehabilitation is aimed at improving risk behaviours associated with CVD (Hartstichting, 2011). This is not without reason, as a more healthy lifestyle could provide an important contribution to CVD risk management. Addressing behavioural risk factors such as smoking, poor diet, physical inactivity and low sleep quality shows to have a positive impact on the prognosis of CVD (Kaminsky et al., 2022; Piepoli et al., 2016; Wilkins et al., 2017). Improving the lifestyle of CVD patients can even have mortality-reducing effects that are comparable to medication intake (Iestra et al., 2005). As a result, CVD-related deaths have reduced within countries that implemented policies related to healthier lifestyles (Roth et al., 2020).

Unfortunately, many patients are not able to maintain a healthy lifestyle once they return to their everyday life, after their rehabilitation has ended (Janssen et al., 2013; ter Hoeve et al., 2015). This is not surprising, as maintaining a healthy lifestyle is a difficult task. The difficulty of transforming intentions into real behaviour, which is called the intention-behaviour gap, makes it challenging for people to maintain healthy lifestyle behaviours that were initiated during rehabilitation (Webb & Sheeran, 2006). Lifestyle behaviours are often driven by automatic processes, such as habits (Rothman et al., 2009) and influenced by environmental factors (Marteau et al., 2012). Furthermore, due to the so-called present bias, people often favour the immediate satisfaction of unhealthy behaviour above the delayed reward of a healthy lifestyle (Liberman & Trobe, 2008). It is therefore not surprising that CVD patients themselves report struggles in developing a healthy lifestyle, and maintaining this healthier lifestyle after cardiac support ends (Murray et al., 2012) which is necessary to prevent recurrent cardiovascular events.

eHealth interventions for CVD patients

Given the fact that maintaining a healthy lifestyle seems so difficult for many CVD patients, there is an increasing need for solutions to help these patients, and eHealth technology can be such a solution. eHealth can be defined as the use of interactive new information and communication technology to support or enhance health and healthcare (Barak et al., 2009; Thomas & Bond, 2014). An increasing amount of eHealth interventions is being developed (Thomas & Bond, 2014) and eHealth is becoming increasingly relevant, which became especially evident during the recent COVID-19 outbreak (Bokolo, 2021; Silven et al., 2020). eHealth can be used to provide both remote and automated healthcare support and can be either web- or mobile-based. An example of eHealth to promote healthy living are wearables to track objective health indicators, that give users insight into their own health and lifestyle behaviour (e.g. blood pressure, steps a day). This provides users with the opportunity to set and track their personalised health goals (e.g. taking 5.000 steps per day). This is just one example of the wide range of technology eHealth can encompass to provide education and skills training.

The use of eHealth within cardiovascular care and cardiac rehabilitation has shown to be effective in both the prevention and treatment of CVD (Beishuizen et al., 2016; Lunde et al., 2018). eHealth interventions show to improve CVD patients' lifestyle behaviours, such as their physical activity levels (Patel et al., 2023) and diet (Thom et al., 2023). Besides, eHealth can be used to support patients for a longer period of time, even after rehabilitation has ended, to ensure durable lifestyle change (Janssen et al., 2013). Given these advantages, the use of eHealth is encouraged in the secondary prevention of CVD (Schorr et al., 2021). Telemonitoring has been successfully implemented in the cardiac rehabilitation of various groups of CVD patients, such as those with myocardial infarction (Treskes et al., 2020) or heart failure (Koehler et al., 2018). These patients home-monitor their health using several devices (e.g. electronic scale, pedometer, blood pressure monitor) which are connected to their smartphone to give them and their healthcare professional insight into their health and behaviour. Thus, eHealth is already imbedded and accepted within cardiac care today, and the use of eHealth will likely increase in the near future. With the rise of eHealth in cardiac care, barriers for proper use are also becoming more evident. eHealth is frequently used as a complementary tool to human care and the interference of a human healthcare professional is still required. However, healthcare professionals indicate to experience barriers in providing lifestyle support (e.g. Jallinoja et al., 2007; Jansink et al., 2010; Warr et al., 2021). For example, professionals indicate that they lack the time to provide this support, that there are no financial resources to facilitate lifestyle support, that they simply do not have enough experience to provide the required support to their patients or have doubts about the effectiveness of such interventions. And although eHealth has been suggested to help overcome these barriers, some professionals indicate to experience an even higher workload from using eHealth (Bellicha et al., 2017).

Automated support

On the upside, eHealth allows not only for the provision of remote support by a healthcare professional, but also for automated support (Barak et al., 2009). In such self-help eHealth interventions, feedback is automatically provided, making the interference of a healthcare professional no longer needed. This makes such eHealth interventions easier to implement on a wider scale (Barak et al., 2009). A practical example of self-help eHealth lifestyle interventions, in a non-CVD context, are online platforms offered by health insurance companies (e.g., Zilveren Kruis, 2021). In such web-based interventions, users are motivated to improve their physical activity levels, eating patterns, stress levels and sleep habits. Via interactive modules, users can set their own goals, track their behaviour, and receive automated feedback. Therefore, the costs are limited, and the insurance company can freely offer it to all its customers to help them engage in a healthier lifestyle.

Working alliance within eHealth interventions

Despite these important advantages of self-help eHealth interventions, there are several issues that are important to consider. One important issue of providing patients with a digital tool, is the lack of a social relationship with a healthcare professional (Brandt et al., 2018). Due to a lack of human contact, the uptake of self-help eHealth interventions is low (Lillevoll et al., 2014; Lin et al., 2018). But even when people do start using the intervention, self-help eHealth interventions suffer from a low level of adherence (Kelders et al., 2011; Kelders et al., 2012; Murray et al., 2013; Wangberg et al., 2008). This poses a problem, given that intervention adherence is related to more positive health outcomes (Donkin et al., 2011). Furthermore, there are inconsistent results concerning the effectiveness of self-help eHealth lifestyle interventions. While some studies show that self-help eHealth interventions are as effective as human-supported ones (Lustria et al., 2013; Webb et al., 2010), other studies show that the absence of (face-to-face) human support causes the intervention to be substantially less effective (Beishuizen et al., 2016; Joiner et al., 2017; Lau et al., 2020). This means that when no human support is provided, people are less likely to start using the eHealth intervention, do not use the eHealth intervention as much as they are intended to, and show less improvement in cardiovascular risk factors or healthy lifestyle behaviours.

This positive influence of human support might be due to the importance of building a relationship during the intervention (Brandt et al., 2018). Within the clinical context, this relationship, or so-called working alliance, is defined as the degree to which a healthcare professional and patient are involved in a useful and collaborative working relationship (Hatcher & Barends, 2006). The quality of the working alliance depends on three aspects, which are the level of agreement on goals that are set for treatment, on tasks that must be performed to reach this goal, and the quality of the relational bond between healthcare professional and patient (Bordin, 1979). Studies show that the quality of the working alliance explains up to a third of the variance in the efficacy of psychotherapeutic interventions (Horvath et al., 2011; Lambert & Barley, 2001). This strong positive relationship between the working alliance and intervention outcomes also holds within an eHealth context (Kaiser et al., 2021). Despite its important contribution to psychotherapy's success, the working alliance has been much less frequently applied within lifestyle-related domains. Nevertheless, a positive working alliance also increases adherence and effectiveness of lifestyle interventions (e.g. Goldberg et al., 2013; Hauser-Ulrich et al., 2020; Kowatsch et al., 2021a; Kowatsch et al., 2021b).

In an eHealth context, a good working alliance has also been shown to be a predictor of effectiveness and adherence in interventions with remote human support (Flückiger et al., 2018; Sucala et al., 2012), and even in interventions with automated support only (Bickmore et al., 2010; Clarke et al., 2016; Hauser-Ulrich et al., 2020; Kowatsch et al., 2021a; Kowatsch et al., 2021b). These latter findings might be explained by the fact that people are not only able to form relationships with other people, but also with digital tools and applications (Nass & Moon, 2000; Reeves & Nass, 1996). This idea originates from the "Computers are social actors-theory", which states that people use similar social rules and heuristics to their interactions with computers as they would do while interacting with other human beings. This behaviour applies to any digital tool, including eHealth interventions. Making the eHealth tool more "human" eases this process, and within eHealth interventions, conversational agents are often used for this task. These conversational agents are computer-based scripts which can mimic human-like conversational behavior such as responding to input, generate output, and turn-taking (Cassell et al., 1999). Studies show that the use of such human-like social rules and heuristics (e.g. showing empathy or humour) by conversational agents can increase the working alliance people experience (Bickmore et al., 2010) and thereby their adherence to the intervention (Lisetti et al., 2013). Given the importance of adherence for intervention effectiveness and thus for durable lifestyle change, it would be worthwhile to investigate the use of conversational agents to promote a working alliance within eHealth lifestyle interventions. Especially because it is yet unclear what human-like social cues and heuristics promote a working alliance with a conversational agent. Therefore, more research is needed before such mechanisms could be applied within tools for a vulnerable CVD patient population.

The present dissertation

This dissertation has the following two aims: (1) mapping out the needs and wishes of both healthcare professionals and CVD patients with regard to (human-supported and self-help) eHealth lifestyle interventions, and (2) investigating if and how self-help eHealth lifestyle interventions could be optimised. The studies described in this PhD dissertation are part of the BENEFIT project erected by a Dutch consortium that aims to facilitate durable lifestyle change among CVD patients through a public–private partnership between academic centres, hospitals, rehabilitation centres, general practices, commercial companies and patient federations (Keesman et al., 2019). eHealth development often takes place without involvement of its core users, the patients and healthcare professionals, leading to eHealth tools that are not intuitive to use and therefore less effective (van Gemert-Pijnen et al., 2011). Together with patients, a multidisciplinary team consisting of cardiologists, psychologists, eHealth developers, and many other experts aimed to develop a so-called "ecosystem" in which the patient is emerged in a health-supportive environment. This ecosystem was built on four pillars that are essential in durable lifestyle change, which are (1) targeting both individual and environmental lifestyle factors, (2) developing interventions in cocreation with stakeholders (such as patients and healthcare professionals), (3) ensuring continuous access to these interventions, and (4) a public-private cooperation. This PhD dissertation describes a part of the research conducted to develop an eHealth platform to facilitate lifestyle changes at the individual level within this ecosystem. The research described in this PhD dissertation aims to evaluate the effect of different forms of automated and personal coaching on lifestyle maintenance. These studies were mainly conducted during the development phase, to optimise lifestyle coaching at the individual level before applying it into the BENEFIT platform.

This PhD dissertation consists of a number of journal articles, formatted as chapters, each contributing to one of the aims of this dissertation. The first part of the dissertation concerns the first aim (1) mapping out the needs and wishes of both healthcare professionals and CVD patients with regard to (human-supported and self-help) eHealth lifestyle interventions. According to the CeHres roadmap, a framework for eHealth development, implementation, and evaluation (Van Gemert-Pijnen et al., 2011), stakeholders should be closely involved in both the development and implementation phase. Therefore, we identified our most important stakeholders and asked their opinions on lifestyle interventions and the use of eHealth. Specifically, **Chapter 2** describes an interview study with healthcare professionals working in cardiac care about lifestyle support and the use of eHealth. Previous studies found that lifestyle interventions are rarely discussed or prescribed to adults with CVD-related complaints during consultations (Hobbs & Erhardt, 2002; Milder et al., 2008; Noordman, 2010). Furthermore, studies showed that healthcare professionals experience various barriers in providing lifestyle support (e.g. Jallinoja et al., 2007; Jansink et al., 2010). Therefore we aim to investigate what factors are important in supporting CVD patients in the uptake of and adherence to a healthy lifestyle and the (potential) facilitators of and barriers to eHealth tools in providing lifestyle support to patients with CVD. We interviewed 16 professionals with various backgrounds (e.g. nurse practitioners, neurologists, physiotherapists) who all treat CVD patients about providing lifestyle support to CVD patients, and the possibilities of eHealth to help them in doing so. To follow up on this, **Chapter 3** describes a survey study investigating the views of CVD patients themselves. In order to get a representative view of their needs and wishes, we conducted a large-scale questionnaire study with members of Harteraad, a Dutch CVD patient association. We asked them whether they would like to be supported by a coach, use an eHealth tool, be supported by friends and family, or be self-supportive while working on a healthy lifestyle. Furthermore, we linked these preferences to demographic variables, to investigate what type of support works best for whom.

The next three chapters concerned the second aim of the dissertation, (2) investigating if and how self-help eHealth lifestyle interventions could be optimised. Specifically, **Chapter 4** concerns a meta-analysis investigating the effectiveness of existing interventions for patients with cardiometabolic diseases. Although meta-analyses on eHealth lifestyle interventions had been performed before, and had also already focused on the comparison between human-supported and self-help eHealth interventions (e.g. Beishuizen et al., 2016; Joiner et al., 2017), the results of these studies were inconsistent. While in some meta-analyses human-supported interventions showed to be more effective, others show no difference between human-supported and self-help eHealth interventions. We argue that this might be due to the quantity and quality of the support offered within human-supported intervention. Therefore, the aims of the meta-analysis are to investigate the effectiveness of eHealth lifestyle interventions for patients with cardiometabolic diseases, whether there is a difference in effectiveness between human-supported and self-help eHealth lifestyle interventions, and whether dose and delivery mode of human support influence the effectiveness of eHealth lifestyle interventions. **Chapter 5** investigates what user expectations play a role in people’s decision to start using either human-supported or self-help eHealth interventions. As described previously, self-help eHealth interventions frequently suffer from low levels of uptake. Before paying attention to optimising self-help eHealth interventions, it is therefore important to investigate how we can make people start using such interventions. In this chapter we used an online experiment to investigate what expectations drive someone’s intention to use a human-supported or self-help eHealth intervention. We offered subjects randomly either screenshots of a human-supported or self-help eHealth intervention, and asked about their expectations towards the intervention's usefulness to achieve their goals (performance expectancy), the intervention's easiness of use (effort expectancy), the extent in which important others would support them in using the intervention (social influence), and the ability to form a relationship with the (automated) coach (working alliance). In **Chapter 6**, we aim to combine the results from the previous chapters to tackle another previously mentioned problem within self-help eHealth interventions, which is a lack of adherence. As we identified a need for self-help eHealth interventions, but at the same time a need for a human touch within lifestyle eHealth interventions, we aimed to make self-help eHealth interventions more attractive to adhere to by making them more human. Therefore, we conducted a field experiment with a self-help app-based physical activity intervention with a conversational agent. We manipulated how human-like the conversational agent within the intervention appeared and behaved, and tested in which condition users experienced the highest level of working alliance, and best adhered to the intervention like intended.

Finally, **Chapter 7** provides a discussion of all five studies in this PhD dissertation. This chapter relates the findings of each study to one another, discusses their (practical) implications, addresses their limitations and gives suggestions for further research.

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2

FACILITATORS OF AND BARRIERS TO LIFESTYLE SUPPORT AND EHEALTH SOLUTIONS: INTERVIEW STUDY AMONG HEALTH CARE PROFESSIONALS WORKING IN CARDIAC CARE

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ABSTRACT

Background: Cardiovascular diseases (CVDs) pose a significant health threat and reduce both people's life expectancy and quality of life. Healthy living is a key component in the effective prevention and treatment of CVD. However, health care professionals (HCPs) experience difficulties in supporting lifestyle changes among their patients. eHealth can provide a solution to these barriers.

Objective: This study aims to provide insights into the factors HCPs find important in the support of patients with CVD in the uptake of and adherence to a healthy lifestyle and the perceived facilitators of and barriers to using eHealth to provide lifestyle support to patients with CVD.

Methods: In-depth interviews were conducted with 16 Dutch HCPs specializing in lifestyle support in cardiac care.

Results: We identified 13 themes, of which the first 12 concerned lifestyle support in general and were related to intervention, patient, or health care. Throughout these themes, the use of eHealth reoccurred as a potential facilitator of or solution to barriers to lifestyle support. Our final theme specifically concerned barriers to the adoption and usability of eHealth.

Conclusions: HCPs do recognize the potential advantages of eHealth while experiencing barriers to using digital tools. Incorporating their needs and values in the development of lifestyle support programs, especially eHealth, could increase their use and lead to a more widespread adoption of eHealth into health care.

Keywords: eHealth; digital health; cardiovascular disease; cardiac care; lifestyle change; lifestyle support; intervention; health care professionals; implementation; interview; facilitators; barriers.

INTRODUCTION

Cardiovascular diseases (CVDs) are the most common cause of death globally (WHO, 2017) and drastically reduce the quality of life (De Smedt et al., 2013). Most CVDs can be prevented and treated by addressing behavioral risk factors such as smoking, poor diet, physical inactivity, and low sleep quality (Piepoli et al., 2016; Wilkins et al., 2017). Lifestyle interventions for patients with CVD have been shown to improve risk factors and decrease cardiac readmissions and mortality (Janssen et al., 2013) and are therefore recommended by national and international guidelines on cardiac prevention and rehabilitation (Hartstichting, 2011; Piepoli et al., 2016). Furthermore, a healthy lifestyle has mortality-reducing effects comparable with those of medication intake (Iestra et al., 2005).

Notwithstanding these advantages, health care professionals (HCPs) seem to be hesitant to discuss — let alone prescribe — lifestyle interventions to their patients (Barnes & Schoenborn, 2012). For instance, studies among Dutch general practitioners found that they are generally unlikely to mention CVD risk factors, such as lifestyle, during their consultations (Noordman et al., 2010) and only provided advice concerning healthy living in 1 out of 6 consultations to people with hypertension complaints (Milder et al., 2008). In addition, only 1 out of 5 primary care physicians indicated that European CVD guidelines concerning lifestyle were being implemented (Hobbs & Erhardt, 2002). In line with this, most patients with CVD have an unhealthy lifestyle (Kotseva et al., 2019). A number of barriers have been identified as possible explanations for the low attention paid to lifestyle changes and their respective programs. HCPs have mentioned a low degree of patient motivation, a lack of knowledge about or experience with providing lifestyle advice, insufficient time during consultations, a lack of financial incentives, little external options to refer their patients to, and HCPs' perception that health promotion is ineffective in CVD prevention and treatment (Brotons et al., 2005; Hobbs & Erhardt, 2002; Jallinoja et al., 2007; Jansink et al., 2010; Riley et al., 2016). These barriers could possibly explain why only half of the patients with CVD are actually offered lifestyle modification programs after discharge (De Luca et al., 2018). To increase the uptake of and adherence to lifestyle interventions among patients with CVD, it is crucial to consider HCPs' needs and barriers.

A potential solution to overcome these barriers could be the increased use of digital tools to provide automated or remote support, which can incorporate interactive web-based components and digital wearables for home measurement, known as eHealth (Barak et al., 2009). Recent studies have shown that eHealth can be effective in the prevention and treatment of noncommunicable diseases such as CVD (Lunde et al., 2018; Beishuizen et al., 2016). Despite these promising results, the acceptance and successful implementation of digital tools in health care is low because of the barriers that HCPs experience (Bally & Cesuroglu, 2019; Peeters et al., 2016; Ross et al., 2016). To design digital interventions that have an impact, human and contextual factors should be taken into account, including the needs and values of stakeholders such as HCPs (Keesman et al., 2019; van Gemert-Pijnen et al., 2011). Interview studies uncovering HCPs' views on lifestyle interventions and their own role in health promotion among their patients (Jansink et al., 2010; Stuij, 2018; Tonnon et al., 2014; Raaijmakers et al., 2013; Geense et al., 2013) and on the use of eHealth in lifestyle support (Brandt et al., 2018a; Brandt et al., 2018b; Smith et al., 2017; Bellicha et al., 2017; Macdonald et al., 2018) have been conducted before. However, to our knowledge, no studies have mapped out the attitudes toward both lifestyle support and eHealth of HCPs specialized in CVD specifically. Importantly, given that the effectiveness and needs related to lifestyle support and eHealth are highly context dependent (van Gemert-Pijnen et al., 2011), specific knowledge is needed in the context of cardiac care.

Therefore, this study aims to gain insight into the facilitators and barriers that HCPs specialize in cardiac care experience in lifestyle support for the prevention and treatment of CVD and to investigate their views on eHealth tools. We performed in-depth interviews with HCPs to answer two main questions: (1) What factors are important in supporting CVD patients in the uptake of and adherence to a healthy lifestyle? (2) What are the (potential) facilitators of and barriers to eHealth tools in providing lifestyle support to patients with CVD?

METHODS

Sample

We interviewed 16 Dutch HCPs (10 women) specializing in supporting patients with CVD and with experience in lifestyle change. To ensure a diverse and representative collection of perspectives, we included professionals with varying backgrounds from multiple institutions located in different parts of the Netherlands (Table 1). Professionals were selected based on eHealth affinity within the department or organization they worked in and asked how they applied eHealth in their own job to verify some level of eHealth experience. In line with these guidelines, 16 interviews would be sufficient for information saturation (Guest et al., 2006).

Table 1. Organization and professional background of respondents (N=16).

Organization and professional background	Values, n (%)
Academic hospital A	
Nurse practitioner working in cardiac rehabilitation	2 (12)
Academic hospital B	
Neurovascular nurse practitioner	1 (6)
Physician assistant specialized in cardiovascular risk factor management	1 (6)
Hospital A	
Physiotherapist working in cardiac rehabilitation	1 (6)
Nurse practitioner working in cardiac rehabilitation	1 (6)
Hospital B	
Physician-researcher working in cardiac rehabilitation	1 (6)
Nurse practitioner working in cardiac rehabilitation	1 (6)
Hospital C	
Neurologist specialized in cardiac rehabilitation	1 (6)
Nurse practitioner working in cardiac rehabilitation	1 (6)
Cardiac rehabilitation center A	
Cardiologist in residence	1 (6)
Lifestyle coach working in cardiac rehabilitation	1 (6)
Cardiac rehabilitation center B	
Physiotherapist working in cardiac rehabilitation	1 (6)
Cardiac rehabilitation center C	
Psychologist specialized in cardiac rehabilitation	1 (6)
General practice center A	
General practitioner specialized in CVD[a] care	1 (6)
Nurse practitioner working in cardiac rehabilitation	1 (6)

[a]CVD: cardiovascular disease.

Procedure

We used convenience sampling and approached organizations within the network of care partners. We asked for professionals within the organization who were most directly involved with lifestyle support of patients with CVD, whom we sent an email with general information about the research goals. After the HCP expressed willingness to cooperate, interview appointments were made by phone and performed at the interviewee's preferred location. Before the start of the interview, information about the research project and the goals and methods of the interview were provided. The interviewee signed the informed consent form, after which the voice recording and interview started. No (financial) compensation was offered to participate.

The interviews were conducted in Dutch, between November 2017 and February 2018, and took 45-90 minutes. One researcher led the interview, whereas another took notes, and roles were alternated between each interview (DRdB and JEvdG). The voice recordings were transcribed and pseudonymized to secure anonymity (Brecht Otto and Pauline van Wolferen). We used a general interview guide approach, as the interviews were based on a semistructured list of questions that allowed for further elaboration based on answers. The questions were divided into six topics (Textbox 1). We asked about both the use of eHealth (digital tools to provide automated or remote support with interactive web-based components) and wearables and sensors (e.g., pedometers). Interview topics were defined based on the research questions and assessed whether they would provide answers to these questions. We also included questions about the interviewees' profiles (e.g., job description and experience with eHealth). This study only discusses the data from interview topics 1-5, which are relevant to our specific research questions. The data regarding the sixth interview topic (reward program to promote healthy living) do not belong to the scope of this study and are used in another publication (de Buisonjé et al., 2021).

Analyses

The transcripts were sorted into meaningful clusters based on a content analysis approach to ensure that insights emerged based on the data [36]. Relevant pieces of data were retrieved from the text and coded and categorized into themes. For each of the transcripts, 2 researchers (DRdB and JEvdG) independently marked quotations in Microsoft Word containing relevant information. These quotations were compared, and a consensus document for each transcript was created. The quotations were transferred to Microsoft Excel, coded in a separate column to allow for interpretation, color coded to indicate whether the quotation was related to eHealth, and subsequently categorized into themes (TRCR). In discussion with a second researcher (MK), a definitive set of 13 themes emerged on which each of the quotations were fit (Textbox 2). Consensus with an independent coder (Magali de Rooy) was reached at once, with an interrater agreement of 74% and sufficient interrater reliability (Krippendorff α=.697), which indicated that the developed list of themes adequately represented the structure of the data. Quotation examples in text were translated into English by 2 researchers (TRCR and DRdB).

Textbox 1. Interview guide.

Facilitating and impeding factors in the uptake of and adherence to a healthy lifestyle for patients with cardiovascular disease

- What do cardiovascular disease patients need to do in their home environment to achieve sustainable lifestyle change?
- What things that seem to work well for cardiovascular disease patients in changing their lifestyle?
- What impedes cardiovascular disease patients in changing their lifestyle?
- What solutions do cardiovascular disease patients have for these barriers?

Facilitating and impeding factors in providing lifestyle support to patients with cardiovascular disease

- How do you provide lifestyle support to cardiovascular disease patients?
- What works well in providing lifestyle support?
- What impedes providing lifestyle support?
- What solutions do you have for these barriers?

Stakeholders involved in providing lifestyle support to patients with cardiovascular disease

- What do you, as an health care professional, need to better provide lifestyle support to cardiovascular disease patients?
- With whom do you cooperate in providing lifestyle support to cardiovascular disease patients?

Facilitating and impeding factors in using eHealth to provide lifestyle support to patients with cardiovascular disease

- What things go well in your use of eHealth to provide lifestyle support to cardiovascular disease patients?
- What impedes your use of eHealth to provide lifestyle support to cardiovascular disease patients?
- What solutions do you have for these barriers?
- What do you, as an health care professional, need to better make use of eHealth to provide lifestyle support to cardiovascular disease patients?

Facilitating and impeding factors in using wearables and sensors to provide lifestyle support to patients with cardiovascular disease

- To what extent do you use wearables and sensors to provide lifestyle support to cardiovascular disease patients?
- What things go well in your use of wearables and sensors to provide lifestyle support to cardiovascular disease patients?
- What impedes your use of wearables and sensors to provide lifestyle support to cardiovascular disease patients?
- What solutions do you have for these barriers?

Textbox 2. Identified themes after coding.

Intervention-related factors

- Autonomy
  - Factors that concern the extent to which the patient has the freedom to make decisions about lifestyle change for themselves
  - Quotations that concern the feeling of control in the process, the amount of self-determination, and insight into one's own health
- Goal setting
  - Factors that are related to setting goals in lifestyle change
  - Quotations concerning the quantity, content, and design of these goals
- Personalization
  - Factors that are related to the adjustment of a healthy lifestyle and revalidation program to the needs and wishes of the patient
  - Quotations that concern the personal relevance, feasibility, and attractiveness of the revalidation process

Patient-related factors

- Motivation
  - Factors that facilitate or impede the willpower to start and/or maintain lifestyle change
  - Quotations that concern the extent to which patients are willing to work on their lifestyle and their intrinsic and extrinsic motivation
- Condition of the patient
  - Physical, mental, or cognitive impairments that impede the patient in the uptake of and adherence to a healthy lifestyle (e.g., pain, depression, stress, addictions, and age)
  - Both conditions that already existed and those because of their illness
- Psychological characteristics
  - Characteristics and traits of the patient that facilitate or impede the uptake of and adherence to a healthy lifestyle
  - Quotations that concern personality or personal predispositions of the patient (e.g., self-efficacy, resistance, and sense of responsibility)
- Environmental factors
  - Factors in the home environment and daily life of the patient that facilitate or impede the uptake of and adherence to a healthy lifestyle
  - Quotations that concern the direct surroundings of the patient, which one cannot control (difficult domestic situations, SES, and access to [un]healthy options)
- Social network
  - Factors in the social circle of the patient that facilitate or impede the uptake of and adherence to a healthy lifestyle
  - Quotations that concern the role of friends, family, and acquaintances in the patient's lifestyle

Health care–related factors

- Format of professional support
  - Factors that determine the way in which support of the patient is shaped and structured and facilitate or impede the uptake of and adherence to a healthy lifestyle
  - Quotations that concern the implementation, frequency, and format of support
- Relationship with the patient
  - Factors that are related to the personal relationship between health care professional and patient

- Quotations that indicate the way in which such a relationship is established and what it should entail
- Continuity of professional support
  - Factors that are related to long-term support of the patient and facilitate or impede maintaining a healthy lifestyle
  - Quotations that concern lifestyle change in the long run, outside the health care environment, and continuing the revalidation process by the patient
- Organization of care
  - Practical factors that influence the provided health care, both physical facilities (e.g., health care professional's practice) and nontangible influences (e.g., regulations, finances) that facilitate or impede lifestyle support
  - Quotations that concern the availability of care and the extent to which health care professionals' can do their job and the way they are ought to do
- Barriers to eHealth
  - Factors that are related to the implementation of eHealth (digital tools) in lifestyle support
  - Quotations that concern the difficulties in using and implementation of technology and data in the current health care system

RESULTS

Barriers to and Facilitators of Lifestyle Support

Of the 13 identified themes, 12 concerned lifestyle support in general (Textbox 2). The subjects of these themes were related to the intervention, the patient, or health care in general.

Intervention-Related Factors

Autonomy

Nearly all (15/16, 93%) HCPs mentioned that patients need to feel a sense of ownership over their lifestyle change process instead of being just another patient undergoing rehabilitation. One HCP was especially concerned about the lack of choice in cardiac rehabilitation:

> *People are forced to do so many things, they end up in an obligatory trajectory. That is already quite a lot. So I think that can be a barrier.* [Quote 89, HCP 8]

Self-monitoring (e.g., heartbeat or weight) and information about both their disease and the benefits of a healthy lifestyle were mentioned by 10 HCPs to be essential for patients to feel a sense of control. This allows them to act independently of their HCPs when they notice irregularities:

> *It is also important for patients that they get more insight themselves.... That they can alert us whenever they are training independently and say "my heartrate shows irregularities or is not going up."* [Quote 73, HCP 1]

However, 3 HCPs mentioned that self-monitoring might have the downside of becoming an obsession, as people could fixate on numbers rather than their own body.

Goal Setting
More than half of the HCPs (9/16, 56%) mentioned the importance of goal setting in a healthy lifestyle. Patients would reach the most success when the number of goals at a given time is limited; when the goals are formulated in a specific, measurable, acceptable, realistic, and timely way; and when the goals are personally relevant for the patient. Accomplishment of these goals provides a rewarding feeling, which increases motivation to continue:

> *I want them to create their own success story. ...I choose something [a goal] of which I guess that person will be able to achieve in the upcoming week. And that turns into motivation...* [Quote 133, HCP 8]

Personalization
Of all HCPs, 56% (9/16) experienced that a lifestyle intervention will succeed when the provided support is tailored to patients' needs, capabilities, and preferences. For instance, for some, it is more important to work on their eating habits, whereas for others, an increase in physical activity is more relevant. At the same time, HCPs mentioned difficulties in finding out what their patients actually wanted and needed, which made it challenging to individualize the program:

> *And I'd really like to get to know the person on the other side of the table, what kind of information that person would like to receive. I find it hard to know: How would someone like to be motivated.* [Quote 148, HCP 4]

Patient-Related Factors

Motivation
A key theme throughout the interviews (14/16, 87%) was the level of motivation of the patient. Intrinsic motivation was deemed essential to successfully complete—or even start—a lifestyle program. Such intrinsic motivation is not always self-evident because of low awareness about the current and future health impact of an unhealthy lifestyle. About 37% (6/16) of HCPs mentioned how the occurrence of the disease acts as the tipping point for patients to change their lifestyle:

> *People already know that they are unhealthy and that they should make changes. Often you will notice that such a crisis causes them to actually do so.* [Quote 54, HCP 13]

To maintain the level of motivation, after the initial scare from the incident has passed, 56% (9/16) of HCPs mentioned that patients need to see progress of their effort, preferably through tangible results (e.g., increased performance durations). Extrinsic motivation, in the form of both material and nonphysical incentives (e.g., positive feedback), was mentioned by 43% (7/16) of HCPs to play a role:

> *Rewards are on multiple levels, a reward can also be that you are just being noticed by your significant other, brother, sister, friend. But it can also be a more literal reward, you know, that you buy something for yourself. Or that you tell yourself, well done.* [Quote 57, HCP 13]

Condition of the Patient

Health-related issues hindering patients from initiating or maintaining a healthy lifestyle were mentioned by 75% (12/16) of HCPs. These issues are physical, cognitive, or mental and are either pre-existing or because of cardiac incidents. For example, reduced mobility in older patients is a physical barrier to physical activities or reaching the clinic. Frequently mentioned mental barriers were depressive symptoms and fear, such as concerns about physical capabilities after a cardiac incident:

> *Especially people who experience persistent heart complaints, that cause a lot of anxiety, they think: I won't push myself. When I start exercising, I will experience it again.* [Quote 177, HCP 4]

Psychological Characteristics

Most HCPs (13/16, 81%) mentioned the role of their patients' personalities either as facilitators or as barriers. Patients need to be disciplined, and most importantly, some level of self-awareness helps to reflect on their own behavior and acknowledge their own role in the process. Patients who come up with excuses for not performing healthy behaviors are most difficult to work with:

> *But there is also a big group of people who are just very resistant to change, who are mainly externalizing and say: "I can't do anything about it". Or who continuously come up with excuses about why things can't change. Yes, that is the most difficult group to work with. That is also the most unhealthy group.* [Quote 215, HCP 15]

In addition to personality characteristics, another frequently mentioned barrier was previously developed bad habits.

Environmental Factors
Factors related to the daily environment of the patients were identified by 56% (9/16) of HCPs. For instance, difficult domestic situations are often given more priority and can therefore reduce the success of a healthy lifestyle initiated in the clinic. Some HCPs (4/16, 25%) explicitly stated that socioeconomic status (e.g., language barriers) affects people's lifestyles:

> *When it comes to handing out flyers as well, I come across situations such as: "I can't read." Not very frequently, but it happens every now and then.* [Quote 230, HCP 10]

According to 25% (4/16) of HCPs, government authorities should take responsibility for creating a healthy environment (e.g., offering healthy food in hospitals, stricter tobacco and alcohol regulations, or regulating the prices of food) and providing health education.

Social Network
The roles of both close (family and friends) and distant others were mentioned by 50% (8/16) of HCPs. Other people function as social controls or exert some level of group pressure. A sense of cohesion through engaging in healthy activities with others is a great motivator:

> *...an exemplary role, sociability, a social aspect, controlling aspect, when you are part of a group people will ask about you: How are you doing, where were you? All those kind of things play a role.* [Quote 246, HCP 1]

The importance of the social network of patients in providing practical and psychological support was emphasized by 38% (6/16) of HCPs. However, HCPs worried that overly critical family members or friends could also negatively influence the process. A second concern was social norms, as some unhealthy behaviors (such as drinking too much alcohol) are less socially accepted and therefore more difficult for patients to be open about:

> *Well, the subject is more of a taboo. It is automatically an issue. When you drink too much, you are an alcoholic. Eating too much, well, that happens to all of us. That we are snacking a little too much.* [Quote 256, HCP 8]

Health Care–Related Factors

Format of Professional Support

Considering the way support should be provided, 50% (8/16) of the HCPs mentioned the importance of frequency. Through frequent repetition of information, healthy behaviors by the patient, and reminders or feedback, a healthy lifestyle remains a topic of interest. However, the frequency of consultations in current practice is too low to do so. A total of 5 (31%) HCPs mentioned that support should be accessible at all times whenever the patient needs it. In addition, to provide tailored support, HCPs need data independent of the patients' self-reports about their progress:

> *...we have tried to use a logbook, but a pedometer can track the walking process outside. You can respond to the objective information you receive. A logbook is just an estimate, you just have to believe that it's true.* [Quote 276, HCP 2]

Most HCPs (10/16, 62%) found education as an important part of the intervention as patients lack knowledge or have misconceptions about their disease and a healthy lifestyle. Therefore, the health care system should play a role in offering trustworthy information, providing patients with concise pieces of information that are easy to understand:

> *...there is so much information available that they have no idea what to trust. ..., especially among the older population who have more respect for health-care professionals, simple advice is really appreciated.* [Quote 288, HCP 4]

Relationship With the Patient:

More than half of the HCPs (11/16, 68%) mentioned that their relationship with patients has a significant influence on the process. A good relationship helps in understanding the underlying reasons for patients' behavior and motivation and creating a safe environment to share their feelings. Support does not end at the physical aspect of cardiac rehabilitation but entails mental support as well:

> *They suddenly are obliged to change a lot of things. I try to focus less on things that have to change, but acknowledge how it affects them. ...Therefrom, they will more easily comply with a lifestyle change in the end.* [Quote 334, HCP 8]

HCPs disagreed about their role as an authority figure. An equal relationship, in which they co-operated with their patients during the revalidation process, was frequently mentioned. However, 18% (3/16) of HCPs recognized that they function as the so-called *big stick* to keep patients on the right track.

Continuity of Professional Support
According to 62% (10/16) of HCPs, long-term support is crucial for maintaining a healthy lifestyle outside the health care environment. When the window of opportunity after a cardiovascular incident disappears, patients are more likely to return to old (unhealthy) habits. However, 43% (7/16) of HCPs mentioned lack of follow-ups or an end evaluation, leaving them with no ability to provide long-term feedback or information about the postrehabilitation success of the lifestyle intervention:

> *... when you want someone to follow through with the lifestyle change, you do have to check whether someone comprehends it and if is able to do so. When you let someone on their own, you will lose that person.* [Quote 353, HCP 4]

Organization of Care
All 16 HCPs (100%) mentioned at least one factor related to the way health care is organized, varying from physical facilities to nontangible influences. Most HCPs (11/16, 68%) mentioned a lack of financial resources and time. Furthermore, the limited co-operation between HCPs involved in cardiac care and those of other health care disciplines was mentioned as a barrier. There are few options for redirecting patients to another professional, disagreements within the extensive group of care providers, and insufficient information sharing between them:

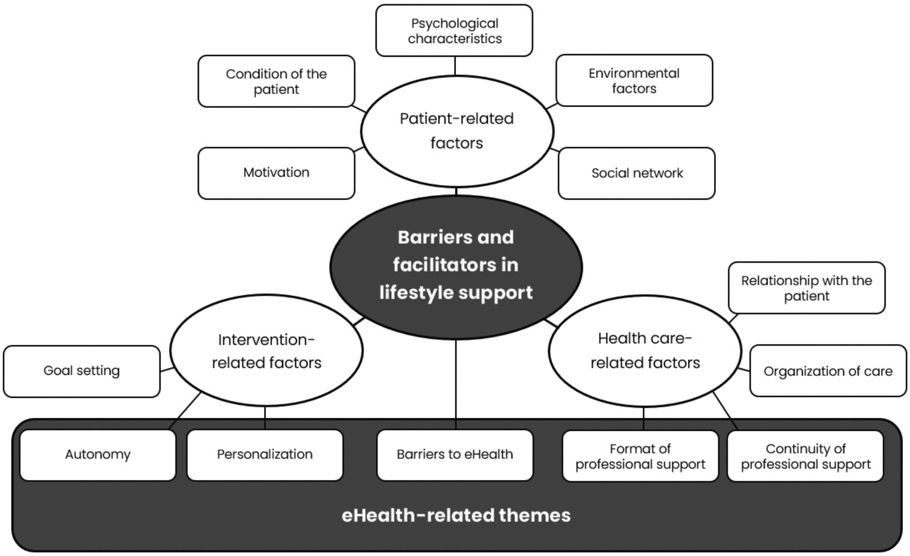
> *The dietician for instance, she keeps her own records, she can't attend the multidisciplinary team meeting due to her planning. I think that is a barrier as well, because we once had a patient who didn't consume enough calories, which caused problems and that person did not feel well...* [Quote 393, HCP 6]

More than half of the HCPs (7/16, 43%) mentioned a lack of attention for lifestyle within cardiac care or health care in general, although this varied greatly between domains (e.g., cardiology and neurology). HCPs indicated that they missed regulations and protocols they could follow in providing lifestyle support.

eHealth in Lifestyle Support
Throughout the 12 themes discussed earlier, the use of eHealth reoccurred as a (potential) facilitator or solution to barriers, most prominently within the themes Autonomy, Personalization, Format of support, and Continuity of professional support (Figure 1). Although eHealth facilitators were more strongly related to

lifestyle support, the barriers HCPs experienced were rather unrelated to lifestyle themes. To put more emphasis on this, the 13th theme concerning barriers in the implementation of eHealth will be discussed in the final part of this section (Barriers to eHealth).

Figure 1. Overview of the identified barriers and facilitators in lifestyle support and their relation to eHealth.



Benefits of eHealth

During analyses, a link between barriers to and facilitators of lifestyle support and potential facilitating benefits of eHealth emerged. The HCPs provided examples of how eHealth could help them.

Autonomy in eHealth

For patients to regain autonomy (theme 1), HCPs indicated a need for education and insight and saw an opportunity for eHealth to provide both. HCPs noticed that by giving patients the opportunity (and therefore the responsibility) of monitoring their own health through a digital tool, they can act whenever necessary (e.g., adjusting their diet when they notice a higher blood pressure). According to HCPs, such insights would also enlarge awareness about unhealthy behavior and provide progress feedback to increase their motivation:

> *We offer cardiac patients who we follow-up via eHealth a pedometer, a digital scale that measures body fat percentages, a blood pressure moni-*

tor and a device to make an ECG. That provides them with insight into how they are doing. [Quote 107, HCP 14]

Furthermore, as eHealth can be individually tailored, HCPs indicated that patients can control what information they receive and how they receive it. Patients can also work on their lifestyle at any time and in any way they wish to, increasing the level of self-management.

Personalization in eHealth
Personalization (theme 3) appeared to be key to lifestyle interventions, but HCPs raised the issue of identifying what patients wanted and needed. They thought that eHealth could help them to get more information about patients and their needs, before and during the intervention (e.g., through web-based intake questionnaires). HCPs believed this could result in better adjustment of their support and more efficient consultations and lifestyle interventions:

In fact, even before someone comes in, you would have to start with: *"This is the goal of the consultation." Based on a test or questionnaire, you look at how someone can best be approached*: *What kind of advice do you prefer? There are probably apps, tools, questionnaires, and other things that can do so.* [Quote 150, HCP 4]

Format of Support in eHealth
Related to the format of support (theme 9), HCPs gave examples of how eHealth, especially its possibilities for remote support, could be beneficial. As digital tools are available at all times and not bound to a physical location, HCPs predicted that it would be much easier for patients to frequently have contact, work on their lifestyle, or receive information. This would also increase the accessibility of support:

That is the advantage of eHealth, that it is flexible, 24/7, which is really convenient. I think that a lot of people ruminate at night and would appreciate to write during nighttime. The possibility to do so at that very moment, not only when you meet your coach again. Then it has already faded away. [Quote 305, HCP 8]

Consistent and automatic digital monitoring would provide more objective data, meaning HCPs would no longer have to rely on single measures during consultations or error-prone self-report measures. Furthermore, eHealth could be used as an educational platform, which HCPs thought they could use to provide patients with reliable and consistent information about their disease and lifestyle.

Continuity of Professional Support in eHealth

Continuity of professional support (theme 11) was mentioned as one of the biggest issues in current cardiac care. Therefore, most HCPs saw prolonged monitoring as a huge advantage of eHealth. Furthermore, this could enable HCPs to provide support in the long run, once patients return to their everyday lives:

> *There are gaps within the healthcare system, which makes it difficult for patients to continue independently. That is where this eCoach steps in. So during cardiac rehabilitation over here, they see the physiotherapist, they see the doctor, they can chat more easily through the portal.* [Quote 359, HCP 6]

Barriers to eHealth

While recognizing these potential advantages of eHealth, HCPs raised some barriers concerning its adoption and usability. The most prominent concern of 63% (10/16) of HCPs was related to the general old age of patients with CVD, as older people are more likely to have little experience with or no interest in technology. Moreover, patients would generally prefer face-to-face contact over digital communication, either during the entire intervention or at least a part of it. One HCP explicitly mentioned the importance of face-to-face intake for a digital intervention to be successful:

> *They tell me: "Oh, I received a mail from online coaching, but I have already so much on my mind, so I just ignored it." ...But then they see me and say: "But now I know that it was you, that is nice!" It comes to life for them, in my experience at least.* [Quote 466, HCP 8]

Difficulties with technological tools and devices, such as bugs and slow development of the technology, were mentioned by 31% (5/16) of HCPs. In addition, they mentioned that there was no help desk for patients or HCPs. Furthermore, it was frequently mentioned by 31% (5/16) of HCPs that many current technological aids suffer from a low level of user-friendliness.

DISCUSSION

Principal Findings

This study aimed to gain insights into the facilitators and barriers that HCPs experience in lifestyle support for the prevention and treatment of CVDs and investigate their views on potential eHealth tools. We interviewed 16 HCPs, resulting in 12 themes relevant to lifestyle support, of which four were related to eHealth. The 13th theme was related to eHealth barriers.

Barriers to and Facilitators of Lifestyle Support

First, we aimed to identify the factors that HCPs find important in supporting patients with CVD in the uptake of and adherence to a healthy lifestyle. We found factors related to the intervention, patient, and health care system to help answer this question.

According to the HCPs, a lifestyle intervention should give patients a feeling of autonomy and possibilities for goal setting and allow for personalization. In line with our findings, in interview studies on lifestyle support for patients with diabetes, HCPs indicated that well-formulated goals create realistic patient expectations (Jansink et al., 2010) and that standardized norms should be adjusted to patients' capabilities (Stuij, 2018). Furthermore, HCPs indicated that it is no longer their role to tell patients to change their lifestyle but rather the patient's responsibility (Stuij, 2018). However, although HCPs in this study named autonomy as an additional facilitator within lifestyle change, other studies reported patient responsibility to be a basic necessity because of low patient motivation (Stuij, 2018) or even seem unrealistic as patients are not always able to independently start or maintain a healthy lifestyle (Jallinoja et al., 2007).

With regard to patient factors, motivation to live healthily, the condition of the patient, psychological characteristics, environmental factors, and social networking were mentioned to be of influence within lifestyle support. HCPs working with people with (a high risk of) CVD (Hobbs & Erhardt, 2002; Noordman et al., 2008; Tonnon et al., 2014), patients with diabetes (Jansink et al., 2010; Raaijmakers et al., 2013; Stuij, 2018), and chronic diseases in general (Geense et al., 2013) recognized similar factors, thereby suggesting that these are relevant within different patient populations. However, although HCPs in our study thought that little awareness of the impact of an unhealthy lifestyle on health contributed to a low level of patient motivation for change, a study with primary care HCPs reported that limited knowledge about risks of CVD is only seldom a barrier for engaging in lifestyle modification (Jallinoja et al., 2007). This discrepancy in results might be because of methodological differences, as the study by Jallinoja et al (2007) included primary care HCPs and not HCPs mostly working in cardiac rehabilitation. Furthermore, primary care HCPs were asked about the relevance of insufficient knowledge to treatment and not lifestyle change per se. In addition, factors reported by patients with CVD themselves are relatively similar to those found in our study (Murray et al., 2012), which suggests that, at least in part, HCPs are able to recognize what patients need in lifestyle interventions.

Finally, several factors related to health care in general were mentioned, including the format of the provided support, continuity of professional support, the way care is organized, and the relationship between the HCP and patient. A high-quality relationship with the patient was also recognized as a facilitator within lifestyle support in other studies, as it would lead to both more collaborative patients and more motivated HCPs (Brandt et al., 2018a; Macdonald et al., 2018). In addition, it would be easier to foster face-to-face encounters [30]. Similar to our results, the lack of time, little governmental responsibility, financial shortcomings, little co-operation between HCPs, and difficulties in referring patients were mentioned as barriers by HCPs involved in the prevention of CVD (Hobbs & Erhardt, 2002; Riley et al., 2016; Tonnon et al., 2014), type 2 diabetes (Jansink et al., 2010; Stuij, 2018), or in (chronic) diseases in general (Brotons et al., 2005; Geense et al., 2013). This shows that such barriers are not unique for lifestyle support in CVD rehabilitation, which provides HCPs and researchers with the opportunity to learn from other disciplines and work together to find solutions (e.g., eHealth tools).

Other studies reported a lack of skills by HCPs to provide lifestyle support or a feeling that lifestyle interventions are ineffective as a barrier to the provision of lifestyle support (Brotons et al., 2005; Geense et al., 2013; Jallinoja et al., 2007; Jansink et al., 2010). These factors were not mentioned in this study, which might be owing to the nature of our sample that included HCPs who were specifically involved in lifestyle support and therefore might have a bigger skill set for and a more positive attitude toward providing lifestyle support.

Barriers to and Facilitators of eHealth

Second, to determine what the (potential) facilitators of and barriers to eHealth tools would be in providing lifestyle support to patients with CVD, the interviewed HCPs described how eHealth could be applied to strengthen facilitators or solve barriers they encountered in lifestyle support. The statements that HCPs made concerning facilitators of eHealth were related to the intervention-related factors, Autonomy and Personalization. These advantages of eHealth have also been recognized by HCPs in other studies. Macdonald et al (2018) reported that HCPs acknowledged that eHealth fosters the *two-way conversation*—a collaborative interaction between patients and HCPs, which explains why eHealth can create well-informed and autonomous patients. As HCPs previously indicated that lifestyle is the responsibility of the patient (Hobbs & Erhardt, 2002; Lunde et al., 2018), eHealth could offer them tools that foster the patient's autonomy. HCPs from other studies also indicated that eHealth helps them to personalize the program by getting to know their patients' needs through the personal diary within the digital portal (Das et al., 2015) and that personalization of an eHealth program is essential to fit the patient's capabilities (Walsh et al., 2018). Furthermore, meta-analyses have demonstrated a positive relationship between both an autonomy-supportive health care climate and personalization of digital intervention content and successful behavior change (Lustria et al., 2013; Ng et al., 2012).

With regard to health care–related factors, we found that the Format of professional support and the Continuity of support were important topics related to eHealth. Other studies have reported similar advantages of eHealth. Brandt et al (2018a) reported HCPs indicated that, because of its format, eHealth provides them with objective and measurable information and that it is not bound to a specific location or moment in time. In addition, some HCPs appreciated being able to follow-up their patients for a longer period, as it can be rewarding and increases their motivation and sense of responsibility to continue providing support (Walsh et al., 2018). Although we did not find a link between eHealth and the HCP-patient relationship, other studies have reported contradictory findings. Das et al (2015) reported that eHealth does not have time constraints, shame, and fear of stigma, which leads to more self-disclosure from patients. However, Brandt et al (2018a) reported that HCPs indicated it is more challenging to establish an empathic relationship in a digital environment. This contrast might be because HCPs seem positive about tools that are an addition to face-to-face contact (Das et al., 2015), but those that replace face-to-face interactions are perceived as less favorable to build a supportive relationship (Brandt et al., 2018a). Furthermore, although we did not find the advantages of eHealth in the organization of care, other studies did. For example, other studies mentioned additional time by reusing old advice (Brandt et al., 2018a), co-operation between HCPs, and accessible alternatives to refer their patients to (Smith et al., 2017) as advantages of eHealth. Methodological differences related to the different care settings and organizational structures the interviewed HCPs worked in could explain this.

Despite the advantages that were recognized by HCPs from both our and other studies (Brandt et al., 2018a; Das et al., 2015; Macdonald et al., 2018; Smith et al., 2017), there is a low level of acceptance and implementation of eHealth in health care (Ross et al., 2016). HCPs in this study formulated several barriers that could offer an explanation. First, HCPs feel that because patients with CVD are older, they prefer face-to-face contact and have little technological experience; therefore, digital tools would not be suitable for this patient population. HCPs in another study made a distinction between current patients with CVD and future ones, as the latter will have substantially more experience in and affinity to technology (Walsh et al., 2018). In addition, the eHealth and face-to-face support preferences of patients with CVD vary greatly (Anttila et al., 2019), which raises concerns about uneven eHealth adoption and unequal health benefits (Lingg et al., 2020). HCPs could possibly contribute to this, as the views and preferences of patients are important in their decision to use eHealth (Walsh et al., 2018). At the same time, Grünloh et al (2018) suggested that some HCPs seem to be unaware of the development of patient skills and knowledge over time. This could mean that once HCPs believe a patient is a technology-averse person, there will be minimal attempts to help the patient become acquainted with eHealth. eHealth acceptance could also be influenced by preference for face-to-face communication of HCPs themselves (Brandt et al., 2018a; Smith et al., 2017), which could be because of concerns regarding the therapeutic alliance with their patients (Walsh et al., 2018). However, others do not experience this issue, as they use eHealth for information sharing (e.g., educational texts) rather than communication purposes (e.g., interacting with patients) (Brandt et al., 2018b).

Other barriers identified concerned eHealth applications themselves, such as bugs and the slow development of digital tools, the lack of a help desk, and a low level of user-friendliness for both patients and HCPs. Other studies mentioned similar concerns, such as limited innovation, being offered digital tools that were still under development, and digital information that is too difficult to interpret and translate into support for their patients (Bellicha et al., 2017; Macdonald et al., 2018). A study on an eHealth tool evaluation showed that, in hindsight, HCPs have specific wishes concerning the utility and design of such tools (Smith et al., 2017). If they were included in the development process at an early stage, such barriers could have been prevented (Bally et al., 2019; van Gemert-Pijnen et al., 2011).

In this study, barriers to eHealth were not related to organizational factors. However, HCPs have previously shown concern about the inflexibility of the health care system and indicated that organizational structures and attitudes of HCPs have a major impact on eHealth acceptance and implementation (Bally et al., 2019; Das et al., 2015; Lingg et al., 2020; Walsh et al., 2018). The lack of financial compensation also played a role according to HCPs from previous studies (Bally et al., 2019; Peeters et al., 2016). Therefore, apart from barriers experienced by individual HCPs, overcoming structural obstacles seems necessary for the implementation of eHealth in health care (King et al., 2012). As many HCPs in our sample were already working with eHealth tools, they might have experienced fewer organizational difficulties and, therefore, did not mention such organizational barriers.

To make eHealth implementation more successful in practice, the results of this study suggest that HCPs do not need to be convinced about the benefits of eHealth but rather that the barriers they experience should be resolved. To overcome these barriers, health policies could play an important role in the provision of support and equipment. This way, HCPs would be able to implement the reported benefits of eHealth in lifestyle support for people with CVD.

Limitations and Future Studies

First, our results were based on the opinions and interpretations of HCPs and not on the actual views of the patients themselves, who might have an alternative view on how eHealth can support them. Future studies could therefore conduct interviews with both HCPs and their patients to compare their views and attitudes toward lifestyle support and the use of eHealth.

Although we intentionally interviewed health care HCPs involved in the lifestyle support of patients with CVD, this specific sample limits the generalizability of our results as our sample has experience with and might be more willing to provide lifestyle support, whereas other HCPs might be less inclined to. It would therefore be interesting to investigate how different levels of experiences with and attitudes toward lifestyle support and eHealth translate into differences in the barriers experienced by HCPs.

Finally, we did not explicitly ask about the association between facilitators of and barriers to lifestyle support and the use of eHealth as a possible solution. Future studies should therefore investigate how eHealth can help overcome barriers related to specific aspects of lifestyle support experienced in various health care settings. These results could provide eHealth developers with a better direction in the development of eHealth interventions.

CONCLUSIONS

This study provides insights into Dutch HCPs' views on lifestyle support and eHealth in cardiac care. We identified facilitators and barriers related to intervention-, patient-, and health care–related factors. HCPs in general showed high approval of lifestyle support for patients with CVD and identified the potential benefits of incorporating eHealth. However, the interviews also revealed several barriers that impede HCPs' use of eHealth in lifestyle support. Incorporating their needs and values in the development of lifestyle support programs, especially eHealth, could increase their use and lead to a more widespread adoption of eHealth into health care.

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3

LIFESTYLE SUPPORT PREFERENCES OF PATIENTS WITH CARDIOVASCULAR DISEASES: WHAT LIFESTYLE SUPPORT MIGHT WORK BEST FOR WHOM?

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ABSTRACT

Background: Lifestyle support is essential in preventing and treating cardiovascular diseases (CVD), and eHealth may be an easy and affordable solution to provide this support. However, CVD patients vary in their ability and interest to use eHealth. This study investigates demographic characteristics determining CVD patients' online and offline lifestyle support preferences.

Methods: We used a cross-sectional study design. 659 CVD patients (Harteraad panel) completed our questionnaire. We assessed demographic characteristics and preferred lifestyle support type (coach, eHealth, family/friends, self-supportive).

Results: Respondents mostly preferred being self-supportive (n=179, 27.2%), and a coach in a group or individually (n=145, 22.0%; n=139, 21.1%). An app/internet to work independently (n=89, 13.5%) or being in touch with other CVD patients (n=44, 6.7%) was least preferred. Men were more likely to prefer being supported by family/friends (p=.016) or self-supportive (p<.001), while women preferred a coach individually or via an app/internet (p<.001). Older patients mostly preferred self-support (p=.001). Patients with low social support were more likely to prefer being coached individually (p<.001), but not support from family/friends (p=.002).

Conclusion: Men and older patients are more interested in being self-supportive, and patients with lower levels of social support could need extra support outside their social network. eHealth could provide a solution, but attention should be paid to spike interest for digital interventions among certain groups.

Keywords: cardiovascular diseases; cardiac care; patient perspectives; lifestyle; eHealth; digital health; self-management

INTRODUCTION

Cardiovascular diseases (CVD) are a major health problem. Within the Netherlands, one out of ten people suffer from CVD, and a quarter of all deaths in 2019 were caused by CVD (de Boer et al., 2020b). Similar patterns can be observed globally, as 32% of worldwide deaths were CVD-related (WHO, 2021). However, studies show that new CVD incidents could partly be prevented by a good diet, sufficient physical activity, sleep, and not smoking (Piepoli et al., 2016; Wilkins et al., 2017). The positive effects of engaging in a healthy lifestyle are comparable to medication intake (Iestra et al., 2005), but many CVD patients have an unhealthy lifestyle (Kotseva et al., 2019). Therefore, lifestyle interventions are recommended by national and international guidelines (Hartstichting, 2011; Piepoli et al., 2016). Within the Dutch context, all CVD patients are referred by their cardiologist to follow cardiac rehabilitation directly after hospital discharge (Hartstichting, 2011). Cardiac rehabilitation consists of physical goals (e.g. improving exercise capacity), psychological goals (e.g. improving emotional wellbeing), social goals (e.g. going back to work), and improving risk behaviours (e.g. physical activity, nutrition, smoking) (Hartstichting, 2011).

Despite efforts to improve their lifestyle during cardiac rehabilitation, many patients experience difficulties to maintain a healthy lifestyle once they return to their everyday life (Janssen et al., 2013; Ter Hoeve et al., 2015). But even though long-term lifestyle support is important, there are barriers in the healthcare domain that may hinder patients from getting this support, such as a lack of time, financial resources, or experience with lifestyle support among healthcare professionals (e.g. Brotons et al., 2005; Jallinoja et al., 2007; Janskink et al., 2010). As a solution, patients are increasingly frequently offered tele-rehabilitation, in which lifestyle support can be offered with the use of eHealth. eHealth can be defined as interactive digital tools used to provide either remote support (e.g. by a healthcare professional) or automated support (e.g. automatically generated feedback) (Barak et al., 2009). Furthermore, eHealth can provide patients with control and a sense of autonomy during the lifestyle intervention (e.g. by providing insight into objective health markers or setting their own goals), and therefore responsibility of their own health (Cohen Rodrigues et al., 2021). eHealth interventions are effective in the prevention and treatment of noncommunicable diseases such as CVD (Beishuizen et al., 2016; Lunde et al., 2018).

However, the willingness of CVD patients to use eHealth varies greatly (Anttila et al., 2019). While some are unwilling to use eHealth due to a lack of skills or interest, others are genuinely interested in using such technology. Identifying these preferences is important as healthcare professionals indicate that the views of their patients are decisive in their decision to use eHealth in their care (Walsh et al., 2018). Many qualitative studies have investigated the views of CVD patients on self-management and eHealth (e.g. Qui et al., 2020; Vosbergen et al., 2013; Walsh et al., 2018). These studies show that patients recognise their own responsibility and role in improving their health, but at the same time need support to achieve a feeling of control over their health (e.g., to help motivate them). However, a quantitative approach investigating patients' needs for different types of lifestyle support is missing. Furthermore, given that patients' needs related to lifestyle support are context-dependent, it would be important to investigate such preferences in the Dutch cardiac care context (van Gemert-Pijnen et al., 2011).

In this study, we will elaborate on a previous study (Anttila et al., 2019) by not only investigating CVD patients' lifestyle support preferences, but also what demographic variables predict these. Furthermore, we will not only ask patients' whether they would like to use eHealth or not, but also further specify the type of eHealth or face-to-face intervention (e.g. individually or in a group) they would prefer. Our research question is therefore "What demographic characteristics predict patients' lifestyle support preferences?" More knowledge about patients' preferences could help provide them the type of lifestyle support that fits their needs, while overcoming abovementioned barriers in the healthcare domain.

METHOD

Design and Sample

We used a cross-sectional study design. People were recruited via the Dutch Harteraad Patient Panel, the official national Dutch CVD patients' association. The panel consists of 2600 members, who are either a patient diagnosed with a heart or vascular disease, or are a close relative to a CVD patient. On a regular basis, the members of the panel receive questionnaires from healthcare professionals, researchers and policymakers to investigate their experiences with cardiovascular health. We included people of 18 years and older who had been diagnosed with one or multiple heart disease(s) (diseases related to the heart, e.g. coronary heart disease), vascular disease(s) (diseases related to the blood vessels, e.g. peripheral artery disease), or both. Panel members who were a close relative to a CVD patient were excluded.

A priori power calculations (Faul et al., 2007) were based on the whole questionnaire, which included questions for multiple research projects (see Procedure and measures), and therefore multiple types of analyses. These calculations showed a required number of 550 respondents, but we continued recruiting after this number as the panel also consisted of close relatives (which would be excluded afterwards) to ensure a sufficient sample size. Respondents were not compensated for their participation. Of the 2600 members who were invited, 792 filled out (part of) the questionnaire. Of this number, 133 respondents were excluded as they were a close relative. Post-hoc power calculations (Faul et al., 2007) based on a logistic regression analysis with an alpha of .05 and a power of

.80 showed that this number was high enough to find an effect of demographic variables on lifestyle support preferences.

Procedure and measures

The study was approved by the Psychology Research Ethics Committee of Leiden University (2020-03-18-T. Reijnders-V1-2312). An email was sent by the Harteraad, inviting respondents to fill out the online questionnaire. After reading and agreeing to the online consent form, respondents were asked whether they were a CVD patient or a close relative to a patient. Next, we asked about the type of CVD (heart or vascular disease), and to complete several general demographic questions (gender, age, education, income, level of social support). All questions were selected and formulated by multiple researchers, and both professionals and experts in the field of CVD. Given the length of the questionnaire and to limit the burden on the patients, we decided to measure these demographics with a single item for each variable. The responses to the demographic variables education and income were transformed into a categorical variables with the categories low, middle and high (CBS, 2019; Nagelhout et al., 2012; Reinwand et al., 2018).

Next, we asked respondents about the type of lifestyle support they would ("If you would start working on your lifestyle, what kind of support would you prefer? Multiple answers are possible."). Respondents could choose one or multiple of the following options: (1) self-supportive (without support from a coach, app or family or friends), (2) support by a coach, in a group on location, (3) support by a coach, individually on location, (4) support by a coach via an app or internet, (5) support by family and friends, (6) working independently via an app or internet without coach, or (7) being in touch with other CVD patients via an app or internet. The question and response options were replicated from a large scale study about the evaluation of an eHealth intervention for cardiovascular disease patients (part of the BENEFIT project (Breeman et al., 2021). The responses to the lifestyle support preference question were transformed into binary variables, indicating whether respondents had selected the particular support type or not. This resulted in 7 variables for each individual lifestyle support type.

The remainder of the questionnaire concerned questions relevant for related research projects (preferences with regard to financial incentives for health behaviour change). At the end of the questionnaire, respondents were debriefed and thanked for their participation. They were provided with a short summary of the results of the study a few weeks afterwards.

Analyses

To analyse the relationship between demographic characteristics and lifestyle support preferences, we conducted subgroup analyses with five separate analyses. We ran chi-square tests of independence with the demographic predictors gender, education, and income, and univariate logistic regression analyses with the predictors age and social support. Preference for being self-supportive, support by a coach in a group, by a coach individually, by a coach via an app or internet, support by family and friends, working independently via an app or internet, and having contact with other CVD patients via an app or internet were the seven outcome variables. Next, to investigate the relative importance of the predictors, we ran multivariate logistic regression models including all 5 demographic predictors. Again, one of the 7 support types was added as outcome variable.

RESULTS

Descriptives

A total of 792 respondents filled out our questionnaire. Of this sample, 133 respondents indicated to be a close relative to a patient and therefore excluded. 659 respondents had once in their lifetime been diagnosed with a heart disease, vascular disease, or both, and were therefore included in our analyses. The mean age was 66 years old (SD = 11.20), and 65% of the respondents were men. Half of the respondents (49.8%) had a high level of education (29.7% middle, and 20.3% low level), and a third of the respondents (35.4%) had a high income (42.2% middle, and 22.5% low income).

Table 1. Demographics (means (SD) or frequencies (%)).

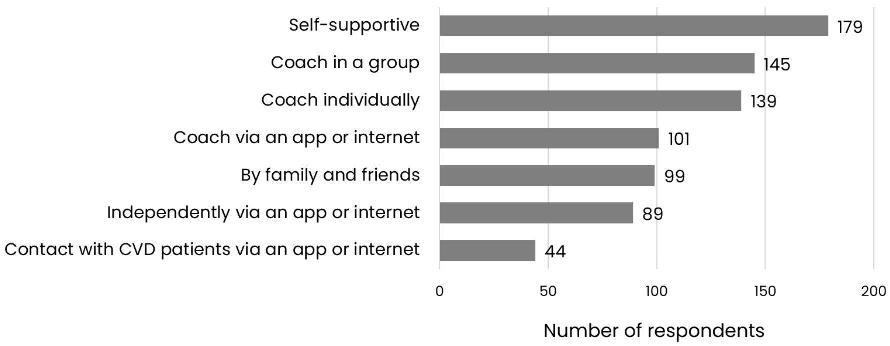
	CVD patients (N = 659)
Age (years), M (SD)	66.08 (11.20)
Gender, n(%)	
Female	230 (34.9)
Male	429 (65.1)
Education, n(%)	
Low	134 (20.3)
Middle	196 (29.7)
High	327 (49.8)

Table 1. *Continued*

	CVD patients (N = 659)
Age (years), M (SD)	66.08 (11.20)
Income, n(%)	
Low (<= €1500)	148 (22.5)
Middle (€1501 – €2500)	278 (42.2)
High (>= €2500)	233 (35.4)
Family status, n(%)	
No partner	143 (21.7)
Partner, living apart	19 (2.9)
Partner, living together	497 (75.4)
Disease status, n(%)	
Heart disease	343 (52.1)
Vascular disease	149 (22.6)
Both heart and vascular disease	167 (25.3)

Looking at the preferred type of lifestyle support of the total sample, a majority of the respondents would prefer to be self-supportive, without a coach, an app or internet, or family and friends (n = 179, 27.2%), followed by being supported by a coach (face-to-face) in a group (n = 145, 22.0%) or individually (n = 139, 21.1%). The least preferred types of lifestyle support were using an app or internet to work independently on one's lifestyle (n = 89, 13.5%) or to be in touch with other CVD patients (n = 44, 6.7%). See Figure 1 for the frequencies of all support types.

Figure 1. Lifestyle support preferences, from most frequently to least frequently chosen.



Demographic variables predicting lifestyle support preferences

All the results discussed below can be found in Table 2.

Gender

Women were more likely to prefer being supported by a coach individually ($\chi2(1) = 13{,}715$, $p < .001$), or by a coach via an app or internet ($\chi2(1) = 22.158$, $p < .001$). Men were more likely to prefer being supported by friends and family ($\chi2(1) = 5.826$, $p = .016$), or to be self-supportive, without coach, app/internet or family/friends ($\chi2(1) = 12.802$, $p < .001$). We found no differences in gender for the preference of being supported by a coach in a group, working independently via an app or internet, or having contact with CVD patients via an app or internet.

Age

If age increased with one year, the likelihood of preferring being supported by a coach, in a group decreased with 1.8% ($\chi2(1) = 5.168$, $p = .023$), by a coach, individually decreased with 4.0% ($\chi2(1) = 25{,}557$, $p < .001$), by a coach via an app or internet decreased with 3.5% ($\chi2(1) = 15.062$, $p < .001$). However, if age increased with one year the likelihood of preferring to be self-supportive, without coach, app/internet or family/friends increased with 2.9% ($\chi2(1) = 11.468$, $p = .001$). We found no significant relationship between age and working independently via an app or internet, having contact with CVD patients via an app or internet, or being supported by friends and family .

Education and Income

We found no significant relationships between education level (low, middle, high) or income level (low, middle, high) and any of the lifestyle support types.

Social support

If social support increased with one unit, likelihood of preferring being supported by a coach individually decreased with 30.1% ($\chi2(1) = 20.938$, $p < .001$), while the likelihood of preferring being supported by friends and family increased with 39.3% ($\chi2(1) = 9.423$, $p = .002$). We found no significant relationships between social support and being supported by a coach in a group, by a coach via an app or internet, working independently via an app or internet, having contact with CVD patients via an app or internet, or being self-supportive, without a coach, app/internet or family/friends.

Overall predictive model including all demographic variables

To check the relative importance of the predictors, we conducted multivariate logistic regressions with all demographic variables included. These analyses showed that all demographic variables were only significantly predictive for the preference of being self-supportive ($\chi2(7) = 25.476$, $p = .001$), supported by a coach individually ($\chi2(7) = 45.185$, $p < .001$), by a coach via an app or internet ($\chi2(7) = 31.665$, $p < .001$), and by friends and family ($\chi2(7) = 14.813$, $p = .038$).

Men ($p = .005$), with a higher age ($p = .017$) and a middle income (compared to a low income; $p = .037$) were most likely to be self-supportive. This is in line with the univariate analyses, only with the addition of a middle income. Younger patients ($p < .001$) with a lower level of social support ($p < .001$) were most likely to prefer support by a coach individually. Patients with a higher level of social support ($p = .014$) were most likely to prefer support by family and friends. Women ($p = .001$) with a younger age ($p = .010$) were most likely to prefer support by a coach via an app or internet. These results are all in line with the univariate analyses. All results of the multivariate logistic regressions can be found in Appendix 1.

Table 2. Univariate logistic regression and Chi square cross tabulation analyses of demographic variable predictors on lifestyle support preferences.

	Gender			Age		Education				Income				Social support	
	Male (N=429)	Female (N=230)				Low (N=134)	Middle (N=196)	High (N=327)		Low (N=148)	Middle (N=278)	High (N=233)			
Self-supportive	136 (31.7%)	43 (18.7%)	$\chi^2(1) = 12.802$, $p < .001$**	Exp(B) = 1.029	$\chi^2(1) = 11.468$, $p = .001$**	39 (29.1%)	54 (27.6%)	86 (26.3%)	$\chi^2(2) = .390$, $p = .823$	42 (28.4%)	67 (24.1%)	70 (30.0%)	$\chi^2(2) = 2.405$, $p = .300$	Exp(B) = 1.165	$\chi^2(1) = 3.625$, $p = .057$
Coach in a group	85 (19.8%)	60 (26.1%)	$\chi^2(1) = 3.434$, $p = .064$	Exp(B) = .982	$\chi^2(1) = 5.168$, $p = .023$*	20 (14.9%)	46 (23.5%)	78 (23.9%)	$\chi^2(2) = 4.820$, $p = .090$	33 (22.3%)	66 (23.7%)	46 (19.7%)	$\chi^2(2) = 1.191$, $p = .551$	Exp(B) = .955	$\chi^2(1) = .311$, $p = .577$
Coach individually	72 (16.8%)	67 (29.0%)	$\chi^2(1) = 13,715$, $p < .001$**	Exp(B) = .960	$\chi^2(1) = 25.557$, $p < .001$**	27 (20.1%)	42 (21.4%)	69 (21.1%)	$\chi^2(2) = 0.82$, $p = .960$	37 (25.0%)	55 (19.8%)	47 (20.2%)	$\chi^2(2) = 1.762$, $p = .414$	Exp(B) = .695	$\chi^2(1) = 20.938$, $p < .001$**
Coach via an app or internet	45 (10.5%)	56 (24.3%)	$\chi^2(1) = 22.158$, $p < .001$**	Exp(B) = .965	$\chi^2(1) = 15.062$, $p < .001$**	16 (11.9%)	30 (15.3%)	55 (16.8%)	$\chi^2(2) = 1.740$, $p = .419$	25 (16.9%)	48 (17.3%)	28 (15.3%)	$\chi^2(2) = 3.052$, $p = .217$	Exp(B) = .887	$\chi^2(1) = 1.697$, $p = .193$
Friends and family	75 (17.5%)	24 (10.4%)	$\chi^2(1) = 5.826$, $p = .016$*	Exp(B) = 1.015	$\chi^2(1) = 2.070$, $p = .150$	21 (15.7%)	29 (14.8%)	49 (15.0%)	$\chi^2(2) = 0.051$, $p = .975$	18 (12.2%)	47 (16.9%)	34 (14.6%)	$\chi^2(2) = 1.755$, $p = .416$	Exp(B) = 1.393	$\chi^2(1) = 9.423$, $p = .002$*
Indepen-dently via an app or internet	54 (12.6%)	35 (15.2%)	$\chi^2(1) = .887$, $p = .346$	Exp(B) = .989	$\chi^2(1) = 1.143$, $p = .285$	18 (13.4%)	18 (9.2%)	53 (16.2%)	$\chi^2(2) = 5.165$, $p = .076$	17 (11.5%)	35 (12.6%)	37 (15.9%)	$\chi^2(2) = 1.840$, $p = .398$	Exp(B) = .845	$\chi^2(1) = 3.060$, $p = .080$
Contact with CVD patients via app or internet	26 (6.1%)	18 (7.8%)	$\chi^2(1) = .749$, $p = .387$	Exp(B) = .979	$\chi^2(1) = 2.770$, $p = .096$	9 (6.7%)	17 (8.7%)	18 (5.5%)	$\chi^2(2) = 1.969$, $p = .374$	11 (7.4%)	23 (8.3%)	10 (4.3%)	$\chi^2(2) = 3.400$, $p = .183$	Exp(B) = .792	$\chi^2(1) = 3.359$, $p = .067$

* $p < .05$, ** $p < .001$

DISCUSSION AND CONCLUSION

Discussion

We aimed to discover the lifestyle support preferences of CVD patients, specified by demographic characteristics. We found that the majority of the patients preferred being self-supportive when working on one's lifestyle, followed by being supported by a coach. The least preferred options were using eHealth independently or to being in touch with other CVD patients. More specifically, women were most likely to prefer individual coaching, either in a face-to-face setting or via an eHealth tool. Men on the other hand were most likely to prefer either support from family and friends, or be self-supportive when working on their lifestyle, without any support from a coach, eHealth, or family and friends. Younger patients were more likely to prefer support from a coach, either face-to-face individually or in a group, or via an eHealth tool, while older patients were more likely to prefer being self-supportive. Patients who indicated to have lower levels of social support were more likely to prefer individual face-to-face support from a coach, but less likely to prefer support from family and friends.

The high preference for being self-supportive may be explained through several factors. Firstly, the majority of our sample consisted of men (65.1%) and our subgroup analyses showed that men seem to be less interested in lifestyle support from a coach or digital tools. This finding is in line with studies showing a gender difference in health seeking behaviours (Yousaf et al., 2015), and that men perceive traditional lifestyle interventions as more suitable for women (Gavarkovs et al., 2016). As especially men have an increased risk of developing CVD and ending up in cardiac rehabilitation compared to women (De Boer et al., 2020b; Virani et al., 2020), it would be important to make lifestyle support more attractive for them. It would be important to spike this interest, as lifestyle interventions are effective in improving CVD risk factors (Janssen et al., 2013). Although men currently show a lack of interest for eHealth, digital tools could be the solution to increase men's interest for lifestyle support. As eHealth can be tailored to individual needs (Krebs et al., 2010), it is more capable than traditional face-to-face lifestyle interventions to meet men's wishes and needs, and thus to make the intervention more attractive to them. Especially as men generally have greater technological affinity (Zhang et al., 2014), such possibilities would be worthwhile to consider. Given our results, another possibility would be to engage family and friends in the lifestyle improvement of men. A study shows that healthcare professionals do recognise the involvement of family members in practice (Birtwistle et al., 2021). Family can help translate healthy lifestyle advice from the consultation room to the home environment, or can help regulate the patient's lifestyle behaviour. Family and friends are an important factor in the behaviour change process and stimulate intervention adherence (Brandt et al., 2018; Miller et al., 2013). The social network could therefore be employed in behaviour change interventions, not only by using the direct network of the patient, but also by creating one in a digital environment (Latkin et al., 2015). Another explanation for the high preference for being self-supportive could be because of our sample. Members of the Harteraad panel represent a group of patients who are likely to have already underwent cardiac rehabilitation, who are more empowered and self-aware of their disease and its consequences. As they probably already learned about lifestyle management, they would be less likely to need any support. It would be interesting for future research to investigate whether CVD patients' lifestyle support preferences differ in the pre- and post-cardiac rehabilitation phase.

Older patients also indicated to be less interested in lifestyle support from a coach, which could be explained by physical restrictions to engage in physical activity (de Boer et al., 2020a). As older patients might experience regular interventions as too physically challenging, or might have physical difficulties to even reach the professional's facilities, they could be less willing to engage in lifestyle support. Again, despite their current lack of interest, tailoring through eHealth could also be useful to promote lifestyle support among older patients (Aalbers et al., 2011). Using eHealth's tailoring capabilities to adapt programmes to older patients' individual physical capabilities could increase their acceptance of lifestyle support, and help those older patients' who have difficulties in reaching the cardiac rehabilitation facilities. It would be worthwhile to consider offering eHealth to an older target population, given that studies show that eHealth interventions are effective in reducing cardiac risk factors among an older people (Beishuizen et al., 2016). Furthermore, older people benefit from a good social environment while working on their lifestyle (Chaudhury et al., 2016). Online tools could therefore be useful for them to get in touch with peers to help them engage in healthy behaviours. Nevertheless, our results indicate that there remains a need to increase the attractiveness of digital tools for an older target population to address their personal needs.

Furthermore, our findings with regard to social support are in line with previous studies. These show that patients with low levels of social support generally have more severe cardiac symptoms, but are also less adherent to interventions (McBrien et al., 2017; Miller et al., 2013). The support of a coach could therefore be particularly important for them. However, although other studies indicate that the social environment could be an important contributor to successful behaviour change (Brandt et al., 2018; McBrien et al., 2017; Miller et al., 2013), our results suggest that patients with lower levels of social support are less likely to prefer support from family and friends. This could be due to the lower availability of family and friends to do so. In that case, creating a social support group (e.g. in a digital environment) could be a solution (Latkin et al., 2016). It would be important though to further investigate whether patients with lower levels of social support would be interested in such forms of lifestyle interventions.

Finally, with regard to the use of eHealth, it is interesting to see that there is a higher preference for the options in which a coach is involved, compared to the option in which eHealth is used either independently, or with other CVD patients. This result is in line with those of previous studies focused on eHealth interventions, which show that the presence of human support is positively related to intervention effectiveness and adherence (Etzelmueller et al., 2020; Karyotaki et al., 2018; Richards & Richardson, 2012). These findings could be due to a need of a relationship between patient and professional (Brandt et al., 2018), which is called the 'working alliance' in clinical terms (Hatcher & Barends, 2006). Studies show that a good working alliance is related to intervention adherence and effectiveness in face-to-face settings (Goldberg et al., 2013; Martin et al., 2000), but also within eHealth interventions (Flückiger et al., 2018; Sucala et al., 2012). As eHealth is becoming increasingly relevant, for example due to the recent COVID-19 pandemic (Bokolo, 2021), it is not unlikely that it will also be increasingly used within cardiac rehabilitation. However, our results show that it remains important to combine eHealth with human attention and support to meet the needs of CVD patients.

Although we had a large number of respondents, and therefore a good representation of the CVD population, a limitation of our study was its digital nature. Although the gender distribution and age of our sample largely corresponds with those of the general CVD population (see e.g. De Boer et al., 2020b), it could be that mostly patients with digital affinity responded to our survey. Future studies could investigate lifestyle support preferences in face-to-face settings (e.g. rehabilitation centres), increasing the chances of including patients with low digital literacy. Furthermore, as mentioned previously, the Harteraad panel consists of CVD patients who are likely to have already underwent cardiac rehabilitation. We would advise future researchers to include CVD patients who did not start rehabilitation yet, to investigate how this might influence their lifestyle support preferences. Finally, although our questionnaire was developed with the expertise of researchers, professionals and experts in the field of CVD, our questions have not been tested for reliability and validity. We would advise future studies to develop valid and reliable measures to assess lifestyle support preferences.

Innovation

Our study contributes to the innovation of cardiac rehabilitation by not only investigating CVD patients' lifestyle support preferences, but also what demographic variables predict these. Furthermore, we gained more specific knowledge about the type of eHealth or face-to-face intervention they would prefer. While the findings show that there is a need to increase the attractiveness of digital tools for older men, we also found that younger women are more positive about using eHealth. The increasing development and use of tele-revalidation could ensure that the needs of underrepresented groups within cardiac care (e.g. younger women) will be met by providing lifestyle support (which is often still provided face-to-face in a group setting) in a different way. Furthermore, although changes in society ask for an increasing use of eHealth (e.g. Bokolo, 2021), our findings show that human contact remains essential during these innovations. The findings could be applied in the provision of patient-centred care, and help collaborate patients and professionals in the provision of a lifestyle intervention that best fits the individual. For example, our findings could help professionals working in cardiac care provide the right type of lifestyle support to their patients, and eHealth developers in the innovation of lifestyle interventions that meet the needs and wishes of patients themselves. This would increase the attractiveness of lifestyle for CVD patients, leading to healthier lifestyles, and therefore a lower risk of future cardiac events.

CONCLUSION

To optimise lifestyle interventions as prevention and treatment of CVD, we investigated CVD patients' preferences with regard to lifestyle support. Men and older patients are generally more interested in being self-supportive while working on their lifestyle, and patients with lower levels of social support might be in need of extra support outside their social network. As lifestyle interventions are effective in improving CVD risk factors, it would be important lifestyle support more attractive for older men. eHealth could potentially provide a solution, but attention should be paid to spike their interest for digital interventions. This knowledge could help to provide patients the right type of lifestyle support, and to further investigate how to reach patients for whom current forms of support are not yet attractive enough. Based on our findings, future studies could focus on the role of comorbidities, patient-provider communication, the content of lifestyle support, and emotional factors within lifestyle and the lifestyle support for people with CVD.

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CHAPTER 3 | APPENDIX 1

1. Multivariate logistic regression analyses of demographic variables predictors on preference for being self-supportive (without coach, app/internet, or family/friends).

	χ2	df	P-value
Model	25.476	7	.001*

	B	SE	Wald	P-value	Exp (B)	95% CI for Exp (B)	
						Lower	Upper
Gender (female)	-.647	.229	7.969	.005*	.524	.334	.821
Age	.022	.009	5.714	.017*	1.022	1.004	1.041
Education							
Middle (vs. low)	.011	.257	.002	.966	1.011	.611	1.673
High (vs. low)	-.129	.248	.269	.604	.879	.541	1.430
Income							
Middle (vs. low)	-.523	.251	4.360	.037*	.593	.363	.968
High (vs. low)	-.334	.277	1.458	.227	.716	.416	1.231
Social support	.096	.085	1.295	.255	1.101	.933	1.299

CI, confidence interval; *, significant values ($p < .05$)

2. Multivariate logistic regression analyses of demographic variables predictors on preference for a coach in a group.

	χ2	df	P-value
Model	12.224	7	.093

	B	SE	Wald	P-value	Exp (B)	95% CI for Exp (B)	
						Lower	Upper
Gender (female)	.178	.226	.615	.433	1.194	.766	1.862
Age	-.014	.009	2.768	.096	.986	.969	1.003
Education							
Middle (vs. low)	.549	.300	3.346	.067	1.732	.691	3.120
High (vs. low)	.642	.289	4.940	.026*	1.900	1.079	3.346
Income							
Middle (vs. low)	.133	.258	.267	.605	1.142	.690	1.893
High (vs. low)	-.129	.298	.189	.664	.879	.490	1.575
Social support	-.009	.086	.010	.920	.991	.837	1.174

CI, confidence interval; *, significant values ($p < .05$)

3. Multivariate logistic regression analyses of demographic variables predictors on preference for a coach individually.

	χ2	df	P-value
Model	45.185	7	.000*

	B	SE	Wald	P-value	Exp (B)	95% CI for Exp (B)	
						Lower	Upper
Gender (female)	.390	.230	2.875	.090	1.476	.941	2.317
Age	-.035	.009	15.639	.000*	.966	.950	.983
Education							
Middle (vs. low)	-.126	.293	.185	.667	.882	.497	1.565
High (vs. low)	-.053	.279	.036	.849	.948	.549	1.639
Income							
Middle (vs. low)	-.015	.264	.003	.955	.985	.588	1.652
High (vs. low)	.295	.302	.956	.328	1.343	.744	2.425
Social support	-.318	.083	14.523	.000*	.728	.618	.857

CI, confidence interval; *, significant values ($p < .05$)

4. Multivariate logistic regression analyses of demographic variables predictors on preference for a coach via an app or internet.

	χ2	df	P-value
Model	31.665	7	.000*

	B	SE	Wald	P-value	Exp (B)	95% CI for Exp (B)	
						Lower	Upper
Gender (female)	.870	.256	11.554	.001*	2.386	1.445	3.940
Age	-0.24	.009	6.669	.010*	.976	.958	.994
Education							
Middle (vs. low)	.156	.343	.208	.648	1.169	.597	2.288
High (vs. low)	.376	.323	1.350	.245	1.456	.773	2.744
Income							
Middle (vs. low)	.333	.291	1.317	.251	1.396	.790	2.467
High (vs. low)	.087	.347	.063	.801	1.091	.553	2.155
Social support	-.010	.099	.010	.921	.990	.816	1.202

CI, confidence interval; *, significant values ($p < .05$)

5. Multivariate logistic regression analyses of demographic variables predictors on preference for support by family and friends.

	χ2	df	P-value
Model	14.813	7	.038*

	B	SE	Wald	P-value	Exp (B)	95% CI for Exp (B)	
						Lower	Upper
Gender (female)	-.469	.286	2.675	.102	.626	.357	1.097
Age	.007	.011	.383	.536	1.007	.985	1.029
Education							
Middle (vs. low)	.059	.320	.034	.853	1.061	.567	1.986
High (vs. low)	.034	.305	.013	.910	1.035	.569	1.883
Income							
Middle (vs. low)	.127	.318	.159	.690	1.135	.609	2.117
High (vs. low)	-.194	.362	.288	.591	.823	.405	1.673
Social support	.291	.118	6.058	.014*	1.338	1.061	1.688

CI, confidence interval; *, significant values (p < .05)

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6. Multivariate logistic regression analyses of demographic variables predictors on preference for working independently via an app or internet.

	χ2	df	P-value
Model	13.137	7	.069

	B	SE	Wald	P-value	Exp (B)	95% CI for Exp (B)	
						Lower	Upper
Gender (female)	.278	.272	1.040	.308	1.320	.774	2.251
Age	-.009	.010	.798	.372	.991	.971	1.011
Education							
Middle (vs. low)	-.577	.363	2.530	.112	.561	.276	1.144
High (vs. low)	.048	.316	.023	.880	1.049	.565	1.947
Income							
Middle (vs. low)	.242	.330	.538	.463	1.274	.667	2.433
High (vs. low)	.594	.366	2.640	.104	1.811	.885	3.709
Social support	-.182	.099	3.341	.068	.834	.686	1.013

CI, confidence interval; *, significant values (p < .05)

7. Multivariate logistic regression analyses of demographic variables predictors on preference for having contact with other CVD patients via an app or internet.

	χ2	**df**	**P-value**
Model	9.057	7	.249

	B	**SE**	**Wald**	**P-value**	**Exp (B)**	**95% CI for Exp (B)**	
						Lower	**Upper**
Gender (female)	-.061	.367	.027	.869	.941	.458	1.933
Age	-.017	.013	1.599	.206	.983	.958	1.009
Education							
Middle (vs. low)	.308	.439	.491	.483	1.360	.575	3.216
High (vs. low)	-.055	.446	.015	.902	.947	.395	2.268
Income							
Middle (vs. low)	.257	.403	.407	.524	1.293	.587	2.850
High (vs. low)	-.340	.509	.445	.505	.712	.262	1.932
Social support	-.196	.130	2.258	.133	.822	.637	1.061

CI, confidence interval; *, significant values ($p < .05$)

4

EFFECTIVENESS OF HUMAN-SUPPORTED AND SELF-HELP EHEALTH LIFESTYLE INTERVENTIONS FOR PATIENTS WITH CARDIOMETABOLIC RISK FACTORS: A META-ANALYSIS

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ABSTRACT

Background: eHealth is a useful tool to deliver lifestyle interventions for patients with cardiometabolic diseases. However, there are inconsistent findings about whether these eHealth interventions should be supported by a human professional, or whether self-help interventions are equally effective.

Methods: Databases were searched between January 1995 and October 2021 for randomized controlled trials on cardiometabolic diseases (cardiovascular disease, chronic kidney disease, type 1 and 2 diabetes mellitus) and eHealth lifestyle interventions. A multilevel meta-analysis was used to pool clinical and behavioral health outcomes. Moderator analyses assessed the effect of intervention type (self-help vs. human-supported), dose of human support (minor vs. major part of intervention), and delivery mode of human support (remote vs. blended). 107 papers fulfilled eligibility criteria and 102 unique (N=20,781) studies were included.

Results: The analysis showed a positive effect of eHealth lifestyle interventions on clinical and behavioral health outcomes (p<.001). However, these effects were not moderated by intervention type (p=.169), dose (p=.698), or delivery mode of human support (p=.557).

Conclusion: This shows that self-help eHealth interventions are equally effective as human-supported ones in improving health outcomes among cardiometabolic disease patients. Future studies could investigate whether higher quality eHealth interventions compensate for a lack of human support.

Keywords: cardiovascular disease; chronic kidney disease; type 1 diabetes mellitus; type 2 diabetes mellitus; eHealth; lifestyle change; human support

INTRODUCTION

Cardiometabolic diseases, i.e. diseases to the heart, are an increasing threat to patients' health and quality of life (Danaei et al., 2014; WHO, 2021). This includes cardiovascular diseases (CVD) and type 1 and 2 diabetes mellitus (T1DM and T2DM), and comprises of conditions such as chronic kidney disease (CKD). These diseases share similar underlying clinical risk factors, such as adiposity, high blood pressure, cholesterol levels, and blood glucose levels (Ryden et al., 2014; Suckling & Gallagher, 2012). Moreover, these four diseases have similar behavioral risk factors, such as smoking, physical inactivity, unhealthy diet, and use of alcohol, which is why a healthy lifestyle is the preferred management strategy for all (Ryden et al., 2014; Suckling & Gallagher, 2012). Participating in lifestyle interventions can, therefore, improve patients' health and quality of life (Piepoli et al., 2016).

Nevertheless, many patients who have participated in cardiac rehabilitation experience difficulties in maintaining a healthy lifestyle in the long-term (Janssen et al., 2013). Research suggests that the use of home-based interventions is more suitable for durable lifestyle change compared to traditional face-to-face interventions (ter Hoeve et al., 2015). For that reason, the implementation of eHealth could be beneficial. eHealth can be defined as the use of information and communication technology, such as the internet, to support or enhance health and health care by means of remote or automated support (Barak et al., 2009). eHealth lifestyle interventions show to be effective in improving cardiometabolic risk factors. For example, eHealth interventions aimed at physical activity or nutrition can improve clinical risk factors such as blood glucose levels (Liang et al., 2011) and blood pressure (Liu et al., 2013), and behavioral risk factors such as fat, fruit and vegetable consumption, and physical activity (Carvalho de Menezes, 2016). Another advantage of eHealth over face-to-face interventions is that the former is easier to implement in a larger and more varied audience. Especially self-help interventions are suitable for widespread implementation, as no human care professional needs to be involved (Barak et al., 2009). Self-help interventions could help reduce the workload for care professionals, and the costs of treatment (Srivastava et al., 2015). Furthermore, studies show that eHealth interventions with low or even no involvement of care professionals are effective in improving clinical and behavioral risk factors among people with CVD (Coorey et al., 2018).

Despite these advantages, previous meta-analyses and reviews showed mixed results regarding the effect of self-help interventions through eHealth. Notably, some studies have found higher effect sizes for digital interventions in which the feedback was provided by a human (Lau et al., 2020). This meant that interventions with fully remote human support (Joiner et al., 2017) or those that additionally incorporated face-to-face human support (otherwise called blended interventions) had more effect (i.e., higher effect sizes) than self-help eHealth interventions without any form of human support. In previous studies, authors have argued that human supported interventions are more effective compared to interventions with only automated feedback because they are tailored to the patient's needs (Lau et al., 2020). Furthermore, human support is found to increase adherence to interventions (Joiner, 2017). In addition, blended interventions would be more effective than fully remote supported interventions because behavior change maintenance is more successful in when they involve face-to-face interactions (Beishuizen et al., 2016). In other studies, however, no differences were found in achieving lifestyle behavior change between human-supported and self-help only lifestyle interventions (Lustria et al., 2013), blended interventions compared to remotely-supported ones (Kloek et al., 2017), and interventions with automated feedback compared to those with human-generated feedback (Webb et al., 2010). These discrepancies in research findings could be explained by the varying 'support dose' (e.g., frequency of contact) within the human-supported interventions. Previous meta-analyses regarding eHealth lifestyle interventions have simply categorized studies into self-help or human-supported, or into blended and remote support. In particular, these meta-analyses made no distinction between the type and channel of human support; This meant that studies in which a clinical psychologist gives daily feedback on assignments, studies in which psychology students give monthly telephone calls based on a script, or studies in which patients have the option to contact a therapist were all treated alike. In contrast, various meta-analyses regarding psychological interventions have looked at these variables in more detail. One of these meta-analyses found that interventions with greater amounts of therapeutic contact encountered lower dropout rates (Pearcy et al., 2016). Other studies found that both administrative support by a layperson and therapeutic support by a professional are equally effective in treating symptoms and preventing dropout (Baumeister et al., 2014; Richards & Richardson, 2012). Similar results have been found in a meta-analysis regarding digital mental health interventions (Leung et al., 2022). Other meta-analyses regarding eHealth interventions revealed that higher intensity of support improves intervention adherence rates (Hoppen et al., 2021; Koelen et al., 2022).

To our knowledge, no other studies have yet focused on the effectiveness of (human-supported and self-help) eHealth lifestyle interventions for multiple cardiometabolic risk factors, or investigated whether the dose of human support in eHealth lifestyle interventions is related to the effectiveness of these interventions. Therefore, the aims of this meta-analysis are: (1) investigating the effectiveness of eHealth lifestyle interventions for people with or at risk of CVD, CKD, T1DM and T2DM on clinical and behavioral health outcomes, (2) investigating whether there is a difference in the effectiveness of human-supported and self-help eHealth lifestyle interventions on clinical and behavioral health outcomes, and (3) investigating whether moderating factors such as dose and delivery mode of human support influence the effectiveness of eHealth lifestyle interventions on clinical and behavioral health outcomes.

METHODS

We preregistered our meta-analysis in the PROSPERO database (PROSPERO 2021 CRD42021269263; Cohen Rodrigues et al., 2021). The meta-analysis was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA; Page et al., 2021).

Search and Study Selection

A systematic literature search was conducted within multiple databases (see Figure 1). With the help of the university's librarian, a search string was created with key search terms related to (1) eHealth, (2) clinical and behavioral outcomes, (3) cardiometabolic diseases, and (4) randomized controlled trials (see Appendix 1 for the full search string). The search was conducted for studies from 1995 (given the increasing use of Internet from that year onward), and was lastly updated on 6 October 2021. After removal of duplicates, titles and abstracts were screened by two of the three independent researchers to identify studies meeting the inclusion criteria. Inconsistencies were resolved in weekly discussions.

Inclusion and exclusion criteria were established with the help of the PICO statement (population, intervention, comparator, outcome; Schardt et al., 2007). Participants of the included studies were required to be (1) 18 years or older, and (2) either have one or more cardiometabolic risk factors, (as determined and specifically mentioned by the authors of the paper) or be diagnosed with CVD, CKD, T1DM or T2DM. Given the primary focus of our study on cardiometabolic patients we decided to, in case of a population with cardiometabolic risk factors only, exclude studies if cardiometabolic patients were explicitly excluded from participation. Furthermore, studies were included if the intervention (3) aimed at improving one or more lifestyle behaviors (physical activity, nutrition, smoking, alcohol intake, sleep), (4) was delivered via eHealth tools such as through a website or mobile-based application (phone, text-messages: videoconferencing could be used, but not as main mode of communication), (5) provided education or skills training (e.g., using behavior change techniques), and (6) was interactive (involving actions of a user and reactions from the program in response to a user's actions). In addition to this, we only included (7) randomized controlled trials, which used as comparator either a passive control (wait-list or usual care), a non-web- or mobile-based intervention, or a less extensive web- or mobile-based intervention. Finally, studies were included if they (8) reported minimally one self-reported or objectively observed clinical (e.g. blood pressure) or behavioral health outcome (e.g., step count), and (9) the full-text was available in English or Dutch. These inclusion and exclusion criteria were used to check for study eligibility, which was again conducted by two of the three independent researchers. Disagreements were resolved in weekly meetings, and if needed, with the help of a third independent researcher. If two papers reported on the same study, we included the one reporting the outcomes most extensively. After the systematic search, we conducted a forward citation search to find relevant papers that either cited one of our included studies or that were written by one of the authors of our included studies. Finally, we ran a backward citation search to look at articles cited by the authors included in our study. In case original data were not available in the manuscript we contacted the relevant authors in writing to ask for the data. Authors were contacted a maximum of two times over a period of three months.

Data Extraction

A predefined coding form was used to extract the data. We extracted (1) study characteristics, (2) population characteristics at baseline, (3) characteristics of each condition (control and intervention), and (4) self-reported or objectively observed clinical or behavioral outcome data. For the population characteristics, we coded the diagnosis of the participants (CVD, T1DM, T2DM, CKD, at-risk population (without diagnosis, but with cardiometabolic risk factors), or mixed patient population), mean age of the participants per group, percentage of female participants per group, and educational level of the participants per group. For the condition characteristics, we coded the type of control condition (passive or active), intervention length (duration of the intervention in weeks irrespective of pre-post design or longer term follow-ups), the type of intervention (self-help or human-supported), dose of human support (minor or major part of intervention), and delivery mode of human support (remote or blended). Type of intervention was coded as ‘self-help” ’if the study investigated an intervention without any involvement from another human coach and could be followed completely independently, and as ‘human-supported’ if a human coach (healthcare professional or layperson) was involved to support the participant in following the intervention. Dose of human support was coded as ‘minor”’ if the study investigated an intervention that was delivered through an eHealth tool, which the patient could practice independently or with some additional involvement of a human coach. It was coded as “major‘’ if the study investigated an intervention which was delivered by a human coach, in which eHealth served as an additional tool that supported the human guidance. Delivery mode was coded as “remote‘’ if human support was solely delivered via mediated forms of communication (e.g. text messages), and as “blended‘’ if the human support was delivered both via digital communication tools and in face-to-face settings. For the outcome data, all self-reported or objectively observed clinical (blood pressure, glucose, cholesterol, weight, CVD composite score, physical activity capacity) and behavioral (physical activity behavior, smoking, nutrition, alcohol, sleep and relaxation) outcome data were extracted. We decided to treat physical activity capacity, such as distance walked in a specific amount of time or oxygen uptake during physical effort (VO2max), as a clinical variable and physical activity behavior, such as steps or minutes of physical activity per day, as a behavioral variable. For each outcome variable baseline and follow-up measures, mean differences (pre-post measure within one group), or change scores (difference between control and experimental group) were extracted. In case of multiple intervention conditions, all conditions were extracted, and in case of multiple control conditions, only the least extensive condition was extracted. To assess the methodological quality, we used the latest Cochrane Risk of Bias tool (RoB 2.0) to extract and assess potential risks at study level regarding the randomization process, deviations from intended interventions (effect of assignment), missing outcome data, measurement of the outcome, and selection of the reported result (Sterne et al., 2019). Studies were assessed as "low", "some concerns", or "high" risk of bias in the above mentioned domains. For each study, two of the three independent researchers conducted both the data extraction and risk of bias assessment, and compared their outcomes (interrater reliability of 78%). Possible differences were all resolved in regular meetings, and if needed, with the help of a third independent researcher. Corresponding authors were contacted in case of missing information on key variables.

Statistical Analyses

An important feature differentiating this study from existing meta-analyses on the effectiveness of eHealth lifestyle interventions for cardiometabolic diseases is our use of a multilevel approach. Rather than conducting a meta-analysis for each outcome separately, a three-level model allowed us to combine different outcome variables from the same study as it can deal with interdepency of effect sizes (Assink & Wibbelink, 2016). The analyses were performed with the Metafor package in RStudio (version 1.4.1103). We estimated pooled effects for all clinical and behavioral outcome variables, using a random effects multilevel model (Assink & Wibbelink, 2016). We used a three-level model to take into account that multiple effect sizes can be nested within a sample. This model allows for effect size variance (level 1), nested in effect sizes (level 2), nested in study samples (level 3). Thus, all outcomes of each study were included in the analysis, and coded with the same study ID. For continuous variables, standardized mean differences (Hedges' G) with 95% confidence intervals were calculated (Hedges & Olkin, 1985). For categorical variables, we calculated odds ratios with 95% confidence intervals, and transformed those to standardized mean differences (Polanin & Snilstveit, 2016). Variances were calculated based on the provided standard deviations or confidence intervals (Higgins et al., 2019). In case outcomes were measured at multiple time points, we included the outcome directly measured after the end of the intervention as defined by the studies. The intention was to prevent a large variety in long-term measurements.

We assessed publication bias by inspecting funnel plots and performed an Egger's test (Egger et al., 1997) with the Metafor package in RStudio. Publication bias results from studies reporting statistically or clinical significant results more often than non-significant results (Egger et al., 1997). Hence, the effect sizes of studies included in the meta-analysis can differ from the general effect size if all (including non-significant) studies would be considered. We determined statistical heterogeneity using log-likelihood-ratio tests for both within-study variance (level 2) and between-study variance (level 3) (Assink & Wibbelink, 2016). Additionally, we conducted moderator analyses to assess the effectiveness of self-help and human-supported eHealth lifestyle interventions, and the effect of dose and delivery mode of human support on the effectiveness of eHealth lifestyle interventions on clinical and behavioral health outcomes. For this, the three-level random effects model was extended to a three-level mixed effects model (Assink & Wibbelink, 2016) with the following moderators: type of intervention (self-help vs. human-supported), dose of human support (minor vs. major part of intervention), and delivery mode of human support (remote vs. blended). Furthermore, we conducted a moderator analysis with the risk of bias-scores (low risk of bias, some concerns, and high risk of bias) and study, intervention and population characteristics (control condition type, intervention length, patient age and diagnosis).

RESULTS

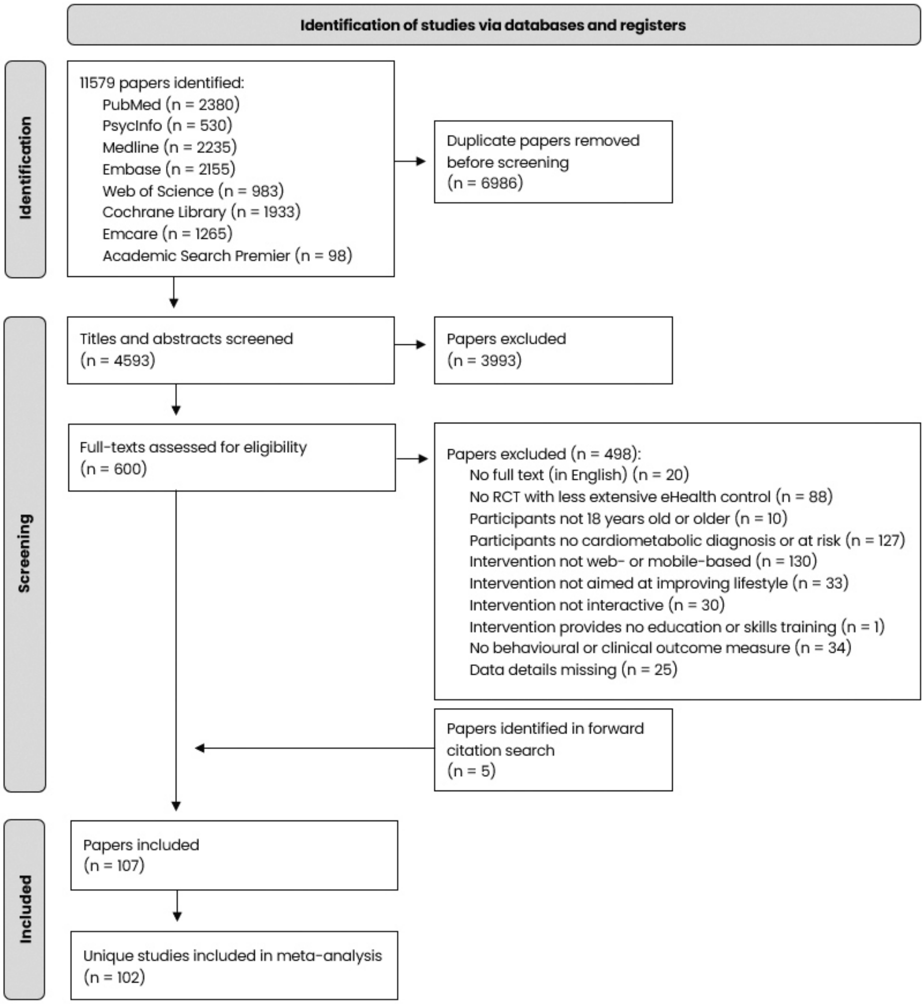
Study Selection

The search resulted in 4593 papers without duplicates. After abstract screening, a total of 600 full-texts were screened for eligibility. 498 papers did not meet the eligibility criteria and were, therefore, excluded. Five more papers were identified during the forward search, which resulted in a total of 107 papers fulfilling eligibility criteria, corresponding with 102 unique studies. The study selection process is summarized in Figure 1 (Pages et al., 2021).

Study Characteristics

The 102 studies produced 809 effect sizes, which all reflected the association between the use of an eHealth lifestyle intervention and either a clinical or behavioral outcome. A total of N = 20,781 patients were included in the studies, of which were N = 3428 CVD patients (26 studies), N = 72 T1DM patients (1 study), N = 7.143 T2DM patients (38 studies), N = 365 CKD patients (3 studies), N = 3,648 people at-risk (19 studies), and N = 6,125 patients from a sample with a combination of two or more of the before-mentioned diseases (15 studies).

Figure 1. Prisma flowchart of literature search and screening.



Sample sizes ranged from 20 to 2724. The mean age of the patients ranged from 35.2 to 75.9 years old. All studies included a combination of female and male patients. The duration of the interventions ranged from 1.5 to 24 months. The majority of the studies investigated the effect of interventions aimed either at physical activity (25), or a combination of multiple lifestyle behaviors (70). 30 investigated interventions (29%) were self-help, while 85 interventions (83%) offered some form of human support. See Appendix 2 for an overview of all studies included in the meta-analysis.

Risk of Bias Assessment & Publication Bias

The methodological quality of the included studies varied, but was overall sufficient. Almost all studies scored 'some concerns' on one of the domains in the Risk of Bias assessment, resulting in a 'some concerns' overall score for the majority of the studies (see Appendix 3). We found that the risk of bias-score did not moderate the association between eHealth lifestyle interventions and clinical and behavioral health outcomes ($F(2, 829) = .637$, $p = .529$). This indicates that there were no significant differences in mean effect size between studies with a low risk of bias-, some concerns-, or high risk of bias-score.

Possible publication bias was initially examined by visual inspection of a funnel plot. The funnel plot showed some asymmetry (indicating possible publication bias). Next, we tested funnel plot asymmetry by regressing the standard normal deviation against the estimate's precision (Egger et al., 1997). The analysis confirmed the visual inspection of the funnel plot, and showed that the intercept significantly deviated from zero, $t(808) = 3.12$, $p < .001$. This means that there are reasons to believe there is a publication bias for studies on eHealth lifestyle interventions.

Effectiveness of eHealth lifestyle interventions

The overall mean effect size of eHealth lifestyle interventions on clinical and behavioral health outcomes is 0.10 (expressed in Hedges' g; $p < .001$). A standardized mean difference of 0.10 is considered as small (Cohen, 1988). This indicates that patients with cardiometabolic diseases who follow an eHealth lifestyle intervention show more improvement in clinical and behavioral health outcomes compared to patients in control conditions. The overall mean effect size of eHealth lifestyle interventions on clinical outcomes only, as well as behavioral outcomes only, were 0.09 ($p < .001$) and 0.13 ($p < .001$), (see Table 1). We did not find a significant difference between the mean effect sizes of eHealth lifestyle interventions on clinical versus behavioral health outcomes ($p = 0.051$).

We conducted additional analyses for each outcome category separately. For the clinical outcome measures, we found significant mean effect sizes of eHealth lifestyle interventions on glucose outcomes (0.16, $p = .022$), weight outcomes (0.12, $p = .015$), and physical activity capacity outcomes (0.14, $p < .001$), but not for eHealth lifestyle interventions on blood pressure outcomes, cholesterol outcomes, and composite score outcomes. For the behavioral outcome measures, we found significant mean effect sizes of eHealth lifestyle interventions and physical activity outcomes (0.17, $p < .001$), and nutrition outcomes (0.13, $p = .007$), but not for eHealth lifestyle interventions on smoking outcomes, alcohol outcomes, and sleep and relaxation outcomes. See Table 1 for all mean effect sizes of eHealth lifestyle interventions on each outcome category.

Table 1. Mean effect sizes (expressed in Hedges' G) for each outcome category.

Outcome category	Nr. of studies	Nr. of ES	Mean ES (SE)	95% CI	*t*-Value	*p*-Value	Within-study variance	Between-study variance
All outcomes	102	809	.100 (.018)	0.065; 0.135	5.635	<.001***	.056***	.014***
Clinical outcomes	92	597	.086 (.019)	0.050; 0.123	4.672	<.001***	.066***	.010**
Blood pressure	49	99	.067 (.042)	-0.016; 0.150	1.597	.101	.034***	.047***
Glucose	55	84	.161 (.069)	0.024; 0.298	2.343	.022*	.000	.220***
Cholesterol	44	157	-.007 (.026)	-0.057; 0.044	-0.270	.788	.003	.016***
Weight	60	138	.117 (.048)	0.023; 0.211	2.463	.015*	.026***	.098***
CVD composite score	9	11	.025 (.031)	-0.044; 0.095	0.814	.435	.000	.000
PA capacity	24	61	.138 (.036)	0.065; 0.211	3.794	<.001***	.022*	.000
Behavioral outcomes	60	212	.131 (.031)	0.069; 0.193	4.165	<.001***	.020***	.031***
PA behavior	49	119	.170 (.038)	0.094; 0.246	4.453	<.001***	.000	.045***
Smoking	11	12	-.086 (.056)	-0.209; 0.037	-1.533	.154	.000	.013
Nutrition	24	74	.133 (.048)	0.037; 0.229	2.756	.007**	.040***	.020*
Alcohol	3	3	-.085 (.085)	-0.449; 0.279	-1.004	.279	.000	.000
Sleep & relaxation	3	4	.081 (.126)	-0.320; 0.482	0.641	.567	.000	.018

Note. ES = effect size (Hedges' G); SE = standard error; CI = confidence interval; PA = physical activity; * $p < .05$; ** $p < .01$; *** $p < .001$

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Heterogeneity

Given the three-level model, we assessed both between-study heterogeneity (variance between studies) and within-study heterogeneity (variance between effect sizes from the same study). For all outcomes, we found significant between-study heterogeneity (σ^2 = .014, χ^2 (1) = 29.53, p < .001), as well as within-study heterogeneity (σ^2 = .055, χ^2 (1) = 499.77, p < .001). For clinical outcomes, the between-study heterogeneity (σ^2 = .010, χ^2 (1) = 8.92, p = .003) and within-study heterogeneity (σ^2 = .064, χ^2 (1) = 440.83, p < .001) were also significant. Also, for behavioral outcomes we found a significant between-study heterogeneity (σ^2 = .034, χ^2 (1) = 22.83, p < .001) and within-study heterogeneity (σ^2 = .021, χ^2 (1) = 26.07, p < .001). Given these significant heterogeneity values, we conducted moderator analyses for all outcomes combined, for clinical outcomes, and for behavioral outcomes separately (see Table 1).

Moderator Analyses

Intervention Type, Delivery Mode, and Dose of Support

To test the effect of intervention type (self-help vs. human-supported), dose of human support (minor vs. major), and delivery mode of human support (remote vs. blended) on the relationship between eHealth lifestyle interventions and clinical and behavioral health outcomes, we conducted moderator analyses. We found that intervention type did not moderate the mean effect size of eHealth lifestyle interventions on all health outcomes (clinical and behavioral health outcomes combined; p = .169) (see Table 2). Moreover, both dose (p =.698) and delivery mode of human support (p =.557) did not moderate the mean effect size eHealth lifestyle interventions on all health outcomes (clinical and behavioral health outcomes combined). We performed the same moderator analyses on the mean effect size of eHealth lifestyle interventions, and on both clinical and behavioral outcomes separately (see Table 2). For clinical outcomes, we again found no significant moderator effect of intervention type (p =.374), dose of human support (p =.439), or delivery mode (p =.308). For behavioral outcomes, we also found no significant moderator effect of intervention type (p =.080), dose of human support (p =.272), or delivery mode (p =.144).

Study, Intervention and Population Characteristics

We conducted several additional moderator analyses to explore whether study, intervention or population characteristics could explain this heterogeneity (see Table 3). Control condition type (passive vs. active; p = 0.344), intervention length (p = .588), mean sample age (p = .053), or diagnosis (CVD, T1DM, T2DM, CKD, at-risk, or mixed; p = .197) did not significantly moderate the mean effect size of eHealth lifestyle interventions on all health outcomes, or on either clinical or behavioral health outcomes separately (see Table 3).

Table 2. Results for the moderator analyses of intervention type, dose of human support, and delivery mode of human support on the association between eHealth interventions and clinical and behavioral health outcomes.

Moderator	Nr. of studies	Nr. of ES	Overall test	*p*-Value of overall test	Mean ES (SE)	95% CI	*t*-Value	*p*-Value of ES
All outcomes								
Intervention type	102	809	$F(1, 807) = 1.900$	.169				
Self-help interventions					.137 (.032)	0.074; 0.201	4.241	<.001***
Human-supported interventions					.086 (.020)	0.047; 0.125	4.292	<.001***
Dose of human support	76	590	$F(1, 588) = .150$	.698				
Minor level					.105 (.036)	0.034; 0.176	2.907	.004**
Major level					.087 (.031)	0.027; 0.147	2.839	.005**
Delivery mode of human support	75	586	$F(1, 584) = .346$	.557				
Remote					.102 (.026)	0.052; 0.152	3.988	<.001***
Blended					.080 (.036)	0.010; 0.150	2.250	.025*
Clinical outcomes								
Intervention type	92	597	$F(1, 595) = .792$	.374				
Self-help interventions					.113 (.035)	0.044; 0.182	3.204	.001**
Human-supported interventions					.077 (.021)	0.035; 0.118	3.610	<.001***

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Table 2. *Continued*

Moderator	Nr. of studies	Nr. of ES	Overall test	*p*-Value of overall test	Mean ES (SE)	95% CI	*t*-Value	*p*-Value of ES
Dose of human support	69	440	F(1, 438) = .599	.439				
Minor level					.111 (.041)	0.030; 0.191	2.696	.007**
Major level					.068 (.037)	-0.005; 0.142	1.834	.067+
Delivery mode of human support	68	436	F(1, 434) = 1.041	.308				
Remote					.099 (.029)	0.042; 0.157	3.386	<.001***
Blended					.063 (.038)	-0.012; 0.137	1.653	.099+
Behavioral outcomes								
Intervention type	60	212	F(1, 210) = 3.100	.080+				
Self-help interventions					.207 (.053)	0.102; 0.312	3.886	<.001***
Human-supported interventions					.101 (.034)	0.034; 0.167	2.993	.003**
Dose of human support	44	150	F(1, 148) = 1.215	.272				
Minor level					.038 (.058)	-0.076; 0.153	0.662	.509
Major level					.117 (.042)	0.034; 0.201	2.790	.006**
Delivery mode of human support	44	150	F(1, 148) = 2.159	.144				
Remote					.062 (.038)	-0.014; 0.138	1.614	.109
Blended					.167 (.062)	0.044; 0.290	2.679	.008**

Note. ES = effect size (Hedges' G); SE = standard error; CI = confidence interval; + < .10; * $p < .05$; ** $p < .01$; *** $p < .001$

Table 3. Results for the moderator analyses of study, intervention and population characteristics on the association between eHealth interventions and clinical and behavioral health outcomes.

Moderator	Nr. of studies	Nr. of ES	Overall test	*p*-Value of overall test	Mean ES (SE)[a]	95% CI	*t*-Value	*p*-Value of ES
All outcomes								
Outcome type	102	809	F(1, 807) = 3.810	.051^{+}				
Clinical outcomes					.086 (.019)	0.049; 0.124	4.500	<.001***
Behavioral outcomes					.142 (.028)	0.087; 0.196	5.109	<.001***
Control condition type	102	809	F(1, 807) = .897	.344				
Passive					.110 (.021)	0.070; 0.151	5.320	<.001***
Active					.071 (.036)	-0.000; 0.142	1.959	.050^{+}
Intervention length	101	805	F(1, 803) = .294	.588	.117 (.031)	0.056; 0.177	3.792	<.001***
Mean sample age	91	750	F(1, 748) = 3.758	.053^{+}	.198 (.053)	0.095; 0.301	3.760	<.001***
Diagnosis	102	809	F(5, 803) = 1.470	.197				
CVD					.146 (.037)	0.075; 0.218	4.000	<.001***
T1DM					.034 (.212)	-0.382; 0.450	.161	.872
T2DM					.104 (.030)	0.046; 0.162	3.497	<.001***
CKD					.024 (.098)	-0.168; 0.215	.242	.809
At-risk					.126 (.038)	0.051; 0.202	3.286	.001**
Mixed patient group					.002 (.046)	-0.089; 0.092	.040	.968
Clinical outcomes								
Control condition type	92	597	F(1, 595) = .653	.420				

Table 3. *Continued*

Moderator	Nr. of studies	Nr. of ES	Overall test	*p*-Value of overall test	Mean ES (SE)[a]	95% CI	*t*-Value	*p*-Value of ES
Passive					.095 (.021)	0.053; 0.137	4.451	<.001***
Active					.059 (.039)	-0.016; 0.135	1.538	.125
Intervention length	91	596	F(1, 594) = .025	.873	.094 (.033)	0.029; 0.158	2.864	.004**
Mean sample age	83	551	F(1, 549) = 2.750	.098	.179 (.058)	0.065; 0.292	3.095	.002**
Diagnosis	92	597	F(5, 591) = 1.244	.287				
CVD					.135 (.039)	0.059; 0.211	3.490	<.001***
T1DM					.183 (.378)	-0.560; 0.926	.483	.629
T2DM					.095 (.031)	0.034; 0.156	3.062	.002**
CKD					.028 (.096)	-0.161; 0.218	.295	.768
At-risk					.095 (.040)	0.017; 0.173	2.390	.017*
Mixed patient group					-.015 (.050)	-0.114; 0.083	-.015	.762
Behavioral outcomes								
Control condition type	60	212	F(1, 210) = .211	.646				
Passive					.141 (.038)	0.066; 0.217	3.692	<.001***
Active					.109 (.058)	-0.004; 0.223	1.900	.059[+]
Intervention length	59	209	F(1, 207) = 1.242	.266	.188 (.057)	0.076;0.301	3.298	<.001**
Mean sample age	55	199	F(1, 197) = 2.441	.120	.243 (.082)	0.081; 0.405	2.960	.003**

Table 3. *Continued*

Moderator	Nr. of studies	Nr. of ES	Overall test	*p*-Value of overall test	Mean ES (SE)[a]	95% CI	*t*-Value	*p*-Value of ES
Diagnosis	60	212	F(5, 206) = .508	.770				
CVD					.122 (.062)	-0.001; 0.245	1.955	.052⁺
T1DM					-.016 (.253)	-0.514; 0.482	-.063	.950
T2DM					.155 (.060)	0.037; 0.273	2.595	.010*
CKD					-.003 (.212)	-0.420; 0.415	-.013	.990
At-risk					.196 (.070)	0.058; 0.334	2.803	.006**
Mixed patient group					.064 (.076)	-0.086; 0.215	.843	.400

Note. ES = effect size (Hedges' G); SE = standard error; CI = confidence interval; ⁺ < .10; * *p* < .05; ** *p* < .01; *** *p* < .001
[a] For continuous predictors: represents the ES size of a participant with an average value on the corresponding predictor

4

DISCUSSION

Our multilevel meta-analysis demonstrated that eHealth interventions are effective in improving cardiometabolic health outcomes. Yet, overall effect size, both on clinical and behavioral health outcomes, was small. The small effect sizes are comparable to other meta-analyses investigating eHealth lifestyle interventions (e.g. 0.139 in Lustria et al. (2013); 0.16 in Webb et al. (2010)). More specifically, eHealth lifestyle interventions positively influenced the clinical health outcomes glucose, weight and physical activity capacity (but not blood pressure, cholesterol and CVD composite score), and the following behavioral health outcomes: physical activity behavior, and nutrition (but not smoking, alcohol and sleep or relaxation).. Furthermore, we found that study, intervention or sample characteristics did not impact the positive effect of eHealth lifestyle interventions on health outcomes. Finally, control group type, intervention length, mean sample age, and diagnosis did not influence the effect of eHealth lifestyle interventions on clinical and behavioral health outcomes.

Contrary to our expectations, our meta-analysis did not show the expected difference between human-supported and self-help eHealth interventions. Both human-supported and self-help eHealth interventions were effective in improving clinical and behavioral health outcomes. Our results contrast other meta-analyses (Beishuizen et al., 2016; Joiner et al., 2017; Lau et al., 2020) which did find a stronger effect of human support in eHealth interventions on improving cardiometabolic risk factors, or a more pronounced effect of blended interventions compared to remotely supported ones. Instead, our results are more in line with studies that indicated that there is no difference in the improvement of cardiometabolic risk factors between human-supported and self-help eHealth interventions (Lustria et al., 2013; Webb et al., 2010), or blended and remotely supported eHealth interventions (Kloek et al., 2017). Although one of the aims of this meta-analysis was to find an explanation for the inconsistent results of human support in eHealth interventions in these different meta-analyses, our results with regard to dose and delivery mode of the support did not provide this explanation. However, these inconsistencies could be due to population-, outcome- or intervention-related factors.

Regarding the first factor that could provide an explanation to inconsistent results of human support, the study population, meta-analyses focusing on the general population did not find a difference between human-supported and self-help eHealth interventions (Lustria et al., 2013; Webb et al., 2010). However, contrary to our results, those studies that focused on a patient or at-risk population did encounter differences between human-supported and self-help eHealth interventions (Beishuizen et al., 2016; Joiner et al., 2017; Lau et al., 2020). Our meta-analysis with patients and an at-risk population did not find these differences, and also no differences between conditions. We did however find that age had a borderline significant effect. Possibly, patients are generally older, and therefore, more in need of human support when using eHealth compared to the general population (Crouch & Gordon, 2019).

With regard to outcome-related factors, our study showed no difference between human-supported and self-help eHealth interventions in the outcome measure we used: effectiveness. Possibly, we would have found a difference if we used intervention adherence as an outcome measure. Multiple studies have shown that self-help eHealth interventions suffer from low levels of intervention adherence, which refers to the extent to which the individual uses the intervention as intended (Kelders et al., 2012; Kelders et al., 2011; Murray et al., 2013; Wangberg et al., 2008). However, meta-analyses on multiple studies investigating intervention adherence to eHealth interventions are difficult to conduct because only a small proportion of the studies report eHealth intervention adherence (Sieverink et al., 2017). As intervention adherence is related to intervention effectiveness (Donkin et al., 2011), the level of intervention adherence could possibly be the missing explanation for the inconsistent results found in previous meta-analyses regarding the possible added contribution of human support to self-help eHealth interventions.

Finally, the effectiveness of human support in eHealth interventions could depend on the characteristics of the specific interventions. In our study, the inclusion criteria was that the tested intervention was delivered via a website or mobile-based application, provided education or skills training, and was interactive. This narrowed down the type of interventions included in our analyses, which may have positively influenced the quality of both human-supported and self-help interventions, and consequently reduced the difference in effectiveness between the two. Some meta-analyses did find a lower effectiveness of self-help eHealth interventions, possibly because they included a broader variety of interventions, including interventions lacking important behavior change techniques or lower quality of interactive components. For example, Beishuizen and colleagues (2016) included interventions without education or skills training, Lau and colleagues (2020) included interventions that were not interactive, and Joiner and colleagues (2017) included any intervention that used some form of digital communication (including social media, DVDs, or videoconferencing). We know that interventions that are more elaborate, for example because they incorporate multiple behavior change techniques, are more effective in improving health behavior (Webb et al., 2010). It is therefore not surprising that automated support is frequently combined with behavior change techniques and persuasive system design principles (Asbjørnsen et al., 2019). Furthermore, an advantage of self-help interventions is that users can customize what behavior change technique features are used in their eHealth intervention, which users appreciate (Coorey, 2018). This means that cardiometabolic patients themselves can decide whether their eHealth lifestyle intervention shows motivational messages (e.g. through push messages on their smartphone) or not, in what frequency they want to track their behaviors (e.g. filling in a food diary daily or weekly) or whether they want to watch all the educational videos or whether they already have enough knowledge on the topic. So the more thorough implementation of behavior change techniques and interactive components as well as the freedom for the user to choose, could positively affect the quality of self-help eHealth interventions.

Finally, it is important to note that our hypotheses with regard to the dose and delivery mode of support were based on findings in mental health interventions. Based on meta-analyses focusing on both eHealth and regular interventions or eHealth interventions only, aimed at patients with obsessive-compulsive disorder (Pearcy et al., 2016), depression and anxiety (Etzelmueller et al., 2020; Karyotaki et al., 2018; Richards & Richardson, 2012) or mental disorders in general (Baumeister et al., 2014) found that human-supported interventions are more effective, and that higher levels of support lead to higher effect sizes. Our meta-analysis however, focused on lifestyle interventions showed contradictory results. Possibly, mental health issues require more complex interventions that might require more human support than self-help interventions. Future studies could investigate whether interventions aimed at mental health improvement necessitate (more extensive) human support compared to interventions aimed at lifestyle behavior change.

Strengths, Limitations and Future Research

A strength of our study is that we used a precise definition of eHealth as a study eligibility criteria. As noted previously, many other meta-analyses on eHealth included a larger variety of digital tools (e.g. DVDs and videoconferencing) or less elaborate types of eHealth interventions (e.g., without interactive or educational components). Our definition created more homogeneity in the inclusion of eHealth studies. Another strength would be the inclusion of four different types of cardiometabolic diseases. Not only is there a high comorbidity between CVD, CKD, T1DM and T2DM, but they also share similar underlying risk factors and have a similar management strategy (i.e. lifestyle modifications; Ryden et al., 2014; Suckling, 2012). Finally, another advantage of our study was our multi-level approach for the meta-analysis. Other studies concerning eHealth lifestyle interventions for people with cardiometabolic diseases used a more traditional univariate approach, and conducted a meta-analysis for each outcome separately. We contributed to these studies by applying a three-level model approach (Assink & Wibbelink, 2016), which does not only deal with interdependency of effect sizes, but also presents an overall picture of the effect of eHealth lifestyle interventions on clinical and behavioral health outcomes.

A number of limitations need to be considered. Firstly, our sensitivity analyses revealed that there was some publication bias. This may have caused the mean effect sizes in our study to be different from the true effect sizes for the effect of eHealth interventions on clinical and behavioral cardiometabolic health outcomes. The results should, therefore, be interpreted with caution. Another limitation of the study was the methodological quality of the included studies. The Risk of Bias assessment resulted in a generally good evaluations of the studies, and we found that Risk of Bias assessment had no moderating effect on the relation between eHealth intervention and clinical and behavioral health outcomes. Since self-management interventions cannot be blinded, almost all studies lacked double blinding, leading to a possible risk of bias due to deviations from the intended interventions and in measurement of the outcome (e.g. health professionals measuring participants blood pressure or weight). Furthermore, only a minority of the studies preregistered their study and analyses, which may cause a risk of bias in selection of the reported results. As another limitation, we should mention that the included studies were substantially heterogeneous on several levels. With regard to the control group, some of the studies had a passive control group (waitlist or care as usual), while in other studies patients in the control group received another intervention. Furthermore, there was a large variety in intervention duration, which ranged from 1.5 to 24 months. There were also big differences in mean age of the study samples, which varied from 35.2 to 75.9 years. In spite of this, our analyses revealed that control group type, intervention length, and mean sample age had no moderating effect on the relation between eHealth intervention and clinical and behavioral health outcomes.

Our study has raised new questions regarding eHealth interventions and human support that would be interesting to address in future research. Adherence to interventions is still poorly defined and underreported. Therefore, we suggest that future randomized controlled trials evaluating eHealth lifestyle interventions implement better intervention adherence measures. This would also enable the investigation of the relationship between human-supported and self-help eHealth interventions on intervention adherence. In contrast to previous meta-analyses, our study did not find a difference between these human-supported and self-help eHealth interventions. As stated before, this inconsistency could be due to the quality of eHealth interventions, as we had strict inclusion and exclusion criteria with regard to the way eHealth interventions were designed and executed. Future meta-analyses could investigate what components make self-help eHealth interventions as effective as human-supported eHealth interventions, and whether lower-quality eHealth interventions benefit more from applying human support. Another suggestion for future research would be to further investigate the need for human support for specific subgroups of patients. For example it is important to specifically examine implementation, intervention adherence and effects of eHealth interventions for patients of lower socioeconomic status including those with less digital literacy or resources (van der Vaart et al., 2019). These variables were reported inconsistently among the included studies and require more attention in future studies.

Moreover, meta-analyses on interventions for psychological outcomes instead of lifestyle outcomes indicate that human support is particularly important for cognitive-behavioral interventions focusing on psychological distress and related outcomes (Baumeister et al., 2014; Etzelmueller et al., 2020; Karyotaki et al., 2018; Pearcy et al., 2016; Richards & Richardson, 2012). Therefore, it would be interesting to investigate whether mental health also influences the need for support in eHealth lifestyle interventions. Finally, the studies included in our analyses were heterogenous in regard to patient groups and outcomes. Most studies focused on CVD and T2DM patients, and to a lesser degree on patients with T1DM and CKD. Despite alcohol use and sleep and relaxation being important risk factors to be address in cardiometabolic disease management, only very few studies targeted these health outcomes. It would, therefore, be important for eHealth researchers to also focus on these less represented patients groups and behavioral risk factors in future studies.

CONCLUSION

Our meta-analysis demonstrated that eHealth lifestyle interventions are effective in improving clinical and behavioral health outcomes among people with cardiometabolic diseases. However, there was no difference between self-help and human-supported eHealth interventions' effectiveness. Neither dose nor delivery mode of support affected human-supported intervention effectiveness. Several population-, outcome-, and intervention-related factors were ruled out as possible moderators of these relationships. These findings add substantially to our understanding of the role of human support in lifestyle eHealth interventions, which is important to make lifestyle interventions accessible for a larger and more varied audience. Although further research is required to unravel the possible added contribution of human support for specific eHealth interventions in subgroups of patients, our results seem promising for the broad application of self-help eHealth interventions in cardiometabolic diseases.

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CHAPTER 4 | APPENDIX 1

Search string.

Randomized controlled trials about eHealth lifestyle interventions to promote lifestyle modification in cardiometabolic disease patients.

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II diab*[tiab] OR non-insulin-dependent diab*[tiab] OR adult-onset diab*[tiab] OR “T2DM”[tiab] OR “T2D”[tiab] OR “TIIDM”[tiab] OR “TIID”[tiab] OR “DM2”[tiab] OR “Diabetes Mellitus”[majr] OR “diabetes mellitus”[tiab] OR “Diabetes Mellitus, Type 1”[majr:noexp] OR type 1 diab*[tiab] OR type I diab*[tiab] OR insulin-dependent diab*[tiab] OR juvenile diab*[tiab] OR juvenile-onset diab*[tiab] OR juvenile onset diab*[tiab] OR “IDDM”[tiab] OR “T1DM”[tiab] OR “TIDM”[tiab] OR autoimmune diab*[tiab] OR “DM1”[tiab]) AND (”Randomized Controlled Trial”[Publication Type] OR ”randomized”[ti] OR ”randomised”[ti] OR ”RCT”[ti] OR random*[ti] OR ”single blind”[ti] OR ”double blind”[ti] OR ”triple blind”[ti] OR single blind*[ti] OR double blind*[ti] OR triple blind*[ti] OR ”Equivalence Trial”[ti] OR ”Pragmatic Clinical Trial”[ti] OR ”Randomized Controlled Trials as Topic”[Mesh] OR ”Equivalence Trial”[Publication Type] OR ”Equivalence Trials as Topic”[Mesh] OR ”superiority trial”[ti] OR ”non-inferiority trial”[ti]) AND (english[la] OR dutch[la]) AND (”1995/01/01”[PDAT] : ”3000/12/31”[PDAT]))

CHAPTER 4 | APPENDIX 2

Table 4. Characteristics of the included studies.

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
Agarwal 2019(a)	50 T2DM and hypertension patients	64.1	44.5	2-arm; Canada	4-month mobile-based intervention aimed at physical activity, nutrition, and sleep	Human-supported, blended, major, layperson	Usual care	Glucose, physical activity behavior
Agarwal 2019(b)	223 T2DM patients	51.8	47.5	2-arm; Canada	3-month mobile-based intervention, aimed at physical activity and nutrition	Self-help	Waitlist	Glucose
Akinci 2019	66 T2DM patients	52.5	72.3	3-arm*; Finland	2-month web-based intervention aimed at physical activity	Human-supported, remote only, minor, layperson	Usual care	Glucose, cholesterol, weight, physical activity capacity, physical activity behavior
Appel 2011	415 CVD patients	54.0	63.6	3-arm; USA	24-month web-based interventions aimed at physical activity and nutrition	(1) Human-supported, remote, minor, professional (2) Human-supported, blended, major, professional	Usual care	Weight
Baer 2020	840 T2DM patients	59.3	60.0	3-arm; USA	12-month web-based interventions aimed at physical activity and nutrition	(1) Self-help (2) Human-supported, remote, minor, professional	Usual care	Weight
Bailey 2020	20 T2DM patients	56.0	45.0	2-arm; UK	2-month mobile-based intervention aimed at physical activity	Self-help	Usual care	Blood pressure, glucose, weight, physical activity capacity, physical activity behavior
Bennett 2010	101 CVD patients	54.4	47.5	2-arm; USA	3-month web-based intervention aimed at physical activity and nutrition	Human-supported, blended, minor, professional	Usual care	Blood pressure, weight

Table 4. *Continued*

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
Bennett 2018	351 hypertension, diabetes, hyperlipidemia, and obesity patients	50.7	68.0	2-arm; USA	12-month mobile-based intervention aimed at nutrition	Human-supported, blended, minor, professional	Usual care	Blood pressure, glucose, cholesterol, weight
Bond2007	62 T1DM and T2DM patients	67.2	45.0	2-arm; USA	6-month web-based intervention aimed at nutrition and physical activity	Human-supported, remote, major, professional	Usual care	Blood pressure, glucose, cholesterol, weight
Bozorgi 2021	120 patients with hypertension	51.8	41.0	2-arm; Iran	2-month mobile-based intervention aimed at nutrition and smoking	Self-help	Usual care	Blood pressure, weight, physical activity capacity, physical activity behavior, nutrition
Cai 2021	100 CVD patients	57.0	35.0	2-arm; China	3-month mobile-based intervention aimed at physical activity	Human-supported, remote, minor, professional	Usual care	Physical activity capacity, physical activity behavior
Chao2019	121 T2DM patients	N.A.	39.0	2-arm; Taiwan	18-month mobile-based intervention aimed at physical activity and nutrition	Human-supported, remote, minor, professional	Usual care	Blood pressure, glucose, weight
Choi2019	100 CVD patients	56.9	38.9	2-arm; USA	3-month mobile-based intervention aimed at nutrition	Human-supported, blended, major, professional	Usual care	Blood pressure, glucose, cholesterol, weight
Chow2021	41 at-risk population	N.A	49.4	2-arm; USA	4-month mobile-based intervention aimed at smoking, physical activity and nutrition	Human-supported, remote, major, professional	Other eHealth intervention	Physical activity behavior, nutrition

Table 4. *Continued*

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
Connely2017	31 T2DM patients	66.7	41.7	3-arm; UK	6-month web-based intervention aimed at physical activity	(1) Self-help (2) Human-supported, blended, minor, professional	Non eHealth intervention	Weight, glucose, physical activity behavior
Dorje2019	312 CVD patients	60.5	18.5	2-arm; China	6-month mobile-based intervention aimed at physical activity and nutrition	Human-supported, remote, minor, professional	Usual care	Blood pressure , cholesterol, weight
Dorsch2020	50 CVD patients	57.4	59.5	2-arm; USA	2-month mobile-based intervention aimed at nutrition	Self-help	Usual care	Blood pressure, nutrition
Duan2018	114 CVD patients	48.7	53.2	2-arm; USA	2-month mobile-based intervention aimed at physical activity and nutrition	Human-supported, remote, minor, professional	Waitlist	Physical activity behavior, nutrition
Duscha2018	32 CVD patients	63.2	52.1	2-arm; China	3-month web-based intervention aimed at physical activity	Human-supported, remote, major, professional	Usual care	Physical activity capacity, physical activity behavior
Engelen2020	208 CVD patients	63.5	31.5	2-arm; The Netherlands	12-month Web-based intervention aimed at smoking, alcohol, and physical activity	Self-help	Usual care	Blood pressure, cholesterol, weight, physical activity behavior, nutrition, alcohol
Fukuoka2015	61 at-risk population	55.3	77.1	2-arm; USA	5-month mobile-based intervention aimed at physical activity and nutrition	Human-supported, blended, major, layperson	Usual care	Blood pressure, glucose, cholesterol, weight
Glasgow2012	463 T2DM patients	58.7	77.4	3-arm; USA	4-month web-based intervention aimed at physical activity and nutrition	(1) Self-help (2) Human supported, remote, major, professional	Other eHealth intervention	Blood pressure, glucose, cholesterol, weight, cardiovascular compost score, physical activity behavior, nutrition

Table 4. *Continued*

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
Gong2020	187 T2DM patients	56.9	41.8	2-arm; Australia	12-month mobile-based intervention aimed at physical activity and nutrition	Human-supported, remote, minor, layperson	Waitlist	Glucose, weight
Grau-Pellicer 2020	41 CVD patients	65.8	49.4	2-arm; Spain	3-month mobile-based intervention aimed at physical activity	Human-supported, blended, major, professional	Usual care	Physical activity behavior
Gunawardena 2019	67 T1DM and T2DM patients	52.5	40.0	2-arm; Sri Lanka	6-month mobile-based intervention aimed at nutrition and physical activity	Self-help	Usual care	Glucose
Hansel2017	120 T2DM patients	56.6	66.7	2-arm; France	4-month web-based intervention aimed at nutrition and physical activity	Self-help	Usual care	Glucose, cholesterol, weight, nutrition
Haste2017	61 T2DM patients	N.A.	N.A.	2-arm; UK	12-month web-based intervention aimed at nutrition and physical activity	Human-supported, remote, minor, professional	Usual care	Weight
Hilmarsdóttir 2021	37 T2DM patients	51.2	63.4	2-arm; Iceland	6-month mobile-based intervention aimed at nutrition, stress and physical activity	Human-supported, remote, minor, layperson	Waitlist	Blood pressure, glucose, cholesterol, weight
Höchsmann 2019	36 T2DM patients	N.A.	52.8	2-arm; Switzerland	6-month mobile-based intervention aimed at physical activity	Self-help	Non eHealth intervention	Blood pressure, glucose, cholesterol, weight, physical activity behavior
Holmen2014	151 T2DM patients	57.3	36.5	3-arm; Norway	12-month mobile-based intervention aimed at nutrition and physical activity	Self-help	Usual care	Glucose, weight

Table 4. *Continued*

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
Houchen-Wolloff2018	60 CVD patients	61.5	10.0	2-arm; UK	2-month web-based intervention aimed at physical activity, nutrition, stress and smoking	Human-supported, remote, minor, professional	Usual care	Physical activity capacity
Humalda2020	99 CKD patients	56.7	16.0	2-arm; The Netherlands	9-month web-based intervention aimed at nutrition	Human-supported, blended, major, professional	Usual care	Blood pressure, nutrition
Imanaka2014	193 at-risk population	50.2	14.0	2-arm; Japan	3-month web-based intervention aimed at nutrition	Human-supported, remote, major,	Non eHealth intervention	Weight
Jahangiry2017	160 at-risk population	44.0	27.0	2-arm; Iran	3-month web-based intervention aimed at physical activity and nutrition	Self-help	Usual care	Blood pressure, glucose, cholesterol, weight
Javaheri2020	34 CVD patients	71.6	25.7	2-arm; USA	1.5-month web-based intervention aimed at sleep	Self-help	Waitlist	Blood pressure, sleep and relaxation
Johnston2016	174 CVD patients	57.6	19.3	2-arm; Sweden	6-month mobile-based intervention aimed at weight management, smoking and physical activity	Self-help	Other eHealth intervention	Cholesterol, weight, smoking
Keyserling2014	385 CVD patients	62.0	48.0	2-arm; USA	4-month mobile-based intervention aimed at physical activity, nutrition, and smoking	Human-supported, remote, major, professional	Usual care	Blood pressure, cholesterol, weight, cardiovascular composite score, physical activity behavior, smoking , nutrition

Table 4. *Continued*

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
Khanji2019	402 CVD patients	65.5	37.0	2-arm; The Netherlands	6-month mobile-based intervention aimed at alcohol consumption, smoking, physical activity, weight, nutrition, stress management	Human-supported, remote only, minor, professional	Usual care	Blood pressure, glucose, cholesterol, weight
Kim2006	73 T2DM patients	N.A.	N.A.	3-arm*; South Korea	3-month mobile-based intervention aimed at physical activity	Human-supported, blended, minor, professional	Usual care	Glucose, physical activity behavior, alcohol
Kim2016	160 patients with hypertension, diabetes, or cardiac arrhythmia	57.6	68.0	2-arm; South Korea	6-month mobile-based intervention aimed at alcohol consumption, smoking and physical activity	Human-supported, remote, minor, professional	Usual care	Blood pressure, physical activity behavior, smoking, alcohol
Kim2019	151 T2DM patients	N.A.	52.0	2-arm; South Korea	2-month mobile-based intervention aimed at nutrition management, physical activity.	Human-supported, blended, major, professional	Non eHealth intervention	Glucose
Kirwan2013	72 T1DM patients	35.2	61.1	2-arm; Australia	4-month mobile-based intervention aimed at diet and physical activity.	Human-supported, remote, major, professional	Usual care	Glucose, nutrition
Kooiman2018	72 T2DM patients	56.3	N.A.	2-arm; The Netherlands	3-month mobile-based intervention aimed at physical activity	Human-supported, remote, minor, professional	Usual care	Glucose, weight
Kouwenhoven-Pasmooij2018	491 at risk-population	51.0	19.3	2-arm; The Netherlands	6-month web-based intervention, aimed depending on patient's profile	Human-supported, blended, major, professional	Other eHealth intervention	Weight, physical activity behavior

Table 4. *Continued*

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
Ku2020	40 T2DM patients	50.0	65.0	2-arm; South Korea	3-month web-based intervention aimed at nutrition and physical activity	Human-supported, remote, major, professional	Non eHealth intervention	Glucose, physical activity behavior, nutrition
Kulick2013	61 at-risk population	52.2	75.3	2-arm; USA	3-month web-based intervention aimed at nutrition	Self-help	Waitlist	Cholesterol, weight, cardiovascular composite score, nutrition
Kumar2020	300 T2DM patient	64.65	60.0	2-arm; India	6-month mobile-based intervention aimed at nutrition	Self-help	Usual care	Glucose
Lear2014	78 CVD patients	60.0	15.0	2-arm; Canada	4-month web-based intervention aimed at physical activity and nutrition	Human-supported, remote, major, professional	Usual care	Blood pressure, glucose, cholesterol, weight, physical activity capacity, physical activity behavior, smoking
Lee2018	148 T2DM patients	52.0	36.5	2-arm; South-Korea	6-month mobile and web-based intervention aimed at physical activity and nutrition	Human-supported, remote, major, professional	Usual care	Blood pressure cholesterol, physical activity behavior, smoking, nutrition
Lee2020	72 T2DM patients	51.6	29.3	2-arm; South-Korea	6-month mobile-based intervention aimed at physical activity and nutrition	Human-supported, remote, major, professional	Usual care	Glucose, cholesterol, weight, smoking, nutrition
Li2019	462 at-risk population	61.5	62.8	2-arm; China	6-month mobile-based intervention aimed at nutrition, physical activity, smoking, alcohol intake.	Human-supported, remote, major, layperson	Usual care	Blood pressure, glucose
Li2020	60 CKD patients	51.3	26.5	2-arm; Taiwan	3-month mobile-based intervention aimed at physical activity and nutrition	Human-supported, remote, major, professional	Usual care	Cholesterol, weight

Table 4. *Continued*

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
Liebreich2009	49 T2DM patients	54.1	N.A.	2-arm; Canada	3-month web-based intervention aimed at physical activity	Human-supported, remote, major, professional	Other eHealth intervention	Physical activity behavior
Lim2021	204 T2DM patients	51.2	35.2	2-arm; Singapore	6-month mobile-based intervention aimed at physical activity and nutrition	Human-supported, remote, major, layperson	Non eHealth intervention	Blood pressure, glucose, cholesterol, weight, nutrition
Lindberg2017	166 T2DM patients	66.6	29.5	2-arm; Sweden	19-month web-based intervention aimed at. nutrition, physical activity, smoking and alcohol consumption	Human-supported, blended, major, professional	Usual care	Blood pressure, glucose, cholesterol
Lisón2020	105 at-risk population	53.2	N.A.	2-arm; Spain	3-month web-based intervention aimed at nutrition and physical activity	Human-supported, blended, minor, layperson	Usual care	Blood pressure, glucose, weight, physical activity capacity, physical activity behavior
Little2017	826 at-risk population	53.7	63.6	3-arm; UK	6-month web-based intervention aimed at nutrition and physical activity	(1) Human-supported, blended, minor, professional (2) Human-supported, remote, minor, professional	Other eHealth intervention	Glucose, cholesterol, weight, physical activity behavior, nutrition
Lorig2006	958 CVD patients	57.5	71.4	2-arm; USA	1,5-month web-based intervention aimed at physical activity an stress management	Human-supported, remote, major, layperson	Usual care	Physical activity behavior, sleep
Lorig2010	761 T2DM patient	54.3	72.7	3-arm; USA	1,5-month web-based intervention aimed at nutrition and physical activity	(1) Human-supported, remote, major, layperson (2) Human-supported, remote, major, layperson	Usual care	Glucose, physical activity behavior

Table 4. *Continued*

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
Lunde2020	113 CVD patients	59.0	22.2	2-arm; Norway	12-month mobile-based intervention aimed at target behavior set by patient	Human-supported, remote, major, professional	Usual care	Blood pressure, glucose cholesterol, weight, physical activity capacity, physical activity behavior
Maddison2015	171 CVD patients	60.2	19.0	2-arm; New Zealand	6-month Physical activity mobile based and web-based intervention aimed at physical activity	Human-supported, remote, minor, layperson	Usual care	Physical activity capacity, physical activity behavior
Maddison2019	162 CVD patients	61.3	14.2	2-arm; New Zealand	3-month Physical activity mobile based and web-based intervention aimed at physical activity	Human-supported, remote, major, professional	Usual care	Blood pressure, glucose cholesterol, weight, physical activity capacity physical activity behavior
McDermott2018	200 CVD patients	70.3	52.5	2-arm; USA	6-month web-based intervention aimed at physical activity	Human-supported, blended, major, professional	Usual care	Physical activity capacity, physical activity behavior
McKay2001	78 T2DM patients	N.A.	N.A.	2-arm; USA, Canada	2-month Physical activity web-based intervention aimed at physical activity	Human-supported, remote, major, professional	Non eHealth intervention	Glucose cholesterol, nutrition
McKay2002	160 T2DM patients	59.5	53.2	4-arm; USA	2-month web-based intervention aimed at nutrition and others	(1) Self-help (2) Human supported, remote, major, professional (3) Human supported, remote, major, professional (4) Human supported, remote, major, professional	Non eHealth intervention	Glucose cholesterol, nutrition

Table 4. *Continued*

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
McLeod2020	429 T2DM and pre-diabetes patients	62.1	50.9	2-arm; New Zealand	13-month web-based intervention aimed at physical activity and nutrition	Human-supported, remote, major, professional	Usual care	blood pressure, glucose, weight, physical activity behavior, nutrition
McMahon2012	152 T2DM patients	61.0	7.0	3-arm*; USA	12-month web-based intervention aimed at physical activity and nutrition	Human-supported, remote, major, professional	Non eHealth intervention	Glucose, cholesterol, weight
Mensorio2019	106 at-risk population	N.A.	N.A.	2-arm; Spain	3-month web-based intervention aimed at physical activity and nutrition	Self-help	Usual care	Weight, physical activity behavior
Murray2018	374 T2DM patients	64.8	71.0	2-arm; UK	12-month web-based interventions aimed at physical activity, nutrition, smoking, alcohol intake.	Self-help	Other eHealth intervention	Blood pressure, glucose
Nolan2018	264 at-risk population	57.6	58.5	2-arm; Canada	3-month Web-based intervention aimed at nutrition, smoking and physical activity	Self-help	Other eHealth intervention	Blood pressure, cholesterol, cardiovascular composite score
Orsama2013	56 T2DM patients	61.9	46.0	2-arm; Finland	10-month Web-based and mobile-based intervention aimed at nutrition and physical activity	Human-supported, remote, minor, professional	Usual care	Blood pressure glucose, weight,
Paldán2021	47 CVD patients	65.1	46.0	2-arm; Germany	6-month mobile-based intervention aimed at physical activity	Self-help	Usual care	Physical activity capacity, physical activity behavior

Table 4. *Continued*

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
Park2021	60 CVD patients	66.8	21.5	2-arm; USA	2-month mobile-based intervention aimed at physical activity	Human-supported, remote, major, layperson	Non eHealth intervention	Physical activity capacity, physical activity behavior
Peacock2020	204 at-risk population	63.5	36.0	2-arm; UK	3-month Web-based intervention aimed at physical activity	Human-supported, blended, major, professional	Non eHealth intervention	Blood pressure, glucose, cholesterol, weight, physical activity behavior
Plotnikoff2017	84 T2DM and at-risk patients	44.7	70.2	2-arm; Australia	5-month web-based intervention aimed at physical activity	Human-supported, blended, major, professional	Waitlist	Blood pressure, weight, physical activity capacity, physical activity behavior
Quinn2011	213 T2DM patients	52.6	50.0	4-arm*; USA	12-month web-based and mobile-based intervention aimed at physical activity and nutrition	Self-help	Usual care	Blood pressure, glucose, cholesterol
Riangkam2021	129 T1DM patients	51.5	39.6	3-arm; Thailand	3-month mobile-based intervention aimed at	Human-supported, blended, major, layperson	Usual care	Glucose
Richard2019	2724 CVD, diabetes or at-risk patients	69.0	47.7	2-arm; The Netherlands, Finland, France	18-month web-based intervention aimed at nutrition, smoking and physical activity	Human-supported, remote, minor, professional	Other eHealth intervention	Cholesterol, cardiovascular composite score, physical activity capacity, physical activity behavior, smoking, nutrition
Siebmanns2021	48 CVK patients	72.5	35.5	2-arm; Sweden	2-month web-based intervention aimed at sleep	Human-supported, remote, major, professional	Other eHealth intervention	Sleep

Table 4. *Continued*

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
Skobel2017	118 CVD patients	59.0	11.0	2-arm; Spain, Germany, UK	6-month web and mobile-based intervention aimed at physical activity	Human-supported, remote, minor, professional	Usual care	Cholesterol, physical activity capacity
Smith2009	41 at-risk population	43.5	N.A.	2-arm; USA	4-month web-based intervention aimed at physical activity	Human-supported, remote, minor, layperson	Waitlist	Blood pressure, glucose, insulin, cholesterol, weight, cardiovascular composite score, physical activity capacity, physical activity behavior
Spring2017	96 at-risk population	40.2	86.0	3-arm; USA	6-month mobile-based intervention aimed at nutrition and physical activity	Human-supported, blended, major, professional	Non eHealth intervention	Weight
Su2021	146 CVD patients	55.8	32.9	2-arm; China	3-month mobile-based intervention aimed at nutrition, stress, smoking	Human-supported, remote, minor, professional	Usual care	Blood pressure, glucose, weight, physical activity behavior
Tanaka2018	112 at-risk population	46.7	0.7	2-arm; Japan	2-month mobile-based intervention aimed at nutrition	Human-supported, remote, major, professional	Waitlist	Blood pressure, cholesterol, weight, nutrition
Tang2013	415 T2DM patients	53.8	40.1	2-arm; USA	12-month Web-based intervention aimed at physical activity and nutrition	Human-supported, remote, major, layperson	Usual care	Blood pressure, glucose, cholesterol, weight, cardiovascular composite score
Thomas2015	154 at-risk population	53.2	79.9	2-arm; USA	3-month web-based intervention aimed at physical activity	Human-supported, blended, minor, professional	Other eHealth intervention	Blood pressure, glucose, weight
Tjam2006	57 T1DM and T2DM patients	N.A.	53.2	2-arm; USA	12-month Web-based intervention aimed at	Human-supported, major, remote, professional	Usual care	Glucose, Cholesterol

Table 4. *Continued*

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
Tomita2009	40 CVD patients	75.9	68.8	2-arm; USA	12-month web-based intervention aimed at	Human-supported, minor, professional	Usual care	Blood pressure, sleep
Turnin2021	282 T2DM patients	59.6	36.9	2-arm; France	12-month web-based and mobile-based intervention aimed at physical activity and nutrition	Self-help	Usual care	Glucose
Van der Weegen2013	199 T1DM and T2DM patients	58.4	53.4	3-arm; The Netherlands	6-month web-based and mobile-based intervention	Human-supported, major, blended, professional	Usual care	Physical activity behavior
Vluggen2021	478 T2DM patients	60.2	32.5	2-arm; The Netherlands	6-month mobile-based intervention aimed at physical activity and nutrition	Self-help	Waitlist	Physical activity behavior
Vogel2017	36 CVD patients	62.8	0	2-arm; Austria	1.5-month mobile-based intervention aimed at physical activity	Self-help	Usual care	Physical activity capacity
Watson2015	65 at-risk population	52.2	55.5	2-arm; UK	12-month web-based intervention aimed at nutrition and physical activity	Self-help	Usual care	Blood pressure, cholesterol, weight, nutrition
Wayne2015	131 T2DM patients	53.2	72.5	2-arm; Canada	6-month mobile-based intervention aimed at nutrition and physical activity	Human-supported, blended, major, professional	Non eHealth intervention	Glucose, weight
Widmer2017	80 CVD patients	63.1	18.5	2-arm; USA	3-month mobile- and web-based intervention aimed at physical activity, nutrition, and smoking	Self-help	Usual care	Blood pressure, glucose, cholesterol, weight, physical activity behavior, nutrition

Table 4. *Continued*

Study	Participants	Age (mean)	Gender (% female)	RCT setting	Intervention group(s)	Support type	Control group	Outcomes types
Widyanata2019	65 T2DM patients	N.A.	56.7	2-arm; Indonesia	3-month mobile-based intervention aimed at nutrition and physical activity	Self-help	Waitlist	Glucose, insulin cholesterol,
Wong2020	438 CVD patients	52.4	34.5	2-arm; China	6-month web-based intervention aimed at physical activity	Self-help	Usual care	Blood pressure, cholesterol physical activity behavior
Wong2021	77 at-risk population	59.0	55.8	2-arm; China	3-month mobile-based intervention aimed at physical activity, stress and nutrition	Self-help	Non eHealth intervention	Blood pressure, glucose, cholesterol, weight, physical activity behavior
Wongrochan-anan 2015	126 T2DM patients	52.5	46.8	2-arm; Thailand	3-month web-based intervention aimed at physical activity, and nutrition.	Self-help	Usual care	Blood pressure, glucose, cholesterol, weight, nutrition
Yu2019	92 T2DM patients	52.3	29.7	2-arm; China	6-month mobile-based intervention aimed at nutrition and physical activity	Human-supported, remote, major, professional	Usual care	Blood pressure, glucose, weight
Yudi2021	206 CKD patients	56.5	31.2	2-arm; USA	2-month mobile-based intervention aimed at physical activity	Human-supported, remote, minor, professional	Usual care	Glucose, cholesterol, weight, physical activity behavior, smoking
Zhang2019	156 T1DM and T2DM patients	53.5	39.1	2-arm; China	6-month mobile-based intervention aimed at nutrition and physical activity	Human-supported, remote, major, professional	Usual care	Glucose, cholesterol, weight

*multiple control conditions, only the least extensive condition was extracted
CVD = cardiovascular disease; CKD = chronic kidney disease; T1DM = type 1 diabetes mellitus; T2DM = type 2 diabetes mellitus

CHAPTER 4 | APPENDIX 3

Table 5. Risk of bias assessment of the included studies.

Study	D1	D2	D3	D4	D5	Overall
Agarwal2019(a)	!	!	+	+	+	!
Agarwal2019(b)	!	!	+	+	+	!
Akinci2019	+	+	+	+	+	+
Appel2011	!	-	-	!	+	-
Baer2020	+	+	!	+	+	!
Bailey2020	!	!	+	+	+	!
Bennett2010	+	+	+	+	!	!
Bennett2018	+	+	+	+	!	!
Bond2007	!	!	+	+	!	!
Bozorgi2021	+	!	+	!	!	!
Cai2021	!	!	+	+	!	!
Chao2019	!	!	+	-	!	-
Choi2019	!	+	+	+	+	!
Chow2020	!	!	+	+	!	!
Connely2017	+	!	+	+	+	!
Dorje2019	+	+	+	+	+	+
Dorsch2020	!	!	+	!	+	!
Duan2018	!	!	+	!	!	!
Duscha2018	!	+	+	+	!	!
Engelen2020	+	+	-	!	!	-
Fukuoka2015	+	!	+	!	!	!
Glasgow2012	+	+	+	!	!	!
Gong2020	+	+	+	+	!	!
Grau-Pellicer2020	!	!	+	!	!	!
Gunawardena2019	+	+	!	+	!	!
Hanswel2017	!	+	+	+	!	!
Haste2017	+	!	!	+	!	!
Hilmarsdóttir2021	+	+	+	+	!	!
Höchsmann2019	+	+	+	+	+	+

Table 5. *Continued*

Study	D1	D2	D3	D4	D5	Overall
Holmen2014	+	+	+	+	+	+
Houchen-Wolloff2018	+	!	!	+	!	!
Humalda2020	+	+	+	+	!	!
Imanaka2014	!	+	+	+	!	!
Jahangiry2015	!	+	-	+	!	-
Javaheri2020	!	!	+	+	+	!
Johnston2016	!	!	+	+	+	!
Keyserling2014	-	!	+	!	!	-
Khanji2019	+	+	+	+	+	+
Kim2006	!	!	+	+	+	!
Kim2016	+	!	+	!	+	!
Kim2019	+	!	!	+	!	!
Kirwan2013	!	!	+	+	!	!
Kooiman2018	!	+	+	+	!	!
Kouwenhoven-Pasmooij2018	+	+	+	!	-	-
Ku2020	!	!	+	+	!	!
Kulick2013	+	!	+	!	!	!
Kumar2020	+	!	+	+	!	!
Lear2014	+	+	+	+	!	!
Lee2018	+	!	+	!	!	!
Lee2020	+	!	+	!	!	!
Li2019	-	!	+	+	+	-
Li2020	!	!	+	+	!	!
Liebreich2009	!	+	+	!	!	!
Lim2021	+	+	+	+	+	+
Lindberg2017	+	+	-	+	-	-
Lisón2020	+	+	!	+	!	!
Little2017	+	+	+	+	!	!
Lorig2006	!	!	+	!	!	!
Lorig2010	!	+	+	!	!	!
Lunde2020	+	!	+	+	!	!

Table 5. *Continued*

Study	D1	D2	D3	D4	D5	Overall
Maddison2015	+	+	!	!	+	!
Maddison2019	+	+	+	+	+	+
McDermott2018	!	+	+	+	+	!
McKay2001	!	!	+	!	!	!
McKay2002	!	!	+	!	!	!
McLeod2020	+	+	+	+	+	+
McMahon2012	+	+	+	+	!	!
Mensorio2019	+	+	–	+	+	–
Murray2018	!	+	+	+	!	!
Nolan2018	+	+	!	+	!	!
Orsama2013	!	!	!	+	!	!
Paldán2021	!	!	+	+	+	!
Park2021	!	!	!	+	!	!
Peacock2020	+	+	+	+	+	+
Plotnikoff2017	+	+	!	+	+	!
Quinn2011	!	+	–	+	+	–
Riangkam2021	+	+	+	+	!	!
Richard2019	!	+	+	+	+	!
Siebmanns2021	!	+	!	!	!	!
Skobel2017	!	!	–	+	!	–
Smith2009	!	+	+	+	!	!
Spring2017	+	+	–	+	!	–
Su2021	+	!	+	+	+	!
Tanaka2018	!	+	+	+	!	!
Tang2013	!	+	+	+	!	!
Thomas2015	+	+	+	!	!	!
Tjam2006	!	!	!	+	!	!
Tomita2009	!	+	+	!	!	!
Turnin2021	!	+	+	+	!	!
Van der Weegen2013	+	+	!	+	+	!
Vluggen2021	+	+	+	!	+	!

Table 5. *Continued*

Study	D1	D2	D3	D4	D5	Overall
Vogel2017	+	+	+	+	!	!
Watson2015	+	+	+	+	!	!
Wayne2015	+	+	+	+	!	!
Widmer2017	!	!	!	+	!	!
Widyanata2019	!	!	-	+	!	-
Wong2020	!	+	+	+	!	!
Wong2021	+	+	+	+	!	!
Wongrochananan2015	!	+	!	!	!	!
Yu2019	+	+	+	+	!	!
Yudi2021	+	+	+	+	+	+
Zhang2019	+	+	+	+	!	!

Domain 1: Risk of bias arising from the randomization process
Domain 2: Risk of bias due to deviations from the intended interventions
Domain 3: Risk of bias due to missing outcome data
Domain 4: Risk of bias in measurement of the outcome
Domain 5: Risk of bias in selection of the reported result

+	Low risk
!	Some concerns
-	High risk

5

USE INTENTION AND USER EXPECTATIONS OF HUMAN-SUPPORTED AND SELF-HELP EHEALTH INTERVENTIONS: AN INTERNET-BASED RANDOMIZED CONTROLLED TRIAL

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ABSTRACT

Background: Self-help eHealth interventions provide automated support to change health behaviors without any further human assistance. The main advantage of self-help eHealth interventions is that they have the potential to lower the workload of health care professionals. However, one disadvantage is that they generally have a lower uptake. Possibly, the absence of a relationship with a health care professional (referred to as the working alliance) could lead to negative expectations that hinder the uptake of self-help interventions. The Unified Theory of Acceptance and Use of Technology (UTAUT) identifies which expectations predict use intention. As there has been no previous research exploring how expectations affect the adoption of both self-help and human-supported eHealth interventions, this study is the first to investigate the impact of expectations on the uptake of both kinds of eHealth interventions.

Objective: This study investigated the intention to use a self-help eHealth intervention compared to a human-supported eHealth intervention and the expectations that moderate this relationship.

Methods: A total of 146 participants were randomly assigned to 1 of 2 conditions (human-supported or self-help eHealth interventions). Participants evaluated screenshots of a human-supported or self-help app–based stress intervention. We measured intention to use the intervention-expected working alliance and the UTAUT constructs: performance expectancy, effort expectancy, and social influence.

Results: Use intention did not differ significantly between the 2 conditions (t_{142}=–1.133; P=.26). Performance expectancy ($F_{1,140}$=69.269; P<.001), effort expectancy ($F_{1,140}$=3.961; P=.049), social influence ($F_{1,140}$=90.025; P<.001), and expected working alliance ($F_{1,140}$=26.435; P<.001) were positively related to use intention regardless of condition. The interaction analysis showed that performance expectancy ($F_{1,140}$=4.363; P=.04) and effort expectancy ($F_{1,140}$=4.102; P=.045) more strongly influenced use intention in the self-help condition compared to the human-supported condition.

Conclusions: As we found no difference in use intention, our results suggest that we could expect an equal uptake of self-help eHealth interventions and human-supported ones. However, attention should be paid to people who have doubts about the intervention's helpfulness or ease of use. For those people, providing additional human support would be beneficial to ensure uptake. Screening user expectations could help health care professionals optimize self-help eHealth intervention uptake in practice.

Keywords: eHealth, use intention, human support, working alliance, UTAUT

INTRODUCTION

eHealth provides the opportunity to provide remote or automated health care support through digital tools (Barak et al., 2009). eHealth is becoming increasingly relevant, for example, because of the physical restrictions during the recent COVID-19 outbreak (Bokolo, 2021). During this pandemic, the demand for health care support increased too. Especially vulnerable groups experienced increased mental health difficulties (Browning et al., 2021; Husky et al., 2020), which require professional support. However, health care professionals already have a high workload and pressure (Simionato & Simpson, 2018) and, in some cases, even experience an additional workload from using eHealth (Bellicha et al., 2017). Self-help eHealth interventions might provide a potential solution to these problems. Self-help eHealth interventions are defined as interventions in which automated support instead of human assistance is provided (Barak et al., 2009). As this means that no human professionals are involved, self-help eHealth interventions are easier and cheaper to widely implement (Barak et al., 2009).

Despite these advantages, self-help interventions generally deal with low levels of adherence (Kelders et al., 2012; Kelders et al., 2011; Murray et al., 2013; Wangberg et al., 2008) and low uptake (Lillevol et al., 2014; Lin et al., 2018). People generally show a higher intention to start with lifestyle changes using an intervention with additional human assistance compared to a self-help intervention (Apolinário-Hagen, 2017). While there has been extensive research on the factors contributing to nonadherence, there is a notable gap in our understanding when it comes to expectations that influence whether individuals will choose to use an intervention before starting. This information is important, as a growing number of eHealth tools are being developed and proven to be effective but hardly used (Ross et al., 2016; Van Gemert-Pijnen et al., 2011). Therefore, the aim of this study is to investigate whether there is a difference in use intentions between self-help and human-supported eHealth interventions and if user expectations influence the intention to use the intervention. If we know what expectations drive people's intention to either use self-help or human-supported eHealth interventions, we could predict and even influence their actual uptake (Venkatesh et al., 2003).

A possible explanation for the low use intention of self-help interventions could be the lack of a relationship with a health care professional (Brandt et al., 2018). This so-called working alliance, the degree to which a health care professional and patient is involved in a useful and collaborative working relationship (Hatcher & Barends, 2006), is an important predictor of intervention adherence and effectiveness (Goldberg et al., 2013; Martin et al., 2000). People are more engaged with the intervention and motivated to work on their goals when they feel supported. This effect is not exclusive to face-to-face settings; it is also evident when internet-based human assistance is involved in the use of eHealth interventions (Flückiger et al., 2018; Sucala et al., 2012). It is even shown to be present in self-help eHealth interventions with automated support, using, for example, a human avatar (Bickmore et al., 2010; Clarke et al., 2016; Hauser-Ulrich et al., 2020). Thus, people can form relationships not only with other people but also with technology (Nass & Moon, 2000). Therefore, we predict that people's expectations toward a potential future working alliance when using an eHealth intervention will influence their intention to use that intervention.

Other important expectations that may influence the use intention of human-supported and self-help eHealth interventions can be found within the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). According to this model, 3 different types of expectations explain people's intention to start with an eHealth intervention. These UTAUT expectations are (1) performance expectancy: the extent to which someone expects that the eHealth intervention will be helpful in reaching their goals; (2) effort expectancy: the extent to which someone expects that the eHealth intervention will be easy to use; and (3) social influence: the extent to which someone expects that important others believe one should use the eHealth intervention (Venkatesh et al., 2003). Although the UTAUT model has been used to explain people's intention to use eHealth in general (Alharbi, 2021; Duarte & Pinho, 2019), to our knowledge, no studies have used this model to investigate differences in people's intention to use either human-supported or self-help eHealth interventions.

In this study, we aim to investigate (1) whether there is a difference in use intention between human-supported and self-help eHealth interventions, (2) whether the expected working alliance predicts the use intention of human-supported and self-help eHealth interventions, and (3) what UTAUT constructs predict the use intention of human-supported and self-help eHealth interventions.

MATERIAL AND METHODS

Design and Sample

In an experiment, people were presented with a sham stress management app. In this app, people would either be supported by a human coach or by an automated coach. We decided to use a student sample, as they experience high levels of stress and could therefore benefit from an eHealth stress intervention (Stallman, 2010), especially given their increased need for support during the COVID-19 pandemic (Browning et al., 2021; Husky et al., 2020). They were asked to evaluate the screenshots of the app and measure their use intention, the 3 UTAUT constructs (performance expectancy, effort expectancy, and social influence), and their expected working alliance. We used a randomized between-participants design with 2 experimental conditions (human-supported or self-help eHealth interventions). Healthy participants aged 18 years or older, who had a sufficient level of grasp in English, were recruited on the campus of Leiden University with internet-based and offline flyers. Power calculations (Faul et al., 2007) identified a minimum sample size of 119 to detect a medium effect (f^2=0.15) with an α of .05, based on a linear multiple regression with 3 predictors.

Procedure and Manipulation

Interested participants could open the internet-based questionnaire and would be offered the internet-based consent form. After reading and agreeing to the informed consent, participants were automatically randomized into 1 of 2 experimental conditions (human-supported or self-help eHealth interventions). In both conditions, participants were instructed to evaluate a nonexistent stress management app for students called “Bye Bye Stress.” They were asked to carefully assess the screenshots of the app and give feedback to help the researchers make the app fit the needs of students. Although the design of the app and the content of the intervention were identical in both conditions, the conditions differed in the type of support that would be offered in the app. In the human-supported condition, the description of the app explained how a human coach would support the participants and provide them feedback. The screenshots of the app showed a picture of a human coach and messages with a human tone of voice (Figure 1). In the self-help condition, the description of the app explained how participants would receive automated feedback. In the screenshots, there was no picture of a human being, and the messages had a neutral tone of voice (Figure 1). All screenshots used in both conditions can be found in Multimedia Appendix 1. After this, participants were asked to complete the questionnaire.

Figure 1. Example screenshot of the app for human-supported (left) and self-help conditions (right).

Measures

Use Intention

The behavioral intention subscale of the UTAUT questionnaire (Venkatesh et al., 2003) was used to assess use intention. The subscale consists of 3 items (eg, "I would intend to use 'Bye Bye Stress' in the next 6 months.") measured on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A higher score indicates a higher intention to use the app. The scale showed a high internal consistency (Cronbach α=.953).

Expected Working Alliance

The expected working alliance was measured with an adjusted version of the Working Alliance Inventory–Short Revised form (WAI-SR) (Hatcher & Gillaspy, 2006), which consists of 12 items measured on a 5-point Likert-type scale ranging from 1 (seldom) to 5 (always). Questions were adjusted to fit the context of the study by using the words "coach," "lifestyle," and "intervention" and being written in the future tense (eg, "The coach and I will collaborate on setting lifestyle goals."). A higher score indicates a stronger expected working alliance. The adjusted version had a high internal consistency (Cronbach α=.917).

Performance Expectancy, Effort Expectancy, Social Influence

The constructs predicting behavioral intention according to the UTAUT model—performance expectancy, effort expectancy, and social influence—were measured with the corresponding UTAUT subscales (Venkatesh et al., 2003). Each subscale consisted of 4 items (eg, "I find 'Bye Bye Stress' useful."), measured with a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A higher score indicates a higher expectation of the app's efficacy in helping the participant, a higher expectation toward the ease of use of the app, and a higher expectation that important others will approve the use of the app. The performance expectancy, effort expectancy, and social influence subscales all had sufficient internal consistency (Cronbach α of .764, .730, .792, respectively).

Manipulation Check

To assess whether participants carefully read the information and whether the manipulation had worked, they were asked to complete a manipulation check question ("During the intervention, I would be supported by…" followed by several options, such as "doctor" or "chatbot").

Analyses

To test whether there was a difference in use intention between conditions, we ran a 2-tailed independent-sample *t* test with use intention as the dependent variable and condition (human-supported vs self-help eHealth interventions) as the independent variable. To test whether the association between condition and use intention differed for different levels of the working alliance, we conducted a univariate general linear model (GLM) analysis with interactions. We added use intention as the dependent variable, condition as a fixed factor, and expected working alliance as a covariate. We analyzed both the main effects of condition and expected working alliance, as well as their interaction effect on use intention. To further investigate the interaction patterns found in the data, we conducted a simple slopes analysis. To formulate the simple slope equations for both the human-supported condition and the self-help condition, the intercept and the slope were obtained from the parameter estimates of the GLM analysis testing the association between expected working alliance and use intention.

To test whether the association between condition and use intention differed for different levels of the UTAUT constructs of performance expectancy, effort expectancy, and social influence, we conducted 3 univariate GLM analyses with interactions. We added use intention as dependent variable, condition as fixed factor, and each of the UTAUT constructs (performance expectancy, effort expectancy, or social influence) as a covariate in 3 separate analyses. We analyzed both the main effects of condition and the UTAUT construct, as well as their interaction effect on use intention. To further investigate the interaction patterns found in the data, we again conducted 3 simple slopes analyses: the intercept and the slope were obtained for both conditions from the parameter estimates of the GLM analyses testing the association between the UTAUT construct and use intention.

Statistical analyses were conducted with SPSS (version 26; IBM Corp) with a significance level set at $P \leq .05$.

Ethical Considerations

The study was approved by the Psychology Research Ethics Committee of Leiden University (CEP19-1125/557). Furthermore, the study was preregistered through the Center for Open Science (Cohen Rodrigues & Reijnders, 2021). Before the start of the study, participants were asked to sign an informed consent form. After completing all the questionnaires, they were debriefed and provided with a few examples of real internet-based stress management interventions in case they needed one. As compensation, participants received course credits.

RESULTS

Demographics

A total of 146 students participated in our study and completed the questionnaire. Their mean age was 21.8 (SD 4.51) years, 103 (70.5%) were female, and 104 (71.2%) were of Dutch nationality (Table 1). There were no significant differences in demographic characteristics between the 2 groups.

Table 1. Baseline demographic characteristics.

Variable	Total sample (N = 146)	Human-supported condition (n = 73)	Self-help condition (n = 73)
Age (years), mean (SD)	21.8 (4.5)	22.0 (4.6)	21.6 (4.4)
Female, n (%)	103 (70.5)	47 (66.2)	56 (76.7)
Nationality, n (%)			
Dutch	104 (71.2)	49 (67.1)	55 (75.3)
European (non-Dutch)	37 (10)	20 (27.4)	17 (23.3)
Other	5 (3.4)	4 (5.5)	1 (1.4)

Use intention per condition

We found no significant difference in use intention between the human-supported condition and self-help condition (t_{142}=–1.133; *P*=.26; Table 2). Furthermore, we found no differences between the 2 conditions in any of the other constructs (Table 2).

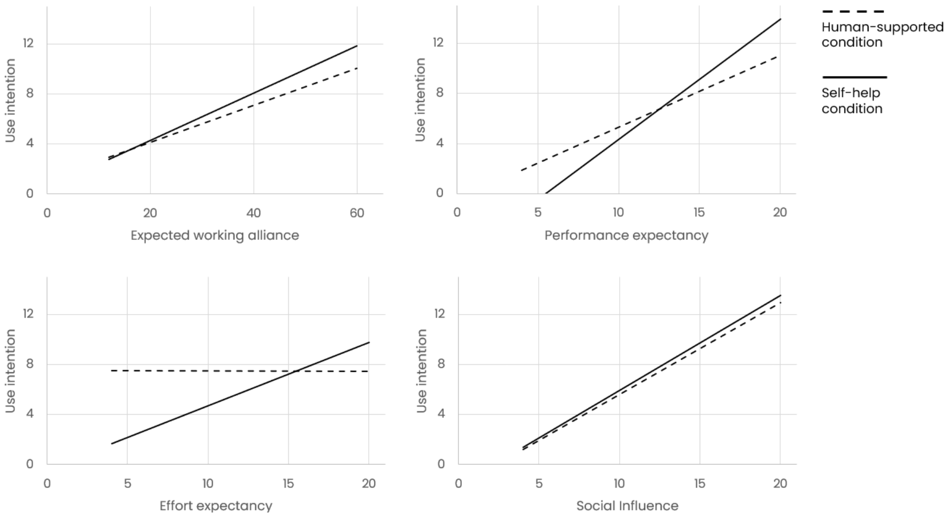
Table 2. Mean scores and SDs of use intention and its predictors.

Variable (scoring range)	Human-supported condition (n = 73), mean (SD)	Self-help condition (n = 73), mean (SD)	*P* value
Use intention (3-15)	7.5 (3.6)	8.2 (3.6)	.26
Expected working alliance (12-60)	42.3 (8.2)	40.3 (8.7)	.16
Performance expectancy (4-20)	13.8 (2.9)	14.0 (2.5)	.69
Effort expectancy (4-20)	16.9 (2.4)	16.8 (2.3)	.94
Social influence (4-20)	12.5 (2.9)	12.9 (3.1)	.66

Working Alliance and Use Intention

The GLM showed no significant association between condition and expected working alliance ($F_{1,140}$=0.051; *P*=.82; η^2=0). However, we did find a significant positive association between expected working alliance and use intention ($F_{1,140}$=26.435; *P*<.001; η^2=0.159). We found no significant interaction effect of condition and expected working alliance on use intention ($F_{1,140}$=0.367; *P*=.55; η^2=0.003; Figure 2).

Figure 2. Simple slopes of the effects of expected working alliance, performance expectancy, effort expectancy, and social influence on use intention.



UTAUT Constructs and Use Intention

The GLM showed no significant association between condition and performance expectancy ($F_{1,140}$=3.34; P=.07; η^2=0.024). We did, however, find a significant positive association between performance expectancy and use intention ($F_{1,140}$=69.269; P<.001; η^2=0.331) and a significant interaction effect of condition and performance expectancy on use intention ($F_{1,140}$=4.363; P=.04; η^2=0.030). An increase in performance expectancy was related to a greater increase in use intention in the self-help condition compared to the human-supported condition (Figure 2).

We also found no significant association between condition and effort expectancy ($F_{1,140}$=3.4086; P=.07; η^2=0.024). However, again, we did find a significant positive association between effort expectancy and use intention ($F_{1,140}$=3.961; P=.049; η^2=0.028) and a significant interaction effect of condition and effort expectancy on use intention ($F_{1,140}$=4.102; P=.045; η^2=0.028). An increase in effort expectancy was related to a greater increase in use intention in the self-help condition but not in the human-supported condition (Figure 2).

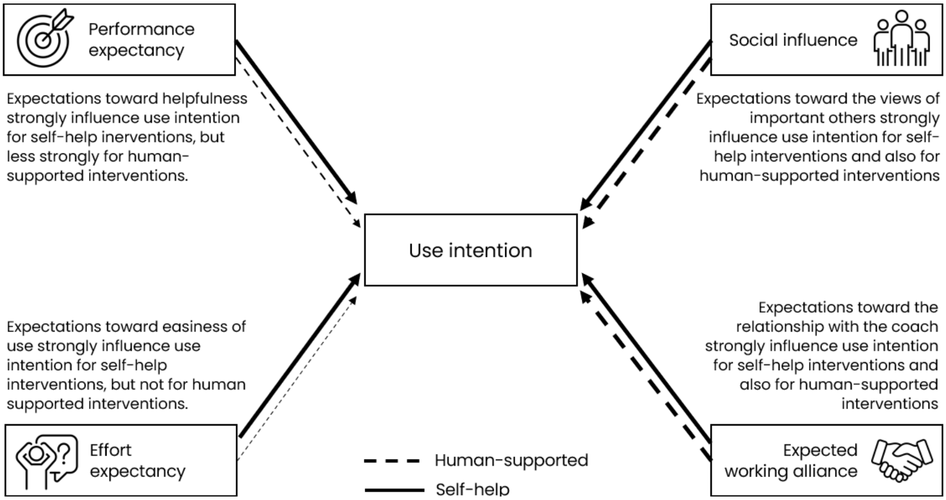
Again, we found no significant association between condition and social influence ($F_{1,140}$=0.003; P=.96; η^2=0). We did find a significant positive association between social influence and use intention ($F_{1,140}$=90.025; P<.001; η^2=0.391) but this time we found no significant interaction effect of condition and social influence on use intention ($F_{1,140}$=0.020; P=.89; η^2=0; Figure 2).

DISCUSSION AND CONCLUSION

Overview

In our study, we asked university students to evaluate a sham stress management app. We aimed to investigate whether there is a difference in use intention for self-help eHealth interventions compared to human-supported ones and what user expectations may influence this. We found that people were as likely to start using a self-help eHealth intervention as an eHealth intervention with human support. More than with human-supported interventions, the perception that the intervention might be ineffective or difficult to use limits the intention to start using self-help interventions. See Figure 3 for an overview of the findings.

Figure 3. Overview of study findings.



Although previous studies show a relatively low uptake and use intention of self-help eHealth interventions (Apolinário-Hagen, 2017; Lillevol et al., 2014; Lin et al., 2018), we did not find differences in use intentions between the self-help and human-supported interventions. Possibly, the health beliefs, perceptions, and skills of our student sample might have played a role in this (van der Waal et al., 2022). Not only do perceptions about the effectiveness or ease of use of an eHealth tool affect the start of an intervention but also perceptions about the risks of getting health-related problems and actually performing the health-promoting behavior (Rosenstock, 1974). Furthermore, a younger age and higher educational level are related to a higher intention to start eHealth interventions in general (Apolinário-Hagen, 2017). Our sample might therefore have been more open to using eHealth interventions and were less influenced by the presence, or lack thereof, of human support. Future research could focus on investigating the role of age and educational level on use intentions of self-help and human-supported eHealth interventions. Another explanation for the differences in findings between our and previous studies (Lillevol et al., 2014; Lin et al., 2018) could be the use of different outcome measures. Although the UTAUT model predicts that use intention can predict actual use, studies do show that people have difficulties translating their intentions into actual behavior (Webb & Sheeran, 2006). The objective measure of uptake might therefore have led to different results compared to the more subjective measure of use intention we used, which would be interesting to additionally take into account. Finally, the study that did find a difference in use intention between self-help and human-supported interventions focused on interventions for mental health, such as depression (Apolinário-Hagen, 2017). It would be interesting to test if the need for social support during eHealth interventions depends on the goal of the intervention (eg, psychological vs lifestyle improvements).

Interestingly, we found that an expected working alliance has an equally strong effect on the intention to use either a human-supported or self-help intervention. This result is in line with previous studies showing a positive effect of working alliance on intervention effectiveness and adherence, both within human-supported (Flückiger et al., 2018; Sucala et al., 2012) and self-help eHealth interventions with automated support (Bickmore et al., 2010; Clarke et al., 2016; Hauser-Ulrich et al., 2020). Our findings show that working alliance is not important only during an intervention but even before the intervention has started in the form of expectations. The similar effect of the expected working alliance in both conditions suggests that people not only are able to actually have relationships with technology (Nass & Moon, 2000) but also seem to expect building one with the technology they are about to interact with. These results would also mean that improving the expected working alliance before the start of an intervention (eg, by designing a digital character that would welcome the user) would be a way to possibly increase the uptake of self-help eHealth interventions.

Finally, we found that performance and effort expectancy had a stronger effect on the use intention of self-help interventions compared to human-supported interventions. Not only the UTAUT model but also models such as the Health Belief model show that perceived benefits and perceived barriers affect whether people start with a health-promoting behavior, such as stress management (van der Waal et al., 2022). What is new, though, is that the perceived effectiveness and ease of use of the intervention have a more pronounced impact on intention to use an intervention for interventions with an absence of human support compared to interventions where human support is available. This suggests that the perception that the intervention might be ineffective or difficult to use diminishes the intention to start using a self-help intervention but not the intention to start using a human-supported intervention. Meta-analyses show that the mere presence of a human being (even a nonprofessional) is a key ingredient in intervention effectiveness and the prevention of dropout (Etzelmueller et al., 2020; Kayotaki et al., 2018; Richards & Richardson, 2012). Just the option of having someone available to provide procedural support (related to performance expectancy) or technical support (related to effort expectancy) seems to be enough for people to be motivated to start something new. The presence of a human coach could act as a buffer against negative expectations, which would make it easier for these people to adhere to the intervention (Miller & DiMatteo, 2013). Possibly, the mere presence of social support in the human-supported intervention could compensate for a lack of self-efficacy (the extent to which one believes in his or her own capabilities (Bandura et al., 1999)) that people may feel when using a new intervention (Fernández et al., 2014; Zhou et al., 2017). This could lower the perceived barriers and increase willingness to start using the intervention (van der Waal et al., 2022). Exploring this further is crucial in a clinical context because individuals with limited social support tend to experience reduced adherence to health interventions and demonstrate less favorable intervention outcomes (Lindfors et al., 2014; Miller & DiMatteo, 2013). Even despite the relatively high use intention of self-help eHealth interventions, these results indicate that it is important to take the user's needs and wishes into account when deciding on the level of human support to provide during an intervention.

Self-help eHealth interventions will become more and more important in health care practice. To ensure uptake of new eHealth interventions, professionals could screen the user's expectations toward the intervention's helpfulness and ease of use beforehand (Table 3). If the user's expectations turn out to be low, it would be useful to incorporate some level of human support into the eHealth intervention to prevent people from dropping out even before the start of the intervention. Additionally, designers of self-help eHealth interventions could pay extra attention toward its perceived helpfulness and ease of use. Preventing negative user expectations toward the intervention's performance or effort expectancy could help increase the uptake of self-help eHealth interventions.

Table 3. Items of the Unified Theory of Acceptance and Use of Technology subscales: performance expectancy (PE) and effort expectancy (EE).

Item	Statement
PE1	I find [name eHealth technology] useful.
PE2	Using [name eHealth technology] enables me to [target behaviour].
PE3	Using [name eHealth technology] will [target behaviour].
PE4	If I use [name eHealth technology] I will know how to [target behaviour].
EE1	My interaction with [name eHealth technology] is clear and understandable.
EE2	It would be easy for me to develop the skills needed to use [name eHealth technology].
EE3	I think [name eHealth technology] would be easy to use.
EE4	It would be easy to learn how to operate [name eHealth technology].

Strengths and Limitations

Our study was not without limitations. For example, although the screenshots of the app were adjusted to the experiences and interests of our sample, it is plausible that the topic of stress management was not equally relevant for all students, which could also have affected use intentions. For future studies, it would be better to tailor the goal of the eHealth intervention (eg, decreasing stress or improving physical activity) to the actual interests of the individual participants to investigate if and how this affects a participant's use intention. Second, we used a university student population to test our hypotheses. People with a younger age and higher educational level have a more favorable attitude toward eHealth interventions in general (Apolinário-Hagen, 2017). To be able to generalize our findings, future research should investigate whether the same effects are found in other populations. It would be interesting to replicate this study with a target population who would benefit the most from eHealth interventions, for example, older patients with a chronic disease, to see if their expectations toward either human or automated support have similar effects on their intention to start with such interventions.

Conclusions

In our study, we investigated what expectations drive the intention to start using self-help and human-supported eHealth interventions. The results suggest that expectations toward the intervention's helpfulness and ease of use are especially relevant regarding the use of self-help interventions. This means that people who have doubts about the intervention's usefulness or usability would benefit the most from additional human support. The question, however, remains whether such expectations are also relevant for actual uptake. Our study provides a basis to further investigate user expectations within a clinical sample, which will provide health care practitioners with the tools to influence the uptake of eHealth interventions.

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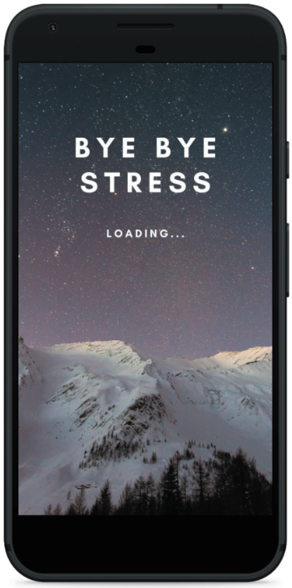
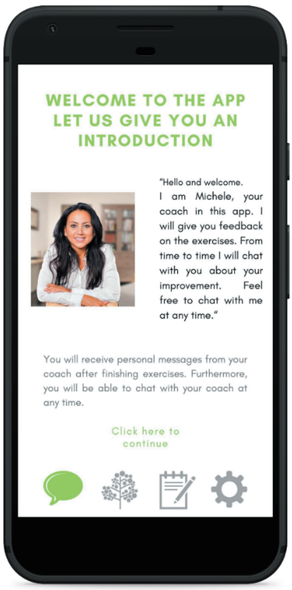
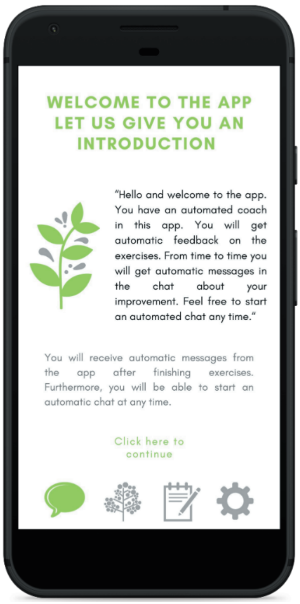
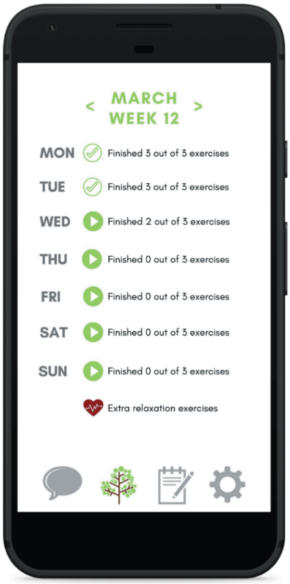
CHAPTER 5 | APPENDIX 1

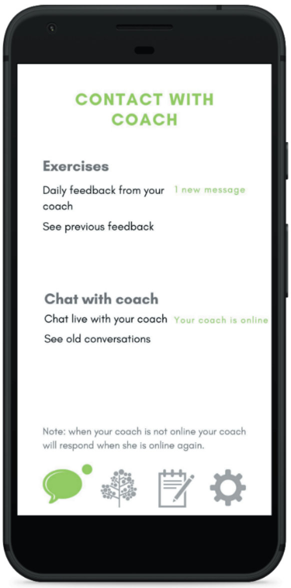
Screenshots shown in human-supported and self-help condition.

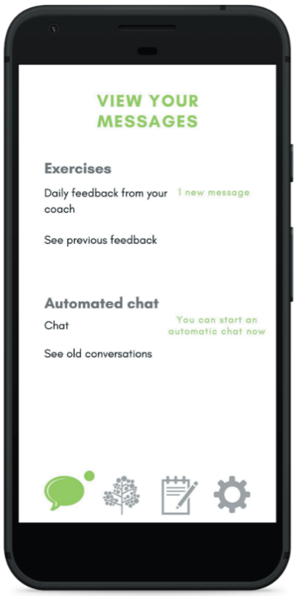
	Human-supported	Self-help
Loading screen		
Welcome screen		

App menu

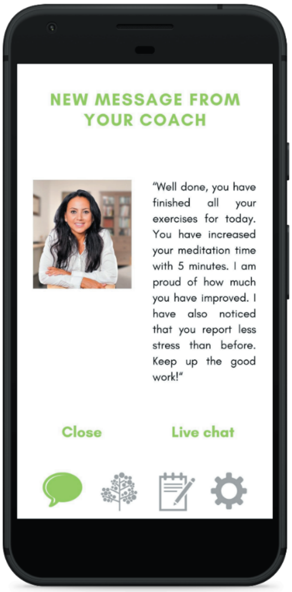


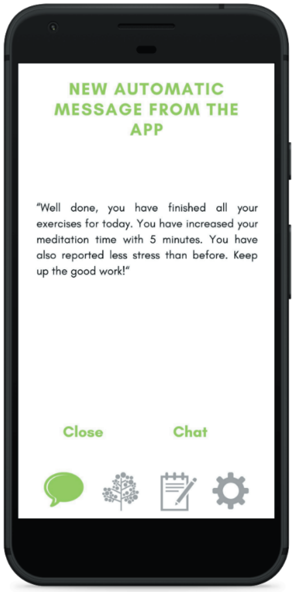
Overview messages



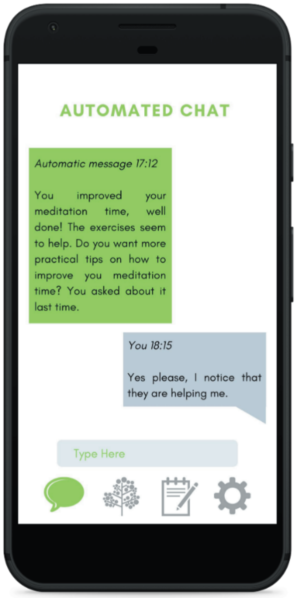


New message

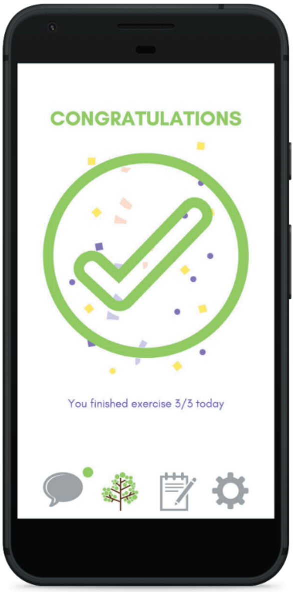
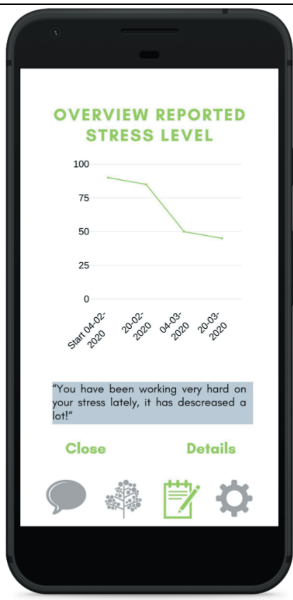




Chat



5

<table>
<tr><td>Exercise completion</td><td>
</td><td></td></tr>
<tr><td>Progress overview</td><td>
</td><td>
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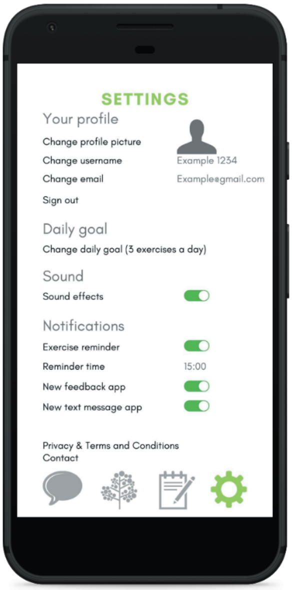
</table>

Settings	 SETTINGS Your profile Change profile picture Change username Change email Sign out Example 1234 Example@gmail.com Daily goal Change daily goal (3 exercises a day) Sound Sound effects Notifications Exercise reminder Reminder time 15:00 New feedback app New text message app Privacy & Terms and Conditions Contact	

6

HUMAN CUES IN EHEALTH TO PROMOTE LIFESTYLE CHANGE: AN EXPERIMENTAL FIELD STUDY TO EXAMINE ADHERENCE TO SELF-HELP INTERVENTIONS

This chapter is accepted for publication in Internet Interventions as:

Cohen Rodrigues, T. R., de Buisonjé, D. R., Reijnders, T., Santhanam, P., Kowatsch, T., Breeman, L. D., Janssen, V. R., Kraaijenhagen, R. A., Atsma, D. E., & Evers, A. W. M. (2024). Human cues in eHealth to promote lifestyle change: An experimental field study to examine adherence to self-help interventions

ABSTRACT

eHealth lifestyle interventions without human support (self-help interventions) are generally less effective, as they suffer from lower adherence levels. To solve this, we investigated whether (1) using a text-based conversational agent (TCA) and applying human cues contribute to a working alliance with the TCA, and whether (2) adding human cues and establishing a positive working alliance increase intervention adherence. Participants (N=121) followed a TCA-supported app-based physical activity intervention. We manipulated two types of human cues: visual (i.e., message appearance) and relational (i.e., message content). We employed a 2 (visual cues: yes, no) x 2 (relational cues: yes, no) between-subjects design, resulting in four experimental groups: (1) visual and relational cues, (2) visual cues only, (3) relational cues only, or (4) no human cues. We measured the working alliance with the Working Alliance Inventory Short Revised form and intervention adherence as the number of days participants responded to the TCA's messages. Contrary to expectations, the working alliance was unaffected by using human cues. Working alliance was positively related to adherence ($t(78)=3.606$, $p=.001$). Furthermore, groups who received visual cues showed lower adherence levels compared to those who received relational cues only or no cues ($U=1140.5$, $z=-3.520$, $p<.001$). We replicated the finding that establishing a working alliance contributes to intervention adherence, independently of the use of human cues in a TCA. However, we were unable to show that adding human cues impacted the working alliance and increased adherence. The results indicate that adding visual cues to a TCA may even negatively affect adherence, possibly because it may create confusion concerning the true nature of the coach, which may prompt unrealistic expectations..

Keywords: eHealth; digital health; lifestyle change; physical activity; intervention; conversational agent; chatbot; adherence; working alliance.

INTRODUCTION

A healthy lifestyle has a positive effect on the number of disease-free years in an adult's life (Nyberg et al., 2020). A multicohort study showed that meeting the recommended physical activity levels, BMI, smoking behavior, and alcohol consumption would lead to an increase of 9.9 disease-free years for men and 9.4 of disease-free years for women (Nyberg et al., 2020). Lifestyle interventions are therefore widely recommended to improve health outcomes such as blood pressure or cholesterol levels (Piepoli et al., 2016). Long-term maintenance of recommended lifestyle behaviors is difficult for most people, yet the uptake and maintenance of lifestyle behaviors can be facilitated by the use of eHealth, which can be defined as the use of new information and communication technology, especially internet technology, to support or enhance health and health care (Barak et al., 2009). An increasing amount of eHealth lifestyle interventions are being developed (Thomas & Bond, 2014), which are shown to be effective in improving lifestyle behaviors (e.g., physical activity) and consequently reduce risk factors that are associated with lifestyle-related diseases (e.g., high blood pressure, high cholesterol) (Beishuizen et al., 2016; Lunde et al., 2018). Within eHealth interventions, support can either be provided by a human professional (human-supported interventions), or automatically through computer technology, meaning that there is no human guidance or human professional involved. Interventions in which there is no support offered through human contact, but only automated support by computer technology, are defined as self-help interventions (Barak et al., 2009). For this reason, self-help interventions are generally easier and cheaper to widely implement to a larger and more varied audience as they require no involvement from healthcare professionals, who may lack time or insufficient experience to additionally offer lifestyle support (Brotons et al., 2005; Jallinoja et al., 2007; Jansink et al., 2010).

There is however a downside to self-help interventions. Adherence, or the extent to which a person uses the eHealth intervention as intended, is often problematic (Kelders et al., 2012; Kelders et al., 2011; Murray et al., 2013; Wangerg et al., 2008). This means that people use self-help interventions less frequently or stop using it earlier than necessary for the intervention to be optimally effective. However, this does not imply that support of a healthcare professional is always necessary for optimal results. Meta-analyses revealed that human contact with a nonprofessional is enough to both ensure intervention effectiveness and prevent individuals from dropping out of the intervention (Etzelmueller et al., 2020; Kayotaki et al., 2018; Richards & Richardson, 2012; Smith et al., 2012). It seems that the mere involvement of another human being, or something that is perceived as having human traits (Haslam et al., 2008), rather than professional guidance is the key ingredient within human-supported interventions. The underlying reason for the found effects of human contact within interventions, could be the participants' need for a personal relationship with a care provider (Brandt et al., 2018). In clinical practice this relationship is called the working alliance, which is defined as the degree to which a healthcare professional and patient are involved in a useful and collaborative working relationship (Hatcher & Barends, 2006). Although the concept of working alliance originated within psychotherapy (Bordin, 1979), it has more recently been applied to the domain of lifestyle interventions (Goldberg et al., 2013; Hauser-Ulrich et al., 2020; Kowatsch et al., 2021b). The quality of the working alliance depends on several factors such as the level of agreement on treatment goals, on tasks that must be performed to reach treatment goals, and on the quality of the relationship between healthcare professional and patient (Bordin, 1979; Horvath & Greenber, 1989). The establishment of a good working alliance promotes intervention adherence and effectiveness, both in face-to-face interventions (Goldberg et al., 2013; Martin et al., 2000) as well as in eHealth interventions with human contact (Flückiger et al., 2018; Sucala et al., 2012). In addition, individuals are also able to form a working alliance with computers (Nass & Moon, 2000; Reeves & Nass, 2000). Individuals can interact with computers as they would do with human beings and apply similar social rules and heuristics. For example, people tend to communicate with their smartphone (e.g., Apple's Siri) in a similar way as they would do with another human being. The establishment of a working alliance in eHealth interventions can also lead to more positive treatment outcomes (Bickmore et al., 2010; Clarke et al., 2016; Hauser-Ulrich et al., 2020; Kowatsch et al., 2021a; Kowatsch et al., 2021b).

So, how can we establish a working alliance in self-help interventions without human contact? For this, so-called conversational agent (CA) can be employed. CAs can be defined as computer-based agents which can mimic human-like conversational behavior such as responding to input, generate output, apply turn-taking) (Cassell et al., 1999). With these characteristics, they can provide automated support in eHealth interventions (e.g., home exercising; Kowatsch et al., 2021b) to promote adherence to lifestyle behaviors. An embodied conversational agent (ECA) is visually present on screen and can provide non-verbal cues (e.g., hand gestures), while a text-based conversational agent (TCA) is able to communicate with text only (Kowatsch et al., 2020). A TCA has the advantage of being easier to develop, being easier to apply in a mobile app, and is therefore more suitable for widespread implementation (Kowatsch et al., 2020). Studies demonstrate that people show more relational behaviors such as facial expressions, and are more positive about the interaction when they believe that their interaction partner is a human being rather than a computer technology (Aharoni & Fridlund, 2007; Appel et al., 2012). To enhance these perceptions while interacting with CAs, human cues could be applied, such as an avatar of a human being, a human tone-of-voice (Sah & Peng, 2015), or lower speed of feedback (Kelders et al., 2015). Furthermore, human cues in textual communication could be mimicked by adding emoticons (Walther & D'Addario, 2001). Besides the appearance of the messages, human cues could also be applied to the content of its messages. Conversation rules which are often used by humans to established a relationship, such as humor, empathy and small talk could also be incorporated as human cues in CA (Bickmore et al., 2005; Schulman & Bickmore, 2009). Studies with CAs show that applying such human cues to the interaction increases the working alliance users experience with the CA (Bickmore et al., 2005) and their intention to use the CA (Lisetti et al., 2013).

To conclude, self-help intervention studies with TCAs have been conducted before to examine their effect on psychological outcomes, only a small number of them focused on improving lifestyle behaviors (Tudor et al., 2020). Furthermore, the effects of human cues are predominantly tested with ECAs (e.g. Bickmore et al., 2005; Lisetti et al., 2013). Therefore, little is known about how human cues affect the working alliance when applied in TCAs, or how the working alliance affects adherence to TCA-supported interventions. Furthermore, the majority of studies tested the effects of either using human cues or not (e.g. Bickmore et al., 2005; Kelders et al., 2015; Lisetti et al., 2013; Sah & Peng, 2015; Schulman & Bickmore, 2009), while it is more interesting to test the effect of different types of human cues and possible interaction effects when combining human cues.

The Present Study

In this study, we will examine the impact of human cues in TCA on establishing a working alliance in a self-help lifestyle intervention. In addition, we will examine the impact of human cues and the working alliance on participant's intervention adherence. With regard to human cues, we will focus on both visual cues (i.e., appearance of the message and TCA) and relational cues (i.e., content of the message). We will test the following hypotheses. First, human cues will improve the working alliance people experience with TCA. Second, an established working alliance and application of human cues will promote participants' adherence to the lifestyle intervention. Finally, the working alliance will mediate the effect of human cues on adherence. To test our hypotheses, we developed a self-help intervention mobile application with which the participant could interact with a TCA and in which we manipulated both visual and relational cues.

MATERIAL AND METHODS

Study Design and Procedure

The three-week field experiment was conducted in March and April 2020. To test our hypotheses, we employed a 2 (visual cues: yes, no) x 2 (relational cues: yes, no) between-subjects design, resulting in four experimental groups: (1) visual and relational cues, (2) visual cues only, (3) relational cues only, or (4) no human cues. Power calculations (G*Power) (Faul et al., 2007) identified that we needed a minimum sample size of 128 to detect a medium between-group effect (f = .25) of cue-type with an alpha of .05 (ANOVA with 4 groups). Given the high attrition rates in similar studies (e.g., Hauser-Ulrich et al., 2020; Kramer et al., 2019), we aimed to recruit about double the required number of participants (i.e., 256).

We recruited healthy participants using voluntary response sampling with flyers on the university campus and via social media (e.g., personal social media channels of thesis students involved in the project, public student social media groups). Inclusion criteria were that participants should be aged between 18 and 30 years old, were able to work on their level of physical activity (i.e., based on a negative response to all questions of the Physical Activity Readiness Questionnaire (PAR-Q) (Thomas et al., 1992), willing to work on their level of physical activity, have access to a smartphone running iOS or Android, and would have sufficient proficiency in English. Participants were promised that after completion of the experiment, they would enroll in a lottery with the chance of winning one of three Fitbit devices, or one of 100 webshop vouchers worth €10,-. In addition, first-year students could receive credits required to complete their first bachelor year for their participation.

After recruitment, participants joined a waitlist until the start of the screening and onboarding on Monday March 16th 2020. A 3-week intervention duration was chosen as this would be enough time to establish a working alliance with the TCA (given that a relationship can be established after a single interaction, e.g. Bickmore et al., 2010; Schulman & Bickmore, 2009), and to be able to measure changes in adherence to the intervention. Participants had to wait a maximum of three weeks before the start of the experiment. A week before the start of the experiment, participants were asked to provide digital informed consent and fill in the screening survey assessing the inclusion and exclusion criteria. Immediately after providing their consent and being screened as eligible to participate, participants received a link to the iOS or Android app store to download the Benefit StepCoach app. Once the app was downloaded, participants were asked to go through the onboarding procedure to correctly configure the app (e.g., allowing push messages and access to step count data via Apple Health or Google Fit), and to complete the baseline survey. Participants were reminded through emails and text messages to complete the onboarding and baseline survey (measuring demographics and baseline characteristics) after 3, 4 and

5 days. Participants were excluded if they did not finish onboarding before the start of the experiment. An automated mechanism within the app allocated participants to one of the four conditions. All participants would start simultaneously in the three-week (21 days) experiment on Monday March 23rd 2020. Each day, the TCA would send the participants one or several short exercises to complete that day (e.g., quiz or worksheet, see Appendix 1 for an overview of daily exercises) via a push notification. After completing the final survey on day 22 (measuring working alliance), participants would receive the debriefing. The study was approved by the Psychology Research Ethics Committee of Leiden University (2020-02-06-T. Reijnders-V2-2056), and the analyses were preregistered via the Center for Open Science (Cohen Rodrigues & Reijnders, 2020).

Participants

In total, 269 participants were recruited during the wait list period, and were invited to the screening survey. Of these, 43 participants did not meet the inclusion criteria. Of the remaining 226 eligible participants, 127 participants downloaded the app, after which 121 participants completed the baseline measurement (attrition rate of 45%). We were unable identify reasons for dropping out between the recruitment and baseline measurement.

Benefit StepCoach Intervention

The aim of the intervention was to enhance participants' physical activity levels by increasing daily step counts. The intervention was based on a combination of important behavior change techniques (BCTs) (Michie et al., 2013), such as providing participants with information on health consequences, setting and reviewing of health behavior goals, and providing social rewards such as appraisal of the participant's efforts. These are intervention components designed to regulate behavior (such as physical activity) by reinforcing factors that facilitate behavior change, and mitigating factors that hinder behavior change (Michie et al., 2013). Participants would receive daily exercises based on BCTs, which would take about 5 to 10 minutes each day to complete (see Appendix 1 for an overview of all daily exercises). The Transtheoretical Model of health behavior change (Prochaska & Velicer, 1997) was used to develop specific exercises that match each phase of the model, as research shows that choosing exercises that fit within the pre-contemplation, contemplation, preparation, action, and maintenance stage stimulates user adherence and effective behavior change. Furthermore, the model would be applicable to our intervention as it has been previously used to target a wide range of health behaviors, including physical activity (Prochaska et al., 1994). For example, in the pre-contemplation phase we let participants formulate why they would like to improve their physical activity, and in the contemplation phase we let participants formulate pros and cons of behavior change. Later, in the preparation phase, we asked participants to formulate a concrete step goal. In the action phase, participants received action-planning and problem-solving exercises to help them reach their goal. Finally, in the maintenance phase, participants reviewed their previous successes to help them maintain the new behavior in the future. For an overview of all the exercises (i.e., active ingredients of the intervention) per phase of the Transtheoretical model, see Appendix 1. The mobile application for our self-help intervention was developed with use of the open-source software of Mobile-Coach (www.mobile-coach.eu) (Filler et al., 2015; Kowatsch et al., 2017), which has been previously used for smartphone-based and chatbot-delivered behavioral interventions (e.g. Stieger et al., 2021; Tinschert et al., 2019). See Appendix 2 for more information about the technical implication. As we developed our own intervention, it was important to test whether it was actually effective in improving participants' physical activity levels. Therefore, we conducted some additional analyses, which showed us that the intervention significantly increased participants' step count independently of the experimental condition (see Appendix 3 for more details).

Text-based Conversational Agent

Participants interacted daily with a TCA, the virtual coach who delivered the intervention and offered various conversational turns. Via the chat feature, the TCA delivered daily exercises (see Appendix 1) and would respond to messages of the participants via conversational turns (see Figure 1). All conversational turns were scripted. Each day would consist of two to four conversational turns. The first message would be sent in the morning at 9:00 am, and the following messages after a reply of the participant. If the participant would not reply on time, the TCA would send a reminder in the afternoon at 3:00 pm.

Across the experimental groups, the exercises and feedback were identical, but the conversational turns differed in cue type the TCA used. We manipulated two types of human cues: (1) visual cues, which were related to the appearance of the message and the TCA (human avatar, use of emoticons, human tone-of-voice, and response delay), and (2) relational cues, which were related to the content of the messages, and to what extent these followed social scripts and human conversation rules (e.g., showing empathy, self-disclosure, humor, small talk, and meta-relational communication) (see Figure 2).

Figure 1. Screenshots of Benefit StepCoach app.

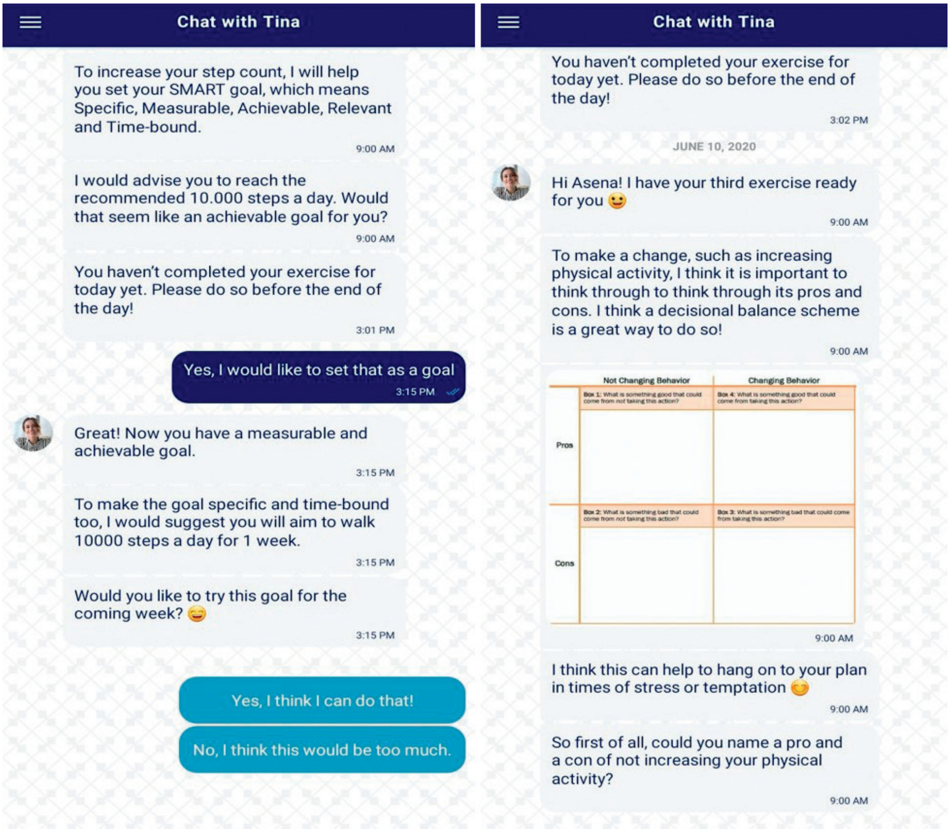
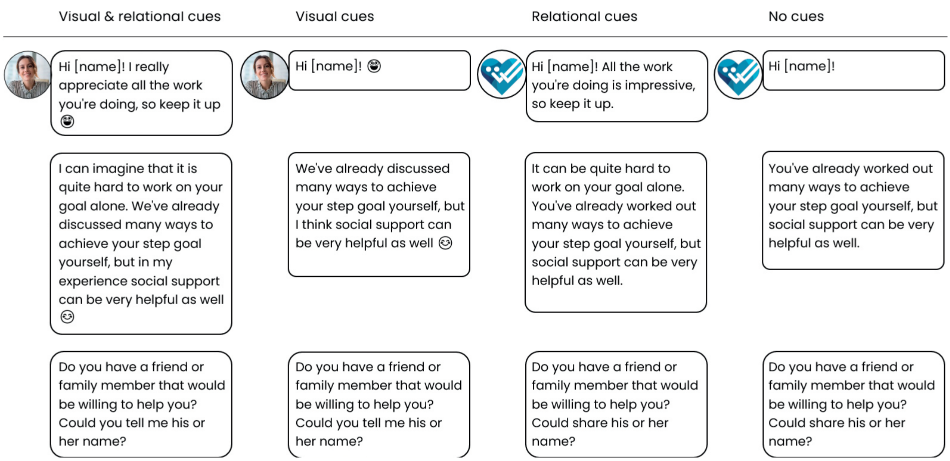


Figure 2. Example of conversational turns per condition.



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Measures

Baseline Measures

During the onboarding week before the start of the intervention, participants were asked to fill in several demographic questions on gender, age, nationality, and educational background. Furthermore, baseline level of physical activity was measured with the International Physical Activity Questionnaire Short Form (IPAQ-SF) (Lee et al., 2011). The questionnaire consists of seven items asking the participants about their time spent on vigorous and moderate physical activities, walking, and sitting during the previous week. The output is a MET (metabolic equivalent of task) score, representing the amount of energy used to carry out the reported physical activities. A higher score indicates a higher level of physical activity. The IPAQ-SF has been shown to have a high test-retest reliability, but minimal concurrent validity (Lee et al., 2011; Craig et al., 2003). Therefore, baseline objective step count data was additionally retrieved from the participant's smartphone during the onboarding week.

Working Alliance

Participants' working alliance with the TCA was measured with a revised version of the Working Alliance Inventory Short Revised form (WAI-SR) (Hatcher & Gillaspy, 2006). The WAI-SR consists of 12 items to measure the experienced quality of the working relationship between patient and professional. All items were measured on a 5-point Likert-scale ranging from 1 (seldom) to 5 (always), subdivided in 3 subscales: agreement on tasks, agreement on goals, and bond. Questions were revised to fit the context of the study by using the words "coach", "lifestyle" and "intervention" (e.g., "The coach and I collaborate on setting lifestyle goals."). A higher score indicates a better working alliance with the TCA. The WAI-SR has been shown to have sufficient test-retest reliability and criterion validity (Hatcher & Gillaspy, 2006), and our revised version showed to have a high internal consistency (Cronbach's α = .95).

Adherence

Participants were marked as "adherent" for a particular day if they had replied to the final message of the TCA before the end of the day (12:00 pm at midnight). The final adherence measure was based on the number of days participants finished each daily session of conversational turns with the TCA. Given the 21 day duration of the intervention, the level of adherence over the whole study could range between 1 and 21 days, with higher number of days indicating a higher level of adherence.

Data Analysis

All statistical analyses were conducted with SPSS (version 26; IBM Corp). We used pairwise exclusion to deal with missing data and a standard *P*-value of .05 was chosen to determine statistical significance. For the first hypothesis (human cues will improve the working alliance people experience with TCA), we performed a Kruskal-Wallis test, with working alliance as our outcome measure and cue condition as independent variable. We chose to conduct non-parametric tests given the small sample size of some groups ($N < 25$) and a non-normal distribution of our data. For the next hypothesis (working alliance and human cues will promote adherence to the intervention), we ran a regression analysis with working alliance as independent variable and adherence as outcome measure and performed a Kruskal-Wallis test with cue condition as independent variable and adherence as outcome measure. This was followed up by the analyses of specific post-hoc analyses to compare different cue groups in the form of Mann-Whitney U tests. For the final hypothesis (working alliance will mediate the effect of human cues on adherence) we planned to conduct a mediation analysis. However, the lack of significant differences in working alliances between groups made this analysis obsolete.

In our preregistration (Cohen Rodrigues & Reijnders, 2020) we also proposed to test intervention effectiveness. Our power calculations identified a minimum sample size of 128 to detect the expected effects of experimental groups on effectiveness. However, as we needed both a valid baseline step count and a minimum of 5 days of step count registered in the final week to calculate intervention effectiveness, we did not have enough power to run these analyses and detect this effect due to insufficient respondents. We therefore decided to report the analyses concerning intervention effectiveness only in Appendix 3.

RESULTS

Demographics

A total of 121 participants completed the baseline measurement. These participants were on average 22.7 years ($SD = 2.8$) old, 84/121 (69%) were female, 73/121 (60%) were of Dutch nationality, and of 91/121 (75%) their current or highest education level was bachelor's degree or higher. Comparative analyses of the demographic characteristics at baseline showed no significant differences between groups (see Table 1).

Table 1. Baseline demographic characteristics (N = 121)

Variable	Visual & relational cues (n = 31)	Visual cues (n = 24)	Relational cues (n = 29)	No cues (n = 37)	*P* value
Age in years					
Median (IQR[a])	22 (4)	23 (3)	22 (3)	23 (4)	.968[d]
Mean (SD[b])	22.65 (2.84)	22.71 (2.79)	22.76 (2.70)	22.54 (3.01)	
Gender, female, n (%)	26 (84)	12 (50)	21 (75)	25 (68)	.055[e]
Nationality, n (%)					.743[e]
Dutch	19 (61)	15 (63)	14 (48)	25 (67.5)	
German	3 (10)	3 (13)	6 (21)	5 (13.5)	
Other	9 (29)	6 (25)	9 (31)	7 (19)	
Education level, n (%)					.306[e]
High school	4 (13)	6 (25)	6 (21)	11 (30)	
Vocational school	1 (3)	1 (4)	0 (0)	1 (3)	
Bachelor's degree	17 (55)	14 (58)	21 (72)	18 (49)	
Master's degree or higher	9 (29)	3 (13)	2 (7)	7 (19)	
Physical activity level					
MET[c] score (per week)					
Median (IQR[a])	2552 (4150)	1506 (2986)	2268 (4730)	2477 (4331)	.134[d]
Mean (SD[b])	4556 (5324)	2928 (5370)	3800 (3373)	3854 (3804)	
Average steps per day					
Median (IQR[a])	2453 (2840)	1531 (2685)	3224 (3222)	2382 (2382)	.357[c]
Mean (SD[b])	3282 (2289)	1912 (1557)	3266 (1601)	3361 (2616)	

[a]IQR = interquartile range; [b]SD = standard deviation; [c]MET = metabolic equivalent of task; [d]Kruskal-Wallis test; [e]Fisher's Exact test

Working Alliance

We found no significant difference in working alliance between the cue conditions, $H(3) = 4.194$, $p = .24$ (see Table 2 for median and IQR per group). However, we did find a positive relationship between working alliance and adherence,

β = .378, $t(78)$ = 3.606, p = .001, 95% CI [0.108; 0.374]. These outcomes indicate that that adding human cues did not lead to a difference in working alliance with the TCA, but that participants who reported a better working alliance were more adherent to the intervention.

Table 2. Median and IQR[a] per group of working alliance (measured after the final day of the intervention with the Working Alliance Inventory Short Revised form) and adherence (number of days participants finished the session of conversational turns).

Variable	Visual & relational cues	Visual cues	Relational cues	No cues	*P* value
Working alliance[a]					
Median (IQR[b])	34 (18)	45 (18)	42 (8)	34 (13)	.24[c]
Adherence					
Median (IQR[b])	6 (12)	7 (14)	16 (14)	14 (15)	.004[c]

[a]The N for working alliance (due to missing data): visual & relational cues: n=19; visual cues: n=14; relational cues: n=22; no cues: n=25
[b]IQR = interquartile range; [c]Kruskal-Wallis test

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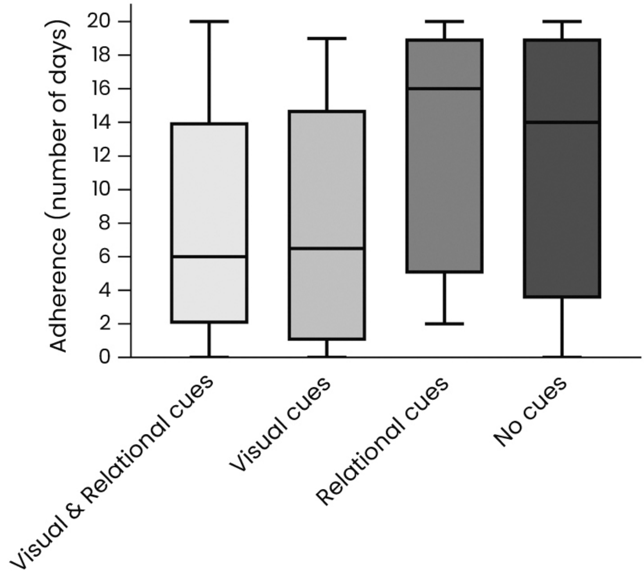
Adherence

We found a significant difference in adherence between the cue conditions, $H(3)$ = 13.125, p = .004 (see Table 2 for median and IQR per group). By visually inspecting the medians, we saw that the differences between groups were not as expected (see Figure 3). The contrast analyses showed that in the relational cues- and no cues-conditions there was a significantly higher adherence than in the other two conditions, U = 1140.5, z = -3.520, p < .001. However, adherence in the relational cues condition was not higher than in the no human cues condition U = 478.0, z = -.760, p = .45. So contrary to what was expected, participants were less adherent to the intervention in the groups in which the TCA used visual cues compared to the groups without visual cues. Furthermore, when the TCA used relational cues, participants were not more adherent than when the TCA used no human cues at all.

Figure 3. Boxplots of adherence (number of days participants finished the session of conversational turns) for the four experimental conditions.



DISCUSSION

We investigated the impact of human cues in TCA on establishing a working alliance and in turn that impact on improving the adherence in a self-help lifestyle intervention. We found no differences in the effect of no, visual and/or relational human cues on establishing a higher quality working alliance with the TCA. Also, using visual or relational human cues did not lead to higher adherence. On the contrary, we found that the use of visual cues could even lead to lower adherence. However, we did find that a higher quality working alliance was related to a better adherence to the lifestyle intervention.

Our results did not show an effect of human cues on the reported working alliance with the CA. What is important to note is that many studies that did find this relationship concern ECAs (Bickmore et al., 2005; Bickmore et al., 2010), while we used a TCA. ECAs generally outperform text-based ones (Lisetti et al., 2013; Zalake et al., 2019), which can be explained by the additional range of design characteristics an ECA can make use of (Loveys et al., 2020). In one study though, there was no difference found between a TCA and an ECA, which the authors argued was due to the lack of incorporating non-verbal communication in the latter one (Friederichs et al., 2014). The inability of our (or any) TCA to use non-verbal communication, may be a reason that we did not find the effect of our TCA with human cues on working alliance as studies with ECAs did. Similar patterns occur in computer-mediated communication between humans, where people are limited in their use of non-verbal communication (Daft & Lengel, 1986). Text-based communication would not be rich enough to transfer ambiguous communication, such as communication aimed at relationship building (Daft & Lengel, 1986), and relationship building requires more time in text-based environments to reach the same quality as in face-to-face situations (Walther, 1992). This might also explain why we did not find an effect of using relational cues on adherence, a finding that contradicts previously mentioned studies with ECAs (Bickmore et al., 2005; Schulman & Bickmore, 2009). Moreover, in studies that did find an improved working alliance with a CA, either the interactions with the agent or in the intervention itself were longer compared to our study (Hauser-Ulrich et al., 2020; Bickmore et al., 2010). In other studies in which a high working alliance was reported within shorter periods of time, the interactions with the CA followed after introduction by a human healthcare professional (Bickmore et al. 2010; Kowatsch et al., 2021b). Therefore it seems likely that a TCA is less able to build a relationship with the user due to lack of non-verbal communication, however it could be that it requires either a longer time period or an introduction in a face-to-face setting to do so. So even though our findings do support that working alliance is an important mechanism within eHealth interventions, it remains unclear if and how it would be possible to foster a relationship with a TCA. Even though the development of an ECA requires more time and financial resources than a TCA, based on both our results and those of previous studies, we hypothesize that self-help eHealth interventions in practice would benefit more from incorporating an ECA. The difference between TCAs and ECAs and their applicability in successful eHealth interventions would be an important topic for future research.

We did find that people who reported a better working alliance with the CA were more adherent to the lifestyle intervention. This result is in line with studies about regular face-to-face interventions (Goldberg et al., 2013; Martin et al., 2000), digital therapy or treatment (Flückiger et al., 2018; Sucala et al., 2012), and self-help eHealth interventions (Bickmore et al., 2010; Clarke et al., 2016; Hauser-Ulrich et al., 2020; Kowatsch et al., 2021a; Kowatsch et al., 2021b). However, our results did not show the positive effects of visual elements that have been reported in previous studies (Bickmore et al., 2005; Bickmore et al., 2010; Sah & Peng, 2015; Schulman & Bickmore, 2009). Instead, we found that using visual cues led to a lower adherence to the intervention. We did not tell participants whether they would be coached by a human being or a computer. This lack of transparency, in combination with a human visual appearance, may have led to unrealistic high expectations that could not be met by the TCA and therefore frustration among users (Luger & Sellen, 2016). Although many studies show that not disclosing the nature of an automated chatbot has a positive effect on user perceptions (e.g., perceived humanness of, or affinity with the chatbot) and user behavior (e.g., being persuaded by the chatbot) (Hendriks et al., 2020;

Shi et al., 2020; Skjuve et al., 2019), Mozafari and colleagues (2020) show that the effects of disclosure depend on whether there are errors in the conversation with a chatbot. In their study with a customer-service bot, they found that when the chatbot was not able to solve a customer's issue, the customer's potential negative responses to these errors could be prevented by disclosing the chatbots true nature beforehand. Although our study concerned a lifestyle intervention rather than customer-service, similar mechanisms could be at play here. As visual cues might have caused participants to wrongly expect they were communicating with a human being and our CA was not always able to respond correctly to participant's messages (as the messages were preprogrammed), informing participants about the nature of the agent could have prevented unrealistic expectations and frustration. In addition, the type of avatar we used in the visual cues conditions might have played a role. We intentionally chose a younger- and healthy-looking female agent both because it resembles the psychology student population, and a young female peer agent is generally preferred in health coaching tasks (Ter Stal et al., 2020; Zhou et al., 2014). However, some literature suggests that male agents are preferred as athletic trainer, which might have influenced the results if our participants perceived the TCA to be an athletic coach rather than a health coach (Ter Stal et al., 2020). Furthermore, another study shows that non-ideal overweight agents are seen as more trustworthy and related to higher use intentions (Van Vugt et al., 2009), which suggests our TCA might have been too slender and healthy looking for its task. All in all, future designers of eHealth interventions with TCAs could consider being transparent about the true nature of the CA, as it would make users more forgiving about possible imperfections of the automated feedback it provides. Furthermore, given the important influence of the type of visual cues, it would possibly be beneficial for future eHealth interventions to better match the visual cues of the TCA with the wishes of the user. For example, one could allow users themselves to choose the looks of the TCA that will support them. Future research could investigate whether such changes would improve adherence to self-help eHealth interventions.

Practical implications

Further knowledge about the development of CAs is not only relevant for researchers working in eHealth or human-computer science, but also for those involved in healthcare practice. eHealth is becoming increasingly relevant, which became especially evident during the COVID-19 pandemic (Bokolo, 2021). Therefore, it is necessary to develop eHealth tools that are efficient, and thus do not put further pressure on the workload of healthcare professionals, but at the same time fulfill the needs and wishes of patients. CAs would be suitable for developing self-help eHealth lifestyle interventions that do pay attention to the relationship with the user. Furthermore, our findings would not only be practically relevant for developing physical activity interventions, but eHealth lifestyle interventions in general. Therefore the findings of our study would be useful for developers that work on self-help eHealth lifestyle interventions, and indirectly for healthcare professionals who could help their patients in providing lifestyle support more easily.

Limitations and Suggestions for Future Work

Besides the strengths of our study such as using a field experiment (with participants using an app-based intervention in real life), measuring objective behavioral data, and testing two different types of human cues, our study also had some limitations. In our preregistration, we proposed to also test intervention effectiveness, yet we did not have sufficient participants and thus power to do so. For reasons of transparency, we do report the analyses on intervention effectiveness in Appendix 3. It is also important to note that our sample size was generally on the small side and that we had problems with non-normality in our data. Although we used nonparametric tests to analyze our data, the results should be interpreted with caution. Even though we already recruited more participants than needed to account for possible dropouts, future studies may aim to recruit more than double the needed participants.

Furthermore, we did not inform our participants beforehand whether they were interacting with a computer or a human being. Therefore the expectations of people might have varied, which could have affected our results. Future studies could keep these expectations constant by being transparent about the true nature of the automated agent. Another option would be to manipulate the description of the CA to more closely represent a human being or a computer, and ask participants about their expectations towards support by a human being or computer, to additionally test expectation effects within self-help interventions.

Finally, to mimic human behavior, we intentionally chose to apply subtle human cues to our CA (e.g., interweaving signs of empathy or small jokes into the feedback). However, participants might not have processed the messages of the agent elaboratively enough to notice these subtle cues, resulting in a lack of effects. Furthermore, because of this subtility, the different types of human cues might have differed too little between each other. We suggest that future studies investigate the differences in applying human cues in TCAs and ECAs. It would be interesting to know whether stronger cues are needed in TCAs to produce similar effects in ECAs, or whether longer interactions do lead to an improved working alliance, and thus adherence. Additionally, given our results, it would be interesting to investigate whether using non-verbal communication is indeed key to establishing a working alliance with a CA, and how to overcome the lack of non-verbal communication within TCAs.

CONCLUSIONS

In this study, we aimed to improve adherence to self-help eHealth lifestyle interventions by applying a TCA which uses (visual and relational) human cues. We replicated that creating a good working alliance with your coach improves adherence to lifestyle interventions. However, more future studies are needed to investigate whether and how factors that work for ECAs, in this case human cues, could also be applied to TCAs to further improve the working alliance and thereby adherence. Future studies could also investigate whether being transparent about the computer-based nature of a CA and thereby setting the right expectations would be important for success. Until future research provides us more insight, our findings suggest that self-help eHealth interventions in practice could possibly better invest in developing an ECA and be transparent about the true nature of the CA that is used. The knowledge gained from our and future studies could help us design better self-help interventions in the future creating higher levels of adherence, and in turn a healthier lifestyle for us all.

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CHAPTER 6 | APPENDIX 1

Overview of the 3-week physical activity intervention based on Behavior Change Techniques (BCTs) and Transtheoretical Model of health behavior change (TTM)

Day	TTM stage	BCTs	Exercise
1	Pre-contemplation	Goal setting	Formulate general goal *Participants are asked to describe what general health improvement they would like to achieve through increasing physical activity levels, and why this would be important to them in order to prepare their mindset for future behavior change.*
2		Information about health consequences	Quiz about behavior and health consequences *By doing the quiz, participants receive more knowledge about how (a lack of) physical activity would affect their health to help improve their attitude towards increasing their physical activity levels.*
3	Contemplation	Pros and cons	Decisional balance worksheet *Participants are asked to critically think about the pros and cons of changing and not changing their physical activity behavior to help them create recognition about advantages and disadvantages of engaging in higher levels of physical activity.*
4	Preparation	Goal setting	Formulate SMART goal *Participants are asked to create a specific, measurable, achievable, relevant and time-bound goal to help them start increasing their step count.*
5		Valued self-identity	Self-affirmation exercise *Participants are asked to think about values that are important to them and how physical activity fits with these values to help stick with the goal they have set.*
6		Prompts/Cues; Action planning	Formulate 'If-then plan' *Participants are asked to set a physical activity-related plan when a specific situation occurs to increase the chances of reaching their goal.*

Continued

Day	TTM stage	BCTs	Exercise
7		Problem solving	Identify barriers and coping strategies *Participants are asked to think about potential barriers that might hinder reaching their physical activity goal and about solutions to overcome these to help them prepare for these situations.*
8		Self-monitoring	Implement short bursts of activities, and compare step-count to yesterday's *Participants are asked to think of a small activity for today that would increase their physical activity level, and to compare their results with yesterday to see how such small steps can help achieve their goal, and motivate them in applying these during the rest of the process.*
9		Action planning; Social support; Barrier identification	Plan physical activity challenge with other person; identify barriers and coping solutions *Participants are asked to involve a peer by asking them to join physical activity challenge to create social support in reaching their goal.*
10	Action	Instructions on how to perform health behavior	Quiz about performing physical activity *By doing the quiz, participants receive more knowledge about types of physical activity and how these increase their step count level to give them with new ideas to turn their intentions into action.*
11		Review behavioral goal(s)	Reflect on goals (day 4) and make adjustments (SMART) *Participants are asked to look back at their goal of day 4, and if needed, create a new specific, measurable, achievable, relevant and time-bound goal to help them increase their step count.*

Continued

Day	TTM stage	BCTs	Exercise
12		Identification of self as role model	Identify own role model, and for whom you are a role model *Participants are asked to imagine themselves as a role model for another person, and how their physical activity behavior could motivate that person to be physically active too, which helps acknowledge the positive impact of their actions.*
13		Demonstration of the behavior; Social comparison; Credible source	Watch video of Usain Bolt interview *Participants are asked to watch a video about an interview with Usain Bolt to give them a positive example of someone to has an active lifestyle, and incorporate his advice into their own physical activity behavior.*
14		Review outcome goal(s)	Reflect on PA challenge (day 9) *Participants are asked about the challenge they would set with a peer and how this resulted in higher levels of physical activity, either to motivate them to use their social support system more often or to think about ways to overcome barriers in involving social support.*
15		Review behavioral goal(s)	Reflect on goals (day 11) and make adjustments (SMART) *Participants are asked to look back at their goal of day 11, and if needed, create a new specific, measurable, achievable, relevant and time-bound goal to help them increase their step count.*
16		Focus on past success	Reflect on rewarding experience of previous physical activities *Participants are asked to think about physical activity they have performed before and its positive consequences to motivate them in engaging in physical activity to reach their goal.*

Continued

Day	TTM stage	BCTs	Exercise
17		Reduce negative emotions; Monitoring of emotional consequences	Stress management and emotional coping *Participants are asked to watch a video with a breathing exercise that would help them in the management of stress and negative emotions, and to think how physical activity would help them in this management to motivate them in increasing physical activity levels.*
18		Self-talk	Positive labelling of upsetting experiences *Participants are asked to think about a negative experience during the intervention and their feelings, after which they are asked to relabel this situation to help them in overcoming similar situations in during future physical activity.*
19	Maintenance	Review outcome goal(s)	Reflect on barriers and coping strategies (day 7) *Participants are asked to think about the potential barrier they mentioned on day 7, and if their solution helped them in overcoming this barrier, to help them with coping strategies that might hinder reaching their physical activity goals in the future.*
20		Incompatible beliefs; Discrepancy between current behavior and goal	Imagine future self and set goals to work towards that *Participants are asked to think about themselves in the future, and to set physical activity goals for the current version of themselves to make themselves satisfied in the future.*
21		Monitoring of emotional consequences; Review outcome goal(s)	Meta-reflection of intervention (what did I learn, what did I like the most, how did I change?) *Participants are asked to reflect on the intervention and their physical activity process and to identify lessons learned that help them in engaging in physical activity in the future.*

Continued

Day	TTM stage	BCTs	Exercise
1-21	All stages	Social reward; Feedback on behavior	Praise for effort and progress; inform participant about daily step counts *On a daily basis, participants were informed about their step count and goal progress, and positively encouraged to keep up with their physical activity or increase their physical activity levels.*

CHAPTER 6 | APPENDIX 2

Technical Implementation of the Benefit StepCoach app

We developed the Benefit StepCoach app as a tool to test our hypotheses. The app was developed with use of MobileCoach software (www.mobile-coach.eu) (Filler et al., 2015; Kowatsch et al., 2017), an open-source software platform for smartphone-based and chatbot-delivered behavioral interventions (eg, Stieger et al., 2021) and ecological momentary assessments (eg, Tinschert et al., 2019). The Mobile Coach platform provided the researchers with a web-based graphical user interface and allowed us to implement the needed intervention logic and content. MobileCoach uses a web server to execute the needed intervention logic and to deliver the content to the MobileCoach-based mobile applications for Apple's iOS and Android platforms. The mobile app was customized to fit the needs of this study and published in the iOS and Android app stores with the name Benefit StepCoach. One of the important features of this app was to automatically and objectively retrieve step counts of the participants. Google Fit (www.google.com/fit/) for the Android app and Apple's Health Kit (developer.apple.com/documentation/healthkit) for the iOS app were used for this purpose. Appropriate interactions were implemented, i.e. asking participants for their permission, to allow the app to access step data. Moreover, each experimental group was assigned a dedicated TCA.

CHAPTER 6 | APPENDIX 3

Analyses with effectiveness as outcome variable

Effectiveness was measured through objective step count data retrieved from Apple Health or Google Fit (depending on the smartphone of the participant). We calculated the mean difference between the average baseline step count (measured in the week before the intervention) and the average step count in the final week of the intervention. Participants were included in the analyses if both a valid baseline step count and a minimum of 5 days step count in the final week were registered.

To test whether the intervention was effective in urging participants to increasing participants' step count (independently of the experimental condition), a (one-tailed) paired samples *t* test was conducted. Our analyses showed a significant increase in the average step count from the baseline week (M=3412.37, SD=2363.17) to the final week (M=4556.77, SD=2545.65), t(42)=-3.975, $p < .001$, 95% CI [-1725, -563].

In addition, due to small sample size, we conducted a nonparametric Kruskal-Wallis test to compare intervention effectiveness between the four different cue conditions. There was no significant difference in effectiveness between the conditions, $H(3) = 2.536$, $p = .47$ (see Table 3 for median and IQR per group). Also the post-hoc Mann-Whitney U tests comparing the three human cues conditions with the no human cues condition ($U = 170.5$, $z = -1.007$, $p = .32$), and the test comparing the condition with both visual and relational cues with the visual cues only and relational cues only groups ($U = 91.0$, $z = -.118$, $p = .92$) showed no significant differences.

Table 3. Medians and interquartile range (IQR) per group of effectiveness (mean difference between average baseline step count and average step count in final week of intervention).

Variable	Effectiveness	
	N	**Median (IQR[a])**
Visual & relational cues	11	1395 (1868)
Visual cues	6	1703 (1831)
Relational cues	11	785 (2460)
No cues	15	438 (4149)

[a]IQR = interquartile range

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SUMMARY & GENERAL DISCUSSION

SUMMARY

There is an increasing number of adults who suffer from cardiovascular diseases (CVD) (Koop et al., 2021; Wilkins et al., 2017; WHO, 2021). These patients would benefit from a healthy lifestyle, as this improves the prognosis of CVD (Kaminsky et al., 2022; Piepoli et al., 2016; Wilkins et al., 2017). However, even though improving one's health and lifestyle is the focus of cardiac rehabilitation, CVD patients need support to also maintain a healthy lifestyle after their rehabilitation has ended (Janssen et al., 2013). And although many eHealth solutions have been developed to provide lifestyle support (Thomas & Bond, 2014), this technology is not as effective as it could potentially be. One of the reasons is the lack of involvement of both patients and healthcare professionals. Many eHealth solutions are being developed without the involvement of those who use the technology, which often results in solutions that are not intuitive to use and therefore less effective than expected (van Gemert-Pijnen et al., 2011). Even though the support of a healthcare professional seems to be an important factor in successful lifestyle change, there are barriers that hinder professionals from providing lifestyle support, such as a lack of time or expertise (Bellicha et al., 2017; Jallinoja et al., 2007; Jansink et al., 2010; Warr et al., 2021). Since the involvement of healthcare professionals is also not always possible or desirable, it is important to further investigate possibilities to provide patients with a self-help eHealth intervention with automated support. This PhD dissertation thus focuses on (1) mapping out the needs and wishes of both healthcare professionals and CVD patients with regard to (human-supported and self-help) eHealth lifestyle interventions, and (2) investigating if and how self-help eHealth lifestyle interventions could be optimised.

Focusing on the first aim of this dissertation, (1) mapping out the needs and wishes of both healthcare professionals and CVD patients with regard to (human-supported and self-help) eHealth lifestyle interventions, Chapter 2 and 3 aimed to investigate the views of both healthcare professionals and patients about lifestyle support and the use of eHealth lifestyle interventions. **Chapter 2** described an interview study with healthcare professionals working in cardiac care. Previous studies showed that professionals experience several barriers that hinder them from successfully supporting their patients (e.g. Bellicha et al., 2017; Jallinoja et al., 2007; Jansink et al., 2010). In this study we focused specifically on the cardiac care context, by interviewing 16 healthcare professionals working with CVD patients about both lifestyle support and the use of eHealth. We identified 12 themes describing the factors that healthcare professionals found important in lifestyle support in general, which were either intervention-, patient-, or healthcare-related. Throughout these themes, eHealth was mentioned to be a (potential) facilitator or solution to barriers that they encountered in lifestyle support. eHealth was deemed to be mainly beneficial in the themes “autonomy”, “personalisation”, “format of support”, and “continuity of professional support”.

For example, professionals indicated that eHealth could provide patients insight into their own health and thereby help them to regain autonomy, or that eHealth could help them gain more information about their patients to help personalise their support. As another example, professionals saw that eHealth gave them the opportunity to provide remote support, which would both improve the format of support for patients experiencing physical restrictions, and provide the opportunity to continue their support in the long-term. In addition to these advantages, we identified a 13th theme which described the barriers that healthcare professionals experienced in the adoption and use of eHealth. For example, professionals were concerned about the old age of their patients and thus low level of digital familiarity, and feared that they would generally prefer face-to-face contact.

To complement this study, **Chapter 3** described a study to investigate whether these experiences and expectations of healthcare professionals are recognized by a CVD patient population. A previous study found that the willingness of CVD patients to use eHealth varies (Anttila et al., 2019). We aimed to elaborate on this by not only asking patients whether they wanted to use eHealth or not, but also further specify the type of eHealth or face-to-face intervention they would prefer, and by investigating what demographic variables predict their lifestyle support preference. To do so, we conducted a questionnaire study among 659 CVD patients who were a member of the official national Dutch CVD patients' association. The results showed us that the majority of the CVD patients preferred being self-supportive when working on their lifestyle (i.e., without support from a coach, an app or internet, or family and friends). This was followed by the options of being supported by a coach (in a group, individually, or via an app or internet). Furthermore, we found that age and gender were a predictor of lifestyle support preference. We found that older patients were more likely to prefer being self-supportive. And whereas men were more likely to prefer being supported by family and friends, or to be self-supportive, women were more likely to prefer being supported by a coach, either individually or via an app or internet.With the second aim of this dissertation in mind, (2) investigating if and how self-help eHealth lifestyle interventions could be optimised**,** we wanted to find out what eHealth solutions have already been developed for patients, and whether these are effective in improving clinical and behavioural health outcomes. In **Chapter 4**, given the inconsistent results about the effectiveness of human support within eHealth interventions (Beishuizen et al., 2016; Joiner et al., 2017; Lau et al., 2020; Lustria et al., 2013; Webb et al., 2010), we compared human-supported and self-help eHealth lifestyle interventions in terms of effectiveness, and whether the amount and delivery mode of human support influence intervention effectiveness. We conducted a meta-analysis including studies testing eHealth lifestyle interventions for adults with cardiovascular diseases, chronic kidney diseases, type 1 diabetes mellitus, and type 2 diabetes mellitus. We focused on all these four cardiometabolic diseases, as they share similar underlying risk factors, and all have a similar behavioural risk factor management strategy in terms of engaging in a healthy lifestyle. Our systematic search resulted in 104 unique studies that were included in the analysis. The multilevel meta-analysis showed that eHealth lifestyle interventions are effective in improving clinical and behavioural health outcomes. However, we did not find a difference between human-supported and self-help eHealth lifestyle interventions. Both intervention types were effective in improving clinical and behavioural health outcomes. Furthermore, we found no difference in effectiveness for the amount of human support (minor vs. major part of the intervention) or delivery mode of human support (remote vs. blended support). Based on these results, we hypothesized that the quality of the eHealth interventions in the included studies could explain the inconsistent results of different meta-analyses, as well as the level of adherence to the intervention.

Given that self-help eHealth interventions generally suffer from a lower uptake and use intention than human-supported ones (Lillevoll et al., 2014; Lin et al., 2018), **Chapter 5** studied whether user expectations predict the intention to use either a human-supported or self-help eHealth intervention. We conducted an online experiment, in which healthy participants were randomly presented screenshots from either a human-supported or self-help lifestyle app. We used expected working alliance with the (automated) coach and the constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) to investigate which expectations predicted the use intention of human-supported and self-help eHealth interventions. The results revealed that subjects intention to start using a self-help eHealth intervention did not differ from their intention to start using a human-supported intervention. We also found no differences between the two types of interventions in terms of the working alliance people expected to have with either the human or automated coach. Nor did we find any difference in the extent to which they expected that important others believe they should use the eHealth intervention. We did however find that the effect of people's expectations about the helpfulness of the intervention and its easiness to use did differ between human-supported and self-help interventions: i.e, when subjects were offered a self-help intervention, their expectation that the intervention would be helpful or easy to use led to a higher intention to use the intervention than when subjects were offered a human-supported eHealth intervention. This effect also works in the opposite direction: when subjects expected that the self-help intervention would be unhelpful or difficult to use, they were less likely to start using the intervention compared to subjects who thought that the human-supported intervention would be unhelpful or difficult to use. In other words, negative expectations towards the intervention's helpfulness and easiness of use lead to a lower willingness to use a self-help intervention compared to a human-supported intervention.

In an attempt to solve the problem of adherence in self-help eHealth interventions, we conducted the study described in **Chapter 6**. Given that the working alliance is an important predictor of adherence within human-supported interventions (Flückiger et al., 2018; Sucala et al., 2012), and that people are able to form relationships with technology (Nass & Moon, 2000; Reeves & Nass, 1996), we aimed to use the concept of working alliance to improve adherence to a self-help eHealth intervention. We applied a text-based conversational agent to an app-based physical activity intervention, and used human cues to promote a working alliance with the user. We used two types of cues, i.e. visual and relational cues, and tested these in an experimental field study. We expected that the conversational agent using the most human cues (i.e. both visual and relational cues) would lead to the highest level of experienced working alliance, and thus highest user adherence to the intervention. In contrast, we found that the use of human cues did not affect the working alliance, but subjects who experienced a higher working alliance were more adherent to the intervention. Furthermore, when the conversational agent used visual cues, subjects were less adherent to the intervention compared to when the conversational agent used no human cues at all. Explanations for these findings might be the differences between embodied and text-based conversational agents and the importance of both non-verbal communication and transparency about the true nature of the conversational agent.

GENERAL DISCUSSION

This dissertation focused on the comparison between human-supported and self-help eHealth interventions, particularly the dilemma of the importance of human support in successful eHealth lifestyle interventions on the one hand, and the barriers that come with the involvement of healthcare professionals on the other hand. With the first aim of this dissertation in mind, (1) mapping out the needs and wishes of both healthcare professionals and CVD patients with regard to (human-supported and self-help) eHealth lifestyle interventions, this discussion first focuses on the views of those who are actually involved, i.e. healthcare professionals and patients, and what we learned about their preferences with regard to lifestyle support and the use of eHealth. Secondly, regarding the second aim, (2) investigating if and how self-help eHealth lifestyle interventions could be optimised, the discussion dives into the role of human support in eHealth lifestyle interventions and how eHealth interventions could be improved for patients.

Needs and wishes of healthcare professionals and patients

Healthcare professionals seem to recognise the benefits of eHealth in providing lifestyle support to CVD patients. According to them, eHealth could especially help in providing patients with a feeling of autonomy, personalising the lifestyle intervention and in both providing remote and prolonged support. Nonetheless, they also mentioned several eHealth barriers, such as preferences for face-to-face contact and user-unfriendly technology. Although the answers of the healthcare professionals in our study were comparable to those of professionals in previous studies, our study did uncover some findings that seem to be unique to our sample of healthcare professionals working in cardiac care. Firstly, with regard to lifestyle support in general, whereas healthcare professionals in other studies reported to have a lack of skills to provide lifestyle support and the feeling that lifestyle interventions are ineffective (Jallinoja et al., 2007; Jansink et al., 2010), the professionals in our study did not mention these barriers. Secondly, concerning the use of eHealth in lifestyle support, our study did not reveal any eHealth barriers related to organisational factors (such inflexibility of the system and a lack of time or financial resources), which previous studies did (e.g. Bally & Cesuroglu, 2020; Peeters et al., 2016). Rather, the healthcare professionals in our study were generally positive about the use of eHealth in their care for CVD patients. Their barriers mostly concerned technical issues or concerns with a lack of face-to-face contact. These findings could be an illustration of the attitude with regard to lifestyle interventions within cardiac care within the Netherlands. Possibly, there is a higher level of consensus about the importance of and/or more experience with (digital) lifestyle interventions among Dutch professionals working in cardiac care due to the relatively high use of eHealth tools in the Netherlands in cardiac care. But there could also be other methodological differences related to the different care settings and organisational structures the interviewed healthcare professionals work in that could explain this. Professionals working in primary care could have different views than those working in cardiac rehabilitation, because of their own and the organisation's experiences with and attitude towards lifestyle support and eHealth. Nonetheless, to solve the insufficient implementation of eHealth into practice (Ross et al., 2016), our results suggest that healthcare professionals do not need to be convinced about the benefits of eHealth, but rather that the barriers they experience should be resolved. In order to overcome these barriers, health policy could play an important role in the provision of support and equipment.

The healthcare professionals we interviewed emphasised that, because CVD patients are older, they prefer face-to-face contact and have little technological experience. Therefore, digital tools would not be most suitable for this patient population and human support would be a better alternative. However, the responses we got from patients suggest that the lack of interest in eHealth interventions among an older population is not so much due to an aversion to technology. This is in line with other studies, showing that older patients are willing to use technology for self-management, as long as they are accessible to use (e.g. larger font sizes) (Cajita et al., 2017; Sivakumar et al., 2023). Rather, older patients, especially older men, seem to be less interested in lifestyle support in general and mostly prefer being self-supportive when working on their lifestyle. This finding could be explained by physical restrictions the elderly experience while engaging in physical activity, which makes it more difficult to follow a lifestyle intervention (de Boer et al., 2020a). Another explanation for the wish to be self-supportive, could be a general need among patients for autonomy or for personalised care (Bente et al., 2021). Our findings are also in line with studies showing a gender difference in health seeking behaviours (Yousaf et al., 2015), and that men perceive traditional lifestyle interventions as more suitable for women (Gavarkovs et al., 2016). Thus, in contrast to what healthcare professionals suggest, the technology itself may not be the problem. Instead, healthcare professionals could focus on the advantages of eHealth to overcome barriers that older men experience with regard to traditional lifestyle interventions. Especially given that men have an increased risk of developing CVD and are thus more often recommended to follow cardiac rehabilitation compared to women (de Boer et al., 2020b; Virani et al., 2020). For example, eHealth could help tailoring the intervention to individual needs of patients (Krebs et al., 2010), such as specific preferred changes in diet, or doing physical exercises at a time and place that suits a patient. Other possible advantage of eHealth, as mentioned by healthcare professionals, are giving patients more autonomy over maintaining their healthy lifestyle and personalising the intervention to their needs. Meta-analyses showed a positive association between both an autonomy supportive healthcare climate and personalisation of digital intervention content, and successful behaviour change (Lustria et al., 2013; Ng et al., 2012). Furthermore, eHealth shows to facilitate self-care behaviours, such as engaging in healthy lifestyle behaviours or self-monitoring (Riegel et al., 2017). These characteristics of digital interventions could provide patients more independence and could therefore possibly convince those patients who indicated to rather be self-supportive to do partake in a digital lifestyle intervention. On the other hand, the use of eHealth could not only help the high-risk group of older men, but also a subpopulation of patients who are now underrepresented in cardiac care, i.e. younger women. Younger women showed to have a more favourable attitude with regard to eHealth, which is why the increasing development and use of digital tools could ensure that also their needs are met by providing lifestyle support in a different way, tailored to their needs.

To conclude, although eHealth offers many opportunities, digitalisation may not be the only solution for all lifestyle-related concerns. The healthcare professionals indicated that the lack of face-to-face contact may be a possible barrier for using eHealth. This is in line with the views of the patients, who indicated to mostly prefer lifestyle interventions in which they would be supported by a coach (either individually, in a group, or via an app or internet). Furthermore, there is evidence that a healthy-lifestyle ecosystem, rather than a single eHealth intervention, might better meet the needs of both patients and professionals (Breeman et al., 2021). Despite the advantages of providing automated support through self-help interventions, such as being relatively cheap, easy to implement and requiring less investment from healthcare staff (Barak et al., 2009), these results indicate that attention should be paid to the human aspect within eHealth interventions. Especially given the great number of studies highlighting the importance of a positive relationship between the patient and the healthcare professional during the intervention on intervention adherence and outcomes (Brandt et al., 2018). This so-called working alliance explains up to a third of the variance in efficacy of psychotherapeutic interventions (Horvath et al., 2011; Lambert & Barley, 2001), also within an eHealth context (Kaiser et al., 2021). This means that eHealth interventions could be offered in a blended way, meaning that self-help features and human support are combined, or that self-help eHealth interventions could integrate some human-like characteristics.

How could self-help eHealth interventions be optimised?

In order to find solutions for the barriers raised by healthcare professionals and patients, we found that self-help eHealth interventions could be promising in lifestyle support among adults with CVD. Our results showed that the level of human support does not necessarily affect an eHealth intervention's effectiveness in improving health outcomes, or a higher intention to start using the intervention. This is contradictory to previous studies showing a lower uptake of self-help eHealth interventions (Lillevoll et al., 2014; Lin et al., 2018) and lower effectiveness of interventions without human (face-to-face) support (Beishuizen et al., 2016; Joiner et al., 2017; Lau et al., 2020). However, we concluded that equal levels of effectiveness between human-supported and self-help eHealth interventions could only be achieved when the quality of the intervention is high enough. The strict inclusion and exclusion criteria of our meta-analysis may have resulted in only including high quality interventions. This may have reduced the difference in effectiveness between human-supported and self-help interventions. For example, some meta-analyses that did find a lower effectiveness of self-help eHealth interventions included a broader variety of interventions, such as those without education or skills training (Beishuizen et al., 2016) or those that were not interactive (Lau et al., 2020). Interventions that are more elaborate, for example by incorporating multiple behaviour change techniques, are more effective in improving health behaviour (Webb et al., 2010). In those interventions, the additional benefits of human support, and thus increase in effectiveness, would potentially be lower compared to its additional benefit in less elaborate, lower quality interventions. It is therefore not surprising that automated support is frequently combined with behaviour change techniques and persuasive system design principles (Asbjørnsen et al., 2019). An important lesson is therefore that it is especially important to consider the quality of the eHealth intervention when little or no human support is provided.

The quality of the intervention shows to also be a point of concern when it comes to start using an eHealth intervention. In line with previous work, we found that the perception of the intervention's effectiveness or easiness of use affects use intention in general (Venkatesh et al., 2003). However, only within self-help eHealth interventions, the perception that the intervention might be ineffective and/or difficult to use, limited the willingness to start using the intervention. This effect is not visible within human-supported eHealth interventions. In line with this, meta-analyses show that the mere presence of a human being (even a nonprofessional) is the key ingredient in intervention effectiveness and prevention of dropout (Etzelmueller et al., 2020; Karyotaki et al., 2018; Richards & Richardson, 2012). It seems that just the option of having someone to provide you procedural or technical support seems to be helpful when the intervention's helpfulness or easiness of use is questionable. But for self-help eHealth interventions where such additional support is not an option, it is especially important that these interventions are perceived as being of a high quality to ensure that people are willing to give them a try.

However, there are some situations in which human support would be preferable. People who question whether they will reach their objectives with the help of the intervention or whether they are capable of easily using the intervention, could possibly benefit from more human support in the intervention. The presence of human support could compensate for a lack of self-efficacy that people feel either while they are starting to use or are already using the intervention (Fernández et al., 2014; Zhou et al., 2017). For example, patients with a low eHealth literacy are less likely to adhere to eHealth interventions (Richtering et al., 2017) and could benefit from such support. The results from Chapter 4 and 5 do offer some preliminary suggestions to offer support within the application of self-help eHealth interventions. Based on our results, we advise healthcare professionals to screen the patient's self-efficacy, or digital or eHealth literacy beforehand, and provide some level of human support if the patient expects any problems or barriers in using the eHealth intervention. Just procedural support could improve patients' perceptions about and their likelihood to start using the intervention, as well as ensure that the intervention is as effective as intended (Etzelmueller et al., 2020; Karyotaki et al., 2018; Richards & Richardson, 2012).

In addition to this, intervention adherence, similar to intervention uptake and effectiveness, might be another factor that would be important to consider in the optimalisation of eHealth interventions. Even though we were unable to assess adherence in our meta-analysis because only a small proportion of studies report eHealth adherence (Sieverink et al., 2017), some studies consistently showed that adherence is problematically low in self-help eHealth interventions (Kelders et al., 2011; Kelders et al., 2012; Murray et al., 2013; Wangberg et al., 2008). Furthermore, given that adherence is related to intervention effectiveness (Donkin et al., 2011), the higher level of adherence within human-supported interventions could explain why human support is related to intervention effectiveness. Given both the low adherence levels and the positive relationship between adherence and effectiveness, it seems that more attention should be paid to optimising adherence within self-help eHealth interventions.

Optimising adherence to self-help eHealth interventions

In contrast to our expectations, we found that the use of visual human cues caused people to be less adherent to the intervention compared to when the conversational agent used no human cues at all. In contrast to our study, many studies that did find a relationship between using human cues and working alliance concern the use of an embodied conversational agent (Bickmore et al., 2005; Bickmore et al., 2010). However, as we used a text-based conversational agent, we were limited in the agent's possibilities to use human cues. An embodied conversational agent can make use of an additional range of design characteristics, such as non-verbal communication. Possibly, the lack of incorporating non-verbal communication might hinder text-based conversational agents from benefitting from establishing a working alliance with the use of human cues (Friederichs et al., 2014). Such relational behaviour in the form of human cues can positively influence the relation between the user and the agent (ter Stal et al., 2020). Nonetheless, text-based conversational agents are more commonly used in healthcare settings than embodied conversational agents (Tudor Car et al., 2020). Furthermore, making a conversational agent look like a human being through visual cues, without being transparent about it being a computer rather than human, could lead to high expectations among the people using the self-help eHealth intervention (Luger & Sellen, 2016). However, as a computer is less capable of providing feedback that meets the wishes of the user than a human being, expectations concerning the quality of the coaching would not be met, possibly leading to disappointment in the conversational agent and thus lower levels of adherence (Mozafari et al., 2020; Rapp, Curti & Boldi, 2021). When a text-based conversational agent explicitly presents itself as non-human, the establishment of a working alliance between the agent and the user is possible (Darcy et al., 2021). In sum, based on our findings, we assume that improving the working alliance could be a solution to improve adherence to self-help eHealth interventions. And although further research is required, we would advise to invest in an embodied conversational agent for any self-help eHealth lifestyle intervention, and to consider full transparency about the true nature of the conversational agent. Furthermore, the different effects for visual and relational cues stress the importance of not only testing the effects of human cues in general, but also the effects of different types of cues (Feine et al., 2019).

The findings within this dissertation could help the development of eHealth lifestyle interventions for CVD patients. Chapter 2 and 3 revealed that healthcare professionals indicated that eHealth solutions could provide a lot of benefits, and that patients were not so much technology-averse but rather prefer being self-supportive or wish for the involvement of some human interaction during their lifestyle support. For those who would like to be self-supportive, a self-help eHealth intervention might be an attractive option, as it provides patients with the tools necessary to work on their lifestyle, whilst preserving their autonomy. As there is no healthcare professional involved though, it would be extra important for these patients to ensure adherence to the intervention. For those who would like human contact during their lifestyle intervention, a conversational agent could make a self-help eHealth intervention more human and increase the feeling of a working alliance during lifestyle support. Although we found that self-help eHealth lifestyle interventions can be as effective as human-supported ones, we also found that concerns about the intervention's helpfulness or easiness of use could prevent some people from using it. All in all, based on the findings in this dissertation, we can conclude that self-help eHealth lifestyle interventions could be a valuable addition to the current rehabilitation programs in cardiac care. They could help CVD patients in starting and maintaining a healthy lifestyle, while at the same time prevent a further increase of the workload of healthcare professionals. However, to ensure intervention uptake, it would be worthwhile to consider combining these self-help eHealth interventions with some level of human contact, and to improve the feeling of a working alliance during the intervention.

Strengths and limitations

The overall strength of this dissertation is the use of various research methodologies. The needs and wishes of healthcare professionals and CVD patients have been investigated with a qualitative interview study in Chapter 2, and a quantitative questionnaire study in Chapter 3. Furthermore, we used a (multilevel) meta-analysis to assess the effectiveness of existing eHealth lifestyle interventions in Chapter 4, and an online experiment to investigate what drives the intention to start using an eHealth intervention in Chapter 5. Finally, to investigate ways to improve a self-help eHealth intervention in Chapter 6, a field experiment measuring real, objective health behaviour was used. These different methodologies each have their own qualities that complement each other and provide a more complete picture of the application of eHealth lifestyle interventions in CVD care and the role human support plays in such interventions. Secondly, an important strength of the current dissertation is its focus on clinical practice. The main aim of each of the studies was to develop knowledge to improve lifestyle support through eHealth in cardiac care. Therefore, we have included the most important stakeholders to investigate what they need and want from an eHealth intervention, and investigated eHealth interventions that have already been developed and used in practice. And although the two experiments in Chapter 5 and 6 did not directly include these stakeholders, their main aim was to find factors that influence the uptake of and adherence to eHealth interventions, which could be applied to cardiac care in a later stage.

However, there are also some limitations that should be addressed. As mentioned above, in Chapter 5 and 6 we did not include stakeholders such as healthcare professionals or patients, but rather a healthy population to investigate use intention and adherence to self-help eHealth interventions. Therefore, these results can only be generalised to a limited extent to the CVD patient population. We chose to use a healthy sample in these studies as we did not want to unnecessarily burden a vulnerable population and rather first test our hypotheses in a healthy population. As human support is seen as essential to successful lifestyle change, studies in which this is replaced by automated support could potentially have negatively influenced the uptake of, adherence to or effectiveness of the studied lifestyle interventions. And given that we tested new principles of which the effectiveness was unknown, we felt it was unethical to test these with a vulnerable population for whom an effective lifestyle intervention is crucial. However, this does mean that further studies are needed before we can apply the results of the studies described in these two chapters to clinical practice. Secondly, please note that the samples of our studies described in Chapter 2 and 3 might not have been fully representative of all healthcare professionals working in cardiac care and the CVD patient population. Although we intentionally interviewed healthcare professionals involved in the lifestyle support of patients with CVD, this specific sample limits the generalizability of our results as our sample has experience with, and might therefore be more willing, to provide lifestyle support. As this sample already has experience with lifestyle support, their attitude towards a healthy lifestyle and eHealth might be different from the attitude of healthcare professionals in general. Furthermore, the sample of Chapter 3 represents a group of patients who are likely to have already completed cardiac rehabilitation, and who might be more empowered and self-aware of their disease and its consequences, and therefore might have a different view on lifestyle support than CVD patients who are still at the start of their rehabilitation trajectory. It would therefore be interesting for future studies to include healthcare professionals with different levels of experiences with and attitudes towards lifestyle support, and CVD patients who did not start rehabilitation yet, to investigate how this might influence their views upon lifestyle support and eHealth.

Future research

Given the importance of a healthy lifestyle for the prevention and treatment of CVD, and the needs and wishes of healthcare professionals and patients, we would advise to further investigate the role of human support in eHealth lifestyle interventions, and the possibilities of using self-help eHealth interventions in cardiac care. First of all, it would be interesting for future studies to investigate what qualities a self-help eHealth intervention needs to make it as effective as a human-supported eHealth intervention. For healthcare professionals, knowing which self-help eHealth interventions are effective would be important in their decision to provide additional human support during the lifestyle intervention. For eHealth developers, it would be important to know what intervention content, such as education and skills training or interactivity, improve the quality of an eHealth intervention to such an extent that human support has no more additional value with regard to effectiveness. Furthermore, we argued that the level of adherence could possibly be the missing explanation for the inconsistent results found in previous meta-analyses regarding the added contribution of human support to self-help eHealth interventions. However, due to the lack of reporting, we were not able to investigate this in our meta-analysis. Therefore, we would also suggest future eHealth studies to more carefully investigate and report adherence levels. Additionally, we would advise to replicate the study described in Chapter 5 with a patient population. Based on our findings with a healthy population, we would advise healthcare professionals to ask about their patients' expectations toward the eHealth intervention's helpfulness and easiness of use before deciding on the amount of support needed for that patient. However, we would recommend to investigate whether the same expectations as those found in our study are decisive in a CVD patient's intention to start using an eHealth intervention. Finally, the results of the study described in Chapter 6 raised several questions that would be important for future studies to address. We would advise to investigate the difference between text-based and embodied conversational agents, and whether non-verbal communication is indeed key for conversational agents to improve the working alliance people experience during the intervention and their adherence to the intervention. Furthermore, we expect that transparency about the true nature of the conversational agent would have a positive influence on intervention adherence, which would be worthwhile to test in a future study. Once we have more knowledge about these mechanisms, we can further investigate how conversational agents can be used to improve the adherence to self-help eHealth lifestyle interventions for CVD patients.

Clinical implications

The results of the studies described in this dissertation have provided insight into the views of healthcare professionals and CVD patients about lifestyle support and the use of eHealth, and demonstrated that self-help eHealth interventions could be a useful alternative for or addition to human lifestyle support. Specifically, we found that healthcare professionals recognise the benefits of using eHealth in lifestyle support. For clinical practice however, it would be important to address certain barriers they experience (such as low user-friendliness or a lack of tech-support) as these might hinder the adoption of eHealth into cardiac care. Concerning the preferences of patients, the most prevalent group within cardiac care - higher-aged men - indicated to mostly prefer being self-supportive in their lifestyle change. This highlights the need to make traditional lifestyle interventions more attractive for them in practice. eHealth provides opportunities for greater personalisation and autonomy, which would be especially attractive for those patients who would rather be self-supportive. Furthermore, our results showed that underrepresented groups within cardiac care - younger women - do find eHealth alternatives attractive. They especially preferred digital interventions in which a human coach was involved. Therefore, eHealth could be recommended to provide suitable lifestyle interventions for all patient groups within cardiac care. Our findings do show however that it would be important to consider different eHealth forms for different patient groups, for example more autonomous and personalised eHealth interventions for men, and blended interventions for women.

Furthermore, the studies in this dissertation demonstrated that human support is not as essential for effective eHealth interventions as previously expected, which is an important finding for clinical practice. As self-help eHealth interventions can be as effective as those with human support in improving cardiometabolic risk factors, healthcare professionals could consider providing such interventions to their patients when they experience barriers in providing lifestyle support themselves. An important finding was that expectations play a role in people's intention to start using the intervention. More specifically, we found that whether people think that the intervention is helpful or easy to use (or not) is decisive when there is no human support available. In practice, this implies that healthcare professionals could screen the patient's expectations towards the intervention's helpfulness and easiness of use beforehand, and provide some level of human support if these expectations turn out to be negative.

Finally, those involved in eHealth practice should not only pay attention to the working alliance between healthcare professional and patient, but also when the patient is engaged in a self-help eHealth intervention. An improved working alliance leads to a better adherence to a self-help eHealth intervention, which in turn increases intervention effectiveness. Our results hint towards the use of embodied conversational agents, which can use relational human cues to increase the working alliance with the user. Our studies also highlight the importance to focus on the working alliance in eHealth development. We would therefore recommend developers to investigate how patients experience the working alliance with the intervention during the design process to ensure their effort results in self-help eHealth interventions that are attractive for patients to adhere to. Healthcare professionals on the other hand could incorporate some form of support when they provide self-help eHealth interventions to their patients. Although such interventions have the potential to be effective, a low working alliance could risk intervention adherence. For example, healthcare professionals could ask patients about their progress in the intervention during consultations, or send brief electronic messages through the eHealth technology. Another possibility would be to consider using blended interventions, in which self-help and human-supported aspects are combined into the same eHealth intervention. All in all, clinical practice should pay attention to the working alliance patients experience when they use any kind of eHealth lifestyle intervention.

Although not all the findings from this dissertation are ready to be implemented into the care of CVD patients, implementation is still an important topic to address at this stage. For healthcare professionals who recognise the benefits of eHealth, the opportunity to improve eHealth implementation is to resolve the barriers they experience. Often, important stakeholders are involved when it comes to the implementation phase of eHealth development (van Gemert-Pijnen, 2011). By structurally involving those who are intended to use the eHealth tool, and specifically resolving the barriers these stakeholders experience, the tool will fit their needs and wishes and therefore be easier to adopt into their daily work practice (Bally et al., 2020). Therefore not only patients, but also healthcare professionals, should be involved when further investigating the mechanisms found in this dissertation. Furthermore, the healthcare context should be taken into account when working on an implementation plan. Although we did not find barriers on the organisational level, organisational structures can either hinder or facilitate the implementation process (Bally et al., 2020; Lingg et al., 2020; Walsh et al., 2018). Think for example about privacy concerns, which may hinder the use of health-related data to personalise automated coaching. Or ethical protocols, which may hinder the acceptance of self-help interventions when compared to actual human support for patient care. Scepticism among the professionals in the organisation might also hinder technological development in their work practices. Keeping the healthcare context in mind during development, could result in eHealth tools that are compatible with the existing workflow and therefore actually be implemented into practice.

Conclusion

This PhD dissertation aimed to find an answer to the dilemma that the role of human support has been shown to be important in successful eHealth solutions for a healthy lifestyle, while the involvement of healthcare professionals is not always possible or desirable.

Concerning the preferences of the users, healthcare professionals and patients could both benefit from using eHealth for lifestyle support, but it is useful to target any barriers that they experience. Technological issues could hinder adoption into cardiac care and should therefore be solved. In addition, eHealth should personalise interventions and increase user autonomy, to also make them attractive for patients who rather receive no lifestyle support.

Concerning human support within eHealth interventions, self-help eHealth lifestyle interventions can be as effective as human-supported eHealth lifestyle interventions in improving cardiovascular risk factors. However, since negative patient expectations can hinder the uptake of self-help eHealth interventions, such expectations should be screened to decide on the level of support a patient might need. To solve problems with non-adherence within self-help eHealth interventions, clinical practice should also focus on improving the working alliance within such interventions.

All in all, this dissertation demonstrates that eHealth interventions could be a promising solution to barriers experienced in the lifestyle support of CVD patients, and that self-help eHealth interventions could be a useful addition or alternative to human support that should be explored. Despite this, patients can benefit from human contact, which is why human aspects of interventions - such as the working alliance - should not be ignored. Even within self-help eHealth lifestyle interventions.

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NEDERLANDSE SAMENVATTING

Het aantal volwassenen dat lijdt aan hart- en vaatziekten (HVZ) stijgt. Voor deze patiënten kan een gezonde levensstijl de prognose van hun ziekte verbeteren. Een gezonde leefstijl is dan ook de focus van de revalidatieprogramma's die patiënten aangeboden krijgen. Maar HVZ patiënten hebben ook ondersteuning na afloop van hun revalidatie nodig om deze gezonde levensstijl op lange termijn vol te kunnen houden. De afgelopen jaren zijn er vele eHealth oplossingen ontwikkeld om ondersteuning te bieden bij een gezonde leefstijl. Toch zijn deze oplossingen niet zo effectief als dat deze in potentie zouden kunnen zijn. Een belangrijke reden hiervoor is dat veel eHealth oplossingen ontwikkeld worden zonder dat degenen die de technologie gebruiken (patiënten en zorgprofessionals) hierbij betrokken worden. Hierdoor zijn eHealth oplossingen vaak niet gebruiksvriendelijk en daardoor minder effectief in het verbeteren van de leefstijl van gebruikers.

Begeleiding door een zorgprofessional is van belang voor een succesvolle leefstijlverandering. Toch zijn ervaren professionals belemmeringen die hen ervan weerhouden om deze begeleiding te bieden, zoals een gebrek aan tijd in de dagelijkse praktijk of te weinig expertise in leefstijlbegeleiding. Aangezien de betrokkenheid van zorgprofessionals bij leefstijlverandering dus niet altijd mogelijk of wenselijk is, zou gekeken kunnen worden naar eHealth oplossingen met geautomatiseerde begeleiding: dit is op grotere schaal inzetbaar, goedkoper, en verlicht het de hoge werkdruk van zorgverleners. Bij menselijke begeleiding is er echter sprake van een therapeutische relatie tussen de zorgprofessional en de patiënt, die de therapietrouw aan de interventie (en daarmee het succes van de interventie) vergroot. Het is de vraag in hoeverre deze therapeutische relatie ook aanwezig is bij geautomatiseerde eHealth interventies.

Dit proefschrift heeft daarom de volgende doelen: (1) het in kaart brengen van de behoeften en wensen van zowel zorgprofessionals als HVZ patiënten met betrekking tot (begeleide en geautomatiseerde) eHealth levensstijlinterventies, en (2) onderzoeken of en hoe geautomatiseerde eHealth levensstijlinterventies geoptimaliseerd kunnen worden.

Met het oog op het eerste doel van dit proefschrift, (1) het in kaart brengen van de behoeften en wensen van zowel zorgprofessionals als HVZ patiënten met betrekking tot (begeleide en geautomatiseerde) eHealth levensstijlinterventies, onderzochten we in Hoofdstuk 2 en 3 hoe zorgprofessionals en patiënten aankijken tegen leefstijlverandering en eHealth levensstijlinterventies. **Hoofdstuk 2** gaat over een kwalitatieve studie onder zorgprofessionals. We interviewden 16 zorgprofessionals, die werken met HVZ patiënten, over leefstijlbegeleiding en het gebruik van eHealth. Op basis hiervan identificeerden we 12 thema's die zorgprofessionals belangrijk vinden in leefstijlbegeleiding, die ofwel gerelateerd zijn aan leefstijlinterventies, patiënten of het zorgsysteem. Binnen deze thema's werd eHealth genoemd als een (potentiële) facilitator of oplossing voor barrières die ze ervaren bij leefstijlbegeleiding. Professionals noemden het nut van eHealth vooral binnen de thema's "autonomie", "personalisatie", "vorm van begeleiding" en "continuïteit van begeleiding". Zo gaven professionals bijvoorbeeld aan patiënten met eHealth inzicht kunnen hebben in hun eigen gezondheid en zo meer autonomie over hun aandoening krijgen. Of dat professionals d.m.v. eHealth meer informatie over hun patiënten kunnen verzamelen om daarmee hun begeleiding beter te personaliseren. Zorgprofessionals zagen ook de mogelijkheid om met eHealth op afstand begeleiding te bieden. Hiermee kunnen ook patiënten met fysieke beperkingen begeleiding krijgen en kunnen professionals ook op lange termijn begeleiding aanbieden. Naast deze voordelen identificeerden we een 13^{e} thema met barrières bij de invoering en het gebruik van eHealth. Zo maakten zorgprofessionals zich bijvoorbeeld zorgen over de hoge leeftijd van hun patiënten en daarmee de lage digitale geletterdheid van deze patiënten, en dat hun patiënten over het algemeen de voorkeur hebben voor persoonlijk contact.

Als aanvulling hierop, onderzochten we in **Hoofdstuk 3** of deze ervaringen en verwachtingen van zorgprofessionals worden erkend door HVZ patiënten zelf. Het doel van de studie was om te onderzoeken wat de voorkeuren van patiënten zijn m.b.t. leefstijlbegeleiding en welke demografische kenmerken deze voorkeur voorspellen. We vroegen 659 HVZ patiënten een vragenlijst in te vullen. We vonden dat de meerderheid van de HVZ patiënten een voorkeur heeft om zelfstandig aan zijn/haar leefstijl te werken (dus zonder begeleiding van een coach, een app of internet, of familie en vrienden) of voor een interventie waarbij zij ondersteund worden door een coach (in een groep, één-op-één, of via een app of internet). Wel zagen we verschillen tussen mannen en vrouwen en tussen patiënten met verschillende leeftijden: met name oudere patiënten zeiden liever zelfstandig aan hun leefstijl te willen werken. Daarnaast gaven vrouwen vaker aan begeleiding te willen van een coach, één-op-één of via een app of internet, terwijl mannen vaker ondersteuning door familie en vrienden willen of zelfstandig aan hun leefstijl willen werken. Aangezien juist oudere mannen een risicogroep zijn voor HVZ, is het van belang dat leefstijlinterventies beter aansluiten op hun wensen en behoeften, bijvoorbeeld door deze d.m.v. eHealth meer te personaliseren (zoals gesuggereerd door de professionals in Hoofdstuk 2).

Voor het tweede doel van dit proefschrift, (2) onderzoeken of en hoe geautomatiseerde eHealth levensstijlinterventies geoptimaliseerd kunnen worden, wilden we eerst onderzoeken hoe effectief bestaande (begeleide en geautomatiseerde) eHealth oplossingen zijn. Eerdere onderzoeken lieten inconsistente resultaten zien: sommige studies toonden aan dat begeleide eHealth leefstijlinterventies veel effectiever zijn dan geautomatiseerde, in andere studies bleken beide soorten interventies even effectief te zijn. In **Hoofdstuk 4** hebben we resultaten van studies naar bestaande eHealth interventies verzameld. Het doel was om te onderzoeken of begeleide en geautomatiseerde eHealth levensstijlinterventies verschillen in effectiviteit, ofwel verschillen in de mate waarin gebruikers na de interventie een gezondere leefstijl hebben. We voerden een meta-analyse uit met studies naar eHealth levensstijlinterventies voor niet alleen patiënten met HVZ, maar ook met chronische nierschade, diabetes mellitus type 1 en diabetes mellitus type 2. Omdat al deze vier cardiometabole ziekten vergelijkbare onderliggende risicofactoren hebben, kan de prognose van deze ziekten op dezelfde manier verbeterd worden, namelijk d.m.v. een gezonde levensstijl. We vonden 104 unieke studies en voegden deze toe aan de multilevel meta-analyse. We zagen dat eHealth levensstijlinterventies effectief zijn in het verbeteren van zowel klinische (bijv. bloeddruk) en gedragsmatige (bijv. aantal stappen per dag) gezondheidsuitkomsten. We vonden hierin geen verschil tussen begeleide en geautomatiseerde eHealth levensstijlinterventies: beide zijn even effectief in het verbeteren van gezondheidsuitkomsten. Daarnaast vonden we voor begeleide interventies geen verschil in effectiviteit tussen interventies waarin veel of weinig begeleiding gegeven werd, en tussen interventies waarin de begeleiding helemaal digitaal gegeven werd of ook deels fysiek. Mogelijkerwijs is de kwaliteit van de eHealth leefstijlinterventies, ongeacht of deze begeleid of geautomatiseerd is, van invloed op de effectiviteit: wanneer de kwaliteit van de interventie hoog genoeg is, kan een geautomatiseerde eHealth interventie een even grote leefstijlverandering teweeg brengen als een begeleide eHealth interventie.

Een bekend probleem met geautomatiseerde eHealth interventies is dat deze vaak te maken hebben met een lagere acceptatie dan begeleide interventies. Mogelijk hebben mensen vooraf bepaalde verwachtingen waardoor zij minder geneigd zijn om geautomatiseerde eHealth interventies te gebruiken. Daarom onderzochten we in **Hoofdstuk 5** welke verwachtingen van invloed zijn op de intentie om begeleide of geautomatiseerde eHealth interventies te gebruiken. We voerden een online experiment uit, waarin gezonde proefpersonen willekeurig screenshots te zien kregen van een begeleide (met begeleiding door een menselijke coach) of geautomatiseerde (met begeleiding door een geautomatiseerde coach) leefstijl-app. We maakten gebruik van de verwachte therapeutische relatie met de (geautomatiseerde) coach en de constructen van de *Unified Theory of Acceptance and Use of Technology* (UTAUT) om te onderzoeken welke verwachtingen de gebruiksintentie voorspellen. We vonden dat proefpersonen even graag een geautomatiseerde eHealth interventie als een begeleide eHealth interventie zouden willen gebruiken. Voor beide soorten interventies verwachtten de proefpersonen ook een even sterke therapeutische relatie te kunnen krijgen met de (geautomatiseerde) coach. Daarnaast vonden we geen verschil in hoeverre ze verwachtten dat belangrijke mensen uit hun omgeving (vrienden en familie) vinden dat ze de eHealth interventie zouden moeten gebruiken. We ontdekten echter wel een effect op de gebruiksintentie van hun verwachtingen over de behulpzaamheid en de gebruiksvriendelijkheid van de interventie: wanneer proefpersonen de geautomatiseerde interventie te zien kregen, vonden we een sterke samenhang tussen hun verwachting over de behulpzaamheid en gebruiksvriendelijkheid en hun intentie om de interventie te gebruiken. Wanneer proefpersonen dachten dat de geautomatiseerde interventie niet behulpzaam of moeilijk te gebruiken zou zijn, waren ze minder geneigd om de interventie te gebruiken. Bij de begeleide interventie vonden we deze samenhang in mindere mate. Mogelijkerwijs dient de aanwezigheid van een menselijke coach als buffer voor negatieve verwachtingen: mensen verwachten dat er iemand is die hen kan helpen als dat nodig is en willen daarom alsnog met de interventie starten.

Ook een slechte therapietrouw (het gebruik van de interventie zoals bedoeld) is een bekend probleem bij geautomatiseerde eHealth interventies. Om een oplossing hiervoor te vinden, voerden we in **Hoofdstuk 6** een veldexperiment uit. In begeleide interventies is de therapeutische relatie is een belangrijke voorspeller van therapietrouw. Daarnaast zijn mensen in staat om niet alleen relaties aan te gaan met andere mensen, maar ook met technologie. Dit bracht ons op het idee om het concept van de therapeutische relatie gebruiken om de therapietrouw bij geautomatiseerde eHealth interventies te verbeteren. We pasten een *Text-based Conversational Agent* (een soort chatbot) toe in een leefstijl-app, welke als doel had om het dagelijkse aantal stappen van de gebruiker te verhogen. De *Conversational Agent* maakte gebruik van menselijke kenmerken om de therapeutische relatie met de gebruiker te stimuleren. We pasten twee soorten kenmerken toe, namelijk visuele (bijv. een menselijke profielfoto) en relationele kenmerken (bijv. het gebruik van humor of empathie), en testten deze in een veldexperiment. Gezonde proefpersonen werden gevraagd om de app voor 3 weken te gebruiken, en werden daarin ondersteund door één van de vier digitale coaches: een coach met (1) geen menselijke kenmerken, (2) alleen visuele kenmerken, (3) alleen relationele kenmerken, of (4) zowel visuele als relationele kenmerken). We verwachtten dat de *Conversational Agent* met zowel visuele als relationele menselijke kenmerken zou leiden tot de sterkste therapeutische relatie en dus tot de hoogste therapietrouw aan de interventie, gevolgd door de *Conversational Agent* met alleen visuele kenmerken of alleen relationele kenmerken. Zoals voorspeld, vonden we dat proefpersonen die een hogere therapeutische relatie met de coach ervoeren, meer therapietrouw waren (ofwel de interventie vaker gebruikten). Maar tegen onze verwachtingen in, toonden proefpersonen een lagere therapietrouw wanneer zij begeleid werden door de *Conversational Agent* met visuele kenmerken (conditie 2 en 4) dan wanneer zij begeleid werden door de *Conversational Agent* zonder deze kenmerken (conditie 1 en 3). De menselijke visuele kenmerken leidden dus tot een lager gebruik van de interventie. Mogelijk kunnen deze resultaten verklaard worden door een gebrek aan transparantie over het digitale karakter van de coach: proefpersonen kunnen door de visuele kenmerken gedacht hebben dat zij door een echt mens begeleid werden, wat tot teleurstelling over de begeleiding van de *Conversational Agent* kan hebben geleid.

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ABOUT THE AUTHOR

Talia was born on December 31st, 1994 in Haarlem, the Netherlands. She started her studies at Mendelcollege Haarlem where she received her VWO diploma in 2013. In that same year, she started her Bachelor's in Communication Sciences at VU Amsterdam, with a minor in psychology. In 2016, Talia started the Research Master Social Psychology at VU Amsterdam. During her studies, Talia worked on research projects related to social robotics in healthcare and education, and she wrote her thesis on fake news. After receiving her Master's degree, Talia started her PhD-project in 2019 at the Health-, Medical- and Neuropsychology unit of Leiden University under the supervision of professor Andrea Evers. Her research was part of the BENEFIT project, a public–private partnership between academic centres, hospitals, rehabilitation centres, general practices, commercial companies and patient federations. The BENEFIT project was funded by the Dutch Hartstichting and aimed to facilitate durable lifestyle change among patients with cardiovascular diseases by developing a so-called "ecosystem" in which the patient is emerged in a health-supportive environment. Talia's research contributed to the development of an eHealth platform to facilitate lifestyle changes at the individual level within this ecosystem and aimed to evaluate the effect of different forms of automated and personal coaching on lifestyle maintenance. Throughout this project, she worked together with a multidisciplinary team consisting of cardiologists, psychologists, eHealth developers, and patients. During her PhD, Talia was also involved in supervising Bachelor and Master thesis students, and presenting her work at international conferences. She finished writing her dissertation "Human support in eHealth lifestyle interventions" in 2023 and obtained her doctorate degree in 2024. Currently, Talia works as a researcher in the public sector, focusing on research topics related to health and healthcare.