

Systematic Literature Review:

Investigating the Methodology and Efficacy of Personalized m-Health

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Abstract

Modern healthcare systems are facing significant challenges due to an ageing population which translates to an increasing amount of people with chronic illnesses. Moreover, there are not enough working-age adults to support them. A potential solution to this issue is m-Health. However, there remain questions about the efficacy and methodology. One of the big questions is whether to shift away from the “one-size-fits-all” approach in favour of a personalized approach. Thereby, the efficacy and methodology of personalized m-Health is investigated. A comprehensive literature search is conducted, and following the abstract and full-text screening, twelve articles were included into the analysis. The most common reason for exclusion was a lack of an outcome measure. Studies were then evaluated based on their study design, elements personalized, and effectiveness. The most common features were personalized text messages and recommendations. 75% of interventions only personalized one feature. Two-thirds of studies reported a significant positive outcome measure. Only one study reported an effect size (moderate; personalized goals). In general, the results of this review indicate the potential of personalizing m-Health, however there is no clear answer in regard to the effect size. More rigorous intervention studies are necessary to evaluate the efficacy of personalized m-Health, and thereby allow for a quantitative analysis on effect sizes. Moreover, an investigation to what extent an intervention should be personalized for the best results needs to be made. Finally, a closer look needs to be taken on related constructs, demographic differences, and which data is used to personalize m-Health.

Keywords: Personalization, m-Health, Intervention, Methodology, Efficacy

Introduction

Modern healthcare systems are facing significant challenges due to an ageing population which translates to an increasing amount of people with chronic illnesses (van Gemert-Pijnen, Kelders, Kip, & Sanderman, 2018). Furthermore, there no longer are enough working-age adults to support the increased amount of old people. The medical healthcare system and infrastructure seems to be in need of an innovative approach, and some suggest a digital implementation would be a potential solution. This provides a cheaper, more cost-efficient approach that can reach more people, empower, and educate individuals, facilitate decision-making through digital tools, allow for personalization, create new possibilities and applications, and increase efficacy (van Gemert-Pijnen et al. 2018). Moreover, an increasing number of people have already decided to take control and self-manage their illnesses. A promising trend that combines both of these solutions is e-Health. A systematic review found the term e-Health to be defined along the concepts of health, technology and commerce, with publications differing in valence of these three facets (Oh, Rizo, Enkin, & Jadad, 2005). In its essence e-Health can also be simply defined as “the use of technology to improve health, well-being and healthcare.” (van Gemert-Pijnen et al. 2018).

Moreover, Van Gemert-Pijnen (2018) defines e-Health interventions as: “An eHealth technology specifically focused on intervening in an existing context by changing behaviour and/or cognitions.” This leads us to the point where technology and psychology are combined to enable successful e-Health technologies and interventions. Well-designed technologies, that can attract and persuade users, are thereby essential preconditions for an effective e-Health intervention. In addition to that, the psychological element needs to be considered, as behaviour change theories, techniques, and persuasive features have been demonstrated to be effective ways of changing behaviours (Michie et al., 2013; Oinas-Kukkonen & Harjumaa, 2009; Webb, Joseph, Yardley, & Michie, 2010)

m-Health

A development relevant to e-Health is that, in modern times nearly all adults (96%) have a mobile phone subscription (Sanou, 2015). Furthermore, internet access is developing as well, with 3.2 billion recorded users in 2015. M-health has been defined (Cho, Lee, Islam, & Kim, 2018) as utilizing mobile technologies as a form of health intervention. Exploring the concept in depth, m-Health often concerns evidence-based solutions, disease preventions and facilitation of self-management (van Gemert-Pijnen et al. 2018). Additionally, increasing amounts of data is tracked through mobile devices, including psychological, social and contextual variables that are passively noted and tracked (e.g. GPS, social media, wearables), which can be utilized to facilitate m or e-Health by better understanding behaviour and testing behavioural theories (Hekler et al., 2016). As previously mentioned, utilizing digital technology can have positive implications for public health efforts and the efficacy of the healthcare system (van Gemert-Pijnen et al. 2018). The trends of mobile phone usage can thereby be implemented as a method of improving health and all related systems and behaviours.

Some studies even go so far as to term recent developments the “m-Health Revolution” due to the potential benefits it brings (Ganasegeran, Renganathan, Rashid, & Al-Dubai, 2017). Moreover, the rapid adoption of m-Health in clinical practice is increasing and is hypothesized to bring many benefits (Ganasegeran & Abdulrahman, 2019). Furthermore, a systematic review on the topic revealed, that theory-based intervention design as well as suitable methodology is required to maximize the efficacy of m-Health (Cho et al., 2018). M-Health interventions have also shown potential to be cost-effective (Larsen-Cooper, Bancroft, Rajagopal, O'Toole, & Levin, 2016). Though despite the increased attention m-Health has been receiving as a form of intervention, efficacy measures rarely have been reported (Cho et al., 2018), indicating a need for further exploration of the effectiveness of m-Health interventions. Moreover, public health studies have criticised a lack of real-world applicability when people rely too much on generalizations (Zvonareva et al., 2018). The

one-size-fits-all approach that is typical for interventions aimed at groups of people does not take enough considerations of their needs and experiences (Caserta, Lund, Utz, & Tabler, 2016).

Furthermore, a recent study (Karway et al., 2020) states a need for interventions to go beyond the “one-size-fits-all” approach and target individual barriers that are hindering the effectiveness.

Personalization

An approach that could go beyond a “one-size-fits-all” methodology is personalization (Hoffman & Podgurski, 2011). Research is already evaluating the readiness of healthcare systems to be developed beyond the “one-size-fits-all” in favour of a personalized approach, also termed “Personalized medicine” (Schee Genannt Halfmann, Evangelatos, Schröder-Bäck, & Brand, 2017). In the context of healthcare interventions personalization typically requires the intervention design to go beyond generalized treatment recommendations, and consider the individual needs and circumstances of the participants and ensure a fit between the user and the intervention (Partridge & Redfern, 2018). However, personalization, and its application to existing models that aim to persuade and adhere users to interventions, has not been extensively researched yet (Kaptein, Markopoulos, de Ruyter, & Aarts, 2015).

A recent literature review (Triantafyllidis et al., 2019) investigated features, outcomes, and challenges in the context of m-Health interventions, where they found that both the effect of m-Health on disease management, but also personalization in this context, needs further research and analysis. Relevant for this study, however, is their finding, that while they generally had mixed results, personalized goal setting in an m-Health context was associated with significantly positive outcomes. The authors even go so far as to conclude that personalized goal setting is an essential part in the majority of effective interventions (Triantafyllidis et al., 2019). This indicates that, a personalized approach to m-Health interventions might be preferable to usual generalized treatment, however this hypothesis requires more rigorous research on the topic (Triantafyllidis et al., 2019).

Aim of the research

Summarizing the previous sections, it seems that, while m-Health interventions are promising tools in the modern era, there are mixed results, and general confusion regarding efficacy, and how to implement and conduct them. The personalization of m-Health interventions seems to be a promising approach; however, a lot of ambiguity remains regarding the efficacy and methodology. Therefore, in an attempt to clear some of the confusion, and provide potential solutions and recommendations for public health officials and intervention designers, the following research questions are formed: *“What parts of the m-Health intervention are personalized?”*, and *“How effective are personalized m-Health interventions?”*. Since several studies were already conducted on m-Health interventions, these questions will be addressed and analysed in the following by means of a systematic literature review. The results will then indicate whether, and on which topic, more research is necessary, and potentially indicate which parts of interventions should be personalized, and whether personalized m-Health interventions in general can be considered effective.

Methods

Search plan

A comprehensive literature search was conducted using the database “Scopus”. The constructs “Personalization”, “M-Health”, “Intervention”, “Methodology”, and “Efficacy” were combined with various alterations of these keywords, to ensure all relevant studies available were included in this review (see Appendix 1).

Study selection criteria

The study reviews literature concerning m-Health applications that are personalized and considers their efficacy. The following criteria classify what is considered to be a relevant study to be included in the analyses.

Inclusion criteria

The first inclusion criteria requires the article to study an m-Health intervention, so a health intervention utilizing mobile technology. The second criteria states that the study must utilize personalization in a way that goes beyond the “one-size-fits-all” approach and considers the needs and circumstances of the participants to ensure a fit between user and intervention. The third criteria states that the study should describe which parts of the intervention are personalized, to allow for the sub-question stated in the introduction to be answered. Furthermore, the fourth criteria requires the article in question to have some mention of efficacy, outcome, or evaluation of the studied interventions. This allows for the evaluation of how effective personalization is in the studies context, and also helps answer the second sub question. The fifth criteria is that the study is published in English, due to a limited time frame and to ensure understanding. Lastly, only peer-reviewed articles will be included.

Exclusion criteria

The first exclusion criteria is, that the study does not describe its methodology and approach using the term “Personalization”. The overlap of the terms is recognized, but studies will be grouped towards the definition of personalization. This means that if a study focused on personalization, mentions a key-word such as tailoring or customization as part of describing the intervention, it will not be excluded, however articles that in their entirety do not mention personalization will be excluded. This allows for a coherent comparison between studies. The second exclusion criteria states, that systematic reviews will be excluded to avoid overlap. The third criteria states that conference papers will be excluded, due to an inability to evaluate efficacy. Moreover, pilot and feasibility studies that had a small participant pool were excluded to ensure only the most reliable and valid interventions were included. Finally, due to the complexity of the topic and time constraints, articles substituting personalization with Artificial intelligence (AI) are excluded, however, if an intervention passes all other criteria and additionally mentions AI or related

constructs, but still allow for an analysis and comparison in the before-mentioned context it won't be excluded.

Data extraction

The studies extracted based on above-mentioned criteria were processed through Endnote and are noted into the Reference list. The included studies are furthermore alphabetically noted in Table 1 and are categorized based on the research questions. First, the date and author are noted, followed by a brief description of the study design. The third column addresses the first research question, providing a brief assessment of which parts of the intervention were personalized. Finally, the last column aims to describe how an outcome measure was taken, whether it was considered significant, and to what extent the m-Health intervention was considered effective.

Results

Search results

The process of the literature search is visualized in Figure 1. The final search string yielded 404 results. Following the abstract screening, 265 Articles were excluded. Next, in the full-text screening 127 additional articles were excluded due to multiple reasons. The most common reason for exclusion was a lack of an efficacy or outcome measure in addition to a general ambiguity in the study design. A total of 85 articles were excluded this way. Next, the second most common (n=27) reason for exclusion was that the article in question was a literature review. Furthermore, 11 articles were excluded because of their design (Pilot/Feasibility studies). Two articles were excluded because of a mis-match between the definitions used for the personalization process. Finally, one study was excluded that substitutes our definition of personalization with a more complex AI approach. The 12 remaining articles are noted in the following (Table 1).

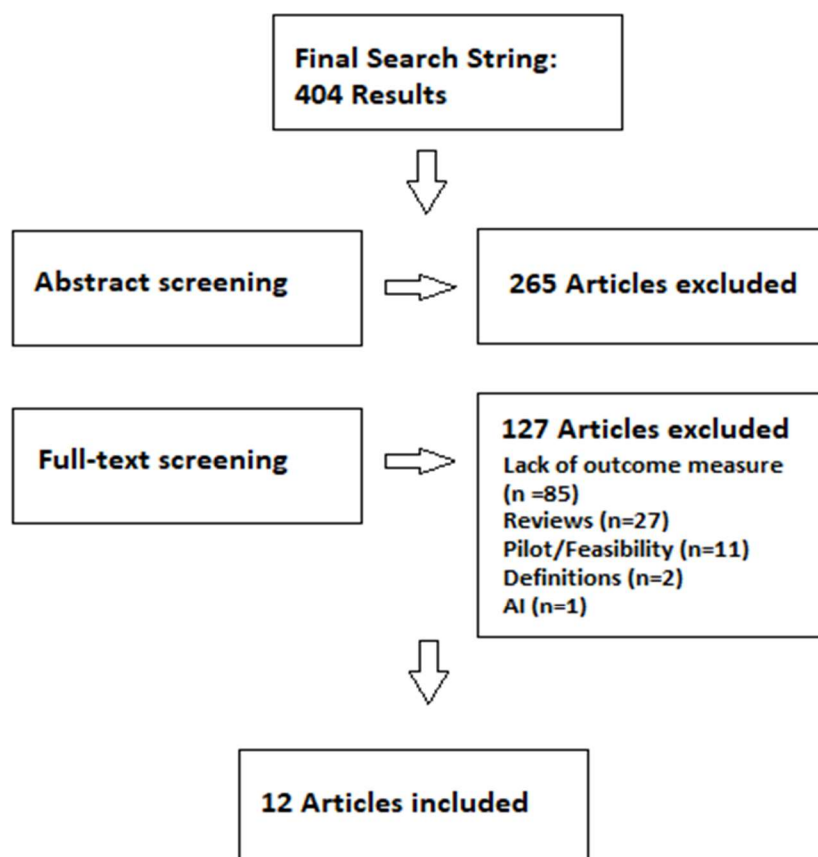


Figure 1. Search strategy and results

Table 1: Study design, elements personalized, data used, outcome measures

Author, Date	Study Design	Elements personalized	Effectiveness
(Bartels et al., 2019)	<i>Aim:</i> To support caregivers of patients with dementia <i>Duration:</i> 6 weeks <i>Participation:</i> n = 50 <i>Design:</i> 3-arm randomized controlled trial; experimental group (Experience sampling method	Personalized feedback	After a 6-month check-up with the participants no sustained intervention effects for carers of people living

	(ESM) self-monitoring and personalized feedback);		with dementia were
	pseudo-experimental group (ESM self-monitoring		found
	without feedback) and a control group (regular		
	care without ESM and feedback)		
(Cheong	<i>Aim:</i> testing the feasibility of personalized m-health	Personalized	In colorectal cancer
et al.,	for colorectal cancer patients undergoing	tasks	patients several relevant
2018)	chemotherapy		outcome measures were
	<i>Duration:</i> 12 weeks		significantly improved
	<i>Participation:</i> n = 102		and symptoms were
	<i>Design:</i> Several relevant measurements and tests		significantly relieved
	are completed at baseline, mid-intervention (6		
	weeks) and at completion of the intervention		
(Dale et	<i>Aim:</i> In addition to usual care, the goal was to	Personalized	Significant positive
al., 2015)	evaluate personalized m-health to facilitate	text	effects of the
	adherence to recommended behaviours	messages	intervention were
	<i>Duration:</i> 6 months		sustained after 3
	<i>Participation:</i> n = 123		months, however, were
	<i>Design:</i> 2-arm randomized controlled trial; Control		not sustained after a 6-
	group: usual care; Experimental group: usual care +		month period
	personalized m-health program; Measures were		
	taken at baseline, mid-way (3 months), and after		
	completion		
(Demirci	<i>Aim:</i> To evaluate engagement with and feedback	Personalized	At 8 weeks postpartum,
et al.,	on a personalized m-health intervention to prevent	text	a significant increase in
2020)	perceived insufficient milk	messages	user satisfaction was
	<i>Duration:</i> From week 25 of pregnancy to 8 weeks		found in the
	postpartum		experimental group
	<i>Participation:</i> n = 250		(84% rated the program

	<i>Design:</i> 2-arm randomized controlled trial; Control group: general text message support; Experimental group: personalized m-Health intervention (MILK)		“helpful” or “very helpful” compared to only 21% in the control group)
(Gomez-Marcos et al., 2018)	<i>Aim:</i> to evaluate the efficacy of adding personalized m-Health to traditional counselling <i>Duration:</i> 12 months <i>Participation:</i> n = 833 <i>Design:</i> 2-arm randomized controlled trial; Control group: counselling only; Experimental group: counselling + personalized m-health app; Relevant outcome measures were taken at 3 months and 12 months	Personalized recommendations	No significant benefit was measured in the overall sample; However, after 12 months there was a significant positive outcome for women and after 3 months a significant positive outcome for participants aged over 65
(Guthrie et al., 2019)	<i>Aim:</i> to evaluate the effect of personalized m-health on blood pressure in adults with hypertension and explore prediction of this through machine learning <i>Duration:</i> 2+ weeks <i>Participation:</i> n = 172 <i>Design:</i> Relevant outcome measures were taken at day 1, 3 and 7 of the intervention	Personalized CBT including personalized goal setting, skill building, and self-monitoring	Adult participants suffering from hypertension had significantly reduced blood pressure following the use of the personalized intervention
(Höchsma nn et al., 2019)	<i>Aim:</i> to evaluate the effect of personalized m-health on facilitating physical activity (PA) in type 2 diabetes patients <i>Duration:</i> 24 weeks <i>Participation:</i> n = 36	Personalized recommendations	The m-Health app with personalized recommendations proved effective by significantly improving

	<i>Design:</i> 2-arm randomized controlled trial; Control group: one-time lifestyle counselling; Experimental group: smartphone game		intrinsic PA motivation and thereby increasing PA adherence over 24 weeks
(Ji et al., 2019)	<i>Aim:</i> to evaluate the efficacy of personalized m-health utilizing real-time patient data for non-small cell lung cancer patients <i>Duration:</i> 12 weeks <i>Participation:</i> n = 64 <i>Design:</i> 2-arm randomized controlled trial; Control group: fixed exercise; Experimental group: fixed-interactive exercise group (personalized m-health); relevant measurements were taken midway (6 weeks) and at the end of the intervention	Personalized recommendations and personalized treatment	A personalized m-health app with the ability to record and monitor real-time data can supplement traditional care and significantly increase several outcome measures in patients
(MacPherson, Merry, Locke, & Jung, 2019)	<i>Aim:</i> to evaluate prompts in the context of m-Health self-monitoring and whether effects change depending on exercise modality <i>Duration:</i> 1 year <i>Participation:</i> n = 69 <i>Design:</i> m-Health data was recorded 1, 3, 5, and 7 days before and after a prompt and compared using t tests	Personalized prompts	The study found significant short-term effects (3-7 days), during the first half of the year, however these were no longer found in the second half of the study
(Mitchell et al., 2018)	<i>Aim:</i> to evaluate whether a multicomponent m-Health intervention together with small incentives can increase physical activity <i>Duration:</i> 12 weeks <i>Participation:</i> n = 78,882	Personalized goals	A significant increase with a modest effect size in mean daily step counts was measured

<i>Design:</i> quasi-experimental pre and post design			
with baseline and several outcome measures			
(Rubinstein et al., 2016)	<i>Aim:</i> to evaluate whether m-health can reduce relevant outcome measures in individuals with prehypertension living in low-resource urban settings <i>Duration:</i> 12 months <i>Participation:</i> n = 637 <i>Design:</i> 2-arm randomized controlled trial; Control group: usual care; Experimental group: monthly motivational counselling calls and weekly personalized text messages	Personalized text messages and personalized calls	While compared to usual care, a reduction in systolic blood pressure was not observed, there was however, a reduction of bodyweight and a reduction in the intake of unhealthy foods. Moreover, participants who received at least three-quarters of their personalized calls, had an even greater reduction in bodyweight and waist circumference. A positive change in nutritional content was also observed in the intervention group
(Spring et al., 2018)	<i>Aim:</i> to evaluate whether a multicomponent intervention including m-Health, coaching, and modest incentives can improve activity and diet in the long-term <i>Duration:</i> 9 months	Personalized remote coaching	Both experimental groups had significant, large, and sustained, positive results compared to the control

Participation: n = 212

Design: 3-arm randomized controlled trial; Control

group: stress and sleep contact control

intervention; Experimental group 1: targeting

outcome measure simultaneously with other diet

and activity targets; Experimental group 2:

targeting outcome measure sequentially with other

diet and activity targets; Measurements at

baseline, 3, 6, and 9 months

What parts of the m-Health intervention are personalized?

Personalized text messages (n=3; 25%) and personalized recommendations (n=3; 25%) were the most commonly used features and the only two features found across several articles. Personalized goals or goals setting was observed twice (16.6%). The other features are only mentioned once respectively. A total of nine interventions (75%) only personalized one feature. Some studies (n=2; 16.6%) personalized two features, and one intervention (8.3%) that evaluated personalized cognitive behaviour therapy, implemented their personalization across the features goal setting, skill building and self-monitoring.

How effective are personalized m-health interventions?

In total eight studies (66.6%) reported a significant positive outcome measure. From all interventions included, only one (8.3%) reported an effect size (Modest). Three studies (25%) reported mixed results, and only one study reported no sustained effects (8,3%). Two studies reported initial effects that either faded after three or six months, respectively. One study (8,3%) reported that only certain demographics sustained significant benefits. Moreover, to understand which features are most effective a quick analysis is made in the following (Table 2).

Table 2. Effectiveness of individual personalized features

Feature	Effectiveness
<i>Personalized text messages</i>	Two-thirds of studies including text messaging reported significant positive outcomes. In the intervention reporting mixed results, effects were sustained after 3 months, however, not after a 6 month period.
<i>Personalized recommendations</i>	Two-thirds of studies including recommendations reported significant positive outcomes. In the intervention reporting mixed results, positive outcomes were found in women after 12 months, and for participants aged 65+ after 3 months
<i>Personalized goals</i>	All studies report significant positive outcomes. Moreover, one of the studies additionally reports a moderate effect size.
<i>Personalized feedback</i>	No sustained intervention effects were found
<i>Personalized tasks</i>	Significant positive outcome measures were reported
<i>Personalized Cognitive Behavioural Therapy (CBT)</i>	Significant positive outcome measures were reported
<i>Personalized treatment</i>	Significant positive outcome measures were reported
<i>Personalized prompts</i>	Mixed effects were reported
<i>Personalized calls</i>	Significant positive outcome measures were reported
<i>Personalized remote coaching</i>	Significant positive outcome measures were reported

From the included studies six features (50%; Goals, tasks, CBT, treatment, calls, coaching) had 100% positive outcomes reported. Personalized goals additionally had 50% of the studies report effect sizes (moderate), the other features had no effect size reported. In two-thirds of included interventions text messages and recommendations were considered significantly effective, the other results were mixed. No sustained intervention effects were found for personalized feedback. Mixed effects were reported for interventions utilizing personalized prompts.

Discussion

A total of twelve studies were included into the analysis that were either experimental or quasi-experimental interventions. Personalized text messages and recommendations were the most commonly used features (n=3), followed by personalized goals (n=2). Several other features were reported once: Personalized feedback, personalized tasks, personalized cognitive behavioural therapy (CBT), personalized treatment, personalized prompts, personalized calls, and personalized remote coaching. Moreover, two-thirds of the included interventions reported positive outcomes measures, and one study reports a moderate effect size. Other than the intervention including personalized feedback (Bartels et al., 2019) which reported no sustained intervention effects, the other studies had mixed results. Since only one study, however, reports an effect size, a quantitative evaluation of how effective the included studies are was not possible. Nevertheless, considering the issues our modern healthcare system is facing, personalization of m-Health needs to be considered as a method of increasing intervention efficacy and as a potential substitute for the “one-size-fits-all” approach. Moreover, a trend emerges in the results regarding which features are most commonly used. The only feature that can be evaluated by the effect size are personalized goals which were demonstrated in an intervention to harbour moderate results. Additionally, only one intervention reported no effects, and only one other feature reported mixed results. The vast majority, despite not giving an indication on the size of the effect, report that their respective interventions did, generally, have a positive outcome. Most interventions use simple features such as text messages or recommendations, however, on average, the studies implementing multiple features were more successful. Six features including goals, tasks, CBT, treatment, calls, and counselling had only positive outcomes linked to them. Other than goals, however, all of these features only were linked to one intervention, thereby the results are not very reliable. Two-thirds of interventions studying personalized text messages and recommendations reported significant positive outcomes. The mixed results in regard to text messages (Dale et al., 2015) found, that, while results were positive after three months, the outcomes were not maintained after six. This study

discussed adherence to recommend lifestyle behaviours through the use of personalized text messages, and additionally is the oldest of the included interventions. This raises questions regarding the methodology, as more recent interventions utilizing text messages show more promising results. In contrast to the other studies, the older intervention (Dale et al., 2015) compares the personalized m-Health with usual care without personalization and m-Health. Thereby, a cost-benefit analysis is necessary to understand if m-Health can replace usual care as studies have indicated cost-effectiveness to be one of the main benefits (Larsen-Cooper et al., 2016). Furthermore, the benefit a text message can provide regarding lifestyle might have simply reached its peak after three months, and a more in-depth method might be required from a certain point. The mixed results regarding recommendations (Gomez-Marcos et al., 2018) for physical activity and reducing body weight also compared a personalized m-health application to usual care, and only had significant positive results for women, indicating a need to explore gender differences when it comes to personalized recommendations. The same study also indicated an increase in outcome measure after three months for participants aged 65+, however no such effect was observed after twelve months, again implying a need to consider demographical differences when personalizing features, or when considering which features are to be personalized. However, this could also be due to elderly participants having a limited capacity to lose weight, so they might have simply reached their goal after three months. This also raises the question if current approaches to personalization are actually considering the full context and needs of the participants if there are such significant differences in accordance with the participants demographics, since one might argue that this should be accounted for in the personalization process. Moreover, this implies that it is also relevant to analyse what data is used to personalize m-Health.

Limitations

The studies limitations include a limited time frame since the research was conducted in the context of a bachelor thesis. Moreover, the literature review and data extraction was not reviewed by a

second author. This could potentially reduce the validity and reliability of the results. Finally, the scope of literature was so great even a slight decrease in the strictness of the in- and exclusion criteria would allow for the analysis of several additional articles. This could potentially change the results, but also increase their reliability. Finally, despite most studies comparing a personalized m-Health intervention with a non-personalized alternative, some interventions also compare personalized m-Health to usual care. These are then difficult to compare with each other since a cost-benefit analysis was not made.

Recommendations

The first recommendation regards further exploring the topic by including articles from the e-Health field, as well as articles discussing artificial intelligence (AI) and other related constructs. This could, for one, allow for an evaluation if the “m-Health Revolution” is truly what some authors claim it is. Is the mobile usage trend the driving factor behind the interventions success or is the concept of digitalizing health in general, and the options it provides, the cause for positive outcomes? This then would imply a need to investigate e-Health in general instead of focusing on m-Health only. Moreover, integrating more complex topics such as artificial intelligence can broaden what is possible with personalization. Most interventions use simple features such as text messages or recommendations, however AI could allow for a holistic personalization approach, since a study attempting to personalize cognitive behaviour therapy indicated significant positive outcomes (Guthrie et al., 2019), with machine learning being part of the research. Additionally, more terms such as customization, individualisation, tailoring etc. can be included into the search string to broaden the range of possible articles even further. It would even be possible to increase the scope even more, by including different technologies that are not officially classified as m- or e-Health but serve a similar purpose. Moreover, an attempt to make a quantitative analysis of efficacy and outcome measures could be conducted in the future to investigate not only whether and what is personalized, but furthermore figure out how much personalization can help, and what the

performance of the alternative is like. This could be especially beneficial for older, less technically adept, target groups, since there has to be a considerable effect size in order to justify the learning of digital literacy skills. For groups that are already comfortable with mobile technology, even a small to moderate effect size could prove a good solution, however these are not the primary targets of the movement to digitalize health, as this study's rationale targets the issue of an aging population with less working-age adults available to manage the problems arising with this (van Gemert-Pijnen et al., 2018). This then raises further questions in a potential analysis, such as how effective interventions are when considering costs, not only financial, but also the time invested by participants to learn relevant skills. Lastly, some of the results indicate a need to consider demographics, such as age or gender differences. Not only are these relevant when considering what to personalize but might also be relevant when put into the position to decide whether or not an intervention should be personalized. So, for certain target groups, when there is only a minor effect it might not be cost-effective to spend the time personalizing. It would be necessary to consider, time, effort, costs, and general efficacy when these are all included in the analysis. Furthermore, what data is used to personalize, needs to be investigated, especially due to the emergence of demographic differences, as one could expect this to be a part of the personalization. Moreover, an investigation into why so many studies keep the personalization at a very minimal, simple level might be beneficial, despite the indication that multiple features could also be effective. However, then a cost-benefit analysis would also be necessary to see if the efficacy is scalable with the costs. This also then raises the question whether personalization is only effective to a certain degree? It would also be beneficial to conduct more studies and interventions with more complex personalization features, in order to compare studies. Furthermore, one could see how a certain feature functions in isolation compared to a holistic personalization approach. Certain, commonly observed, features should also be evaluated in the context of large-scale studies that consider the effect size. Consequently, a cost-benefit analysis can be made to find the most effective methods behind personalizing technology and healthcare systems. Finally, the features that had solely

positive outcomes also need further rigorous investigation regarding the effect size and together with that the cost-effectiveness of such methods.

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Appendix

Appendix 1: Search String

Search string 1: Personal OR Personalisation OR Personalization OR Personalized OR Personalised OR Personalizing OR Personalising OR Modification OR Specification OR Change* OR Enhance* OR Custom*

Search string 2: E-Health OR eHealth OR M-Health OR mHealth OR technolog* OR device* OR platform* OR videoc* OR tele* OR mobile OR *phone OR SMS OR web* OR “virtual Reality” OR virtual OR “augmented reality” OR wearable* OR smart*watch* OR game* OR online OR computer OR Gadget OR Program* OR App*

Search string 3 (discontinued): Interv* OR Interce* OR Involv* OR Program* OR Plan OR “medical treatment”

Search string 4: Method*

Search string 5: (effect* OR effic* OR benefit* OR advantage* or signific*)

Search string 6 (discontinued): review*

Appendix 2: Search log

S1: (Personal OR Personalisation OR Personalization OR Personalized OR Personalised OR Personalizing OR Personalising OR Modification OR Specification OR Change* OR Enhance* OR Custom*) AND (E-Health OR eHealth OR M-Health OR mHealth OR technolog* OR device* OR platform* OR videoc* OR tele* OR mobile OR *phone OR SMS OR web* OR “virtual Reality” OR virtual OR “augmented reality” OR wearable* OR smart*watch* OR game* OR online OR computer OR Gadget OR Program* OR App*) AND (Interv* OR Interce* OR Involv* OR Program* OR Plan OR “medical treatment”)

S2: Personal* AND (E-Health OR eHealth OR M-Health OR mHealth OR technolog* OR device* OR platform* OR videoc* OR tele* OR mobile OR *phone OR SMS OR web* OR “virtual Reality” OR virtual OR “augmented reality” OR wearable* OR smart*watch* OR game* OR online OR computer OR Gadget OR Program* OR App*) AND (Interv* OR Interce* OR Involv* OR Program* OR Plan OR “medical treatment”)

S3: Personaliz* AND (E-Health OR eHealth OR M-Health OR mHealth OR technolog* OR device* OR platform* OR videoc* OR tele* OR mobile OR *phone OR SMS OR web* OR “virtual Reality” OR virtual OR “augmented reality” OR wearable* OR smart*watch* OR game* OR online OR computer OR Gadget OR Program* OR App*) AND (Interv* OR Interce* OR Involv* OR Program* OR Plan OR “medical treatment”)

S4: Personaliz* AND (E-Health OR eHealth OR M-Health OR mHealth OR technolog* OR platform* OR tele* OR web* OR “virtual Reality” OR virtual OR “augmented reality” OR wearable* OR smart*watch* OR game* OR online OR computer OR App*) AND (Interv* OR Interce* OR Involv* OR Program* OR Plan OR “medical treatment”)

S5: Personaliz* AND (E-Health OR eHealth OR M-Health OR mHealth OR technolog* OR platform* OR tele* OR web* OR “virtual Reality” OR virtual OR “augmented reality” OR wearable* OR smart*watch* OR game* OR online OR computer OR App*) AND Interv*

S6: Personaliz* AND (E-Health OR eHealth OR M-Health OR mHealth OR technolog* OR “virtual Reality” OR virtual OR “augmented reality” OR wearable* OR smart*watch*) AND Interv*

S7: Personaliz* AND (E-Health OR eHealth OR M-Health OR mHealth) AND Interv*

S8: Personaliz* AND (E-Health OR eHealth OR M-Health OR mHealth) AND Intervent*

S9: Personaliz* AND (E-Health OR eHealth) AND Intervent*

S10: Personaliz* AND (E-Health OR eHealth OR M-Health OR mHealth) AND Intervent* AND Method*

S11: Personaliz* AND (E-Health OR eHealth OR M-Health OR mHealth) AND Intervent* AND Method* AND effect*

S11: Personaliz* AND (E-Health OR eHealth OR M-Health OR mHealth) AND Intervent* AND Method* AND (effect* OR effic* OR benefit* OR advantage* or signific*)

S12: Personaliz* AND (E-Health OR eHealth OR M-Health OR mHealth) AND Method* AND (effect* OR effic* OR benefit* OR advantage* or signific*)

S13: Personaliz* AND (E-Health OR eHealth OR M-Health OR mHealth) AND Method* AND (effect* OR effic* OR benefit* OR advantage* or signific*) NOT conference*

S14: Personaliz* AND (E-Health OR eHealth OR M-Health OR mHealth) AND Method* AND (effect* OR effic* OR benefit* OR advantage* or signific*) NOT conference* AND review*

S15: Personaliz* AND (E-Health OR eHealth OR M-Health OR mHealth) AND Method* AND (effect* OR effic* OR benefit* OR advantage* or signific*)

Date	Search String	Results	Articles used	Notes
19.03	S1	1,777,885	-	Too much, remove words custom etc.
19.03	S2	1,566,347	-	Too much, Personal* -> Personaliz*

19.03	S3	183,124	-	Too much, remove words (device, videoc*, tele, mobile, *phone, SMS, gadget, program*) (Tech -> eHealth)
19.03	S4	178,722	-	Too much, remove words (“medical treatment”, Involv*, Interce*, Program*, Plan,) (General treatment -> interventions)
19.03	S5	77,190	-	Too much, remove words (platform*, tele*, web*, game*, online, computer, app*) (narrow on eHealth)
19.03	S6	40,028	-	Too much, remove words (technolog* “virtual Reality”, virtual, “augmented reality”, wearable*, smart*watch*,) (again narrowing on eHealth)
19.03	S7	6,126	-	Too much, Interv* -> Intervent*
19.03	S8	5,467	-	259 articles from 2020; remove mHealth
19.03	S9	4,055	-	Still shows some mHealth articles (add mHealth therefore again) 161 articles in 2020; (add: another search variable Method*)
19.03	S10	4,384	-	208 articles from 2020; add effect* for a test
20.03	S11	163	-	Good search; add some words for testing (effic*, benefit*, advantage*, signific*)

20.03	S11	207	-	Found some additional good sources; remove intervent* for a test
20.03	S12	404	-	Additional good sources; added element of reflection in the methodology of personalization; potentially enough articles to investigate effectiveness (remove conference* for a test)
20.03	S13	381	-	Not sure if it's wise to exclude conferences? Added review* for S14 for the introduction
21.03	S14	1	-	Remove review* and conference* back to S12
21.03	S15	404		Taking some sources for the introduction