

A Meta-analytical View on the Acceptance of Mhealth Apps

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Abstract: Never before has there been such a driving transformation of healthcare concerning digitalization as in early 2020 due to the pandemic. The digital transformation in the health sector holds great potential to meet the challenges of demographic change, the financial burden on the health system and the shortage of skilled workers. One digital solution is the usage of modern information and communication technologies (ICT), such as mhealth applications (mhealth apps). However, the usage of mhealth apps especially in the German healthcare system is still evolving and the usage rate of mhealth apps among the population is rather low. To understand acceptance-relevant factors for the usage, this meta-analytical study presents two samples before and during pandemic times (survey times 2019 and 2021). To analyse these samples the UTAUT2 acceptance model in an extended version was applied. The additional factors are online privacy, trust and health literacy. In total 644 participants took part. The results show, that the factors habit, hedonic motivation, performance expectancy, social influence and effort expectancy contribute most strongly to the intention to use mhealth apps as well as the added factor trust. The decisive factor for the user profiles was age.

1 INTRODUCTION

Shortly after the first study in this paper was collected, the infectious disease SARS-CoV-2 (coronavirus or COVID-19) spread worldwide. As never before, the virus has driven digitalization in healthcare. The pandemic holds the opportunity to bring forth new approaches to digitalization in healthcare, which are currently being developed and applied. Video consultations with doctors, platforms used for clinical data collection (for example, (climedo, 2020)), digital help for monitoring COVID-19 and health apps are some examples of digital applications, that have gained new prominence. All these telemedicine offerings have given digitalization a new key role in healthcare, primarily to prevent the spread of infections. These digital solutions should not only help in the healthcare sector in the acute phase of the pandemic, but also sustainably improve healthcare beyond that. The potential of the technical prerequisites (infrastructure, end devices) already exists, but the widespread use of digital ICT in healthcare is still far from being achieved. The interlinking of digital and realistic health services is, in addition to technical conditions and developments on the part of the health


system, also dependent on the acceptance of potential users.


2 STATE OF THE ART

In the following mhealth apps, acceptance factors and user diversity is described.

2.1 Mhealth Apps

A trend that has aroused great interest in society in very recent years is the use of smartphone apps for self-determined measurement of health parameters. Maintaining and optimising one's own health as well as increasing health awareness contribute to recording the technical possibilities for measuring vital parameters, physical activities as well as exchanging these data with other users. Despite the wide range of health apps on the market, usage is low at 14 per cent in Germany (Meinungsforschungsinstitut, 2019). Most popular among these apps are sports, nutrition and weight management apps. Considering that diseases can be prevented through a healthy lifestyle, plenty of exercise, a healthy diet and sufficient sleep, it is beneficial if health-related mhealth apps trigger lively interest and use among end users. After all, the po-

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tential that mhealth apps offer for good healthcare is very rich. However privacy concerns and usage barriers arise (Powell et al., 2014). mhealth apps are a highly relevant topic from various perspectives - either from a health policy point of view, from a social point of view or from an economic point of view. The current state of research still has many research gaps with regard to user acceptance and user diversity. Especially in the german-speaking countries, the empirical research on the acceptance of health apps is very incomplete. For this reason, this study aims to investigate the user-specific and acceptance-relevant motivations and factors for the use of mhealth offerings for health maintenance.

2.2 Measuring Acceptance

This study is based on the description of attitudinal acceptance and considers acceptance in this context as the willingness to use a health app (technological innovation). Numerous acceptance models have attempted to map the factors influencing the development of acceptance. The majority of current acceptance models are based on the *Theory of Reasoned Action* (TRA), postulated by Fishbein and Ajzen (Fishbein and Ajzen, 1977). TRA contains basic assumptions that were adopted in the development of subsequent acceptance models. The theory states that actual behaviour is the immediate predictor of the use of a technology in terms of the behavioural or usage intention. This behavioural intention is in turn determined by the attitude towards the behaviour and the social norm. In the chronological sequence of the development stages from the Technology Acceptance Model (TAM)1 to TAM3, the *Unified Theory of Acceptance and Use of Technology* model (in short: UTAUT) was developed, which unites the predecessors of the TAMs (Venkatesh and Bala, 2008). The models were developed with a focus on predicting adoption in the work context. With the increased use of technological innovations outside the work context, the UTAUT and also the UTAUT2 including three additional predictors, such as *hedonic motivation, monetary value and habit* (Venkatesh et al., 2012) covered a possible model proposal for investigation in the commercial context or beyond, e.g. the digital health sector. Therefore, the conceptual basis of the study is the acceptance model UTAUT2 with its seven factors. Due to previous studies (Schomakers et al., 2022) three further constructs were added to the model: (1) trust in apps, (2) online privacy and (3) ehealth literacy.

2.3 Extension of UTAUT2 Model

The application of the UTAUT2 in the health sector requires a renewed adaptation. Empirical studies have shown that specifically when investigating the acceptance of mhealth apps, various factors can be both motive and barrier at the same time and play a decisive role in the willingness to use them. Trust (Deng et al., 2018), online privacy (Peng et al., 2016)

and ehealth literacy (Griebel et al., 2018); represent factors to be considered. **Trust** is a multidimensional construct that is conceptualised in different ways depending on the discipline. This paper focuses on the dimension of technical trust. Trust in technology arises from the expected predictability, credibility and usefulness of the technology (Lippert, 2002). In the context of health, trust is of relevance since one's own health is a valuable resource. People who do not see health apps as serious and safe support, but rather a risk to their own health, will not use them. In the context of ICT, many studies have been conducted investigating trust in online banking (Luarn and Juo, 2010), eCommerce (Lee et al., 2006) or social media (Lankton and McKnight, 2011). However regarding trust in mhealth apps the state of the art is very limited. Since previous studies have shown that trust is an important indicator of the intention to use a technology, it is included in this investigation (Deng et al., 2018). With the many technical and health benefits of using mhealth apps, there are factors that work against using such offerings from the user's point of view as e.g. the **online privacy** attitude. It is a multidimensional construct that can be measured across different dimensions. For instance, the behaviour of a person, such as the degree of disclosure of one's own data on the Internet, is used to analyse online information privacy (Acquisti et al., 2015).

Data classified as particularly sensitive may include, e.g., genetic information, information about psychological behaviour, illnesses or sexual preferences (Valentino-Devries, 2010). Especially through the use of mhealth apps, it is possible to draw conclusions about the person via the phone number (ibid.), which triggers concerns about social discrimination among users (Applebaum, 2002). Various studies confirmed that online privacy is an important factor for the intention to use digital health offers

(Deng et al., 2018). Therefore it is included in this study. **ehealth literacy** - For everyday life, it is relevant to have a certain ability to deal with one's own health and to make conscious decisions about one's own health care, disease prevention or even health promotion. For a long time, the physician, the pharmacy magazine or even advice from relatives

and family were the most important source of health information. With the advent of digital ICT in the form of ehealth (e.g. platforms) or mhealth apps, users must have certain digital skills in order to benefit from the offers. The possibility of acquiring health-relevant knowledge via mhealth apps e.g. can be seen as an individual and also social opportunity. However, the great added value of mhealth apps for improving health care and health care provision, networking and self-determination of the individual can only be guaranteed if the user is able to use them profitably for himself. ehealth literacy is seen as both a motive and a barrier for the use of ehealth applications from a technical and user perspective (Griebel et al., 2018). The construct of ehealth literacy no longer only describes the ability to find reliable health information on the internet but also the handling of interactive digital health platforms, the use of mhealth apps or the internet – search for and communication with health care providers. So far, ehealth literacy as a basic prerequisite for the use of ICT in the context of acceptance research has only been investigated for ehealth applications. Studies that examine the construct of ehealth literacy with regard to the complexity of operating options of health apps and additionally integrate the relevant factors into the UTAUT2 model are currently missing in empirical research. That is why it is considered in this study.

2.4 User Diversity

A main requirement for the use of mhealth apps is that they must be operable by different types of users. A general categorisation of the user group is difficult because of the diversity that users have in terms of their age, gender, app experience, health status, etc. The need to capture the diversity of users is an important part of understanding the readiness to use mhealth apps (Peng et al., 2016). Only if users are understood in terms of their diversity it is possible to develop individually tailored solutions and thus achieve the acceptance of many users. For this reason, socio-demographic factors such as age, gender, health status as well as app experience are considered in this study.

3 METHODOLOGICAL PROCEDURE

To get insights into users’ attitude towards the usage of mhealth apps, an online survey was administered twice to different samples, first in 2019 and secondly in 2021. Three research questions were leading the study: (1) Which factors are relevant for the acceptance of mhealth apps? (2) Do the extended factors

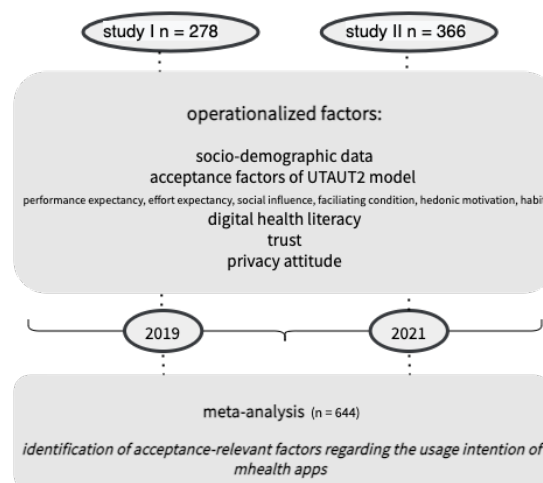


Figure 1: Overview of meta-analytical study design.

contribute to the prediction of acceptance? and (3) Which user types or profiles can be formed based on the socio-demographic factors?

3.1 Study Design

To address the research questions, a meta analysis was chosen, which statistically analyses data from independent primary studies that focused on the same question. The determined effects of the independent studies are then summarised with the aim of obtaining a more precise estimate of an overall effect (Glass, 1976). Figure 1 gives an overview of all factors which were included in the meta analysis. Answering the online survey took about 20 minutes. The questionnaire consisted of three parts. In the first part participants were familiarized with the topic of mhealth apps. Furthermore they were informed, that participation was voluntary, and not rewarded and that they could withdraw from the study at any time. In a second part, demographic data was assessed. The third and thus also the main part comprised the acceptance-relevant factors of the extended UTAUT2 Model. In the following a detailed description of the empirical measurements will be outlined.

3.2 Evaluation Measures

In the questionnaire all items had to be evaluated on a six-point Likert-scale from no agreement at all to total agreement. **Demographic Data.** In the first part the participants’ age, gender, their highest educational attainment and experience with the use of mhealth apps was assessed. **UTAUT2 Factors.** To measure attitudes towards health apps, items based on Venkatesh’s UTAUT2 model (Venkatesh and Davis, 2000) were partially adopted and adapted to the context in

terms of content. For the *performance expectancy* factor, the question was raised to what extent the use of mhealth apps can have a personal advantage. *Effort expectancy* evaluates how much effort the user has to make using the mhealth apps. *Social Influence* includes the social environment of the participant in the consideration and asks what influence related persons have on the willingness to use a mhealth app. *Facilitating condition* measures whether the user has the necessary resources and assistance available to use mhealth apps. *Hedonic Motivation* or rather *fun* to use a health app was asked as well as *habit* which describes a regular practice with a health app. Finally the *intention* to use a health app as a useful application in everyday life was assessed. In contrast to the original UTAUT2 model, actual usage behavior was not measured, as no usage data was collected as part of the studies. The price of a mhealth app was also disregarded, as the studies only refer to fictitious health apps. Online privacy attitude, trust and ehealth literacy were added to the model.

Added Factors to UTAUT2. Attitudes regarding individual *online privacy* in the use of mhealth apps were assessed with the *Mobile User's Concerns for Information Privacy Scale* (MUCIP) from (Xu et al., 2012). The scale measures the perceived privacy in dealing with online data and represents a valid measurement instrument, which in the original explicitly refers to smartphone use. The three dimensions were surveyed with three items each: (1) perceived surveillance of the user, (2) perceived invasion of privacy and (3) concerns about secondary use of the data (second use). In the original, the scale is measured on a seven-point Likert scale. In order to relate it statistically to other scales and to avoid the a central tendency as a response bias, the response format was changed to a six-point one. *Trust* in service and technology was collected as an extended construct for the UTAUT2 model. The items were adapted from Körber (Körber, 2018). To measure *ehealth literacy* the *Digital Health Literacy Index* (short: DHLI) according to van der Vaart (van der Vaart and Drossaert, 2017) was assessed. In the original version, the DHLI measures operating, search of information and search for information skills. The items were reformulated for the use of mhealth apps to search for health-related information.

3.3 Sample Description

The questionnaire was part of a university seminar and thus participants were recruited from the students' environment via social networks. As can be seen in table 1 the two samples were very homoge-

nous except of the grade of school education and app experience. The sample of study I showed a high educational degree and a very high app experience ($M = 4.64 / \text{max.} = 6$). In contrast, the sample of study II had a low level of education and very little work experience ($M = 1.21 / \text{max.} = 6$). The average age in study I was around 30 years and in study II around 40 years rounded off. The proportion of women and men was almost equally distributed. The health status was averagely high in both samples.

3.4 Statistical Meta-analysis

In order to be methodologically precise and correct, due to the different samples, a procedure was chosen that allows each study to be considered as a single study and still obtain cumulative results. The R package "metacor" (Laliberté et al., 2014) was used as the statistical evaluation program. The estimation procedure used was the DerSimonian-Laird (DSL) procedure (IntHout et al., 2014). The random-effects model (RE model) incorporates heterogeneity between studies by considering the effects as random. The method uses the correlation coefficients of the individual studies as effect sizes. These are to be interpreted as confidence intervals and stand as an indicator of significance with the p-value.

4 RESULTS

The statistical results for the UTAUT2 factors from the original model are described first, followed by a summary of the extended factors as well as the description of a user profile based on the samples. Significance level of the correlations range from $* = p < .05$, $** = p < .01$ to $*** = p < .001$.

UTAUT2 Factors. In the meta analysis, only one significant difference between the individual UTAUT2 constructs could be found. The factor *facilitating condition* differed statistically significant ($r = .135 (.230, .037)$ $p = 0.003$) which implies that necessary resources and assistance availability to use mhealth apps has changed. All other factors do not show any statistically significant variability and can be concluded as homogeneous. This means that the constructs of the different studies can be summarised and be seen as stable and explainable acceptance factors. The highest influence on the intention to use health apps was: (1) *habit* ($r = .787 (.815, .756)$, $p = \text{n.s.}$), (2) *hedonic motivation* ($r = .670 (.710, .625)$, $p = \text{n.s.}$), (3) *performance expectancy* ($r = .636 (.695, .569)$, $p = \text{n.s.}$), (4) *social influence* ($r = .390 (.510, .255)$, $p = \text{n.s.}$), (5) *effort expectancy* ($r = .361 (.412,$

Table 1: Demographic data of study I and II separated by collection time.

		study I 2019 n = 278	study II 2021 n = 366
age [years]	M (SD)	29.98 (14.39)	37.90 (18.67)
sex	women	57%	60%
	men	43%	40%
education	no certificate	1%	31%
	certificate of secondary education	5%	35%
	general certificate of secondary education	7%	8%
	general qualification for university degree	87%	26%
health status		4.49 (.92)	4.28 (1.07)
app experience		4.64 (.89)	1.21 (.48)

.276), $p = n.s.$) and finally (6) *facilitating condition* ($r = .135 (.230, .037)$, $p = .003$).

In Study I, the habit and usage intention had the highest relationship ($r = .804^{**}$), followed by the relationship between performance expectancy and hedonic motivation ($r = .715^{**}$), hedonic motivation and usage intention ($r = .677^{**}$), and the relationship between hedonic motivation and habit ($r = .600^{**}$) as well as between performance expectancy and usage intention ($r = .600^{**}$). Study II showed also the highest correlation between habit and usage intention ($r = .775^{**}$), followed by hedonic motivation and performance expectancy ($r = .704^{**}$), usage intention and hedonic motivation ($r = .665^{**}$), usage intention and performance expectancy ($r = .665^{**}$) and facilitating condition and effort expectancy ($r = .662^{**}$). All other correlations from study I and II were moderate and can be found in table 2.

Impact of Extended Factors on Intention to Use. Perceived online privacy, ehealth literacy and trust were included in the meta analysis as comparable extended constructs. The correlations between the extended factors were not statistically significant. Thus, the results in the individual studies can be summarised. Trust had the strongest positive influence on intention to use ($r = .577 (.639, .508)$, $p = n.s.$).

All other correlations were negative, meaning the higher the perceived invasion ($r = -.215 (-.110, -.315)$, $p = n.s.$), the concern of secondary use ($r = -.189 (-.113, -.263)$, $p = n.s.$), the perceived surveillance ($r = -.186 (-.111, -.260)$, $p = n.s.$) and the ehealth literacy competence ($r = -.037 (.204, -.274)$, $p = n.s.$), the lower the intention to use a smartphone with a mhealth app.

Impact of Socio-demographic Data Among Each Other and on Intention to Use. Figure 2 shows the significant relationships between socio-demographic data and the intention to use. For a better overview, only the significant relationships have been included in the graph and non-significant ones have been omitted. The variables are each connected

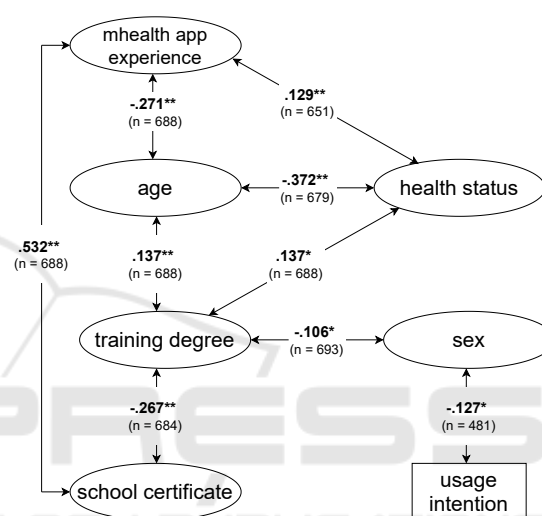


Figure 2: Overview of meta-analytical study design.

with arrows on which the positive or negative correlation is shown by indicating the correlation coefficient, together with the sample size from which the significant effect results. Regarding **age**, older participants were found to have a lower health status ($r = -.372^{**}$) as well as a lower experience with apps ($r = -.271^{**}$) in contrast to younger. However, older participants showed a higher training degree ($r = .132^{**}$) in comparison with younger participants. Significant influences of the user factor **sex** was found. Women reported to be willing to use a mhealth app more often than men ($r = -.127^*$). Moreover, they had a lower training degree than men ($r = -.106^*$). Another statistically significant correlation was found within the **app experience**. The more experienced the participants considered themselves to be in dealing with apps, the better their health status ($r = .129^{**}$) and the better their education ($r = .532^{**}$).

Table 2: Correlation between UTAUT2-factors (PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating condition, HM = hedonic motivation, UI = usage intention). Upper correlations in bold refer to study I, lower correlations in italics refer to study II.

UTAUT2 factors	PE	EE	SI	FC	HM	H	UI
PE	1	.438**	.320**	.280**	.715**	.551**	.600**
EE	<i>.349**</i>	1	-.047	.510**	.371**	.226**	.365**
SI	<i>.358**</i>	<i>-.084</i>	1	-.150*	.376**	.512**	.456**
FC	<i>.235**</i>	<i>.662**</i>	<i>-.152**</i>	1	.201**	-.058	-.081
HM	<i>.704**</i>	<i>.428**</i>	<i>.332**</i>	<i>.293**</i>	1	.600**	.677*
H	<i>.599**</i>	<i>.205**</i>	<i>.444**</i>	<i>.098</i>	<i>.569**</i>	1	.804**
UI	<i>.665**</i>	<i>.332**</i>	<i>.326**</i>	<i>.180**</i>	<i>.665**</i>	<i>.775**</i>	1

5 DISCUSSION

The meta-analysis' aim was to aggregate the results of the two studies conducted and to examine them with regard to acceptance-relevant factors. It was found that five factors were prominent in measuring mhealth app acceptance: habit, hedonic motivation, performance expectancy, social influence and effort expectancy. The strongest influence on the intention to use was found with the factor *habit*. Due to the fact that the use of smartphones with integrated apps is familiar to the sample studied, it has become a self-evident process (Möller, 2016). Habit is understood as an action once learned that runs automatically without conscious control (Stangl, 2018). Thus, the functions of the app corresponds to the habitual actions performed when using a health app. As a recommendation for mhealth app developers it can be maintained that the operation of the app must be simple and include the usual interaction gestures (touch gestures) when using the smartphone. **Hedonic motivation** was the second most important factor. This result was already reflected in the state of research on the use of health apps in other studies (Peng et al., 2016). In order to achieve a high usage rate of health apps, playful elements must be included in the app that motivate and give pleasure. Playful solutions in the form of gamification or augmented reality (computer-supported reality approaches) are approaches that should be incorporated in the development of health apps. Scientific results on the success of integrating playful approaches to promote health already exist (Schlomann et al., 2019), and can serve as orientation. The third most important factor was **performance expectancy**. This result is in line with other studies on health app acceptance research (Alam et al., 2020). The performance expectation reflects the utility of the app in terms of fitness apps, monitoring a health situation, managing and controlling certain health conditions. As a recommendation it can be stated that the app must have appropriate techni-

cal functions that enable the monitoring, management and control of fitness or a disease. The app's performance (e.g. measuring vital parameters) must be of a high standard. **Social influence** was ranked fourth most important. It refers to the degree to which people perceive that others they care about believe they should use a health app. Using a health app strengthens the ability to connect with other users they consider important. The ability to share data about personal fitness levels with other fitness app users is an important aspect of maintaining motivation that must be further considered in technical development. **Effort expectancy** was the last influencing factor and describes how much effort the user has to make using the app. Therefore, one recommendation could be that the app should obtain a simple and easy-to-follow menu structure. **Facilitating condition** was the only factor that differed in the meta analysis. It describes the knowledge of how to use a mhealth app. Since the sample of study II did not bring a lot of app experience, this factor was not homogenous with the other result. The second research question focused on the added UTAUT2 factors to measure the intention to use. Trust contributed strongly to the intention to use. The state of research on the influence of trust on intention to use could be proven with this study. One recommendation that emerges from the results is that mhealth app providers must transparently explain quality aspects and trustworthiness. This includes information about the possibilities of the app as well as the risks and limitations. The influence of online privacy on intention to use had been confirmed in this study

(Deng et al., 2018). Concerns about data theft or sharing the information with third parties were particularly high for health-related data. Thus, it can be recommended that the protection of privacy must be guaranteed by technical data protection measures. Users must decide for themselves if and with whom they want to share data. Studies related to eHealth solutions have already shown that the higher the digital

skills and knowledge of understanding and processing health-related information, the higher the willingness to use it (Griebel et al., 2018).

Based on the results of this study no statistically effect could be observed for mHealth apps. The third research question focused on which user groups can be formed on the basis of socio-demographic data. Thus, in this work, a user group was determined in terms of content on the basis of the positive correlations between two variables, and conversely, another user group from the negative correlations. The following different characteristics emerged: one group consists of young, low-educated, however healthy and app-experienced participants who are willing to use health apps. The other group consists of older participants with good health, little experience in using mhealth apps however with a higher educational attainment. This group has a low intention to use apps. Both groups differ significantly from each other. Age is to be regarded as the decisive factor that influences all other factors. The older the participants, the less experience they have in using apps (Searcy et al., 2019) and expertise in using digital ICT in the health sector

(van der Vaart and Drossaert, 2017), which are relevant for the acceptance of health apps. Due to their diversity, the different types of users require technical and content solutions that are specially adapted to them and contribute to increasing acceptance.

6 LIMITATION AND OUTLOOK

The findings from the present study have provided insights into acceptance-relevant factors regarding the intention to use mhealth apps. However, the context of our study was limited. First of all the study was mainly conducted in the students surrounding at university which resulted in a rather young sample. Even though results could be detected for exactly this type of user group, further studies should focus on broader samples to present a representative whole. Moreover, this study only evaluated an associated mhealth app. In order to receive real data in terms of hand-on-experience, it is necessary to develop a mhealth app with different features and evaluate the usability with regard to acceptance-relevant factors. Furthermore, the app area of mhealth apps is divers and include all health care areas from information, prevention, care of complaints or also products, self-management, therapy, rehabilitation in the form of aftercare and monitoring. Further studies should consider the different fields and include them in acceptance studies. The ability to operate a mhealth app is a basic pre-

requisite for the willingness to use it. The acceptance of mhealth apps must also be investigated on people who are ill, as otherwise there is an overestimation of the capability and an underestimation of the actual needs. In addition, research activities should be investigated with regard to the needs and requirements of mhealth apps on behalf of limited users who require barrier-free access due to their physical, mental or even cognitive condition. It is important to understand how the requirements of healthy people for the design of mhealth apps differ from those of people with poorer health, in order to develop mhealth solutions that can be adequately tailored to the corresponding user groups. Due to lack of evidence so far on the effectiveness specifically with regard to care and therapeutic apps (Payne et al., 2015), further long-term studies are needed.

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