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Usage Behaviour and Adoption Criteria for Mobile Health Solutions in Patients with Chronic Diseases in Gastroenterology

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Keywords

UTAUT2 · mHealth · Acceptance of technology · mHealth adoption · Gastroenterology · Digitalization in gastroenterology

Abstract

Introduction: Mobile Health (mHealth) applications allow for new possibilities and opportunities in patient care. Their potential throughout the whole patient journey is undisputed. However, the eventual adoption by patients depends on their acceptance of and motivation to use mHealth applications as well as their adherence. Therefore, we investigated the motivation and drivers of acceptance for mHealth and developed an adapted model of the Unified Theory of Acceptance and Use of Technology (UTAUT2). ***Methods:*** We evaluated 215 patients with chronic gastroenterological diseases who answered a questionnaire including all model constructs with 7-point Likert scale items. Our model was adapted from the Unified Theory of Acceptance and Use in Technology 2 and includes influencing factors such as facilitating conditions, performance expectancy, hedonic motivation, social influence factors, effort expectancy, as well as personal empowerment and data protection concerns. Model evaluation was performed with structural equation modelling with PLS-SEM. Bootstrapping was performed for hypothesis testing. ***Results and Conclusion:*** Patients had a median age of 55.5 years, and the gender ratio was equally distributed. Forty percent received a degree from a university, college, technical academy, or engineering school. The majority of patients suffered from chronic liver disease, but patients with inflammatory bowel diseases, GI cancers, and pancreatic diseases were also included. Patients considered their general technology knowledge as medium to good or very good (78%). Actual usage of mHealth applications in general was rare, while the intention to use them was high. The leading acceptance factor for mHealth applications in our patient group was feasibility, both in terms of technical requirements and the intuitiveness and manageability of the application. Concerns about data privacy did not significantly impact the intention to use mobile devices. Neither the gamification aspect nor social influence factors played a significant role in the intention to use mHealth applications. ***Interpretation:*** Most of our patients were willing to spend time on a mHealth application specific to their disease on a regular basis. Acceptance and adherence are ensured by efficient utilization that requires minimum effort and compatible technologies as well as support in case of difficulties. Social influence and hedonic motivation, which

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were part of UTAUT2, as well as data security concerns, were not significantly influencing our patients' intention to use mHealth applications. A literature review revealed that drivers of acceptance vary considerably among different population and patient groups. Therefore, healthcare and mHealth providers should put effort into understanding their specific target groups' drivers of acceptance. We provided those for a cohort of patients from gastroenterology in this project.

Introduction

Mobile Health (mHealth) refers to mobile technologies that support medical care and public health [1]. MHealth applications not only often improve the management of chronic diseases [2] but can also have an impact on health-related quality of life [3, 4] and reduce costs for the healthcare systems [5, 6]. Its capabilities can reach patients in any country in almost any geographic area and any population structure, thus allowing powerful scaling effects in providing healthcare.

MHealth applications allow tailoring healthcare to particular patient groups' needs [7, 8]. Especially for patient groups with chronic diseases, regular smartphone-based monitoring of existing symptoms could be of great benefit. For example, a timed Stroop test via smartphone can be used to measure psychomotor speed in patients with liver cirrhosis and thus screen for progression of hepatic encephalopathy [9]. Similar applications can also be found for inflammatory bowel disease (IBD) that are primarily designed for regular completion of symptom questionnaires [10]. Smartphones and smart devices have become an essential part of everyday life for many people. With functions such as the recording of pulse and ECG, pedometer, sleep behaviour monitoring, and others, they offer the opportunity for more intensive and continuous monitoring. Easier symptom monitoring, data integration into medical care, and thus eventually early recognition of changes in health status may be highly beneficial.

The global Sars-CoV2 pandemic has made an important contribution to the expansion of numerous digital approaches. Downloads of mHealth applications have doubled since 2019, those allowing online appointment booking with the most increase [11].

Despite the need and potential, mHealth applications are underutilized, and usage reality falls short of mHealth app capabilities. Individual studies showed below-average use despite limited physical healthcare [8, 12–16]. Reasons for underutilization are diverse and may include the fear of misuse and improper use of personal, sensitive data [17, 18]. Additionally, if complexity of mHealth applications is considered too high, there is no constant use [19]. Especially then, there is a lack of training and instruction but also support during use, e.g., by the healthcare provider [19]. Another factor to consider is that healthcare providers are lacking time and incentives to prescribe mHealth applications as well as follow up on and support adherence [20].

Patient acceptance of digital prevention and treatment strategies, both fully comprehensive versions as well as supplements to existing healthcare, has not been adequately studied. While greater benefits and the possibility of more effective treatment suggest acceptance and demand, reliable studies are lacking. In Germany, it is possible to obtain reimbursement of a health app's cost by the health insurance company if effectiveness of the application has been proven for the specific indication and the application has passed a dedicated approval process [21]. Then, the health app is officially called "Digitale Gesundheitsanwendung" (DiGA). Although the user numbers of DIGAs offered are constantly increasing, the user numbers for digital health applications for diseases such as diabetes, depression, chronic pain disorders, etc. fall far short of their potential care [22].

To better understand the needs of our patients and pin down their drivers of mHealth acceptance, we designed a questionnaire based on the second, extended "Unified Theory of Acceptance and Use of Technology" (UTAUT2) and surveyed a gastroenterological patient collective from our university hospital outpatient clinic. When referring to the term "mHealth," we comprise the variety of applications available in the market, whether reimbursed by the German healthcare system as "DIGA" or not. The theory of planned behaviour, which builds the base for UTAUT2, was developed, applied, and validated in market research for the study of purchasing decisions. However, this model was found to be insufficient for assessing the acceptance and use of digital technologies, so it was adapted and extended into the new model of the "Unified Theory of Acceptance and Use of Technology" (UTAUT) by Venkatesh et al. in 2003. Subsequent adjustments led to an extended version (UTAUT2). We extended UTAUT2 with latent constructs dealing with data security concerns, which have already been validated in a different context by Rosset et al. [23, 24]. As Salgado already validated in a cohort of patients with chronic diseases, utilization of mHealth applications may strengthen personal empowerment (PeM); therefore, we included this construct in our model, too [25].

Several authors have already validated the UTAUT2 model for healthcare. In a study by Salgado et al. [25], the construct of PeM was added to the model and validated using 322 patients. This construct describes how patients gain self-confidence and self-efficacy to play an active role in their healthcare [25, 26]. The constructs of the UTAUT2 model adapted to healthcare (developed by Salgado et al. [25]) were adjusted. The constructs of mHealth usage behaviour and expected performance (see above) were adapted from Tavares et al. [27]. Additional items which consider data security issues, proposed by Schwepe et al. [24], were included to depict data security concerns.

In the theory of our model, the perception of an application's performance (performance expectancy [PE]) as well as the pleasure in using it (hedonic motivation [HM]) influence behaviour intention (BI). Furthermore, enabling social influence (SI) and effort expectation (effort expectancy [EE]) affect BI. Technical prerequisites need to be met (e.g., availability of terminal device such as smartphone) (facilitating conditions [FC]) for positive intention to use and actual use behaviour (UB). We assume, as shown by Davies et al. and Venkatesh et al. [28, 29], that the intention to use a technology predicts its actual use.

Methods

Study Design

We conducted a multivariate quantitative empirical study to assess patients' drivers of acceptance and positive intention to use mHealth applications. To model usage intention and corresponding reasons, UTAUT2 was adapted (Fig. 1).

All of the above-mentioned constructs (Table 1) influence behavioural intention in this model which in turn directly affects actual behaviour. In addition, some confounders were identified that influence the individual interactions in the model: age, gender, experience with technology in general, disease group, and educational background.

The construct "price value" which is part of UTAUT2 was neglected in our model for two reasons. First, Salgado et al. [25] validation showed that price value plays only a minor role in the behaviour and acceptance of a medical population. Furthermore, any digital health application that is listed as DIGA can be reimbursed by health insurance.

Another construct, "habit," refers to the quasi-automatic utilization of a technology that occurs through habit. Although this construct has been shown to be a good predictor of the use of various technologies, it is evident from exploratory patient interviews with the present cohort that mHealth offerings have not been used for long and are used rather infrequently in some groups, so that this construct was not considered in the underlying model.

Since data security issues were mentioned as barriers of mHealth use in the literature as well as exploratory patient interviews in our outpatient department, we also included the construct "data security concerns" in our model. Schwepe et al. [24] examine privacy as a barrier to entry and incorporate their items into the UTAUT2 model. Since the perceived level of data protection and, in particular, the perceived level of privacy vary greatly from country to country and culture to culture, this model, which has been validated for German-speaking countries, was used as a basis.

Since applications are currently not available and are not routinely used among our patients, actual usage could not be assessed. Therefore, we assessed patients' willingness to use mHealth applications and defined behavioural intention as the dependent variable in our model. We state the assumption that BI serves as the best approximation for actual UB.

All constructs were measured with a minimum of two reflective items (reflective measures are caused by the latent construct; the latent construct is reflected in the indicators and is thus interchangeable). To determine whether our model is valid and confirm assumed drivers of acceptance, we performed structural equation modelling (SEM) with the SmartPLS software [31]. Descriptive statistics were performed with R and SPSS.

Interview Method and Validation

We conducted structured interviews among patients with chronic gastroenterological diseases. The items corresponding to the model were measured with 7-point Likert scales and answered from "strongly disagree" to "strongly agree."

Data Preparation

First, all patients were excluded from the analysis who responded to less than 50% of the questions. Furthermore, standard deviations were calculated for all answers given per questionnaire and those ($n = 3$) excluded where the standard deviation of all questions' answers was below 1 to exclude patients who indifferently ticked the same answer for each question. Afterwards, missing values were imputed with expectation maximization method with SPSS.

Hypotheses Testing

First, we hypothesized that the model fits our data. Then, our hypotheses evaluated whether PE, EE, HM, SI, FC, as well as the formative construct of PeM and privacy concerns, impact patients' intention to use mHealth applications (BI) significantly. Additionally, we included age, gender, educational status, and knowledge about digital applications in general in our model and tested their impact on BI.

Results

Baseline Characteristics of Cohort

The population of participants consisted of patients with chronic gastroenterological diseases from the Mannheim University Hospital outpatient clinic. Patients who presented for an outpatient appointment at our gastroenterological outpatient clinic between November 2021 and January 2022 were asked to fill out questionnaires. From 250 questionnaires taken, 32 were excluded because only 50% or less of all questions had been answered. Additionally, three questionnaires were excluded because of a standard deviation below 1. A total of 215 questionnaires were included in the final analysis. Table 2 provides an overview of the participants' characteristics, Figure 2 provides age distribution, and Table 3 provides gender distribution.

Self-Reported Knowledge with Computers and Mobile Applications in General

The majority of patients participating in the study considered themselves familiar with computers and mHealth applications in general. Seventy-eighty percent of participants reported average (55 patients, 25.7%), good (66 patients, 30.8%), or even very good (46 patients, 21.5%) knowledge which indicates a technically literate sample.

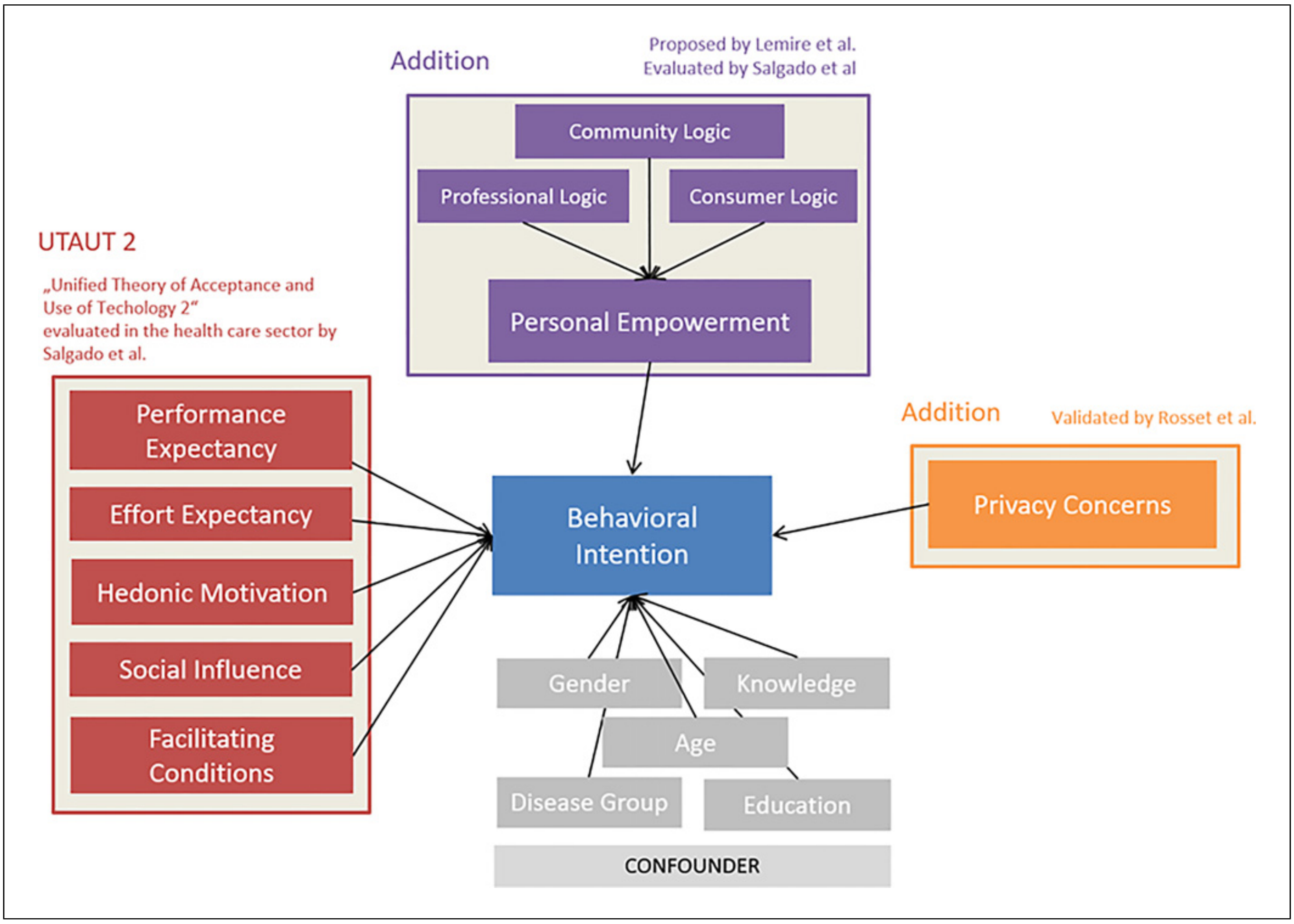


Fig. 1. Model explaining the behaviour intention to use mHealth applications.

Table 1. Independent variables and explanations

Construct	Abbreviation	Explanation
Performance expectancy	PE	Describes the user's expectation about the benefit of the application [25, 27]
Effort expectancy	EE	Describes the user's expectation about the effort of use [25]
Hedonic motivation	HM	Describes the user's expectation about the fun and pleasure that the application will bring [25, 30]
Social influence	SI	Describes the extent to which a user expects his or her social environment to believe it would be useful for the user to use an application [27]
Facilitating conditions	FC	Describes existing support for the use of mHealth applications [25]
Personal empowerment	PeM	Describes the process by which the user gains self-efficacy and self-confidence, which is crucial for actively participating in the management of their healthcare and in making decisions about it [26]
Professional logic	PePL	Describes personal empowerment through increased health literacy which comes because of better expert knowledge and leads to stricter compliance with the provider's (e.g., doctor's) instructions [26]

Table 1 (continued)

Construct	Abbreviation	Explanation
Consumer logic	PeCL	Describes the personal ability to make a competent decision about one's own actions based on one's own judgement and knowledge base [26]
Community logic	PeCCL	Describes personal empowerment based on a sense of belonging and participation in a society and experiencing collective support [26]
Privacy/data security concerns	DP	Includes different dimensions of data security concerns that may hinder the patient from using mHealth applications [23, 24]
Behaviour intention	BI	Describes the patients' intention to use mHealth applications for managing their disease [25, 27]

Table 2. Patient characteristics

Age, years, median	
All patients	55.5
Chronic inflammatory bowel syndrome	46.7
Liver diseases	54.3
Chronic pancreatic diseases	58.7
Oncologic diseases	62.6
Gender, *n* (%)	
Male	102 (47)
Female	112 (52)
Diverse	1 (1)
Primary education, *n* (%)	
High school/A-levels	76 (36)
Middle school equivalent (Mittlere Reife)	69 (32)
Lower secondary education (Volks-/Hauptschule)	60 (28)
Other	8 (4)
Higher education, *n* (%)	
Vocational training	56 (27)
Training at a vocational school, commercial school	41 (21)
University or college	32 (16)
Technical school, master school, technical school, vocational or technical academy	30 (15)
Technical college or engineering school	18 (9)
Still in vocational training, e.g., student, trainee, pre-vocational training year or traineeship and had no professional degree yet	7 (3)
Other	2 (0.1)

Some patients suffered from more than one disease in more than one disease group. AIH, auto-immune hepatitis; PBC, primary biliary cirrhosis; PSC, primary sclerosing cholangitis; IBD, inflammatory bowel disease.

Use Behaviour to Date

We assessed patients' actual use of mobile applications concerning fitness tracking and potential interactions with their healthcare providers. The vast majority of our patients reported not yet using mHealth applications (see Fig. 3, for results). Only 52% of all patients stated to use mHealth services, from occasionally to frequently, to research health information. Regular vital sign monitoring, organization of medical care, or direct contact with the provider were generally not used.

We additionally asked patients about their general willingness to use the mHealth applications, that are mentioned above in the future (see Fig. 4). Additionally, we directly asked for the willingness to utilize an app that is specifically tailored to their disease and disease management. The median response was 5 on a 7-point Likert scale, indicating high general willingness to utilize an app tailored to patients' specific disease. Willingness to participate in support groups via mHealth is predominantly negative in our sample. The intention to use mHealth for symptom tracking and monitoring or participation in studies or medical consultations is predominantly positive.

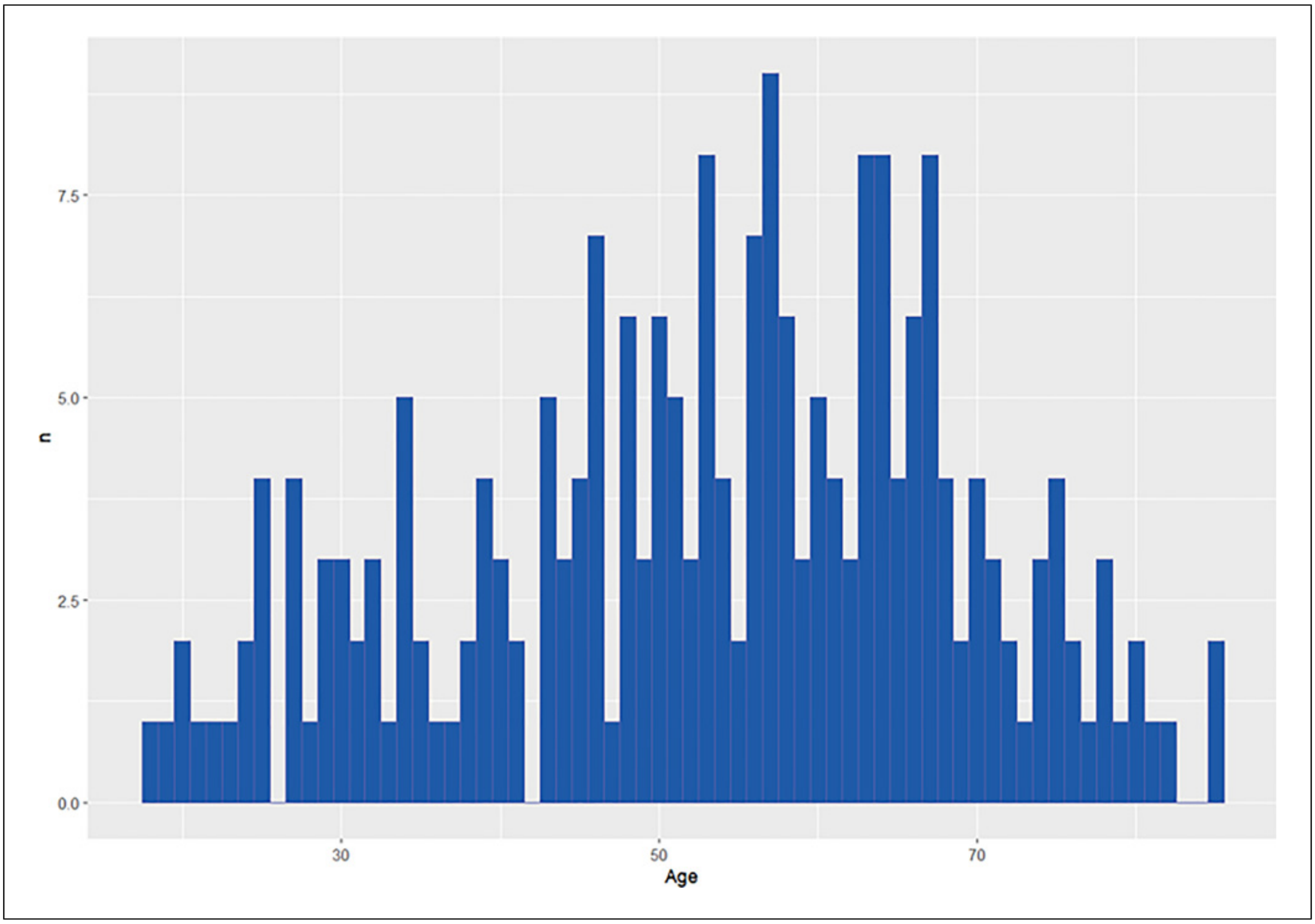


Fig. 2. Age distribution of all patients included in the analysis.

Table 3. Gender distribution in patient cohort

	Total	Liver	IBD	Oncology	Pancreas	Other
Male	102	85	10	5	3	3
Female	112	94	16	2	4	1
Diverse		1				

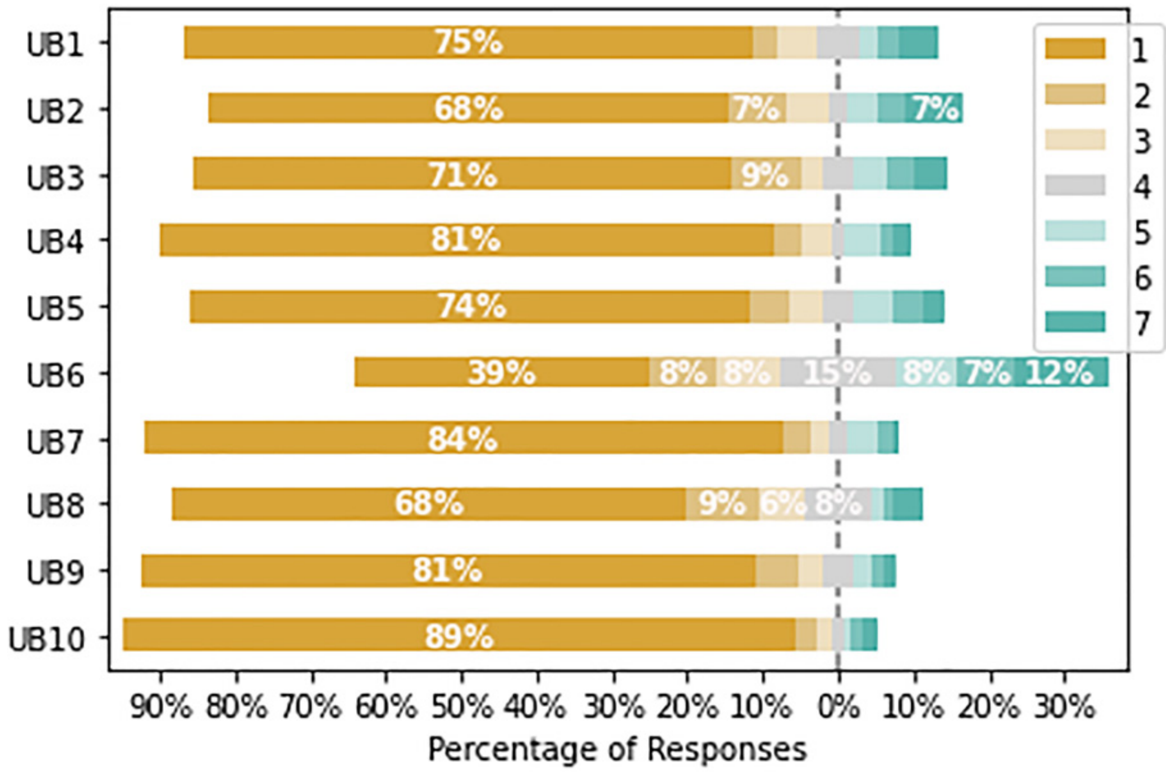
Patients with chronic disease of the liver, IBD, oncologic disease, or pancreatic diseases. Figures of different diseases add up to more than total number because some patients presented with more than one disease group.

Once per week, utilization peaks in all disease groups except from patients with pancreatic diseases who tend to a lower utilization time. The most frequent response among all patients was a preferred utilization frequency of about once a week (n = 70/185, 38%). Nearly daily use for about 5 min (14.1%), 15 min (7.1%), 30 min (3.2%), or more than 30 min (3.2%) were the favourite time to invest for 27.6% of the patients. 15% preferred utilization times less than once a month, and 20% would not use mHealth applications every week but still several times a month.

About 70% of all patients considered it easy to become skilled in using mHealth applications which complies with the general estimation about the knowledge in dealing with mobile applications. The majority of patients indicated that there were sufficient technological resources, compatibility, and support to use mHealth applications.

Drivers of Acceptance

The perception of potential PeM enabled by mHealth possibilities was diverse. Forty-seven percent felt more empowered by mHealth technologies to make decisions among different therapy approaches, especially through better information (Personal Empowerment – Consumer Logic, Item 1 [PeCL1] [PeCL2: 53%]). Many patients also expected the embedding in the community to be positive: half of the patients felt empowered by mHealth to better understand other people with a similar condition (Personal Empowerment – Community Logic, Item 1 [PeCCL1]: 47.5%). Fifty-eight percent felt implementing their healthcare provider's advice was easier with the help of

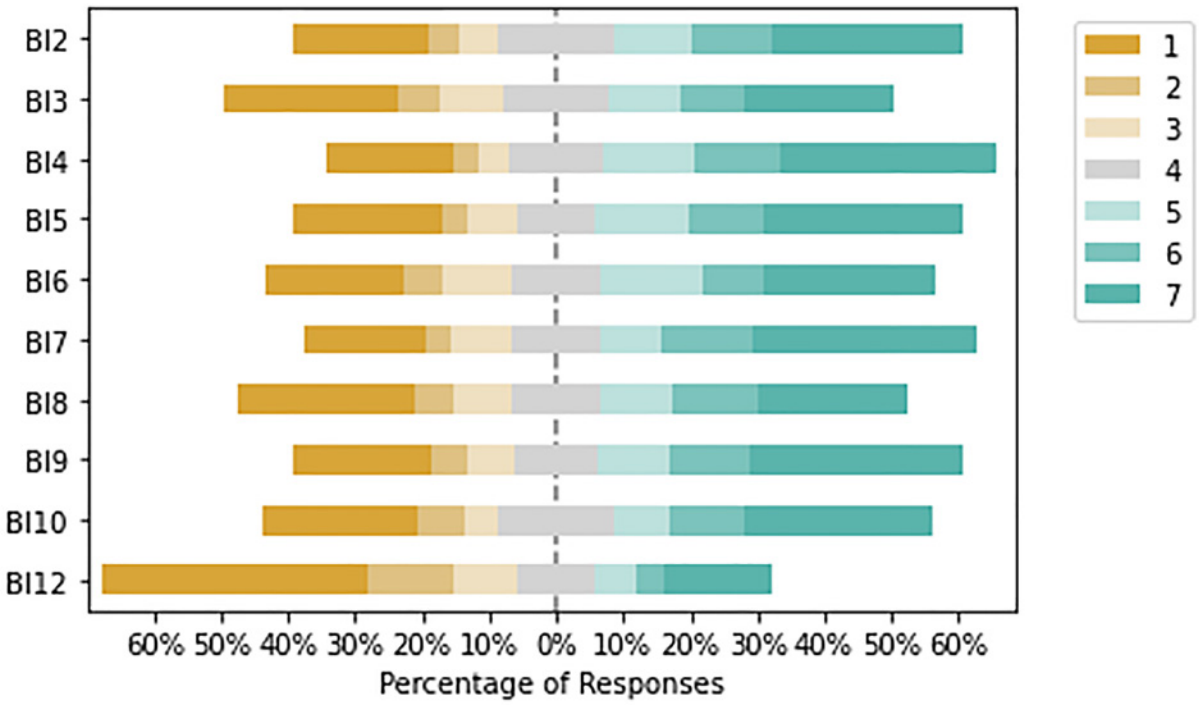


Dimensions of actual use behaviour	Total (Median, [Q1, Q3])
... The collection of biometric data for medical tracking (blood pressure, heart rate, blood sugar, etc. ...). (UB1)	1 [1, 1]
... The collection of biometric data for well-being (fitness apps). (UB2)	1[1, 2]
... Accessing a patient portal (managing appointments, accessing clinical analysis results, requesting online prescriptions, etc.) (UB3)	1[1, 2]
... Monitoring of therapy (tracking prescribed medications/medication intake). (UB4)	1[1, 1]
... Scientific observational studies (e.g., drug, app, or innovative treatment study) (UB5)	1[1, 2]
... Health information research (UB6)	3[1, 5]
... Symptom monitoring and consultation (use of digital health platforms with artificial intelligence algorithms to analyze symptoms, e.g., ADA Health) (UB7)	1[1, 1]
... Medical consultation/appointment remotely (or with other healthcare professionals). (UB8)	1[1, 2]
... Requesting medical consultation from home (UB9)	1[1, 1]
... Participation in patient support groups or online communities. (UB10)	1[1, 1]

Scale from 1 to 7 corresponds to 'strongly disagree', 'disagree', 'partly disagree', 'neutral', 'partly agree', 'agree', 'strongly agree'

Fig. 3. Response patterns of actual use behaviour.

mHealth (Personal Empowerment – Personal Logic, Item 1 [PePL1]). Fifty-four percent assume that access to recognized expert knowledge will lead to a better understanding of personal health (PePL3). See Figures 5–7 for response distribution of the constructs EE (Fig. 5), FC (Fig. 6), and PeM (Fig. 7).



Dimensions of intended use behaviour	Total (Median, [Q1, Q3])
... The collection of biometric data for medical tracking (blood pressure, heart rate, blood sugar, etc. ...). (BI2)	5[3, 7]
... The collection of biometric data for well-being (fitness apps). (BI3)	4[1, 6]
... Accessing a patient portal (managing appointments, accessing clinical analysis results, requesting online prescriptions, etc.) (BI4)	5[3, 7]
... Monitoring of therapy (tracking prescribed medications/medication intake). (BI5)	5[2, 7]
... Scientific observational studies (e.g., drug, app, or innovative treatment study). (BI6)	5[2, 7]
... Health information research. (BI7)	5[3, 7]
... Symptom monitoring and consultation (use of digital health platforms with artificial intelligence algorithms to analyze symptoms, e.g., ADA Health) (BI8)	4[1, 6]
... Medical consultation/appointment remotely (or with other healthcare professionals). (BI9)	5[2, 7]
... Requesting medical consultation from home (BI10)	4[2, 7]
... Participation in patient support groups or online communities. (BI12)	2[1, 5]

Scale from 1 to 7 corresponds to 'strongly disagree', 'disagree', 'partly disagree', 'neutral', 'partly agree', 'agree', 'strongly agree'

Fig. 4. Response patterns of intended use behaviour.

Results of Structural Equation Modelling and Hypothesis Testing

Effort expectancy, functional capacity, and gender have a significant effect on behaviour intention. In our pursuit to delineate the intricate relationships amongst various latent constructs, we employed a comprehensive SEM framework. These constructs, inherently intangible, were operationalized using multi-item measures, which respondents evaluated on a 7-point Likert scale. Table 4 displays the standardized path coefficients as well as t statistics and p values of the relationships between the latent variables.

One such construct, PE, examined respondents' conviction about the efficacy of mHealth interventions in their healthcare, precisely whether mHealth applications may support critical aspects of their healthcare (PE1),

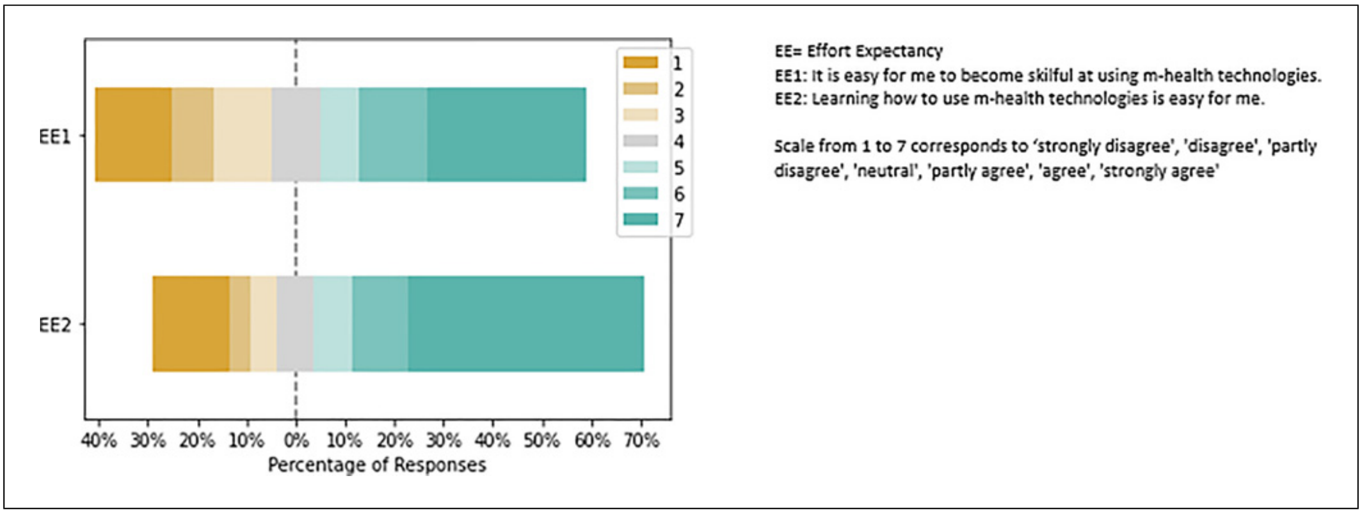


Fig. 5. Response distribution for the construct "effort expectancy."

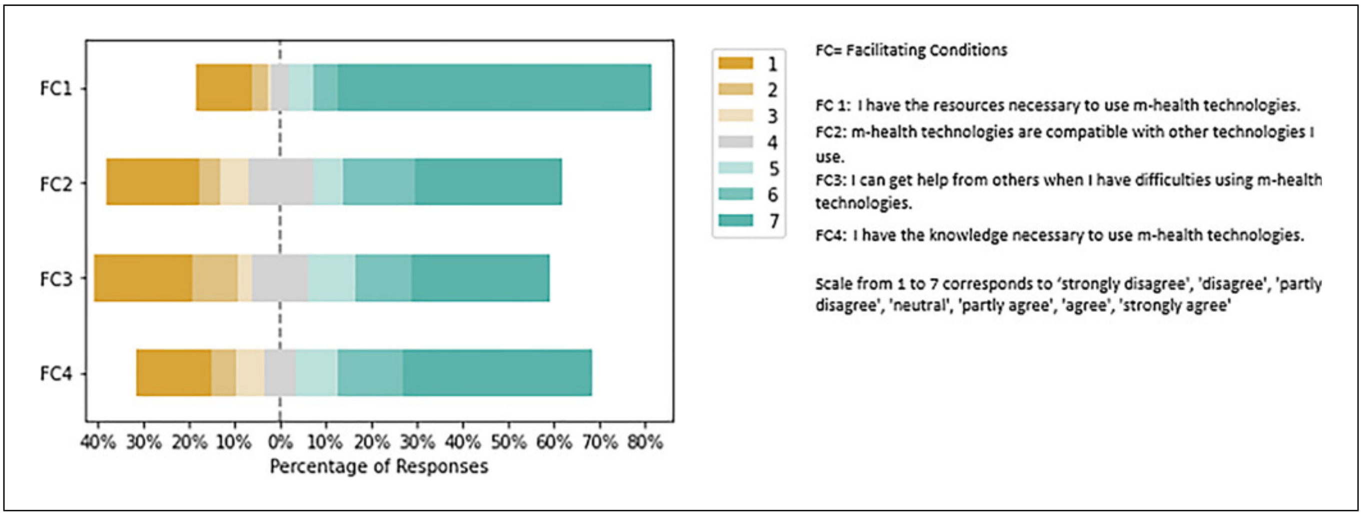


Fig. 6. Response distribution for the construct "facilitating conditions."

enhance their effectiveness in managing their health (PE2) or will be generally useful in managing their healthcare (PE3). Although opinions were mixed, our model showed that this belief did not have a strong impact on their decision to use mHealth. Answers were highly diverse, about 20% of the patients were indifferent (PE1: 25%, PE2: 17%, PE3: 22%), 47% answered in favour of this perception (PE1: 39%, PE2: 55%, PE3: 48%), and 25% rejected this perception (PE1: 23%, PE2: 28%, PE3: 26%).

Another aspect was about the patients' perception of whether they had the tools and conditions ready for using mHealth applications. The majority felt prepared, and this perception of FC's presence positively impacted their intention to use these technologies.

Ease of use or level of effort (EE) also mattered significantly. When patients felt mHealth technologies were straightforward and user-friendly, they were more inclined to use them. Contrastingly, SI, which includes societal expectations and pressures to adopt mHealth, did not resonate strongly with our cohort, as evinced by both primary data (more than 50% disagree) and model outcomes.

Hedonic motivation, or the intrinsic pleasure derived from mHealth utilization, though perceptible in the data, surprisingly lacked significant predictive prowess in our model. More than a third of patients considered mHealth applications to be either enjoyable (HE2) or fun (HE1) (52% and 33%, respectively, answered from 5 to 7 on the Likert scale). A fifth of

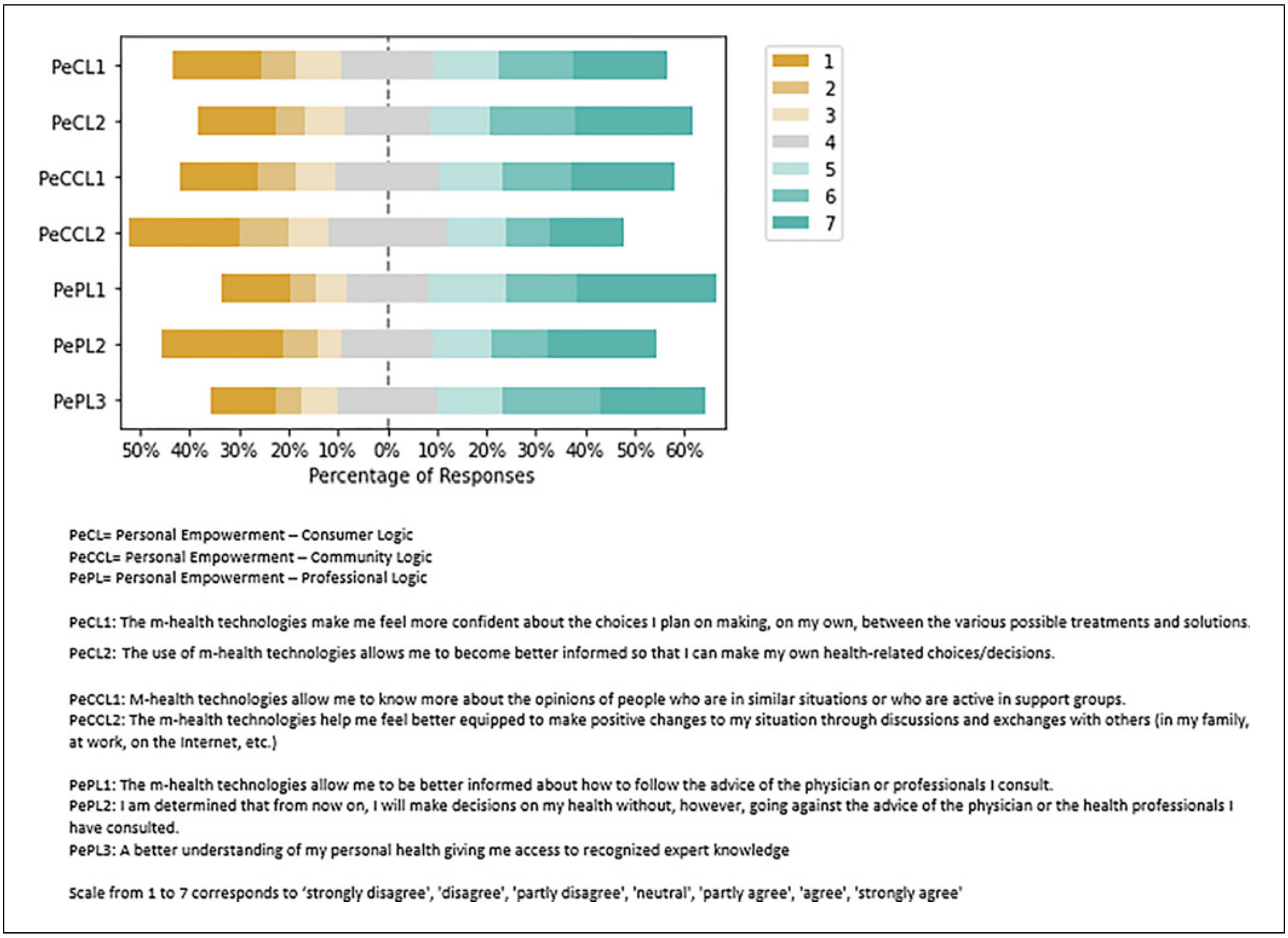


Fig. 7. Response distribution for the construct "personal empowerment."

patients were indifferent (HE1: 21%, HE2: 14%), and the others thought mHealth applications were neither fun (42%) nor enjoyable (30%).

Data security emerged as a prominent concern among patients. More than 70% of patients agreed that fitness app providers should put more effort into preventing unauthorized access to personal data, and this data protection should take place no matter of the cost (Data Protection Concerns, Item 1 [DP1] and Item 2 [DP2]). Additionally, more than 80% considered it important to know how their personal data is being used and that personal data should never be sold to other companies (DP3, DP4). 62% were concerned that fitness applications are using their personal data for other purposes without permission (13% were indifferent, 25% were not that concerned) (DP8). Only 53% were concerned that fitness applications were collecting too much personal data, 13% were indifferent, and 34% did not consider this important (DP5). Seventy-one percent of patients think twice before giving personal data to a health application (DP6), 51% (DP7), and 64% (DP14) were even bothered when thinking about giving personal data to health applications. Eighty-four percent stated that people should have the right to decide for themselves how their information is collected, used, and shared (DP15). For 75%, good privacy policies should be clearly and visibly disclosed (DP10), and the core of privacy is control over personal data (DP12). About 80% thought that fitness app providers should take more steps to ensure that unauthorized individuals do not have access to personal data (DP13).

In our model, however, data security concerns did only play a minor role in BI ($\beta = 0.02$) and were not significant ($p = 0.715$) in influencing the intention to use mHealth applications (hypothesis 10). PeM through mHealth was another area we explored. Over half of the patients felt that mHealth made them more informed and confident about their treatment decisions. Our model confirmed that feeling empowered positively influenced their intention to use mHealth.

The degree of PeM established by mHealth applications was also measured in our questionnaire. The perceptions from the consumer perspective that mHealth

Table 4. Hypothesis testing with Bootstrapping of the SEM model

	Sample's path coefficient	*t* statistics	*p* values
H1: PE → BI	0.114	1.135	0.256
H2: EE → BI	0.208	2.151	0.032
H3: HM → BI	0.058	0.670	0.503
H4: SI → BI	0.057	1.019	0.308
H5: FC → BI	0.260	2.701	0.007
H6: PePL → PeM		See table 5	
H7: PeCL → PeM		See table 5	
H8: PeCCL → PeM		See table 5	
H9: PeM → BI	0.197	1.875	0.061
H10: DP → BI	0.020	0.366	0.715

Model fit: SRMR = 0.069. BI, Behaviour Intention, DP, Data protection concerns, EE, Effort Expectancy, FC, Facilitating Conditions, HM, Hedonic Motivation, PE, Performance Expectancy, PeM, Personal Empowerment, SI, Social Influence; H, hypotheses. Grey shades indicate significance $p < 0.05$; light grey shades indicate significance $p < 0.1$. H1 – Performance expectancy has a positive influence on mHealth behaviour intention. H2 – Effort expectancy has a positive influence on mHealth behaviour intention. H3 – Hedonic motivation has a positive influence on mHealth behaviour intention. H4 – Social influence has a positive influence on mHealth behaviour intention. H5 – Facilitating conditions have a positive influence on mHealth behaviour intention. H6 – Professional logic has a positive influence on personal empowerment. H7 – Consumer logic has a positive influence on personal empowerment. H8 – Community logic has a positive influence on personal empowerment. H9 – Personal empowerment has a positive influence on mHealth behaviour intention. H10 – Data protection concerns do have a negative influence on mHealth behaviour intention.

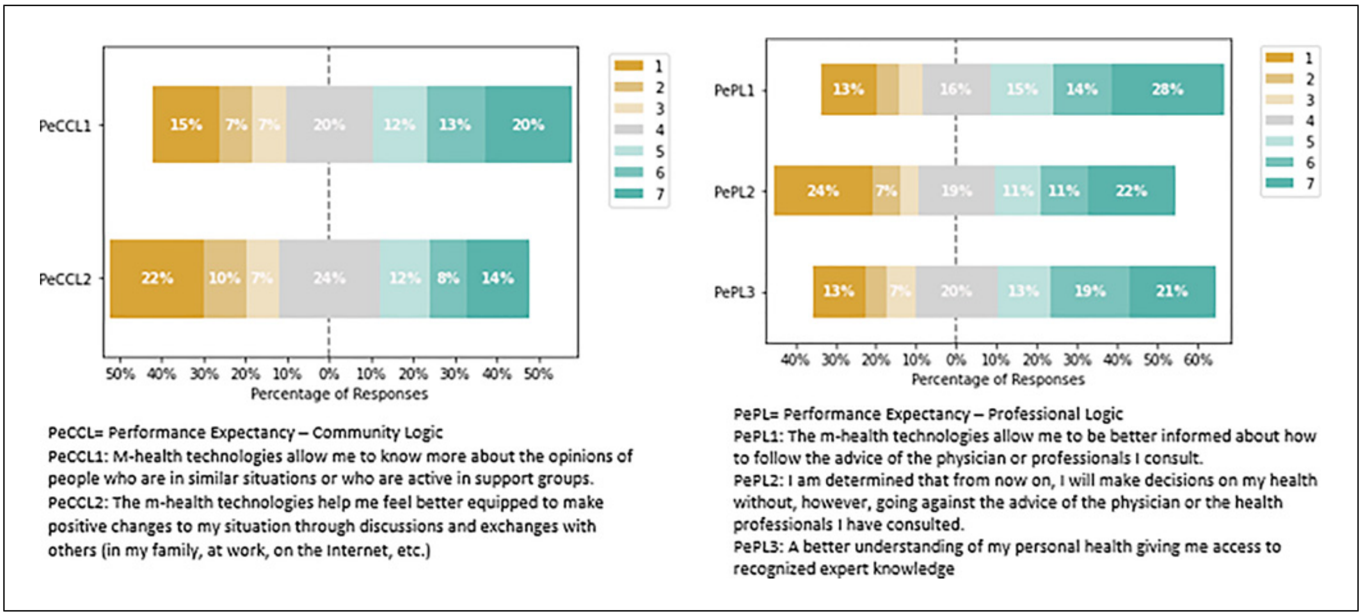


Fig. 8. Percentage of answers for "personal empowerment – community logic and professional logic."

technologies made patients more confident (PeCL1) as well as better informed and thus more decisive (PeCL2) about their treatment decisions yielded consent for more than 50%. Understanding the community logic by getting to know more about the opinions of people in similar situations (e.g., support groups) or by enabling helpful and supportive discussions with family members, friends, and work colleagues was distributed almost equally in favour and against (see Fig. 8). MHealth technologies might also enable patients to become experts in their

Table 5. Outer loadings, significance and collinearity assessment for the higher order construct PeM

HOC	LOC	Outer weight	*t* statistics	*p* values	Outer loadings	VIF
PeM	PeCCL	0.232	2.015	0.044	0.837	2.422
	PeCL	0.480	3.692	<0.001	0.939	2.935
	PePL	0.377	2.447	<0.001	0.942	3.949

H6 – H8 are accepted, PeCL, PeCCL, and PePL are significantly forming PeM. VIF <5 indicates no significant affection by collinearity. The response patterns for the different drivers of acceptance included in the acceptance model are depicted in Figures 5, 6, 7 and 8.

disease and disease management, thus improving their compliance and adherence to physicians' advices. When asking for this PL-aspect of PeM, slightly more than half of the patients answered from 5 to 7 on the Likert scale, supporting this aspect (see Fig. 8). In our model, CL, CCL, and PL significantly represent the higher order construct PeM, whereas PeM was positively influencing BI to use mHealth technologies on a significance level of $\alpha < 0.1$ ($p = 0.061$) (see Table 4 for H6, H7, H8, and Table 5 for outer loadings and collinearity assessment).

Lastly, to make sure our findings were robust, we assessed reflective indicator outer loadings for all constructs. Following Hulland et al. [32, 33], we removed factors with loadings below 0.5. All indicators proved good reliability with Cronbach's alpha >0.7. Composite reliability of >0.8 indicates good internal consistency in our model. Convergent validity was assessed with the average variance extracted (AVE) and was >0.6 for all items, thus indicating convergent validity [34]. Additionally, our model incorporated demographic variables, including age and gender, but also educational attainment, and general technological literacy.

Discussion

Past studies have identified various reasons for the hesitation in adopting mHealth applications, with the acceptance drivers varying widely across populations [12–15]. Our study specifically examines mHealth acceptance among patients with chronic gastroenterological conditions. The majority of our patient cohort, despite an average age above 50, exhibited good technological literacy. We found that mHealth use is generally low, primarily limited to seeking health information. However, a significant interest was noted in biometric tracking and symptom monitoring, indicating that mHealth tools focussed on disease tracking could be most beneficial for gastroenterology patients.

Drivers of Acceptance

Our goal was not only to clarify the general readiness for mHealth use but also to investigate the essential drivers of acceptance. We developed a theoretical model based on the already established theory of UTAUT2 and extensions chosen for our collective. Parameter estimation and validation of the variance-based SEM were performed to best represent the complexity of the underlying theory and understand the influencing factors of the intention to use mHealth applications.

The driver of acceptance with the highest path coefficient was the latent construct FC. Availability of technical devices such as mobile phones or tablets, as well as contact persons in case of operation difficulties, are examples for this construct. This seems quite evident, because only barrier-free access to mHealth technologies allows their usage. However, it needs to be emphasized that adequate support from third parties in case of ambiguities as well as acquired knowledge and skills are also among the factors that allow access. Even if healthcare providers cannot provide a device, they could build capacities through the provision of skills training and assistance which was also shown by several authors [19, 20]. For providers of digital health applications, too, an easily accessible, low-threshold support portal throughout the entire period of use could be a key success factor.

The second most important factor was the construct EE, which describes the user's expectation about the effort it takes to use the mHealth application and comes along with the self-perceived confidence of acquiring skills in mHealth use. Most patients consider it easy and doable to learn to use mHealth technologies. This complies with the perceived knowledge and skills about dealing with technologies in general, which were medium to very good for the majority of our patients. Most of the patients consider themselves as quick learners and are not afraid of getting used to mHealth technologies. We conclude that patients have both the motivation and the necessary acceptance factors to use mHealth applications. However, it remains to be clarified why mHealth applications are rarely used. One reason is the lack of availability. The German DiGA directory was searched for keywords for all diseases in the gastroenterology field given by our patients and yielded no results.

In our acceptance model, the constructs SI, HM, PE, and DP were not significant influencers of the intention to use mHealth applications. The responses provide some interesting insights about patients' perceptions: mHealth use out of social expectation or peer influence likewise does not appear to be a primary motivator for the majority of patients. Most patients expect to find using mHealth enjoyable, but a majority do not expect it to be specifically fun to use. The hedonistic aspect is not a priority for our patient group.

While patients are indifferent about whether mHealth technologies affect crucial aspects of their healthcare, most patients find the use of mHealth to be helpful in their disease management and consider it beneficial for the effectiveness of their healthcare. Regarding data protection aspects, it matters most to the patients that the user is informed in a very transparent manner and can decide which information is collected, used, and shared. Providing solid data protection and information about the data usage flow fosters trust and thus long-term usage and adherence, even if it is not significantly influencing the initial mHealth usage in our model.

In general, most of our patients were willing to spend some minutes once a week on a mHealth application specific to their disease, which must be considered by manufacturers and providers when designing the applications. Our results about time investment and EE are supported by Vaghefi et al. and Zhou et al. [18, 19] research: mHealth needs to be convenient and require low effort, especially considering data collection. The willingness to use a mHealth application rises when data collection happens through passive sensing without the need of frequent active input by the user. Efficient utilization is key and an interface as well as navigation that accelerate the interaction with the application ensure acceptance and adherence.

Yuan et al. [30] examined 317 young adults at a university in the USA and applied the UTAUT2 model to assess their predictors to use health and fitness applications. In contrast to our findings, they found PE, HE, price value, and habit to be significant predictors of their intention to use mobile applications. EE, SI, and FC, however, did not predict the intention to use significantly. Price value was not included in our study since the German system allows cost coverage by health insurance. Louissant et al. [35] studied 102 cirrhosis patients and discovered that the perceived performance of an mHealth app significantly influences the intention to use mHealth applications. In our study, for the overall cohort, PE was no significant predictor for BI; however, our overall cohort included a variety of gastroenterological patients.

This outlines that drivers of acceptance for different population groups vary to a considerable extent, and further analyses are necessary to understand the generalizability of the results and build a universal model explaining drivers of acceptance in patient groups. We employed the UTAUT2 adapted for healthcare, a data collection tool deeply grounded in behavioural science. Since we facilitated the UTAUT2 model and expected the actual UB to directly correlate with the BI, our results must be interpreted with some caution. Notably, while data security, enjoyment, and social aspects matter, only perceived effort and resource availability significantly impact usage intent. This suggests a necessity for robust support systems by healthcare and mHealth providers for gastroenterological patients. However, understanding drivers of acceptance of a mHealth application's target group is key success factor for fully exploiting the mHealth benefits; thus, usability research must become more important as mHealth applications spread.

Conclusion

Patients with gastroenterological diseases show a great interest in digital services to manage their disease. The leading acceptance factor here is feasibility. Concerns about data privacy are present and relevant but do not have a significant effect on the intention to use in our model. Nevertheless, mHealth applications must be available (which is not the case for many of our patients' diseases), known, and their content must be tailored to the interests and focus of the target group, which in our case is on tracking symptoms and therapies and allowing better and more effective disease management. Particularly relevant for acceptance among our patient group is the simplicity of use and compatibility with existing technologies, but also a strong support system in case of difficulties.

Statement of Ethics

Ethics approval has been obtained by the Ethics Commission II, medical faculty Mannheim, University of Heidelberg (2020-592-N). Written informed consent was obtained from all study participants.

Conflict of Interest Statement

The authors declare no conflict of interest.

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Author Contributions

Isabella Wiest conceived and designed the analysis, collected the data, performed the analysis, and wrote the manuscript with support of Andreas Teufel, Maurizio Sicorello, Matthias Ebert, and Kakharman Yesmembetov. Andreas Teufel made substantial contributions to the conception and design of the trial and was involved in data collection and supervised the project. Maurizio Sicorello contributed in data analysis and corrections of the paper. Kakharman Yesmembetov contributed in data collection. All authors discussed the results and contributed to the final manuscript.

Data Availability Statement

All data generated or analysed during this study are included in this article. Further enquiries can be directed to the corresponding author.

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