Predicting Remote Monitoring Patients' Non-compliance Behavior Through App-mediated Communications

Abstract

Remote patient monitoring (RPM) has been widely used for monitoring patients' health and tracking their behavior outside the traditional healthcare setting. One important behavior to understand is patients' compliance with medical advice and treatment regimes. Existing methods detect non-compliance based on health parameters i.e., weight and vital signs, which can only be identified by the deterioration in health conditions. This study proposes an RPM system artifact to record patients' feelings and concerns through short messages; these messages are used to develop a non-compliance prediction model. A prototype of the design artifact was implemented and tested with chronic patients taking home hemodialysis. Our model revealed that the counts of messages recorded is related to non-compliant behavior, and the negative emotions depicted in the messages implied a higher likelihood of non-compliance. Our study demonstrated the feasibility of understanding patients' status based on non-health parameters and its application to understanding patients' sentiments during RPM.

Keywords: Remote patient monitoring (RPM), sentiment analysis, Home Hemodialysis (HHD), noncompliance, machine learning

1. Introduction

Remote patient monitoring (RPM) has rapidly become a widely used approach for monitoring patients' health and to provide early interventions outside the traditional healthcare settings (Vegesna et al., 2017). RPM systems typically use information and communication technologies (ICT) to capture data from individuals, e.g., from their homes, and electronically transmit the data to health professionals (Piau et al., 2019) at a health facility such as hospitals. The rapid growth of telemedicine technology has accelerated the adoption of RPM, with strong evidence of benefits for both healthcare providers and patients. In addition, RPM has played an important role during the COVID-19 pandemic where social distancing was mandatory The remote healthcare market's annual growth rate is estimated to be 38% from 2016 to 2025 (Hossain, 2016).

One of the key challenges in RPM adoption is to promote patients' medical compliance and provide prompt inventions (Lim et al., 2016; Hale et al., 2016); patient compliance is essential to ensure high-quality treatment results (Sanabria et al., 2019). In a traditional setting where patients are treated at a health service facility, non-compliance behavior can be detected by direct observation of patients' behaviors or analyzing the change in health parameters (e.g., vital signs and weight) by routine inspection by health professionals. In an RPM setting, however, where patients' health parameters and status are shared electronically, detection of non-compliance behavior is restricted due to sole reliance on deterioration of health parameters, without direct observation, and thus inducing lag and limiting timely interventions.

In this study, we investigate whether an RPM system can be designed to capture additional data, together with the standard health parameters, to understand patients' non-compliance behavior, and to then develop a prediction model to detect non-compliance behavior. Prior research has shown that patients' communicative behavior with clinicians is correlated with their health behavior. The importance of analyzing patient-clinician communication has also been emphasized by many researchers (Roter and Hall, 2009; de Jong et al., 2014). Therefore, an RPM system could be designed to offer a channel for patients to share their feelings and concerns and collect more data about patients in addition to their health parameters.

We adopt a design science orientation, which conceptualizes research as learning via the building of artifacts designed to meet an identified need (Hevner et al., 2004). We argue that existing RPM system designs to detect non-compliance behavior (Alshurafa et al., 2017; Zamanifar, 2021) are limited in capturing health parameters, and are inadequate respond to patient non-compliance behavior based on other factors such as their communicative behavior. Most of these studies focused on establishing designs to analyze relationships between health parameters with non-compliance behavior such as interdialytic weight gain (IDWG), and failed to take into account of the patients' mental status or sentiments into their study design. An important factor in our design is the use of kernel theories, which ensure that our design science efforts are theory-infused (Sein et al., 2011). The kernel theories appropriate for this work were drawn from the literature on RPM system architecture, patients-clinician communication literature, and multimodal communication theory (Taglialatela et al., 2015). By expressly recognizing the importance of patient's communication messages during RPM, we hope to confirm the impact of non-health parameters, such as sentiments, on patients' behavior and provide a new direction for better understanding of patients' status. Machine learning algorithms were employed to develop a prediction model for non-compliance behavior based on patients' non-health parameters. Specifically, we propose the use of counts of weekly messages and derivation of emotions via sentiment analysis, from the messages shared by patients during RPM.

The study demonstrated the feasibility of understanding patients' behavior based on non-health parameters and highlighted the importance of analyzing patients' emotions during the remote monitoring process. The study therefore contributes to the literature on information system design and provides practical guidelines to improve the efficiency in patients monitoring during RPM.

2. Literature Review

2.1. Remote Patient Monitoring (RPM)

RPM is a healthcare delivery method that provides real-time monitoring and health-related information storage using technology or digital devices to enhance the structured health care service and patient self-care. A potential cost-effective solution is offered by RPM to handle the issues of financial viability and home visit acceptability by reducing face-to-face interactions. Most proposed architectures for RPM have three main components (Hassanalieragh et al., 2015), including data input, data storage and data analytics. The data input device is typically involve the installation of mobile applications (or apps) on mobile devices or sensors on wearable devices. This component aims to collect and store patients' health data. After completing the data collection, the dataset would be stored into the second component, which is the data center of the connected health facility. Data center including cloud server provides a platform to store both patients' and healthcare providers' information and ensure security and privacy. The last part of the architecture is data analytics which refers to data processing and data presentation based on the collected data for the clinicians to aid in their decision making.

Compared with traditional care, RPM has shown to significantly improve both self-reported and medical compliance during therapy since patients are given with greater freedom and flexibility. (Hale et al., 2016). Furthermore, RPM provides a more reliable approach and supplies more data for clinicians to better track patients' behaviors and attitudes for further study of patients' non-compliance. However, some barriers also exist in the RPM which avoid patients from adopting the system and bringing negative impacts. In particular, social isolation is one of the most common obstacles highlighted by patients. Many patients mentioned that being alone is the main reason why they refused to choose RPM and remote treatment (WWalker et al., 2015). Improved communication between the patient and the clinician is the key to handling this issue and to improve patients' experience (Ong et al., 2016). A stable and convenient channel is necessary to ensure effective communication where patients can express their feelings and opinions with their clinician.

2.2. Non-compliance behaviour

Compliance behavior is identified based on whether patients follow the prescribed treatment regimens. Patient's compliance behavior is widely studied in the context of drug-taking, exercises, therapy sessions, diet controls and lifestyle changes. Patient compliance has a significant impact on the efficiency of treatments. Saran et al. (2003) believed that patient compliance is essential to ensure high-quality treatment results and reduce the risk of mortality. DiMatteo (2004) also stated that non-compliance behavior (e.g., ignoring medical recommendations, resisting attending sessions, and rebellious mood) would waste resources and money for health service provisions.

Non-compliance behavior can be influenced by patients' demographics, lifestyles, mental status, and external supports (Leggat et al., 1998; Ibrahim et al., 2015; Kutner et al., 2002; Burman et al., 1997; Kimmel et al., 1998). In a traditional setting, non-compliance can be detected through both indirect and direct methods. Indirect methods include self-reported behavior, pill counts, and interviews (Beernink et al., 2021). For example, for renal patients taking regular dialysis sessions, a non-compliant behavior can be observed through skipping or shorting treatment sessions (Kimmel et al., 1998; Ibrahim et al., 2015; Kutner et al., 2002; Leggat et al., 1998). Direct detection can be achieved through analyzing biological markers (Beernink et al., 2021), as non-compliance is likely to lead to a change in health conditions. For example, in chronic dialysis treatment, inter-dialytic weight gain (IDWG) is used as a standard to assess non-compliance (Leggat et al., 1998; Ibrahim et al., 2015), which measures the fluid taken between two hemodialysis sessions. A higher IDWG score would lead to fluid overload, which is associated with a high risk of hospitalizations and causes poor outcomes of treatment (Wong et al., 2017).

The direct methods of detection have a higher sensitivity and specificity than the indirect methods. However, direct methods only identify the non-compliance behavior when it causes changes in health conditions, and sometimes it is too late to provide intervention. Therefore, it is important to understand what are the other factors that be incorporated into the detection of non-compliant behaviors.

2.3. Patients-clinician communication and multi-modal communication theories

Multi-modal communication which refers to the use of multiple signal channels simultaneously during communication is a basic feature of human language (Taglialatela et al., 2015). Louwerse et al. (2012) proved synchronized behavior in multi-modal communication.Richardson and Dale (2005) and Shockley et al. (2003) also discovered relevant information such as unintentional synchronization behavior which means a person's behavior can be impacted by another one during communication. For example, two people's body posture, gestures, and movements could be synchronized during conversations. In addition, much research emphasized the influence of emotional expression and interaction (Knutson, 1996; Van Kleef, 2009; Mehu, 2015). They mentioned that user's emotion should be regarded as a communication signal as both emotional expressions and reactions could change people's perceptions and behaviors. They mentioned that user's emotion should be regarded as a communication signal as both emotional expressions and reactions could change people's perceptions and behaviors. The usage of emotional components can effectively increase the transformation of information to help people better understand the content and make appropriate responses in conversations.

Communication is significant for patients and health providers in RPM. A suitable communication strategy can improve effectiveness of consultations which would impact patients' satisfactions and compliance (Farquharson et al., 2011). Roter and Hall (2009) and Bauer and Moessner (2012) mentioned that patient compliance is also related to several factors in communication, such as the frequency of questioning, positive or negative status, and the amount of information. Moreover, in digital environment, the impact of text-messaging on patients' perceptions has been confirmed by several researchers (Nsagha et al., 2020; Välimäki et al., 2012). Therefore, specific aspects of communication like sentiment, are important factors in understanding non-compliant behaviors.

3. The design of communication-based non-compliance prediction method

3.1. Design artifact of the RPM system

Employing the multi-model communication theory (Taglialatela et al., 2015) and the existing literature on RPM system architecture (Hassanalieragh et al., 2015) as our kernel theories, we present a meta-design that comprises a system artifact enabling the sharing of information and emotion for patients and an algorithm predicting the non-compliance behavior of patients as shown in Figure 1 below.

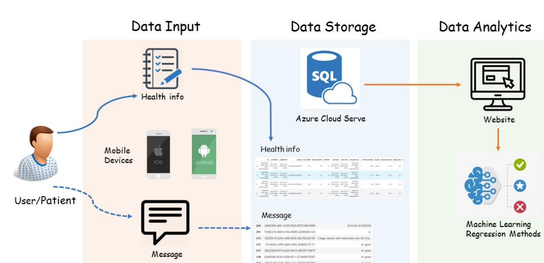

Figure 1. RPM System Artifact

The RPM architecture is adapted from the literature (Hassanalieragh et al., 2015), which includes application to capture data, cloud server for data storage, and analytics component.

The first component is data capturing through digital applications (or apps) designed for patients, which allows them to record health parameters specified by their clinicians. Patients are also allowed to post a short simply text message every time when they submit their health data. The feature of sharing messages was designed to enhance the connection and mutual attention between health care professionals and patients which could relieve social loneliness and help clinicians discover problems timely. The implementation of the message feature also allows us to make sentiment analysis and predictions to prove the impact of online communication and sentiments in the text messages is another factor that would improve the prediction results.

The second component is the data storage which should be able to handle both structured data and unstructured texts.

The third component consists of different analytical features derived from the data captured. The meta-design of capturing, storing, and analyzing unstructured text messages will serve as the core for understanding patients' non-compliance using non-health data.

3.2. Prototype and context of study

With the above meta-design, we have developed an RPM system for patients undergoing hemodialysis at home (named as HHD system thereafter) and tested the system with patients in a public hospital in Australia. The ethics approval has been obtained before this project commence; written informed consent was obtained from all participants.

Hemodialysis is a renal replacement therapy that establish a connection between person and machine to filter the wastes in the blood and return blood finally. Normally, end-stage renal disease (ESRD) patients need to take hemodialysis three times a week and each session takes three to four hours (Sockrider and Shanawani, 2017).

Patients participated in our study recorded their dialysis sessions using an app, and recorded their health parameters including weights. blood pressures, etc., together with text messages.

3.3. Defining non-compliance

The majority of the hemodialsyis patients are recommended to take three dialysis sessions every week (Flythe et al., 2013). Skipping dialysis sessions is a common type of non-compliance among patients taking hemodialysis. (Kimmel et al., 1998; Ibrahim et al., 2015; Kutner et al., 2002; Leggat et al., 1998).

In the context of our study, clinicians restated that completing the number of prescribed sessions is important for the participants and they need to complete at least three dialysis sessions each week. Thus, non-compliance behavior was defined as completing less than three dialysis sessions in a week. The non-compliance behavior is coded on a weekly basis.

4. Evaluating the Meta-design

To evaluate the feasibility of using text messages shared by patients for predicting non-compliance, we developed new prediction algorithms based on the counts of weekly messages and the sentiments in the messages to predict non-compliance behavior.

4.1. Descriptive statistics

The records of 338 patients undergoing hemodialysis treatment were obtained from the trial of the prototype from 2014 May to 2021 March, resulting in a total of 53,768 dialysis sessions. Each dialysis session refers to the use of the HHD app to record health parameters, session details including time / date, and a text message that conveys the patient's emotional state. We have excluded sessions with inactive users or unusual session duration (less than 3 hours or more than 6 hours per session). Patients who recorded less than 30 sessions or sessions with unusual duration were removed. As we are interested in patients' non-compliance every week, we aggregate the data shared by patients by weeks.

After data cleaning and processing, the final patient details are described in Table 1. 190 (88.0%) patients experienced at least one non-compliance behavior during treatments which last in average of 79 weeks. Just 12% patients remained compliant throughout the whole treatment.

4.2. Text messages

Patients have shared health status, feelings, technical problems and greeting messages to clinicians via the messages function of the RPM system. Some sample messages include: *'Went into Nepean Private for a minor procedure on my bladder.'*, *'feels good'*, *'problems with weighing scales'*.

Of the 17,223 weekly records, 7,938 (46%) of them have more than one messages per week (Table 2). Two features from the messages on a weekly basis: the counts of weekly messages and the sentiments in the messages.

4.2.1. The counts of weekly notes. The descriptive statistics of the weekly messages is shown in Table

Table 1. Descriptive statistics of patients

Patient Details	N (% or IQR)
Patients	N = 216
Totally Weekly Session	17223
Male	155 (71.8%)
Female	61 (28.2%)
Patients with at least one non-compliance identified	190 (88.0%)
Patients complying to the dialysis sessions	26 (12.0%)
Average Weekly Sessions	2.8
Weekly Session	
1	1227 (7.2%)
2	2863 (16.6%)
3	11351 (65.9%)
>3	1782 (10.3%)
Treatment Duration	
Average	79 weeks
Min	8 weeks
Max	292 weeks
S.D.	69.0

2. The average counts of weekly messages (over three sessions) are 0.88 and patients seldom submit messages to all sessions. More details about weekly messages with non-compliance are displayed in Table 3.

Table 2. The count of messages weekly

Session Details	N (% or IQR)
Total Weekly Records	17223
Has Message	7938 (46.0%)
Weekly Message	
0	9285 (54.0%)
1	3606 (20%)
2	1757 (10.2%)
3	2255 (13.1%)
>3	320 (1.8%)
Average count of weekly messages	0.88
S.D.	1.15

4.2.2. Sentiments in the messages. Valence Aware Dictionary and Sentiment Reasoner (VADER) tool was used to understand the emotions in the text messages shared by patients (Hutto and Gilbert, 2014). VADER is a dictionary and rule-based sentiment analysis tool and was originally developed to understand sentiment expressed on social media messages. VADER analysis assigns four scores to each sentence: negative, positive, neutral and a compound score. A higher value in one negative, positive or neutral indicates a higher likelihood of being inclined toward the corresponding emotion finally.

Table 3. Weekly messages with Non-compliance

Non-compliance Identified in the week	**NO**	**YES**
Weekly records	13133 (76.3%)	4090 (23.7%)
Counts of weekly messages		
0	6602 (71.1%)	2683 (28.9%)
1	2691 (74.6%)	915 (25.3%)
2	1265 (72.0%)	492 (28.0%)
3	2255 (100%)	0 (0.0%)
>3	320 (100%)	0 (0.0%)

The compound score is calculated by adding up the valence scores for each word in the lexicon, adjusting them according to the rules, and then normalizing them to between -1 (most extreme negative) and +1 (most extreme positive). The compound score is the final result utilized to classify messages into three sentiment groups. Messages with negative compound scores would be classified into the negative group and positive compound scores correspond with the positive group. Others with 0 compound scores belong to the neutral group.

In the final dataset, messages in the same week would be appended together for sentiment analysis and sessions with no messages were treated as 0. The distribution of the three sentiments in the messages collected in our study are displayed in Table 4.

Table 4. Distribution of sentiments (VADER)

Positive	2417
Neutral	4223
Negative	1298

To have a better understanding of the potential association between sentiments and non-compliance behavior, we present the distribution of sentiments against the non-compliance behavior in Table 5. It indicates that patients with negative emotions in their messages have a higher proportion of displaying non-compliance behavior in the treatment.

4.3. Models to predict non-compliance

We have constructed two models to predict the non-compliance. Model 1 is merely based on the number of weekly sessions in the past. Model 2 is developed to incorporate the two proposed features derived from the weekly messages.

Non-compliance is the dependent variable of the model and is a binary variable. The independent

Table 5. Distribution of emotions with Non-compliance

Non-compliance Identified in the week	NO	YES
Weekly records	6531 (82.3%)	1407 (17.7%)
Sentiments		
Positive	2051 (84.9%)	366 (15.1%)
Neutral	3444 (81.6%)	779 (18.4%)
Negative	1036 (79.8%)	262 (20.2%)

variables include number of weekly sessions, counts of weekly messages, and sentiments in the message. Weekly session number means the number of sessions for each patient in a week which is also the criteria for classifying non-compliance. The weekly message is similar to weekly sessions which counted the counts of online messages posted by patients after each session in a week. The sentiment score is the last component which is measured by VADER tool to extract sentiments from the messages.

Four weeks of recorded data of every patient were used to measure the deviations and make predictions. We used four weeks according to the work Dietrich et al. (2021) which stated that four weeks is the shortest and most significant monitoring period to detect a deviation in patients' behavior. Similar findings have also been widely used in many compliance analysis research (Varghese et al., 2021; Moffatt et al., 2019).

We employed three prediction methods to develop the prediction model: Random Forest (RF), Decision Tree (DT), and Support Vector Machine (SVM). DT is a non-parametric supervised learning method for classification and regression. The purpose of the model is to make predictions based on learning simple decision rules inferred from data variables. It is easy to implement and meets the requirements for training on large data sets (Quinlan, 1999). RF is a supervised learning algorithm that ensembles decision trees for classification and regression. A number of categorical decision trees from different samples are fitted and averaged to increase the accuracy and to reach stable prediction (Breiman, 2001). SVM is another supervised learning algorithm and works well on both linear and nonlinear classification problems (Cortes and Vapnik, 1995).

To better compare and access the results of prediction models, mean accuracy, stand deviation and Area Under Curve of Receiver Operating Characteristics Curve (AUC-ROC) were applied. Mean accuracy and standard deviation were calculated through 10-flod cross-validation method and AUC-ROC were measured by confusion matrix.

The mean accuracy with stand deviation results of the three machine learning algorithms is summarized in Table 6 below. Standard deviation values are shown in brackets and represent the dispersion of the mean accuracy results. Model 1 is also known as basic model which include only counts of weekly sessions refers to be considered as a control group to make comparison. Modal 2 is the model we developed which include number of weekly sessions, counts of weekly messages, and sentiments in the message. The impact of both weekly message counts and sentiments can be confirmed by comparing the results of two different models.

Table 6. Predicting non-compliance

	Model 1	Model 2
DT	0.642 (0.019)	0.764 (0.012)
RF	0.646 (0.020)	0.805 (0.011)
SVM	0.602 (0.034)	0.762 (0.015)

Method 1: method without communication factors.
Method 2: new method developed in this study which consider both weekly notes and emotions.

Model 1 shows that it is possible to predict non-compliance merely based on past weekly sessions (non-compliance). Among all the three machine learning methods, RF displays the best performance which reached the highest accuracy of 64.6%. Our results also demonstrate that incorporating the features of text messages (Model 2) improves the accuracy in predicting non-compliance compared to the baseline model (Model 1). The best prediction was 80.5%.

Table 7. AUC-ROC results

	Model 1	Model 2
DT	0.59	0.84
RF	0.59	0.86
SVM	0.58	0.73

The summary of AUC-ROC results is displayed in Table 7. The value of AUC-ROC denotes the ability of the models to differentiate different classes. RF method achieved the highest result in Model 2 of 0.86. Higher AUC score (close to 1) means better distinction between the classes while a score less than 0.5 means the classifier is unable to distinguish between the classes.

From the results, both weekly sessions and sentiments were shown to be significantly correlated with non-compliance and were able to make predictions. RF method has the best performance among all the models and were able to identify non-compliance by exploiting communication factors.

5. Discussion and contributions

The goal of this study was to design a prediction model of non-compliance behavior using non-health indictors in an RPM setting. We implemented an RPM prototype to allow home hemodialysis patients to share their feelings and concerns through short text messages. The data collected confirm that patients are willing to share a variety of contents through text messages using RPM systems, and the messages convey different sentiments. Our result showed that the use of messages is more accurate in predicting non-compliance than simply based on past non-compliant behaviors.

We discovered that patients' non-compliance behavior in the RPM method is highly correlated with communication which was collected through online messages and affect patients' behaviors during treatments. Sentiment has been confirmed to be a significant factor that impact patients' behavior. Negative sentiment had a higher probability of leading to non-compliance behavior by skipping dialysis sessions. In addition, the use of sentiments also resulted in improving the accuracy of prediction in all the machine learning methods used in this study. RF is the most suitable prediction model which achieved the highest accuracy in both single and multiple variable analysis. The best results were achieved in multiple analyses which combine weekly dialysis sessions numbers and sentiments in the message peaked at 80.5% when the reference duration is four weeks.

Theoretical contribution. The study contributed to the telehealth (and remote patient monitoring) literature by highlighting the importance of understanding patients' sentiments in the remote setting. We proposed a simple and feasible model of collecting patients' sentiments, which has extended the telehealth literature that call for mechanisms to improve co-presence built into RPM system, so as to reduce patients' feeling of isolation and anxiety during the process. Addressing patients' needs to express themselves and improve the understanding of their emotions in a less-costly way using algorithms are essential to improve the quality of remote health service.

Practical contribution. The study proposed a new design and developed a prediction model that can detect non-compliance among home hemodialysis patients. Our findings can potentially help clinicians better predict and prevent non-compliance behavior and therefore provide timely interventions.

6. Limitation and future work

This study has few limitations. First, as we used clinical data, the data distribution is unbalanced which impacted the prediction results. In order to reduce the influence from the unbalanced data, we employed weight-balanced method. As future work, we will explore other methods to mitigate he unbalanced data. Second, as the purpose of the study is to explore the impact of sentiment that exists in communication on RPM patients' behavior, we did not assess the reason why patients expressed different sentiments. Further work will focus on gaining a deeper understanding of patients' sentiment and potential reasons of non-compliance behavior. More evaluation would be processed on special situations like sentiment shift or unusual conditions.

7. Conclusion

Our study confirms the impact of sentiment conveyed by online communications on RPM patients' behaviors, and that communication is an important factor needed to be considered in understanding non-compliance behavior. We developed a prediction model to make predictions based on patients' sentiment analysis derived from their communications (text messages). Compare with positive or neutral sentiment, patients with negative emotions have higher possibility to show non-compliance in the future.

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