Patient Compliance Behavior in a Mobile Healthcare System: An Integration of Theories of Rational Choice and Planned Behavior

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Abstract

The lack of patient compliance to medical recommendations and treatments suggested by doctors has long been a significant problem. In practice, patient education is considered an important intervention to empower patients and increase their compliance. It has been advocated as a means of improving patient medical knowledge and compliance. However, evidence of the efficacy of computer-aided patient education is still relatively limited; little is known on how the latest mobile technologies affect patients’ compliance behavior. Based on Rational Choice Theory (RCT) and Theory of Planned Behavior (TPB), we propose and test a research model to investigate the compliance behavior of patients supported by a mobile healthcare system. We conducted a field survey with actual patients in the U.S. who used the system, and employed SEM techniques for data analysis. Overall, we found strong support for using RCT and TPB as a key theoretical foundation to assess patients’ compliance behavior.

1. Introduction

Medical practice is becoming increasingly complex in terms of treatment options, use of new technologies for assessments, and the need for patients and their caregivers to be familiar with general medical procedures. This trend will only intensify in the years to come. Accordingly, informed consent—the process by which a patient is provided with comprehensive and impartial information regarding a planned operative procedure in advance so that he/she understands the implications of the procedure before consenting—has become an important and suggested practice [1]. Therefore, it is critical to understand how to mitigate the complexity of medical practice information and to educate patients with personalized and relevant information to help them make informed decisions.

Currently, in patient-centered health care, the role of patients as active partners, instead of passive recipients of diagnostic testing and medical treatments, has been widely accepted [2]. One of the most crucial problems in healthcare service delivery is patients’ lack of valuable information and knowledge related to their doctors’ diagnosis and treatment procedures. This gap can result in miscommunication and misunderstanding between doctors and patients, compromised patient-doctor relationships, poor patient compliance and drug adherence, undesirable medical outcomes, and unhappy patients. Due to a lack of relevant knowledge, patients may not be able to ask doctors appropriate and important questions, may feel vulnerable, and may experience hesitation in complying with doctors’ recommendations. They may not know how to phrase or ask questions or even what questions are important to ask. Such a lack of compliance can be a particularly pressing healthcare issue, as stated below:

“The failure to adhere to medical recommendations is a significant and multifaceted healthcare problem. Estimates are 30% to 70% of patients do not fully adhere to the medical advice of their physicians. Moreover, 80% of patients are unsuccessful in following recommendations for behavioral changes such as smoking cessation and dietary restrictions.” [3, p. 208].

A number of studies have suggested that standard verbal and written consent information is often poorly understood by patients and their families [4]. Traditional and routine methods of providing patients with information relevant to their clinical decision-making (e.g., personal verbal interaction) are often sub-optimal and are increasingly problematic due to the increased complexity of medical procedures. Studies have shown that doctors and patients often disagree regarding the reasons for a specific consultation and actions taken therein [5]. As John Cox, the CEO of Visible Health, notes that
“somewhere around the order of 80 percent of all information communicated between a physician and a patient is lost when a patient walks out of the room.” In view of these issues, it is not surprising that patient compliance with healthcare recommendations is found to fall short of expectations nearly every time it is studied [6].

Patient education is considered an important intervention to empower patients [7] and increase their compliance [3]. Computer-aided patient education has been advocated as a new means of improving patient compliance and self-awareness and of enabling patients to better understand treatment protocols, avoid complications, and practice positive health behaviors. Patient education can also help healthcare providers reduce re-admissions, improve patient satisfaction, and increase patient loyalty. It can also increase patients’ knowledge about their disease, which may motivate them to make behavioral changes that help improve clinical outcomes [8]. However, evidence of the efficacy of computer-aided patient education is still relatively limited [9].

Nonetheless, patients intend to play a stronger role in understanding medical treatments before making treatment decisions. To do so, they often turn to the Internet and mobile devices to seek relevant information. Accordingly, patient adoption of mobile health is booming [10]. Over half of smart phone users in the United States access medical information from their mobile devices. With ownership rates and mobile device capabilities continuously expanding, physicians, pharmacists, other medical professionals, and patients are increasingly using healthcare-related mobile applications. There are 17,000 healthcare-related applications available for Apple and Android platforms that are geared purely toward medical use. Examples of the latter are Mobile MedlinePlus, miniAtlas Pediatrics, drawMD, 52 Weeks for Women's Health (National Institutes of Health), BMI Calculator (National Institutes of Health), embryo (National Library of Medicine), and FluView (Centers for Disease Control and Prevention).

As patient-centered care continues evolving, it is essential to understand the impact of personalized mobile patient education on patient compliance and patient-doctor relationships. This study aims to address this research void and provide new insights to the emerging personalized mobile approach to patient education. To do so, we proposed a new theoretical model to examine patients’ compliance behavior with recommended medical treatments based on Rational Choice Theory (RCT) and Theory of Planned Behavior (TPB). We then tested our model with actual patients who are seeking medical treatments from doctors and given the access to a mobile healthcare system that provides them with personalized information about the recommended treatments. Overall, we found strong support for our model.

In the remainder of this paper, we present an adaptation of the theoretical foundations of RCT and TPB for our context and propose testable hypotheses. Subsequently, we describe the research methodology to test the hypotheses, followed by explaining our analysis process and results. Finally, we discuss the study’s results, contributions, limitations, as well as directions for future research.

2. Theory and Hypotheses

As noted, little theory-based empirical research has addressed patient compliance issues. We believe that several theories that have been recommended for compliance research are not in fact designed for a compliance-specific context. We thus seek for theories that may fit in a compliance context. Accordingly, our model is developed based on Rational Choice Theory (RCT) and Theory of Planning Behavior (TPB), as adopted by Bulgurcu et al. [11] in an information systems security compliance context. Their model’s central concept is that one’s attitude toward compliance and subsequent intentions to comply are determined by a cost-benefit analysis process involving rational choices. However, in determining their final compliance intentions, people also consider less rational factors such as social influence (i.e., subjective norms and descriptive norms) and personal efficacy to comply (i.e., response efficacy and self-efficacy).

We believe that RCT and TPB provide an excellent theoretical foundation for our context of patient compliance with doctors’ treatment recommendations, as facilitated by a mobile healthcare IT artifact. Our key theoretical extension for this context is to add a ‘benefits of noncompliance’ construct, which was conspicuously absent in the Bulgurcu et al. [11]’s model. As a key contribution to the literature, we exclude attitudes from our model and focus on intentions and actual behaviors. Figure 1 depicts our core model. We now explain the theoretical background and development of hypotheses.

2.1 Use of rational choice theory (RCT)
RCT attempts to explain socially conformant and deviant behaviors under the basic premise that (1) people are rational and self-interested, (2) people act rationally when making decisions, and (3) people try to increase positive outcomes rationally through cost-benefit analyses [12]. We believe the potential fit of RCT for patient-related decisions in health care is high. It is increasingly common for patients to carefully review and consider their medical options before complying with a doctor’s medical recommendations. In fact, when patients disagree with or do not like such recommendations, they often elicit alternative opinions from other doctors. Thus, our contextual adaptation of RCT assumes that patients would like to use mobile healthcare education systems that provide additional information about a medical treatment recommended by their physician.

In rational decision making, an individual first recognizes alternative courses of action [12] and then contemplates the likely outcomes of each course of action. Because people have preferences for outcomes, each outcome is associated with costs and benefits depending on how much satisfaction and dissatisfaction that an outcome might produce for an individual [13]. Hence, an individual's perception of potential outcomes of an action shapes the assessment of potential costs and benefits that accrue to the individual. Individuals balance their assessments of the costs and benefits of potential courses of action to determine the best available option.

Researchers have applied RCT to several contexts to explain a person’s choice between conformity and deviance. Examples include economics, criminology, organizational trust, information searching, and consumer purchasing. Bulgurcu et al. [11], for example, leveraged RCT in an information system security compliance context to explain the core portion of their model, which deals with individuals’ assessments of consequences of IT policy compliance.

We adopt the same RCT assumptions as Bulgurcu et al. [11], which are based on the work of McCarthy [13]. First, we base rationality on one’s preferences and perceptions of costs and benefits—not on externally calculated costs and benefits. Because an individual’s perception of costs and benefits influences preferences [14], the costs and benefits of alternative courses of action are subjective and reflect a decision maker’s preferences; however, this process is rational because people base decisions on their assessment of costs, benefits, and preferences. We thus adopt the same conceptualizations of costs and benefits as Bulgurcu et al. [11] did. We include the benefits of compliance, costs of compliance, and costs of noncompliance instruments as constructs in determining attitude, intentions, and behaviors related to compliance [11], but modify them for our context: benefits of compliance are patients’ beliefs about the potential benefits of compliance with a specific medical treatment recommendation. Costs of compliance are patients’ beliefs about the potential costs of complying with a specific medical treatment recommendation. Costs of noncompliance are patients’ beliefs about the potential costs of not complying with a specific medical treatment recommendation.

If RCT holds in our context, we posit that patients should also rationally consider the benefits of noncompliance. A patient may calculate a higher benefit than cost in purposefully violating their doctor’s recommendations and, as a result, engage in noncompliant behaviors. Implicit or explicit motivations form the basis of these calculations. For example, a patient could derive pleasure from rejecting a physician’s advice because he/she feels the physician is arrogant, misinforming, or generally unlikeable. Hu et al. [15] recently proposed the natural existence of these considerations and described them as the “perceived mental pleasure of committing the [undesired] act” (p. 57). We term these considerations intrinsic maladaptive benefits. In addition, we term “perceived material benefits of committing the [undesired] act” (p. 57) as extrinsic maladaptive benefits. Together, they form benefits of noncompliance.

A key assumption of RCT and our model is that not all benefits and costs are monetary or extrinsic; intrinsic and emotional considerations can also influence cost-benefit considerations. In addition, rationality is based on one’s preferences, which include one’s emotions and intrinsic motivations [13]. We thus do not eliminate intrinsic considerations. When making a particular decision, individuals may appraise the value of cultural, social, and psychological interests [13]. McCarthy [13] argued further that anger, jealousy, rage, hatred, and a host of other emotional states are motives influencing a decision maker’s appraisal of the costs and benefits of courses of action. This influence occurs because emotional states are not independent of preferences [14-16]. Thus, an assessment of costs and benefits made while experiencing strong emotions might be markedly different from assessments made at other times. For example, when individuals are angry, this emotional state can modify their preferences and directly affect their cost-benefit calculations and eventual behavior. Based on our
contextualization and extension of RCT, we thus predict the following:

H1a. An increase in the perceived benefits of compliance with a recommended medical treatment, as supported by a mobile healthcare education system, will increase patients’ intentions toward treatment compliance.

H1b. An increase in the perceived benefits of noncompliance with a recommended medical treatment, as supported by a mobile healthcare education system, will decrease intentions toward treatment compliance.

H1c. An increase in the perceived costs of compliance with a recommended medical treatment, as supported by a mobile healthcare education system, will decrease intentions toward treatment compliance.

H1d. An increase in the perceived costs/threat of noncompliance with a recommended medical treatment, as supported by a mobile healthcare education system, will increase intentions toward treatment compliance.

H2. An increase in the intention toward compliance with recommended medical treatment, as supported by a mobile healthcare education system, will increase the degree of actual medical treatment compliance.

2.2 Use of theory of planned behavior

We replicate the TPB extension to RCT established by Bulgurcu et al. [11]. We use the TPB to account for the formation of attitudes from beliefs, norms, and self-efficacy, which can then be used to predict subsequent behaviors [17]. The TPB implicitly assumes that individuals seek to attain an objective and that they need to assess the extent to which the technology under consideration can help them [18]. Given the volitional nature of information security policy (ISP)-compliant behavior, such compliance is likely explained by intentions that can be predicted by attitudes, which are in turn based on relevant beliefs regarding context-specific behavior [19].

We use TPB in the same manner as Bulgurcu et al. [11] and Herath and Rao [20] did, but again, for theoretical concision, we omit attitudes and focus on intentions and behaviors. This decision has been shown to be highly efficacious in the technology acceptance model (TAM) [21]. We thus extend TPB’s key constructs to our context, including normative beliefs, self-efficacy to comply, and intention to comply.

Normative beliefs represent a person’s perceived social pressure to comply with a recommendation, as informed by a person’s important social referents for the context [11]. Normative beliefs are also known as social influence, which comprises subjective norms and descriptive norms [20]. We apply the same concepts to our research model. Following compliance literature [20, 22], in our context, subjective norms represent the degree to which patients believe other key people (e.g., family, friends, co-workers) in their lives want them to comply with a treatment recommendation. Descriptive norms represent a patient’s beliefs about what is commonly done by most patients or members of the general public in terms of compliance with a specific medical recommendation.

According to TPB, norms affect individuals’ intentions [17]. In a security compliance context, Siponen [23] found that norms work due to the desire of conforming to the group to which one belongs; this was also reported by Mishra and Dhillon [24]. Psychology researchers have long proposed that conformity to groups is due to norms and the pressures that norms place on individuals within a group [25]. Assuming these social norms also play a role in patients’ compliance decisions regarding medical recommendations, the following hypotheses should hold:

H3. An increase in subjective norms about the desirability of a recommended medical treatment will increase the degree of patients’ actual medical treatment compliance.

H4. An increase in descriptive norms about the desirability of a recommended medical treatment will increase the degree of patients’ actual medical treatment compliance.

Finally, in addition to social norms, self-efficacy is a long-established component of TPB that we believe is highly significant for the medical treatment compliance context, because it covers patients’ basic self-assessment regarding their ability to effectively follow medical advice and regarding whether they believe that a recommended treatment is efficacious. Based on the literature on compliance [11, 20], we define self-efficacy in our context as a patient’s judgment of his/her personal ability, competency, and knowledge in complying with a recommended medical treatment. Likewise, response efficacy is a patient’s judgment of the likely effectiveness and positive outcomes associated with a recommended medical treatment. Assuming that these efficacy judgments play a role in patients’ decisions regarding medical recommendations, the following hypotheses should hold:

H5. An increase in the perceived response efficacy toward following a recommended medical
treatment will increase the degree of patients’ actual medical treatment compliance.

H6. An increase in the perceived self-efficacy toward following a recommended medical treatment will increase the degree of patients’ actual medical treatment compliance.

2.3 Adding key covariates and counter-explanations to the research model

In addition to those likely theoretical factors, we searched the literature for patient-specific covariates and counter-explanations that could also explain why a patient can be positively persuaded by both a mobile healthcare education system and a doctor’s recommendation. We feel that the most promising covariates for these factors are gender, age, education level, computer proficiency, Internet general use, Internet medical use, patient trust in a doctor, number of prior treatments, medical treatment knowledge, number of major diseases, number of major surgeries, and personal general health assessment.

Considering our study’s inclusion of a system, we also adopted TAM-related factors as covariates, including degree of use, perceived usefulness, perceived usability, and enjoyment of a mobile healthcare education system. Figure 1 depicts our operational model.

3. Method

To validate our research model, we conducted a field study with real patients who actually used the ABC Company’s mobile healthcare system in multiple states of the United States. Survey respondents were instructed to provide their assessments and perceptions of that mobile system and of how the use of this mobile system influenced their compliance behavior. In total, we received 126 survey responses over 2.5 months. We excluded one response because it left the majority of the survey questions unanswered; thus, we analyzed 125 valid survey responses using structural equation modelling (SEM) techniques.

3.1 Survey respondents

From the middle of June 2013 to the end of August 2013, we collected 125 valid survey responses, of which 110 (88%) were from plastic surgery patients, 9 (7.2%) were from obstetrics patients, and 6 (4.8%) were from patients in other medical fields. All 125 valid surveys were completed by females. The average age of the respondents was 39.6. Regarding their educational background, 16.8% have attended a high school or secondary school, 26.4% attended some university but have not completed a degree, 12.8% have an Associate’s degree, 30.4% have a Bachelor’s degree, 10.4% have a Master’s degree, and 3.2% have a Ph.D. degree.

3.2 The mobile patient education system and field survey

ABC Company is a software company in the United States. Its software products focus on mobile healthcare systems. To address the problem of the lack of relevant medical information or knowledge among patients and improve patient-doctor communication, patient experience, and the quality of healthcare delivery, ABC Company launched a new mobile healthcare system, which has been successfully deployed at hundreds of clinics and hospitals in the United States. This mobile healthcare system is accessible through multiple mobile devices across platforms, such as iPhone, Android phones, iPad, Kindle, and other types of tablets.

We posted an online flyer through the websites of various clinics that have adapted this mobile healthcare system to invite their patients to participate in our field study. Only patients who actually logged in the mobile system were able to see the flyer. In exchange for participation, we provided a US$10 honorarium for each survey respondent who provided valid and complete responses.

3.3 Measures
All of our constructs and measures were directly adapted or modified from existing validated research. We customized some existing measures of constructs to make them relevant to our medical context. Measures of benefits of compliance and costs of compliance were adapted and modified from the scale developed by Bulgurcu et al. [11]. Benefits of treatment noncompliance and costs/threats of noncompliance constructs were customized to the medical context based on Posey et al.’s [26] instruments. Subjective norms and descriptive norms constructs were modified based on the validated instruments developed in [20]. Response efficacy and self-efficacy constructs were adapted from [27]. Intention toward treatment compliance and degree of actual compliance constructs were based on the modifications of similar measures from [11] and [15].

4. Results

We employed partial least squares (PLS), a component-based SEM technique, to test our research model, because the model includes second-order reflective constructs in addition to first-order constructs [28]. SmartPLS software version 2.0 was used to validate both the measurement and structural properties of our research model. We also utilized the bootstrapping method with 500 re-samples to compute the significance levels.

4.1 Measurement model and factorial validity checks

To test the measurement model, we examined both internal consistency reliabilities and convergent and discriminant validity of the measurement items. Because all our constructs are reflective, we computed Cronbach’s alpha, composite reliability, and the average variance extracted (AVE). All of them exceeded the recommended threshold values for Cronbach’s Alpha (>0.70), composite reliability (>0.70), and AVE (>0.50), respectively, thus the results confirm internal consistency reliabilities and support convergent validity. We also assessed whether common-method bias was a problem [41], and test results indicate that it was not a concern in this study.

4.2 Structural model

Next, we assessed the structural model to examine the path coefficients and their statistical significance. Figure 2 provides an overview of the PLS results. Benefits of compliance positively influenced intention toward treatment compliance ($\beta = 0.255; p < 0.01; H1a supported$), costs of compliance negatively impacted intention toward treatment compliance ($\beta = -0.146; p < 0.05; H1c supported$), and cost/threat of noncompliance significantly influenced intention toward treatment compliance ($\beta = 0.302; p < 0.001; H1d supported$); however, costs of compliance had no effect on intention toward treatment compliance ($\beta = 0.014; insignificant; H1b not supported$). The results also indicate that intention toward treatment compliance ($\beta = 0.278; p < 0.05; H2 supported$), response efficacy ($\beta = 0.334; p < 0.01; H5 supported$), and self-efficacy ($\beta = 0.261; p < 0.05; H6 supported$) significantly influenced degree of actual treatment compliance. However, subjective norms and descriptive norms had no significant influence on patients’ actual treatment compliance behavior (H3 and H4 not supported). Overall, this research model explains 67.4% variance in patients’ actual compliance behavior.

5. Findings and Contributions

Overall, we find strong support for using RCT as a key theoretical foundation for the assessment of patients’ compliance with medical recommendations given in a context in which such recommendations are supported by a mobile patient education system. Specifically, we find that intentions toward treatment compliance can be predicted by a patient’s calculations of compliance benefits, costs of compliance, and cost/threat of noncompliance. Only ‘benefits of noncompliance’ was found to have no impact. The findings are beneficial for physicians to make informed decisions on what strategies they can take to persuade their patients more effectively to comply with their treatment recommendations based upon the patients’ cost-benefit analysis.

Support for the TPB is not as strong as that for RCT, but this difference leads to some interesting insights. First, beliefs (in our context, cost-benefit assessment from RCT) are shown to influence intentions, and intentions are shown to influence actual compliance behaviors. Surprisingly, subjective and descriptive norms do not play a significant role in compliance decisions. This is especially interesting because most of our patients were considering various plastic surgery treatments. We expected that if any medical treatment would be highly subject to social norms, it would be plastic surgery. This turns out not to be the case. Instead, self-efficacy and response efficacy are very strong drivers.
67.4% variance in patients’ actual compliance behavior. We thus conclude that our model is both parsimonious and efficacious in explaining patient behavior. We therefore need to conduct additional field studies with all-male and/or mixed-gender groups in different medical settings.

Second, although we had nine respondents from the obstetrics field, it would be useful to test different types of patients, because they might display different compliance behaviors during different stages of their treatment processes. Therefore, future longitudinal research is needed to understand more accurately how mobile patient education interventions play a role in influencing patients’ compliance behavior when patients can access customized education materials anytime and anywhere.

Third, and most challenging, we were not allowed to test patients who were not using the mobile healthcare system. This kept us from determining to what degree the cost-benefit considerations, norms, and efficacy influences came from the mobile education system versus from the doctor or patients. Given the medical practice limitations of this issue, the only way this can be determined is to focus on compliance intentions, not actual behaviors, in an artificial experimental setting. The difficulty of such experimentation, however, is that it would still need to be geared toward providing information about a specific treatment to those seeking information about potential treatment under a given condition. Otherwise, such an experiment would have no personal salience to respondents and would thus undermine the key assumptions of RCT and TPB. Consequently, we believe that the best way to continue this research is to work first with medical groups that have not adopted the mobile healthcare education system but plan to do so, and to study the overall implementation process longitudinally.

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