How does personalization in eHealth interventions work?

A systematic literature review

Author: F. Ellenberger (s1978349)

University of Twente

The Netherlands

Supervisor: PhD candidate Mrs. ten Klooster

Dr. S.M Kelders

Keywords

Systematic review; eHealth interventions; Personalization

Abstract

Background: Personalizing eHealth interventions to the specific needs of individuals is difficult but has been done for many years. The effectiveness of eHealth interventions is suggested by research to a certain extent but there is no standardization of methods and definitions of personalization and it is still used interchangeably with tailoring (Sebri & Savioni 2019). This issue is highly debated in the literature and makes the evaluation of effectiveness more difficult. Therefore this study aims an interesting approach to systematically research the process of personalization in Ehealth interventions.

Objective: To examine how the process of personalization is being done in eHealth interventions, these research questions need to be answered: What data is being used to personalize? (1); What focus does the personalized eHealth intervention have? (2) What eHealth intervention categories are there in personalized eHealth? (3)

Methods: A systematic literature search was done in Pubmed until the timeframe of June 2020. The study type was not an exclusion criteria, but studies were only included if they clearly indicated how they personalized their eHealth intervention, which technology they used, data they used to personalize and if they had an existing intervention and not a suggestion for the future.

Results: The search strategy resulted in 35 studies which were included in this systematic literature review. Multiple categories of studies were established, language-based interventions (n=16) being the most prevalent. Five different types of data were identified that were collected for personalization purposes with outcomes data (n=33) being the most collected. Also, what the data is used for or the focus of the personalization was split into four categories with disease/illness management (n= 21) being the most focused on.

Discussion: The conclusion of the review was the identification of different categories in personalized eHealth intervention, and the confirmation of the diverse topics that personalization and eHealth interventions are. The future of personalized eHealth

interventions lies in the research that is being done in the standardization of the diverse methods and definitions of personalization. For future research, the effectiveness should be researched with the data collection types and its usage. To reach eHealth interventions full potential the development needs to be more accompanied with the implementation and evaluation process.

Introduction

In the last years, the health care sector has expanded its usage of technology, in its pursuit to meet the demands of the public for more efficient and safer care. The health care sector tries, among other things to meet those demands with eHealth interventions. EHealth interventions will be defined as the use of emerging information and communication technology, especially the Internet, to improve and promote health care which not only focuses on the physical and clinical outcomes but also well-being and quality of life (Norman et al.,2007; Sebri & Savioni, 2019). The growing interest in these interventions is confirmed by the gradually increasing number of articles published from 2006 - 2015 reporting eHealth interventions per year (Boogerd, Arts, Engelen & van de Belt, 2015). EHealth interventions can target the general public, a specific target group or a single individual depending on the goal of the intervention. Also, there can be a fixed timeframe for an intervention or interventions that support self-management for an unlimited period of time. An eHealth intervention is constructed around these aspects: program content, multimedia choices, interactive online activities, guidance and supportive feedback (Barak, Klein & Proudfoot, 2009).

Research found evidence for eHealth interventions effectiveness and the positive impact of the benefiting behaviours that these interventions had (Barak, Klein & Proudfoot, 2009; Barak, Hen, Boniel-Nissim & Shapira 2008). It has shown its positive impact of eHealth interventions for physical health as well as for mental health issues like depression and anxiety (Norman et al., 2007; Lipschitz et al., 2019). This confirms the wide-ranging support eHealth interventions have gotten over the years. On the other hand, Norman et al. (2007) and Lipschitz et al (2019) report that the issue lies not with the effectiveness of the eHealth intervention but with the adoption of the behaviours or cognitions that were targeted to be changed or improved. Adoption evaluates if the targeted behaviours or cognitions have been applied and can be utilised in real-life situations by the target-group (Finch et al., 2012). EHealth interventions effectiveness in terms of adoption is an issue that is highly debated about in research and an issue in several eHealth interventions (Hennemann, Beutel & Zwerenz,2017; Li et al., 2013; Granja, Janssen & Johansen, 2018). Additionally, many Ehealth interventions were implemented without a theoretical framework and the evaluation of its impact was limited (Kocaballi et al., 2019). So, it can be suggested that there seem to be opportunities to improve eHealth interventions.

One of those ways to make eHealth interventions more effective is by developing them in a more personalized manner (Finch et al., 2012; Ryan et al., 2019; Sebri & Savioni, 2019). Personalization in health care is supposed to be more productive and efficient than usual care which is why personalized medicine has become one of the core areas of public research funding and is a rising topic in healthcare (Schleidgen et al., 2013; Lustria et al.

,2013). Personalized eHealth approaches can be defined as the eHealth approaches that use the specific biological characteristics, environment, needs, and lifestyle of an individual to create ad hoc therapy and other possible remedies to match those specific characteristics of patients (Sebri & Savioni, 2019). Through distinctive diagnosis with different reactions of treatments, healthcare has always been aware of the difference and variability of individuals, and patients personalized needs.

Yet it can be very costly for someone to receive care or take part in interventions in a personalized manner since personalized care for individuals needs more time and effort than general care. There is also a psychological viewpoint on personalization in Ehealth interventions that personalization can help tailor different technologies to be more effective at behaviour change by looking at users' unique motivations, personalities, or preferences, which will make them more likely to be effective in evoking change (Hsieh, Munson, Kaptein & Oinas-Kukkonen, 2014).

However, there are also some limitations and issues with personalization that need to be investigated. Firstly, the great variability on how personalization is carried out, which are differences in intervention features, formats, and levels of interactivity, also influences its effectiveness (Lustria et al., 2013; Ryan et al.,2019; Sebri & Savioni, 2019). Secondly, this great variability might be the consequence or reason for the confusion in definitions around the topic of personalization. The term "tailoring" instead of personalization was used in definitions, but there is a debate that tailoring is too broad since it could mean that only a little improvement in one component of the eHealth intervention has been altered to the individual needs (Ryan et al.,2019; Schleidgen et al., 2013; Sebri & Savioni, 2019; Hennemann, Beutel & Zwerenz , 2017; Li et al., 2013; Granja, Janssen, & Johansen, 2018). Personalization has been reported by some researchers as a more extensive way to tailoring or tailoring being a part of personalization (Sebri & Savioni, 2019; Hennemann, Beutel & Zwerenz, 2017; Li et al., 2013). In a vast amount of studies, these two terms are used interchangeably (Sebri &

Savioni, 2019), which makes the analysis of the distinctive process and application of personalization more difficult.

Furthermore, personalized eHealth interventions can have different types of theories, methods and goals which is another reason why a systematic review reported the definitions in literature as wide-ranging and confusing (Sebri & Savioni, 2019). This is in line with findings by Finch et al. (2012) who also suggested that eHealth interventions are diverse and complicated. They have the need for multiple perspectives and collaborative work so that the familiarity with products and definitions can make the interventions more effective. It indicates the focus on the standardization of measurements in eHealth interventions and underlines the improvements that can be made. One of them being that standardized personalization can be used reliably and can be compared in all kinds of contexts: mental health, physical conditions or other contexts of a study.

In conclusion, personalization has the opportunity to make eHealth interventions more effective if the process, methods and definitions of personalization are clear. However, this is not the case yet and the focus of most intervention does not lie in how personalization is specifically applied. There is no standardized way of categorizing personalized eHealth interventions in research to compare those but a widely spread cluster of different definitions, features, formats and contents.

This study investigates how the process of personalization works in eHealth interventions, since before tackling effectiveness, the setup which research described to be problematic needs to be explained. To answer this question the type of personalized eHealth intervention in terms of technology, as well as the focus of the intervention is important. To gain more insight and information which kind of eHealth interventions are being more personalized and to make comparison what kind of technologies and focuses of interventions are common. Also, the data that needs to be collected for personalization is interesting, since you do not fully know in current studies what they base the personalization on. It is necessary to conduct a systematic literature review to be able to compare as many studies of personalized eHealth intervention as possible and provide valuable information for researchers and designers to take a different look on personalization, than just its effectiveness. Consequently, It is rather important to see all the issues personalization and eHealth interventions still have in its process and if these can be confirmed. The purpose is to answer the following research questions :

- What type of eHealth interventions are being personalized?
- What data is being used to personalize in eHealth interventions?
- What is the focus of personalized eHealth interventions?

Methods

Literature search

A comprehensive literature search is used to go through the database PubMed, since it focuses directly on healthcare-related topics. Additionally, “tailoring“ has been included and will be used interchangeably with personalization. out of the reason that a vast amount of included studies used it interchangeably and to avoid the difficulties of defining personalization. The search terms that were utilized were “Personalization”, “Tailoring” and “eHealth ”. Each construct of the search term was identified through studying the relevant literature and through advise, as well as the shared search key of an expert in the field. To see the details of the search strategy see Appendix A.

The inclusion and exclusion criteria described below were used to classify which articles were worth considering. After the removal of duplicates, the titles were reviewed. The next step was to screen the abstracts. If they did not reveal information about the technology of their intervention or that their intervention is “tailored or “personalized” these articles were excluded. Lastly, full-text articles were read and screened by one person. The search focused around the construct of eHealth and personalization, which means technological devices (e.g.

phones, tablets, computers) needed to be included in the study as well as some kind of personalization. If inclusion was still debated, the consensus was found by including a variety of personalized eHealth interventions if the data collection for personalization, the technology that has been used, and focus of the intervention were clearly identifiable and explained.

Inclusion and Exclusion Criteria

The criteria for inclusion in the systematic review were : (1) Only studies that describe the personalization or tailoring process of an eHealth intervention in an explicit and understandable manner, which means clearly explaining its methods and definitions of personalization; (2) Only studies describing a personalized eHealth intervention that has actually been developed ; (3) the study was published in English.

The exclusion criteria were as follows: (1) No systematic reviews were included because they are considered as secondary sources and only primary sources are accepted. (2) Personalization is only a result, outcome or suggestion of a study on how to improve components or the entire intervention ; (3) Not a complete personalized eHealth intervention, still in the design and improvement phase of the intervention; (4) the intervention has personalization but no technological components and in turn is not an eHealth intervention with personalization; (5) If there is the same eHealth intervention in several studies with a different aim, earlier versions of the intervention always will be excluded.

Data Extraction

The process of data extraction of this systematic review was loosely based on the guidelines of the Cochrane Handbook for Systematic Reviews of Interventions (Higgins & Green, 2011). Firstly, a data extraction form was generated based on the research question and the sub-questions to be able to identify the most relevant information and to be able to compare the studies. Secondly, the data extraction began and all relevant information from the included studies was copied into the form. This form included four categories with their own subcategories to receive more precise results. The four categories are information about the study, data collection for personalization, the type of personalized eHealth intervention and the focus of the eHealth intervention (see Appendix B).

The first category was Information about the studies which were categorized by the name of the study and the author as well as the date of publication. To answer the research questions the other three categories were used. After evaluating the included studies, it was difficult to make up inductively defined categories, because of the aforementioned high variations in methods, definitions and structures in personalized eHealth interventions. Which is why, the decision was made to make use of pre-defined categories from similar literature about eHealth interventions as well as inductively defined categories, to also create categories if studies did not fit the pre-defined categories.

The first research question, which relates to the distinction of personalized eHealth intervention was answered by sorting them into five main categories: Category 1: Interactive, Predominantly Language-Based Interventions; Category 2: Communication Technology for Synchronous Interpersonal Interaction ; Category 3 Platforms with User-Generated and Shared Content. After investigation of the included studies it was decided to use pre-defined categories based upon Kip et al. (2018) and their extensive research on categorizing eHealth interventions. This decision was made because of three of the six different categories about types of technology in eHealth interventions that Kip et al. (2018) proposed, matched with the types of technology in the included studies and their type of technology.

To answer the second research question, which kind of data is collected to personalize, five different types of data were identified and distinguished: Health risk and health status, patient medical history, current medical management, outcomes data and current attitudes. Current attitudes was an inductively produced data type based upon the included studies which also collected psychological components. After investigation of all included studies, the other data types were decided to be pre-defined and based on Fernandez-Luque, Karlsen, Bonander (2011) who researched data extraction for health personalization in a solely medical setting but their data types gave clear guidance on what kind of data should be collected.

Lastly, the third research question was answered by what the eHealth intervention actually focuses on, which was divided into three different categories: Diagnosis and risk prediction, Doctor-patient communication and Disease/illness management. All included studies were considered and three categories were found to match those which were pre-defined and based upon Sebri & Savioni (2019) who reported that they were the healthcare fields in which personalization had the most influence in the last years.

Results

Search Results

The search strategy resulted in 79 articles from which 35 articles were seen as eligible and included. Those studies have been conducted in the timeframe from the 16th of June 2015 up until 1st of June 2020 (see Figure 1 for the full flow diagram of article selection). The full results will be available in Table 1 in Appendix B where all included interventions can be seen, which is structured around the three research questions. The Table includes the author, the year and the name of the intervention. Firstly, it includes the type of data that is collected, to answer the first research question. Secondly, it includes the focus of the eHealth intervention to answer the second research question. Lastly, the third research question is answered by the category of personalized eHealth intervention the interventions belongs to.

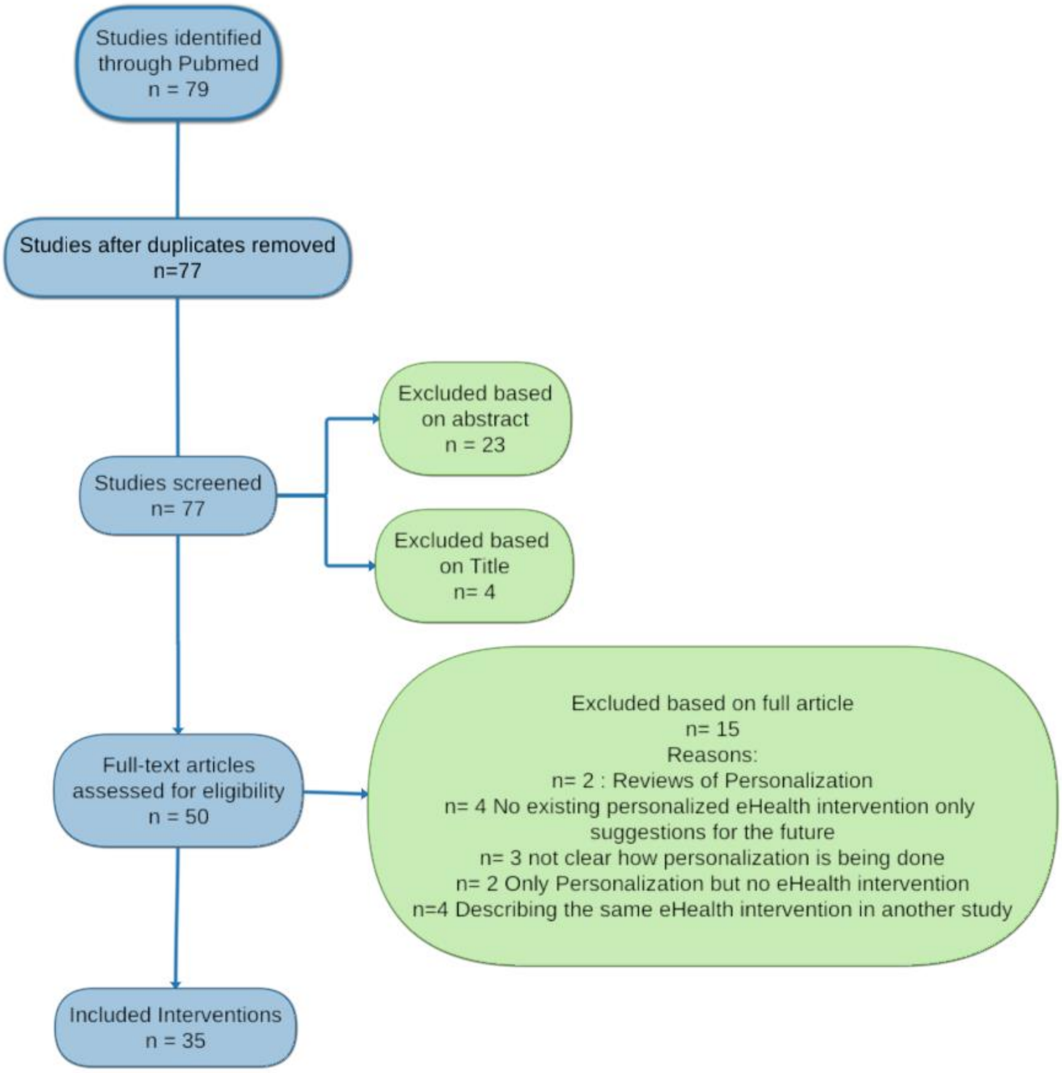

Figure 1. Flow diagram of study selection

Data collection of personalized health intervention

The included studies were categorized into the following types of data, which are used to personalize the eHealth interventions: Health risk and health status (n= 29), Patient medical history (n= 19), Current medical management (n= 31), Current attitudes (n= 21), and Outcomes data (n= 33). Every study collected at least two sets of data types and five studies managed to collect even all five data types (Tiong et al., 2016; Dunphy, Hamilton, Spasic & Button, 2017; Negarand, Zolfaghari, Bashi & Kiarsi, 2019; Brekel-Dijkstra, Rengers, Niessen, de Wit & Kraaijenhagen, 2015), so they have a considerably and valid amount of individual data that they used to personalize their intervention to the individual needs of their target groups.

The *Outcomes data* was the data type which was the most collected in all studies, only two studies did not include them. This means it is the most used data type for personalized information. In this review *Outcomes, data* is data that encompasses the effects of health care and the progress of health care interventions, which includes any data that is coming back as a product of the eHealth intervention and which is being used to further personalize the intervention. Examples of the included studies on how such *Outcomes data* are used to personalize is, using in-game progress results, to update game scenarios accordingly to your physical fitness level (Konstantinidis et al., 2016).

The data collected of *Current medical management* was the second-highest data type that eHealth intervention collected to personalize. *Current medical management* can be understood as all the medical management that has been done for a specific illness or issue that the individual is exhibiting. An example of data from *Current medical management* is a web-based health risk assessment for cardiovascular disease where it is asked: “what medical treatment are you undergoing to tackle your illness?” This data is then used to create a risk profile for the client with a suggestion for particular health-promoting activities according to the at-risk level the client has (Psmooij et al., 2018).

The third most collected was data about the *health risk and health status*, which is checking for certain health risks an individual might have, which can have to do with family history and genetics, environment that he/she is living in and/or substances that are being used. An example would be, to collect data with a test or a questionnaire on their risk of alcohol consumption and a test for their blood alcohol level. This leads to set a personalized goal for alcohol consumption and personalized information to fulfil one's plan (tracker application, self-monitoring) (Wilson, Palk, Sheehan, Wishart & Watson, 2017).

The second least collected data type is *current attitudes*, which can be defined as collecting data on how individuals feel and think about their illness or issue, so their cognitive experience with their illness. An example is a cognitive behavioural therapy which collects data on the opinions and attitudes of women and their distress while undergoing assisted reproductive technology. Which was used to decide what kind of module the person needs to follow and how much personalized support each patient needs from the therapists (Van Dongen, Nelen, Inthout, Kremer & Verhaak, 2016).

The least collected data type was *patient medical history*, which involves any previous medical encounters, past medical problems that might not have to do with the main illness or issue. An example of *patient medical history* is to collect data on suicidal ideation and collect information on sociodemographic risk factors to see if the patient had suicidal ideations. This will help prevent suicidal ideation or suicide in the future because the therapist will be informed about the seriousness and then can take better-personalized action to the individual (Meyer et al., 2017).

The focus of eHealth interventions

After the data is collected, to make the eHealth intervention more tailored to the individual it is also interesting to know what the eHealth intervention actually focuses on, which is why three categories have been chosen: Diagnosis and risk prediction (n=12), Doctor-patient communication (n=3), Disease/illness management (n=19).

The highest number and the vast majority of eHealth interventions focused on *Disease/illness management. Disease/illness management* is everything that is collected on how you deal with a specific illness or issue on how that can be tailored more to your individual needs. This does include prescriptions if the focus really lies on the management of the disease. An example would be a telehealth system that checks how you currently manage your life with breast-cancer and then adapts an adequate tailored exercise program according to your intensity of exercise before, treatments and other issues(Galiano-Castillo et al., 2016).

The second highest was *Diagnosis and risk prediction,* which only has to do with the uncertainty if the individual has an illness. It is trying to give information about if the individual might have a disease or is at- risk to develop an illness. This does not mean that a diagnosis can be made solely on this basis, but that the personalization of the interventions had the goal to predict risks or try to diagnose in combination with other instruments what the issue might be. An example is, the study of Berger et al. (2019) who focused on pragmatic weight gain prevention and checked how much at-risk those people were, then created tailored behaviour change goals and checked this with tracking and self-monitoring (daily weighings).

The lowest number was *Doctor-patient communication,* which means that only a few interventions focused on improving *Doctor-patient communication* by personalizing their eHealth intervention. *Doctor-patient communication* can be all interventions that have the aim of improvement of talking or communicating with a healthcare-professional. An example is Van der Meij et al. (2018) where an e-consult function enables patients to chat with the health-care provider who gives day-to-day feedback tailored to their personal situation and seriousness after having abdominal surgery.

Personalized eHealth intervention categories

To create a certain overview of all the very distinctive personalized eHealth interventions, three different types have been chosen to sort them into different eHealth interventions: Category 1: Interactive, Predominantly Language-Based Interventions (n=16); Category 2: Communication Technology for Synchronous Interpersonal Interaction (n=8); Category 3: Platforms with User-Generated and Shared Content (n=11).

Combination of Results

Table 2 combines the different results for the three research questions and establishes an overview for each of the personalized eHealth intervention categories and their type of data collection, data usage and focus of personalization.

Table 2. *Personalized eHealth intervention categories, Type of Data collection, Focus of personalization*

Personalized eHealth intervention categories	Type of Data collection	Focus of personalization
Category 1: Interactive, Predominantly Language-Based Interventions : n = 16 (45,71%)	Health risk and health status : n = 14 (87.5 %) Patient medical history: n = 9 (56.25%) Current medical management: n = 14 (87.5 %) Current attitudes: n = 10 (62.5%) Outcomes data: n =15 (93.75%)	Diagnosis and risk prediction: n = 7 (43.75%) Doctor-patient communication: n = 0 (0%) Disease/illness management: n = 9 (56.25%)
Category 2: Communication Technology for Synchronous Interpersonal Interaction : n = 8 (22,86%)	Health risk and health status : n = 6 (75%) Patient medical history: n = 5 (62.5%) Current medical management: n = 7 (87.5 %) Current attitudes: n = 4 (50%) Outcomes data: n = 7 (87.5 %)	Diagnosis and risk prediction: n = 1 (12.5%) Doctor-patient communication: n = 3 (37.5%) Disease/illness management: n = 4 (50 %)
Category 3: Noninteractive, Algorithmic-based interventions: n = 11 (31.43%)	Health risk and health status : n = 9 (81.82%) Patient medical history: n = 4 (36.36%) Current medical management: n = 9 (81.82%)	Diagnosis and risk prediction: n = 3 (27.27%) Doctor-patient communication: n = 0 (0%) Disease/illness management: n = 8 (72.73%)

	Current attitudes: n = 7 (63. 64%) Outcomes data: n = 9 (81.82%)

The table shows several interesting relationships between the categories and the data collection and focus of the personalization.

Firstly, the interactive, predominantly language-based interventions (n=16) had the most studies compared to other categories. Furthermore, it targets the data collection of outcomes data (n= 15) which is the highest with 93.75% of all studies inclusion, current medical management (n=14), and health risk and health status (n=14). It also has high scores in the current attitudes (n=10) and patient medical history (n= 9), but this could be because of the high amount of included studies. Moreover, the personalization of the eHealth intervention focuses solely on disease/illness management (n=10) as well as diagnosis and risk prediction (n= 7) and none on doctor-patient communication. The types of personalization that were used were, tailored feedback, monitoring, risk assessment and personalized reminders (Galiano-Castillo et al., 2016; Kouwenhoven-Pasmooij et al., 2018; Wilson, Palk, Sheehan, Wishart & Watson, 2017; Dunphy, Hamilton, Spasic & Button, 2017).

Secondly, the third category Platforms with User-Generated and Shared Content (n= 11) had the second-highest amount of eHealth interventions in its category. It focused mostly on medical management (n=9), outcomes data (n=9) and health risk and health status (n=9). Additionally, almost solely used personalization in the interventions for disease/illness management (n=8). Only three studies focused on diagnosis and risk prediction (n=3). It focuses on 72.73% of its included studies the most on disease/illness management.

Thirdly, the second category communication technology for synchronous interpersonal interaction has the least amount of studies (n=8) and indicated as well as the first category that the data of current medical management(n=7), outcomes data (n=7) and health risk and health status (n=6) which is most collected. Category two is quite versatile on what is the focus of their personalization, it is the only category where all four types of data usage applied to interventions. Although, also 50% of all studies focused on disease/illness management.

Discussion

This systematic review about how the process personalization in eHealth intervention is applied provided a systematic overview on different topics. Firstly, most included studies were in the category of language-based interventions which means that personalization is applied mostly to these eHealth interventions that use technologies which are language-based. This is in line with Kip et al. (2018), who also had a majority with language-based interventions in their study. Secondly, the data which was collected the most to personalize eHealth intervention was outcomes data, which means that progress and results of eHealth interventions components get used the most to personalize an eHealth intervention. Since disease/illness management was more than half of the focus of all included eHealth interventions, it is the most significant focus of personalized eHealth interventions. Also, it has a way higher number of studies than diagnosis and risk prediction and doctor/patient communication together. So especially, doctor/patient communication with only being the focus of three studies might not be a focus of so many other interventions.

Additionally, current medical management, and health risk and health status were the second and third most prevalent collected data, which means these data types and topics of risk and management with a disease have an important impact on how personalization is done. The most significant focus of eHealth interventions is disease/illness management which is closely connected with the data type current medical management. Additionally, the second biggest focus was diagnosis and risk prediction, which fits with the result of health risk and health status data being collected frequently in the included studies. More collected data means more information about you being on the web, but at the same time could mean better care for you if you trust the process and intervention. This advantage and disadvantage for data are called the privacy paradox that Guo, Zhang & Sun (2015) researched.

Strengths and limitations

The main strength of this study is that it used a systematic approach based on the Cochrane guidelines to provide an overview of the research of the process of how personalization works in eHealth interventions. In addition, not many studies focused yet on the data extraction except Fernandez-Luque, Karlsen and Bonander (2011) which inspired this systematic literature review. This means the study could more accurately tell how personalization was applied, through identifying the data and intervention type and observing what the focus of the eHealth interventions was. Despite the thorough execution, it does have several limitations.

First of all, categorisation of the actual personalization and effectiveness has not been researched in this study which is needed for fully valid information on the appliance of personalization.

The differences of eHealth interventions was surprising but might be part of the problem why it is so hard to find definitions and standardisation of personalization in research (Sebri & Savioni, 2019). This issue led to the idea of creating many categories but there were not enough studies that fitted the criteria, so only three categories were chosen. Having more categories might improve the preciseness and validity which eHealth interventions belong in which category. Lastly, the pre-defined categories were used and they matched well with the studies since first the included studies were considered and inductively defined categories should have been chosen. It was difficult to come up with any and research revealed, they were some constructs matched exactly the constructs the included studies needed. But, inductively defined categories are solely based on the included studies and have therefore more validity but pre-defined categories have been used before in the same context. This means that through pre-defined categories the reliability of the constructs being used for researching personalized eHealth intervention rose.

Recommendations for future research

Lastly, category three about interventions with online platforms which was the second-highest after the first category seemed to have a future in this eHealth industry since more and more platforms, websites or applications are being used. There you have your own account, can share progress, see results, get personalized feedback which is line with Norman et al (2007) and Sebri & Savioni (2019) research suggests personalization focuses more on the well-being and quality of life than only on the physical and clinical outcomes.

Moreover, research needs to focus more on what the different data is specifically used for and if the personalization of that data was effective. A recommendation would be to make a systematic review on the topic of personalization effectiveness combined with the type of data that is used in eHealth interventions. The effectiveness can with the data collection show added value in terms of the better accuracy of personalized eHealth interventions effectiveness. It would be possible to see how data collection supports personalization and if interventions collect any or enough data to personalize effectively.

Conclusion

Based on the results of this review, the conclusion is that personalized eHealth interventions have three different categories of eHealth interventions, five different data types and three different focuses of personalized eHealth interventions. This data collection is the biggest added value of the study and should be used in research further to describe personalization processes. This study will be interesting for other reviews and meta-analyses for personalization in eHealth interventions to know what might be interesting to get full insight into all of the important aspects like the utilization of data, focus and type of eHealth intervention.

Appendices

Appendix A

Keywords literature search

Personalization	Tailoring	E-health

(((Personalization) AND (Tailoring)) AND (E-health) review

Appendix B

Intervention	Authors, Year	Data collection for personalization	Data usage for personalization	Categories
Personalised Perioperative Care by E-Health After Intermediate-Grade Abdominal Surgery	Van der Meij et al, 2018	Health risk and health status Current medical management	Doctor-patient communication	Category 2
Telehealth System: A Randomized Controlled Trial Evaluating the Impact of an Internet-Based Exercise Intervention on Quality of Life, Pain, Muscle Strength, and Fatigue in Breast Cancer Survivors	Galiano-Castillo et al., 2016	Current medical management Outcomes data	Disease/illness management	Category 1
Effectiveness of the blended-care lifestyle intervention 'PerfectFit': a cluster randomised trial in employees at risk for	Kouwen hoven-Pasmooij et al., 2018	Health risk and health status Patient medical history Current medical management Outcomes data	Diagnosis and risk prediction	Category 1

cardiovascular diseases				
Development and proof of concept of a blended physiotherapeutic intervention for patients with non-specific low back pain	Kloek, van Tilburg, Staal, Veenhof & Bossen, 2019	Health risk and health status Patient medical history Current medical management Outcomes data	Disease/illness management	Category 2
Evaluation of a Mobile Application for Pelvic Floor Exercises	Han, Grisales, Sridhar,2019	Health risk and health status Outcomes data	Disease/illness management	Category 3
Making Prescriptions "Talk" to Stroke and Heart Attack Survivors to Improve Adherence: Results of a Randomized Clinical Trial (The Talking Rx Study)	Kamal et al., 2018	Patient medical history Current medical management Outcomes data	Treatments	Category 2
An e-health strategy to facilitate care of breast cancer survivors: A pilot study	Tiong et al., 2016	Health risk and health status Patient medical history Current medical management Current attitudes Outcomes data	Disease/illness management	Category 3
Steering Clear of Driving After Drinking: a Tailored e-Health Intervention for Reducing Repeat Offending and Modifying Alcohol Use in a High-Risk Cohort	Wilson, Palk, Sheehan, Wishart & Watson, 2017	Health risk and health status Current medical management Outcomes data	Diagnosis and risk prediction	Category 1
A Hybrid Web-Based and In-Person Self-	Berube et al., 2018	Health risk and health status	Disease/illness management	Category 3

Management Intervention Aimed at Preventing Acute to Chronic Pain Transition After Major Lower Extremity Trauma: Feasibility and Acceptability of iPACT-E-Trauma		Current medical management Outcomes data		
Effectiveness of Technologically Enhanced Peer Support in Improving Glycemic Management Among Predominantly African American, Low-Income Adults With Diabetes.	Heisler, Choi, Mase, Long & Reeves, 2020	Health risk and health status Current medical management Outcomes data	Doctor-patient communication	Category 2
Acceptability of a digital health intervention alongside physiotherapy to support patients following anterior cruciate ligament reconstruction	Dunphy, Hamilton, Spasic & Button, 2017	Health risk and health status Patient medical history Current medical management Current attitudes Outcomes data	Disease/illness management	Category 1
The Balance Protocol: A Pragmatic Weight Gain Prevention Randomized Controlled Trial for Medically Vulnerable Patients Within Primary Care	Berger et al., 2019	Current medical management Current attitudes Outcomes data	Disease/illness management	Category 2
A Web-Based Exercise System (e-CuidateChemo) to Counter the Side Effects of	Ariza-Garica et al.,2019	Patient medical history Current medical management Current attitudes	Disease/illness management	Category 3

Chemotherapy in Patients With Breast Cancer: Randomized Controlled Trial		Outcomes data		
A Tailored Online Safety and Health Intervention for Women Experiencing Intimate Partner Violence: The iCAN Plan 4 Safety Randomized Controlled Trial Protocol	Ford-Gilboe et al., 2017	Health risk and health status Patient medical history Current attitudes Outcomes data	Diagnosis and risk prediction	Category 1
The user experiences and clinical outcomes of an online personal health record to support self-management of bipolar disorder: A pretest-posttest pilot study.	Van den Heuvel et al., 2018	Current medical management Current attitudes Outcomes data	Disease/illness management	Category 1
mHealth use for non-communicable diseases care in primary health: patients' perspective from rural settings and refugee camps	Saleh et al.,2018	Health risk and health status Current medical management Outcomes data	Treatments	Category 1
A Nationally Scaled Telebehavioral Health Program for Chronic Pain: Characteristics, Goals, and Psychological Outcomes	Mochari-Greenberger,Peters, Vue & Pande, 2017	Health risk and health status Patient medical history Current attitudes Outcomes data	Treatments	Category 2
From Evidence-Based Research to Practice-Based	De Cocker	Health risk and health status Outcomes data	Disease/illness management	Category 1

Evidence: Disseminating a Web-Based Computer-Tailored Workplace Sitting Intervention through a Health Promotion Organisation	et al., 2018			
Evaluating the Effect of Monitoring through Telephone (Tele-Monitoring) on Self-Care Behaviors and Readmission of Patients with Heart Failure after Discharge	Negarand, Zolfaghari, Bashi & Kiarsi, 2019	Health risk and health status Patient medical history Current medical managment Current attitudes Outcomes data	Doctor-patient communication	Category 2
Personalized prevention approach with use of a web-based cardiovascular risk assessment with tailored lifestyle follow-up in primary care practice – a pilot study	Brekel-Dijkstra, Rengers, Niessen, de Wit & Kraaijenhagen, 2015	Health risk and health status Patient medical history Current medical managment Current attitudes Outcomes data	Diagnosis and risk prediction	Category 1
Tailored e-Health services for the dementia care setting: a pilot study of 'eHealthMonitor'	Schaller et al., 2015	Health risk and health status Patient medical history Current medical managment Current attitudes Outcomes data	Disease/illness management	Category 3
Self-monitoring and personalized feedback based on the experiencing sampling method as a tool to boost depression treatment: a protocol of a	Bastiaansenet al., 2018	Health risk and health status Current medical managment Current attitudes Outcomes data	Diagnosis and risk prediction	Category 1

pragmatic randomized controlled trial (ZELF-i)				
Does additional support provided through e-mail or SMS in a Web-based Social Marketing program improve children's food consumption? A Randomized Controlled Trial	Rangelov, Bella, Marques-Vidal & Suggs, 2018	Health risk and health status Patient medical history Current medical managment Current attitudes Outcomes data	Disease/illness management	Category 1
Adherence and factors affecting satisfaction in long-term telerehabilitation for patients with chronic obstructive pulmonary disease: a mixed methods study	Hoaas, Andreassen, Lien, Hjalmarsen& Zanaboni, 2016	Health risk and health status Patient medical history Current medical managment Current attitudes Outcomes data	Diagnosis and risk prediction	Category 2
Effectiveness of an Internet-Based Perioperative Care Programme to Enhance Postoperative Recovery in Gynaecological Patients: Cluster Controlled Trial With Randomised Stepped-Wedge Implementation	Bouwsma et al., 2017	Health risk and health status Patient medical history Current medical managment Current attitudes Outcomes data	Disease/illness management	Category 1
Substance Use, Bullying, and Body Image Disturbances in Adolescents and Young Adults Under the Prism of a 3D Simulation Program:	Langer, Aguilar-Parra, Ulloa. Carmona-Torres & Cangas, 2016	Health risk and health status Current attitudes Outcomes data	Diagnosis and risk prediction	Category 3

Validation of MySchool4web				
e-Therapy to reduce emotional distress in women undergoing assisted reproductive technology (ART): a feasibility randomized controlled trial	Van Dongen, Nelen, Inthout, Kremer & Verhaak, 2016	Health risk and health status Patient medical history Current medical managment Current attitudes Outcomes data	Diagnosis and risk prediction	Category 1
Design, implementation and wide pilot deployment of FitForAll: an easy to use exergaming platform improving physical fitness and life quality of senior citizens	Konstantinidis et al., 2016	Health risk and health status Current medical managment Outcomes data	Disease/illness management	Category 3
Physiotherapists' experiences with a blended osteoarthritis intervention: a mixed methods study	Kloek et al., 2018	Current medical managment Outcomes data	Disease/illness management	Category 3
The talent study: a multicentre randomized controlled trial assessing the impact of a 'tailored lifestyle self-management intervention' (talent) on weight reduction	Melchart, Doerfler, Eustachi, Wellenhofer-Li & Weidenhammer ,2015	Current medical managment Outcomes data	Disease/illness management	Category 1
Involving End Users in Adapting a Spanish Version of a Web-Based Mental Health Clinic for Young People in Colombia:	Ospina-Pinillos,2020	Health risk and health status Current attitudes Outcomes data	Diagnosis & risk prediction	Category 3

Exploratory Study Using Participatory Design Methodologies				
Efficacy of a Web-Based Tailored Intervention to Reduce Cannabis Use Among Young People Attending Adult Education Centers in Quebec	Cote et al.,2018	Health risk and health status Current medical managment Current attitudes Outcomes data	Diagnosis & risk prediction	Category 1
Development of a Suicidal Ideation Detection Tool for Primary Healthcare Settings: Using Open Access Online Psychosocial Data	Meyer et al., 2017	Health risk and health status Patient medical history Current medical managment Current attitudes Outcomes data	Diagnosis & risk prediction	Category 3
Responding to personalised social norms feedback from a web-based alcohol reduction intervention for students: Analysis of think-aloud verbal protocols	Marley, Bekker & Bewick, 2016	Health risk and health status Patient medical history Current medical managment Current attitudes Outcomes data	Diagnosis & risk prediction	Category 1
Mobile Application–Assisted Cognitive Behavioral Therapy for Insomnia in an Older Adult	Chen, Hung & Chen ,2016	Health risk and health status Patient medical history Current medical managment Current attitudes Outcomes data	Disease/illness management	Category 1

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