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Reporting health data in waiting rooms with mobile technology: Patient expectation and confirmation

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Reporting Health Data in Waiting Rooms with Mobile Technology: Patient Expectation and Confirmation

Abstract

Objectives: Hospitals and medical staff use digital devices such as mobile phones and tablets to treat patients. Prior research has examined patient-reported outcomes, and the use of medical devices to do diagnosis and prognosis of patients, but not whether patients like using, and intend to use in future, mobile devices to self-report medical data. We address this research gap by developing a theoretical model based on the expectancy confirmation model (ECM) and testing it in an empirical study of patients using mobile technology to self-report data.

Design: This study adopts a non-interventional cross-sectional research design. Randomly-selected patients provided data via survey and physical measurements. The target population comprises adults visiting a healthcare laboratory to get their blood drawn.

Materials and Methods: We surveyed 190 randomly-selected patients waiting for treatment in the clinic. They were surveyed at two points in time – before and after their blood was drawn – on their demographic characteristics, research variables concerning their use of mobile devices to provide medical information, and perceived clinical data (blood pressure, height and weight). The research model was tested using structural equation modeling.

Results: The study found strong support for the research model, with seven of eight hypotheses being supported. Both self-disclosure effort and feedback expectation positively affect both perceived feedback quality and confirmation. Contrary to expectations, perceived feedback quality was not found to affect confirmation. Perceived feedback quality, along with confirmation, was found to positively affect satisfaction, which was found to affect intention to disclose medical data through mobile technology.

Conclusions: The study's findings support the proposed path from feedback expectation and self-disclosure effort to confirmation to satisfaction to disclosure intention. Although perceived feedback does not affect confirmation, it affects satisfaction. Overall, we believe the results provide novel insights to both scientific research community and practitioners about using mobile technologies for self-reporting medical data.

Keywords: Healthcare, expectation confirmation model, disclosure intention, mobile devices, self-reporting.

1. Introduction

Mobile devices have gained prominence for collecting and providing medical information. Modern health services frequently use tablets and smartphones for patients to report symptoms, communicate with doctors, or seek referrals or prescriptions (Garfield et al., 2011). However, the information provided by patients can be expanded further. For example, if patients self-report medical data, such as blood pressure and weight, it can be entered into their records, giving the treatment provider *a priori* insights about the conditions of the patients.

Health providers understand the potential of mobile devices for strengthening ties with patients, and provide many health services through them (Ben-Zeev et al., 2015; Neubeck et al., 2015). Prior studies show that patients can independently and reliably report on a variety of measures (Okura et al., 2004), and use mobile devices to learn about medical topics (e.g., Chou et al., 2012). Moreover, patients' experience with, and expectations from, medical technologies affects their reuse of these technologies (Culliton et al., 2018).

This study examines the factors affecting patients' satisfaction with mobile technologies to self-report medical anthropometric (height and weight) and physical (blood pressure) data, and their intention to continue self-reporting. If patients are satisfied with the effects of their self-reported medical data, and continue to self-report them, they would save some time during their visit to the clinic, which becomes especially important during current COVID pandemic. We examine the factors affecting patients' use of mobile devices using a theoretical model based on the expectation confirmation model, and test it using data from 190 patients.

2. Research Background

Self-reporting by patients is integral to planning and improving treatment. It is important that patients provide reliable information about their health and are satisfied with the process and its outcomes. Accordingly, a considerable body of literature examines patient-reported outcomes

(PROs)[1], an umbrella term used to evaluate patients' perceptions, feelings, attitudes, or clinical outcomes. Prior research (see **Appendix A**) has used various methods to study the effectiveness of PROs, including surveys of patients and health professionals (e.g., Tanaka et al., 2020), and qualitative methods such as interviews and focus groups (e.g., Wilcox et al., 2016).

Prior PRO studies focus on the design, development, and usability of web-interfaces or mobile applications. Patients are more likely to use mobile devices to report data with visual rather than textual interface (Turchioe et al., 2020). Some studies examine algorithms involving analytics used by healthcare professionals to maximize the effectiveness of self-management and deliver high-quality care (Cho et al., 2019; Gogovor et al., 2017), or use machine learning algorithms to study medical data (Huang et al., 2019; Meng et al., 2020). Finally, some studies focus on technology development and use in case of patients suffering from specific diseases. A study of the use of health portal by patients suffering from depression and anxiety found that people use mobile devices more for self-assessment if it delivers personalized feedback (Cronin et al., 2018). Other examples include studies of the effect of the design of Internet-of-Things (IOT) and wireless sensor devices on data self-reporting by diabetic patients (Chatterjee et al., 2018) and the effect of web-based virtual nursing intervention to promote self-management and medication adherence for kidney transplant patients (Côté et al., 2019).

This paper contributes to the literature on PROs in two ways. First, it develops insights into the factors affecting patients' satisfaction with using mobile technologies to self-report medical data and their intention to continue doing so. This is important because if patients are satisfied with the consequences of their self-reported medical data, and therefore continue to self-report them using mobile devices, their need to visit medical clinics would decrease.

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[1] We thank an anonymous reviewer for suggesting this stream of literature.

Second, in contrast the broad nature of PROs, this paper's focus is more specific – on the reporting of medical anthropometric (height and weight) and physical (blood pressure) data. This data is part of the basic physical examination for all patients, but may require clinical actions for the otherwise previously healthy population. These tests can be conducted by healthcare workers, but require the patients' cooperation in scheduling, and then arriving at the clinic. This study addresses the possibility of obtaining such data from patients without their visiting the clinic.

3. Theory Development

3.1. Theoretical Lens

To examine why patients continue or discontinue using mobile technology for self-reporting, this study adopts the expectation confirmation model (ECM) as the theoretical framework. ECM suggests that individuals form expectations about a specific product, and are satisfied when those expectations are met or exceeded (Bhattacherjee, 2001; Marcengo & Rapp, 2014). However, understanding expectations of potential is a challenging task in the context of information technologies, especially when they support different functional areas, promise a broad array of benefits, or offer functionally that users may find difficult to understand (Nevo & Chan, 2007). This might be true in case of mobile devices when used by patients to self-report medical data. The patients may lack medical knowledge and prior experience with the self-reporting functionality of mobile devices, but believe that this may lead to expedited feedback and improve their medical diagnosis and care.

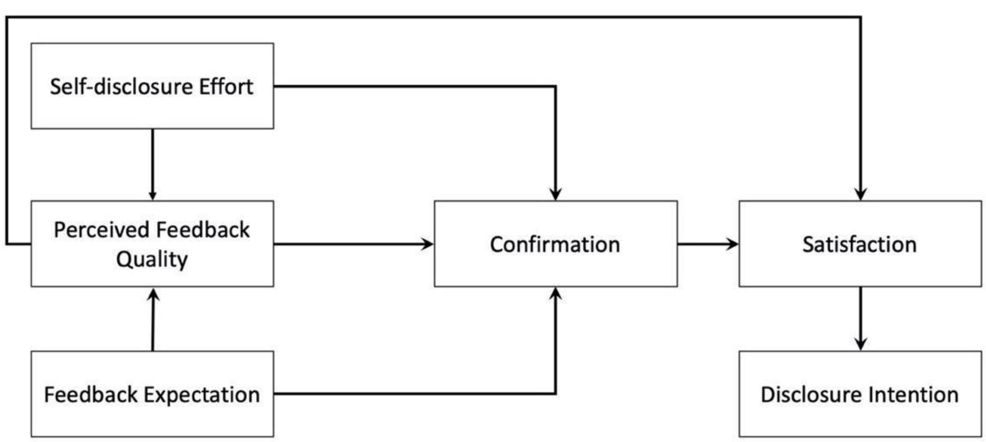
ECM has five components: (1) the user's "expectations" from the new system; (2) "perceived performance," or the user's perception about the system's performance; (3) "confirmation of beliefs," or the user's judgement of the new system, where she continually compares prior expectations to performance; (4) the user's "satisfaction" with the system; and (5) the user's "behavioral intention," or intention to continue using the system (Oliver, 1980).

3.2. Research Hypotheses

This paper's research model includes five constructs adapted from the above ECM constructs: (1) feedback expectation, i.e., the patient's expectation regarding the feedback from using the mobile device for self-reporting medical data; (2) perceived feedback quality, i.e., perceptions regarding the feedback based on the shared data; (3) confirmation, i.e., whether the patients' experience from self-reporting of the medical data matches expectations; (4) satisfaction with self-reporting through the mobile device; and (5) disclosure intention, i.e., the patient's likelihood of self-reporting through the mobile device in future. In addition, we include the effect of self-disclosure effort, which is based on the perceived ease of use construct from prior literature on technology adoption (Davis, 1989; Davis et al., 1989) and success (Sabherwal et al., 2006). Based on ECM, and prior studies on the feedback patients receive via digital media (e.g., Chou et al., 2012), we posit the following hypotheses (see Figure 1).

H1: Self-disclosure effort positively affects: (a) perceived feedback quality; and (b) confirmation.
H2a: Feedback expectation positively affects: (a) perceived feedback quality; and (b) confirmation.
H3: Perceived feedback quality positively affects: (a) confirmation; and (b) satisfaction.
H4: Confirmation positively affects satisfaction.
H5: Satisfaction positively affects disclosure intention.

Figure 1. The Research Model



4. Research Design

We collected the data from patients visiting the laboratory of a healthcare center to get their blood drawn. We conducted the study in the waiting room to utilize the patients' waiting time and avoid inconveniencing them. We invited every fifth patient arriving at the clinic to provide data using mobile technologies. If a patient declined, we invited the patient arriving next. If this patient agreed, we selected the fifth patient after her to participate, and so on.

The target population comprises adults (18 years or more). In the study plan, we aimed to exclude patients with extreme blood pressure levels (specifically, patients with systolic and diastolic blood pressures outside 110-180 and 50-100 ranges, respectively) as they would require immediate help. However, we encountered no such cases. The survey was started by 211 individuals. After excluding 21 incomplete responses, we used data from 190 participants. This sample size exceeds the 161 needed to detect effects, based on a desired statistical power of 0.8, anticipated effect size of 0.3, six latent variables, 19 items, and a p-value of 0.05.

5. Data Collection

5.1. Measuring weight, height and blood pressure.

Medical instruments are widely used in the clinic and annually checked by a maintenance company. All the instruments used for the study were properly working. Blood pressure was measured using the same gauge for all patients. The patients were first asked to rest for 10-15 minutes, and three measurements were then taken at 1-2 minutes intervals with the third measurement being recorded. Height and weight were measured on a digital apparatus near a laboratory room. All patients were guided on the measurement process to avoid inaccuracies. We retrieved the information about chronic diseases and medications from the medical files.

We provided the patients an online survey via a mobile device. The survey was conducted using Qualtrics, ensuring anonymity. The survey was conducted at two points – before (when the patient was asked about demographic details and how she perceived the importance of mobile technology for matters of health) and after (when the rest of the survey was transmitted) the blood test. The survey's preface explained that the study was on using mobile technology for health matters, participation was only with the patient's consent, and participation would have no influence on the treatment. A member of the research group (a certified nurse) transmitted the survey and the measurements. In addition, the branch's staff received explanations about the study and its goals, so that they could provide feedback on the patient-provided measurements.

5.2. Ethical Aspects of Data Collection

The following ethical aspects were considered in collecting data: (1) In order to safeguard the patients' privacy, the data was collected by only one author (a certified nurse). (2) The clinic's management provided a written authorization to collect the data. (3) All the data were anonymously saved under a code and it was impossible to go back to the patient's details after the survey was submitted. (4) Prior approval was obtained from the healthcare facility's Helsinki Committee, which waived the need for a written informed consent from the patients.

6. Measures

We used scales from prior literature, and adapted them to the study context to measure all six constructs (see **Appendix B**) based on inputs from the lab team regarding the feedback they provide to patients. All items were measured on a 7-point Likert scale, ranging from 1 = "do not agree at all" to 7 = "agree very much" for all constructs except satisfaction, as mentioned below.

In the last few decades, numerous people have moved from Russia to Israel, where the study was conducted. So, some patients prefer Hebrew and others prefer Russian. The survey was validated in English, then translated to Hebrew and Russian, and then back to English. During a pilot study, six bilingual participants (who spoke English and either Hebrew or Russian) read the various versions and did not find any differences.

Before the participants entered the lab to draw blood, we measured *feedback expectation* using a good-bad scale (Ajzen & Fishbein, 1977). After the blood test, we measured: *self-disclosure effort* by asking three questions about patients' perceptions of the process of reporting their data via the mobile (Davis, 1989); *perceived feedback quality* using four questions about the feedback received via the mobile phone (Davis et al., 1989); and *confirmation* using three items (Bhattacherjee, 2001). We also measured both dependent variables – satisfaction and disclosure intention – after the blood test: *satisfaction* using a four-item scale (Spreng et al., 1996), and *disclosure intention* using three items (Mathieson, 1991).

We also collected data on *control variables*, including gender, education level, year of birth, country of origin, and clinical indicators such as height, weight, blood pressure and chronic diseases. The patients provided information on clinical indicators through the survey. A certified nurse (also an author) later did the measurements, completed the medical data from the patients' medical files, and retrieved information about their chronic diseases (i.e., diabetics/high blood pressure/myocardial infarction/stroke/lung diseases/malignancy) and routine drug usage.

7. Analysis

All the data were analyzed using *Stata* 15.1. We checked the normal distribution of the continuous variables using the Shapiro-Wilk test. Relationships among demographic, biological, and research variables were examined using either *t*-tests for two independent samples, or Mann-Whitney if the distribution was not normal.

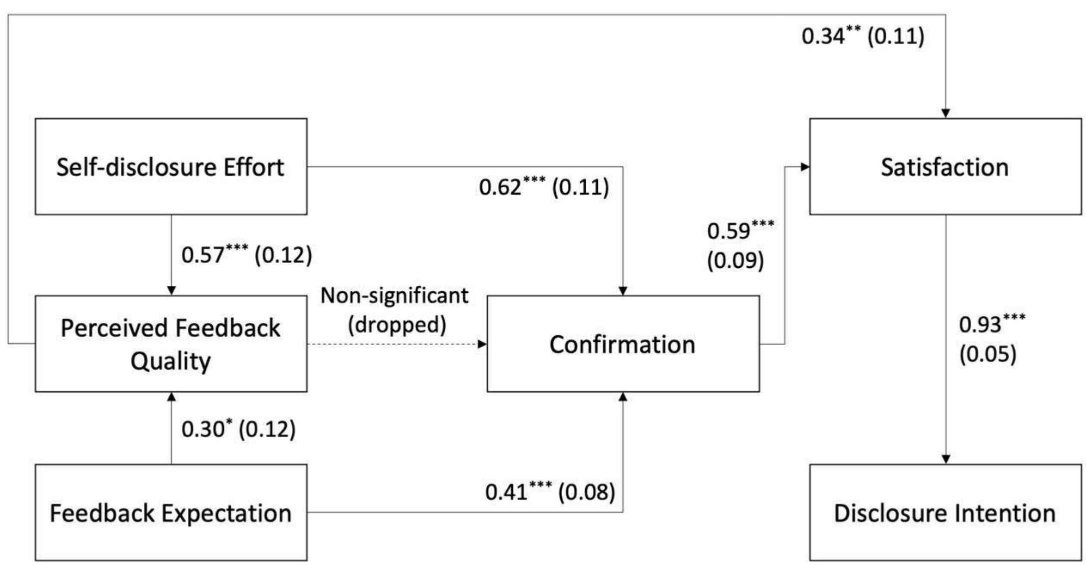
We tested the research model using structural equation modeling (SEM), which allows for simultaneously testing relationships among multiple independent and multiple dependent variables, while including the individual items measuring each variable. More specifically, we used the Stata command *sem* to test the research model.

8. Results

8.1. Demographic Characteristics of the Sample

As seen in **Table 1**, most study participants were women (55%), and distributed almost equally among baccalaureate or over (35%), high school to baccalaureate (33%), and elementary to high school (31%). The first language of a majority of participants was Hebrew (59.89%). The mean reported height (169.45 cm.) differs somewhat from the measured height (169.41), while the mean reported weight (69.08 kg) differs somewhat from the measured weight (69.35). The reported mean values (of systolic blood pressure (126.64) and diastolic blood pressure (81.08) differ from the corresponding measured values (129.65 and 82.39, respectively). The participants' mean age and mean body mass index were 46.5 years and 24.15, respectively.

Figure 2. The Results



* $p < 0.05$; ** $p < .01$; *** $p < .001$; $n = 190$. Standardized beta coefficients are reported, with standard error in parentheses.

Model fit statistics: $\chi^2 = 148.88$, d.f. = 81; χ^2/df = 1.74; Root Mean Squared Error of Approximation (RMSEA) = 0.06; Comparative Fit Index = 0.93; Tucker-Lewis Index = 0.91.

8.2. Results for the Research Model

Table 2 provides the reliabilities, means, and standard deviations of the constructs, and their inter-correlations. On testing the theoretical model, the path for H3a (i.e., from perceived feedback quality to confirmation) was non-significant (0.12, $p = 0.61$), and was therefore excluded. This led to a model with satisfactory goodness of fit indices, with all the paths being significant in the refined model and no modification index over ten. **Figure 2** depicts the results. Thus, all the hypotheses except H3a are supported (**Table 3)**. Results show that self-disclosure effort positively affects perceived feedback quality (H1a) and confirmation (H1b). Feedback expectation positively affects perceived feedback quality (H2a) and confirmation (H2b). Perceived feedback quality positively affects satisfaction (H3b). Confirmation positively affects satisfaction (H4), and satisfaction positively affects disclosure intention (H5), respectively.

9. Discussion

This study has investigated factors affecting patients' satisfaction with using mobile technologies to self-report medical data and their intention to continue doing so. The results largely support the theoretical model based on ECM. Both self-disclosure effort and feedback expectation positively affect both perceived feedback quality and confirmation. Surprisingly, perceived feedback quality does not affect confirmation. One possible explanation for this non-significant effect may be that the patients receive feedback *after* providing self-reports, and is not based only on the self-reports. Instead, the lab staff also provides other feedback to patients having irregular conditions, such as maintaining healthy diets, regular exercising, taking medication, visit to the doctor, etc. As a result, the perceived feedback quality may be less salient to them when considering confirmation. However, perceived feedback quality – along with confirmation – positively affects satisfaction, which positively affects intention to disclose medical data through mobile technology.

The study contributes to theory and practice. **Theoretically**, the study shows how ECM can provide insights into the self-reporting of medical data through mobile technology. It thus extends the literature on PROs and the use of mobile technologies in healthcare context (e.g., Reychav et al., 2019). Drawing upon the ease of use concept from technology adoption literature (Davis, 1989; Sabherwal et al., 2006), the paper has added the self-disclosure effort construct to the five traditional constructs from ECM. The importance of effort is shown by the empirical support for its effect on both perceived feedback quality and confirmation, which affects satisfaction, and through it future disclosure intention. Thus, the study shows the value of considering effort in addition to performance expectations when viewing the determinants of confirmation, thereby contributing to the ECM literature. The study also contributes to the broader technology adoption literature by showing the effects of effort, performance expectations, and confirmation on satisfaction and continued use intention.

From a **practical** viewpoint, this study suggests that self-reports of patients can be used for follow-up purposes and to formulate treatment plans. In addition, the study suggests that the more the patients see benefits in self-reporting within the framework of their treatment plan, the higher the chance that they would feel a higher satisfaction and would be committed to continue reporting. Devising a reliable treatment plan requires a variety of clinical indicators about the patient, such as blood pressure, height, and weight. In today's digital age, the patients themselves can provide clinical personal data by using technological tools. However, since treatment is an ongoing process, it is important to encourage the patients to continue self-reporting clinical data as a part of building their treatment plan and following up on it. This study has, using ECM, provided insights into ways in which this can be done. More specifically, the results point to two key factors: (a) setting reasonable feedback expectations for the patients (so that those expectations are subsequently met in an effective fashion); and (b) reducing the effort patients need to self-disclose their medical data through mobile devices.

The study's results should be viewed in the light of its **limitations**. First, it was conducted at one healthcare facility. Second, we collected survey data from patients at two points in time, but used a single method to measure all constructs. Finally, we sampled participants based on every fifth patient arriving at the healthcare facility. A more randomized selection, e.g., randomly varying the patient selection frequency, would have enhanced the sample's randomness.

10. Conclusion

The study supports the theory-based expectations that in self-reporting medical data via a mobile device, if the patients' expectations regarding the feedback they receive and the device's ease of use (i.e., the effort needed to self-report) are met, they would be more satisfied and would be likely to continue self-reporting. Reporting clinical indicators via mobile devices also has a social aspect, so if an individual is satisfied with using mobile devices to self-report medical data, she might influence others in her network to do so as well.

11. Summary Table

Prior Studies	Our Contribution
• A considerable body of literature on patient-reported outcomes (PROs), an umbrella term used to evaluate patients' perceptions, feelings, attitudes, or clinical outcomes. • Research has provided insights on the use of mobile devices by patients and medical professionals in learning (Choe et al., 2014; Okura et al., 2004). • Research has stressed the importance of self-reporting of data by patients on various indicators (Culliton et al., 2018; Reychav et al., 2019).	• This study contributes to literature on PROs by developing insights into the factors affecting patients' satisfaction with using mobile technologies to self-report medical data and their intention to continue doing so. • The study applies the ECM model to healthcare, and shows the value of considering effort in addition to performance expectations when viewing the determinants of confirmation, thereby contributing to the ECM literature. • The study's findings indicate that self-disclosure effort and feedback expectation positively affect confirmation, but perceived feedback quality does not.

	• Both perceived feedback quality and confirmation positively affect satisfaction, which positively affects the intention to disclose medical data through mobile technology.

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Table 1. Demographic Attributes of Study Participants

Variable	Mean (SD)	Range	N (%)
Gender			
Female			104 (55)
Male			86 (44.79)
Education			
Academic			68 (35.41)
Tertiary			62 (33.33)
Primary and secondary			60 (31.25)
Age	46.48 (16.71)	18 – 90	190
Native language			
Hebrew			114 (59.89)
Non-Hebrew			76 (40.10)
Height (cm.)			
Measured	169.41 (8.39)	146 – 191	190
Has a chronic illness			
Yes			116 (60.41)
No			74 (39.58)
Weight (kg.)			
Measured	69.35 (11.83)	47.8 – 99.5	186
Systolic blood pressure			
Measured	129.65 (12.36)	110 – 168	190
Diastolic blood pressure			
Measured	82.59 (5.93)	61 – 97	190
BMI	24.15 (4.01)	17.62 – 39.86	186

Table 2. Reliabilities, Descriptive Statistics, and Correlations

Variable	Reliability[a]	Mean (SD)	Min (Max)	1	2	3	4	5
1. Feedback Expectation	.72	1.83 (0.61)	1.00 (4.33)					
2. Self-disclosure Effort	.66	2.52 (1.34)	1.00 (7.00)	.04				
3. Perceived Feedback Quality	.56	1.65 (0.52)	1.00 (4.00)	.26**	.00			
4. Confirmation	.82	2.81 (0.78)	1.00 (5.00)	.46**	.07	.39**		
5. Disclosure Intention	.75	2.16 (0.77)	1.00 (6.00)	.38**	.16**	.34**	.58**	
6. Satisfaction	.69	1.92 (0.59)	1.00 (4.67)	.38**	.10	.40**	.55**	.65**

**p < .01

[a] Reliability is assessed using standardized Cronbach alphas.

Table 3. Summary of Hypotheses Results

Hypothesis	**Supported**
H1a: Self-disclosure effort positively affects perceived feedback quality.	Yes
H1b: Self-disclosure effort positively affects confirmation.	Yes
H2a: Feedback expectation positively affects perceived feedback quality.	Yes
H2b: Feedback expectation positively affects confirmation.	Yes
H3a: Perceived feedback quality positively affects confirmation.[a]	No
H3b: Perceived feedback quality positively affects satisfaction.	Yes
H4: Confirmation positively affects satisfaction.	Yes
H5: Satisfaction positively affects disclosure intention.	Yes

[a] This path was included in the theoretical model, and in the original structural equation model. But it was non-significant, and therefore excluded from the final structural equation model. The fit indices and standardized beta coefficients in Figure 2 are for the final model, i.e., after removing this path.

Appendix A: Literature Review on Patient-Reported Outcomes (PROs)

Source	Study
Athilingam et al. (2016)	The study demonstrates the use of mobile platform having embedded interactive heart failure education by patients. The study made use of Mayer's Cognitive Theory of Multimedia Learning, Sweller's Cognitive Load, Instructional Design Approach, and Problem-Based Learning, was utilized to develop and test the mobile app.
Caballero-Ruiz et al. (2017)	The study presents Sinedie, a clinical decision support system designed to manage the treatment of patients with gestational diabetes. The study was conducted in Spain to remotely evaluate patients allowing them to upload their glycaemia data at home directly from their glucose meter, as well as report other monitoring variables like ketonuria and compliance to dietary treatment.
Chatterjee et al. (2018)	Using persuasion theory, the study discuss the design and implementation of an Internet-of-Things (IoT) and wireless sensor system which patients use in their own homes to capture daily activity, an important component in diabetes management.
Cho et al. (2019)	The study was conducted to understand patients' experiences using a real-time medication monitoring pill bottle linked to an HIV self-management app. This study demonstrated that tracking medication adherence and receiving push-notification medication reminders through the electronic pill bottle connected to the app encourages and supports persons living with HIV in adhering to their medication regimens.
Côté et al. (2019)	Kidney transplant patients were provided web-based virtual nursing intervention to promote self-management and medication adherence. Patient experience shows the intervention is acceptable and can help better manage medication intake.
Cronin et al. (2018)	This study explored aspects of how patient-provided health information could be obtained through an electronic portal and presented to inform and engage patients while also providing information for healthcare providers. The survey was administered to self-reported healthy volunteers (no medical conditions) and individuals with a self-reported diagnosis of anxiety and/or depression. Results indicated a strong desire among healthy people, patients with chronic diseases, and healthcare providers for a self-assessment portal that can collect patient-reported outcome metrics and deliver personalized feedback.
Ghandour & Ghandour (2019)	The aim of the study was to report and analyse the experiences of different user groups using PCHR for Multidisciplinary Care Team (MDCT) including the advantages, disadvantages, barriers and obstacles, and the current state of personally controlled health records (PCHR). The key findings of this research showed that those who can benefit the most from PCHRs are the least able to use it. It suits those who have basic knowledge about computers and the internet and those who can afford to use them. PCHR is also best suited for individuals who are motivated about their health despite their health condition.
Gogovor et al. (2017)	The study was conducted on individuals with chronic pain in Canada. The study aims to understand the technology features for the development of an internet-based self-management program. Internet-based programs contain automated, communication and decision support features that can address information and care gaps reported by patients and clinicians. The results of this study indicate that interactivity, personalization, and tailored messages, combined with therapist contact will maximize the effectiveness of an Internet-based chronic pain program in enhancing self-management.
Greysen et al. (2018)	The study was conducted to efficacy of patient engagement with their patient portals during hospitalization and after discharge. All participants were supplied with a tablet during their inpatient stay and assistance with portal registration and initial login as needed. Additionally, intervention group patients received a focused bedside education to demonstrate key functions of the portal and explain the importance of these functions to their upcoming transition to post-discharge care. However, results indicated statistically non-significant, trend towards higher inpatient engagement and post-discharge use of key portal functions among patients.
Hamm et al. (2019)	The aim of the study was to present guidetomeasure-3D, a web-enabled 3D mobile application that enables older-adult patients to carry out self-assessment measurement tasks, and to carry out a mixed-methods evaluation of its performance, and associated user perceptions of the application, compared with a 2D paper-based equivalent. The study revealed that older adults using guidetomeasure-3D achieved improved levels of accuracy and efficiency along with

Source	Study
	improved satisfaction and increased levels of confidence compared with the 2D paper-based equivalent.
Huang et al. (2019)	The study did emotion analysis and sentiment analysis on the patient reported data in remote patient monitoring (RPM) setting.
Iribarren et al. (2020)	The study was conducted on tuberculosis (TB) patients in Argentina to explore the factors governing the use of mobile application. Based on the findings from seven participants, it was concluded that access to answers to frequently asked questions, tracking of progress, and graphical user interface for easier and shorter data entry times and usability were the key factors governing the use of mobile application.
Kakkanatt et al. (2018)	This study aims to develop data curation process that supports healthcare analytics. The process consists of the following steps: collection, understanding, validation, cleaning, integration, enrichment, and storage. It has been successfully applied to the processing of a variety of data types including clinical data from electronic health records and observational studies, genomic data, microbiome data, self-reported data from surveys, and self-tracked data from wearables from more than 600 subjects.
Lee & Kim (2019)	The study was conducted to compare the use of two types of mobile apps among women with dysmenorrhea and premenstrual syndrome — one app was designed considering patients' needs and the other was selected based on number of users worldwide. Results indicate that when a menstrual app. reflected users' needs, they recorded their symptoms more often and reported higher app quality, satisfaction, and intention to recommend.
Lilholt et al. (2016)	The study examined the association between chronic obstructive pulmonary disease (COPD) patients' use of Telekit and their functional health literacy and the association between their use of Telekit and their specific technological communication skills.
Macis et al. (2020)	The study tested the developed HEREiAM platform for telemonitoring in terms of usability, ease of use, usefulness, and quality of the proposed system on elderly living alone by administering validated questionnaires to them.
Mayberry et al. (2019)	The study explored the use of text messaging for self-management among type 2 diabetic patients. Results indicate that texts increased awareness, created dialogue, and improved health behaviors
Meng et al. (2020)	The study made use of machine learning algorithms to suggest that patient-reported outcomes can be monitored in real time using activity trackers.
Nissen & Lindhardt (2017)	The study was conducted on chronic obstructive pulmonary disease (COPD) patients. The purpose was to investigate the patient perspective on receiving tele-medicine with weekly submission of readings and regular video consultations (Net-COPD) as an alternative to visits in the respiratory outpatient clinic and investigating the role of telemedicine in management of severe COPD. Participation in telemedicine increased the patient empowerment primarily by the sharing of data with a permanent staff of nurses.
Peleg et al. (2017)	The study demonstrates the MobiGuide, patient-centered mobile decision-support system for patients and for their care providers. The study discusses the architecture of the system.
Polubriaginof et al. (2019)	The study studied the discrepancy between patients' self-reported data on race and ethnicity and data from electronic health records.
Rodríguez et al. (2017)	The purpose of the study is to evaluate whether mobile or wearable devices are appropriate to self-report pain levels. The study found that users preferred the wearable device over the mobile application and that a wearable to self-report pain should be designed specifically for this purpose.
Turchioe et al. (2020)	The study was conducted to compare patients' understanding of self-reported outcomes across mediums — text-only, non-graph, and graph visualizations to self-monitor their health status.
Turvey et al. (2020)	The study was conducted to explore the association between patients' race and gender, and patient consent policy preference for health information exchange.
Vest et al. (2019)	This study sought to determine the association between adoption of enterprise HIE vs a single vendor environment for health information exchange. Results indicate that patients benefit more from a single vendor environment approach than attempting to foster exchange across multiple electronic health record (HER) vendors.

Appendix B: Survey Items[a]

Construct	Items
Self-disclosure Effort	It was technically challenging to report my health conditions with mobile phone.* It was time-consuming to report my health conditions with mobile phone. Reporting my health condition with mobile phone imposed a burden on me.
Perceived Feedback Quality	The laboratory/physiotherapist considers my self-report in making healthcare recommendation. I appreciate the quick attention of laboratory/physiotherapist to my self-report. The laboratory/physiotherapist's recommendation caters to my self-reported conditions.*
Feedback Expectation	I expect that the laboratory/physiotherapist will take my self-report into account while making healthcare decisions I look forward to the prompt feedback from the laboratory/physiotherapist on my self-report. I hope that the recommendation from the laboratory/physiotherapist will address my self-reported conditions.
Confirmation	The experiences from self-reporting are better than what I expected. The benefits from self-reporting are worth the troubles. Most of my expectations regarding self-reporting are positively confirmed.
Satisfaction	How do you feel about your overall experiences from self-reporting? (Extremely satisfied - Very dissatisfied)* How do you feel about your overall experiences from self-reporting? (Very pleased - Absolutely displeased) How do you feel about your overall experiences from self-reporting? (Very contented - Totally frustrated) How do you feel about your overall experiences from self-reporting? (Absolutely delighted - Very terrible)
Disclosure Intention	I feel encouraged by the results of self-reporting I will continue reporting my health conditions in the future. I have hesitancy toward further self-reporting.*

[a] The items marked with an asterisk were dropped while refining the measures after data collection.