Predicting Remote Monitoring Patients' Compliance Through App-mediated Communications

YE CAI

SID: 510090014

Supervisor: Prof. Jinman Kim
Associate Supervisor: Dr. Na Liu

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School of Computer Science
The University of Sydney
Australia

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Abstract

Remote patient monitoring (RPM) has gradually replaced many parts of traditional treatment and rapidly become one of most important approaches for remote patients to share information for healthcare providers to promote and intervene in compliance behaviors in chronic treatment. Many indicators would impact the noncompliance, but communication factors were ignored on both traditional and RPM settings. It is necessary to investigate the relationship between communication with noncompliance behavior in remote patient monitoring (RPM) systems. A new method was proposed to handle this concern and improve the prediction outcomes. Three machine learning algorithms were utilized to evaluate the performance. Overall, 49,131 session records were available after data preprocessing. 216 (95.6%) patients posted at least one note after sessions. The VADER lexicon was utilized to measure the emotion score and classified them into three groups: positive, negative, and neutral. In total, negative emotions imply a higher likelihood of noncompliance. In the new method, communication variables greatly improve the prediction performance and random forest achieved the highest accuracy (80.5%, 0.011). Finally, communication factors have been shown to be significantly associated with noncompliance and the new method proposed in this study will further benefit the RPM service.

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CHAPTER 1

Introduction

Remote patient monitoring (RPM) has rapidly become a widely used approach for collecting patients' data outside traditional healthcare setting. RPM uses information and communication technologies (ICT) to capture data from individuals at different locations, and electronically transmit the data to health professionals (Piau et al., 2019). With the arrival of the digital information era, more internet-connected and wearable devices are public which allows the widespread of telehealth, and more non-invasive technologies can be integrated into the RPM method to improve the healthcare outcomes (Farias et al., 2020). The remote healthcare market's annual growth rate is estimated to be 38% from 2016 to 2022 and the global Internet of Things (IoT) market in telehealth areas is expected to reach $534.3 billion by 2025 (Hossain, 2016; Shahzad et al., 2021). The rapid growth of telemedical technology accelerates the adoption of RPM which brings more benefits for both healthcare providers and patients. RPM enhances the ability of clinicians to monitor patients and make decisions in non-traditional settings with digital technologies (Vegesna et al., 2017). One of the key functions of RPM is to promote chronic patients' medical compliance and provide prompt interventions (Lim et al., 2016; Hale et al., 2016), as patient compliance is essential to ensure high-quality treatment results (Saran et al., 2003; DiMatteo, 2004).

In a traditional setting, noncompliance behaviour is found to be associated with 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). Noncompliance can be detected through both indirect and direct methods. Indirect methods include self-reported behaviour, pill counts, interview, and direct detection can be achieved through analysing biologic markers (Beernink et al., 2021). The direct methods of detection have a higher sensitivity and specificity than the indirect methods. In an RPM setting where patients' biomarkers and health status are shared electronically, the direct detection of noncompliance behaviour based on the anomalies in patients' condition becomes possible. However, direct detection of non-compliance based on biomarkers has lagged effect as non-compliant behaviour can only be detected if deterioration in health conditions happened.

In this study, we are interested in whether an RPM can be designed to capture more information than biologic markers to understand patients' non-compliance behaviour, so as to develop a method to predict the noncompliance behaviour before happening. In particular, we aim to design a system feature with predictive method based on patients' communications via the RPM platform.

Recent study suggests that during remote monitoring, patients' communicative behaviour with clinicians is also correlated with their health behaviour. With the popularity of RPM, the electronic communication service has been implemented in most applications to replace face-to-face consultation. The importance of analysing patient-provider communication has also been emphasized by many researchers but there is little evidence that communication can refine self-management and clinic interventions to affect adherence (Roter and Hall, 2009; de Jong et al., 2014).

To address the problem, we follow a design science orientation, which conceptualizes research as learning via building of artifacts designed to meet an identified need. We argue that the several existing alternatives to detect non-compliance behaviour RPM systems design (Alshurafa et al., 2017; Zamanifar, 2021) are likely to be inadequate in the context of providing a proactive way to respond to patient non-compliance behaviour based on factors other than health indicators. An important input to our effort 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 include the co-presence theory (Campos-Castillo and Hitlin, 2013) and multimodal communication theory (Taglialatela et al., 2015). By expressly recognizing the importance of patients-clinicians communication during RPM settings, we hope to overcome concerns noted in prior research about the lagging effect in detection of non-compliance. Several machine learning methods would be used to classify and calculate the accuracy of predictions. The result will prove whether the number of messages would affect compliance and the role of emotions in communication. More suggestions about how to improve health care services and more tips about communications can be proposed to increase patients' satisfaction and reduce nonadherence.

CHAPTER 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 the first one realized by installing applications on mobile devices or sensors on wearables. This component aims to collect and store patients' treatment data. After completing data collection and storage, the dataset would be transmitted into the second component, the data centre of Healthcare Organization. Data centre like cloud server provides a platform utilized to store both patients' and healthcare providers' information and ensure security and privacy. The last part of the architecture is data analytics which means completing data processing and presenting visualizations based on recording sessions to help clinicians better evaluate patients' status and discover potential problems timely.

Compared with traditional care, RPM could significantly improve both self-reported and medical adherence during therapy (Hale et al., 2016). RPM also provides a more reliable approach and supplies more data for healthcare providers to better track patients' behaviours and attitudes for further study of patients' noncompliance. However, the RPM method would also bring negative effects on patients to adopt remote treatment and reduce noncompliance. 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 remote monitoring treatment (Walker et al., 2015). Communication is the key to handle this issue. A stable and convenient channel is necessary to ensure effective online communication where patients can express their feelings and opinions with clinicians. Researchers also argue that the RPM system needs to ensure effective two-way communication between patients and health providers in order to improve patients' experience (Ong et al., 2016).

2.2 Hemodialysis

End-stage renal disease (ESRD) occurs when kidneys lose abilities that filter wastes and excess fluids from the blood to maintain the normal operation. Kidney transplant is one way to cure, but only 25% of ESRD patients can accept a functioning transplant instantly (Collins et al., 2005). For patients who are on a waiting list or unsuitable for kidney transplantation, hemodialysis is essential for them to survive (KRAUS et al., 2007; de Fijter, 2010) 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, ESRD patients need to accept hemodialysis three times a week and each session takes 3 to 4 hours (Sockrider and Shanawani, 2017).

2.2.1 Noncompliance Behavior

In center-based hemodialysis, non-compliance definitions always relate to personal behaviors which are evident and able to be directly observed like skipping or shorting sessions (Kimmel et al., 1998; Ibrahim et al., 2015; Kutner et al., 2002; Leggat et al., 1998). This classic character is utilized in most research to analyze the relationship between risk factors and survival. In addition, the medical parameter is another aspect to be considered during identify non-compliance behavior. Although this aspect is impossible to straightly point out the unusual status, more accurate judgment can be achieved by combining personal behaviors. Both Leggat et al. (1998) and Ibrahim et al. (2015) regarded interdialytic weight gain (IDWG) as one of standard to assess non-compliance which is one of the medical parameters to measure the fluid taken between two hemodialysis sessions. A higher IDWG score would lead fluid overload which is associated with a high risk of hospitalizations and causes poor outcomes of treatment (Wong et al., 2017). Normally, the patients were considered non-compliance when IDWG exceed 5% of dry weight (DW) or more than 1.5kg. Therefore, non-compliance behavior definition in the traditional medical settings includes two aspects, personal behavior, and medical parameter respectively. Both could provide help to classify patients and analysis the key factors with nonadherence.

2.2.2 Factors

There are several factors that can be used to predict noncompliance behaviors in traditional medical settings, and they are grouped as internal (lifestyle and mental status), external (external support), and controversial (demographic).

Internal indexes are also known as psychological or behavior impact which means they are related to patients' mental status and lifestyle includes depression, alcoholism, and smoking. Depression is one of the classic mental statuses which would bring a negative impact on adherence. Both Somerset et al. (2011) and Ibrahim et al. (2015) indicated that patients who suffer from depression or stay in depression symptoms have more risk to appear nonadherence behavior. The depression score of noncompliant patients was significantly higher than others. In addition, lifestyle such as alcoholism, smoking, and malnutrition is another internal influence that can be regarded as the main antecedents of persistence. Research shows that alcoholism is one of the most important risk factors closely linked with non-compliance (Burman et al., 1997). Meanwhile, Leggat et al. (1998) and Kutner et al. (2002) stated that smoking is another strong predictor which would reduce motivation and increase sensitivity. Moreover, Ibrahim et al. (2015) and Alp Ikizler et al. (2013) observed that adherence is also associated with nutritional status, which is another factor to predict the patients' behaviors in advance.

External impact always come from outside resources including social support and patients' wellbeing which would improve the quality of life and having a positive influence on patient. Several studies have proved the significant relationships between compliance and social support or quality of life. Lower levels of social support and poor quality of life would directly increase the negative perceptions and possibility of skipping the session in therapy (Wang et al., 2020b; Kimmel et al., 1998; Ibrahim et al., 2015). To minimize the number of compliance and refine outcomes of therapy through clinic, homelessness also needs to be solved as homelessness is strongly related to the failure of treatment in many countries like New York, England, Ireland, and Denmark (Burman et al., 1997).

Therefore, both internal and external indicators are essential to predict nonadherence during traditional treatment in clinics or medical centers. However, controversial factors exist which means the elements have arguments, and hard to ensure the impacts and relationships with compliance. Demographic that includes age and race is one of most common controversial parts of the prediction. Many researchers like LLeggat et al. (1998) and Shamaskin et al. (2012) believed that age is vital in prediction as younger patients are more likely to appear non-compliant behavior than older patients. Ibrahim et al. (2015)

reported a contrary conclusion which is no significant impact has been observed between age and compliance. A similar situation occurs on the education level which is another classic factor. Both Leggat et al. (1998) and Ibrahim et al. (2015) stated that educational level does not obviously contribute to compliance, but Wang et al. (2020b) and Bland et al. (2008) emphasized the importance of helping lower education patients understand the progress and content of the therapy to increase their positivity. More studies may focus on finding the relationships between different factors and observe whether these controversial factors are associated with other direct factors and can be group as one element.

2.3 Home Hemodialysis (HHD)

In traditional hemodialysis sessions, patients need to go to the clinics by themselves, which generates lots of transportation expenses. Meanwhile, it also takes many public resources as the clinic has to arrange stuff for operation and supervision. The processes which occupy huge time and cost for both patients and health care providers is one of the main reasons for home hemodialysis (HHD) became the prior choice and the global trend. HHD is a cost-effective treatment method that started in the early 1960s. It allows patients to undertake three weekly sessions of treatment at home by themselves. In Australia, the cost of achieve dialysis at home was about 30% lower than in center which means more budget can be utilized to supply a better service (Agar et al., 2019). Patients are also enjoying the freedom, flexibility and better quality of life which could help them re-establish self-identity and improve compliance in HHD (Cases et al., 2011). Although a big difference exists between two types of treatment, the definition of non-compliance behavior is similar and remote settings are more biased to personal behavior judgments like frequency of attendance and duration of sessions. More effort is spent on analyzing the barriers and how to reduce the impact.

2.3.1 Barriers to the Adoption of HHD

In the remote monitoring context, more factors have been considered which are not emphasized in the traditional setting but are essential in remote monitoring. Part of the factors could bring benefits and strength to prohibit nonadherence, others are barriers to patient acceptance and adoption of the digital environment.

The strength of remote monitoring can be divided into two parts based on different stakeholders, patients, and clinics respectively. From the perspective of the patient, the biggest benefits are freedom and flexibility. Cases (2011) confirmed that patients enjoy the freedom and flexibility which could help them re-establish self-identity and improve compliance of therapy. Diefenbach-Elstob et al. (2017) also highlighted the importance and necessary of flexibility in the unsupervised treatment which could increase the attendance rate in each session. Implement of remote patient monitoring systems could also bring benefits for health care providers like saving money and resources. One of the most important reasons about home hemodialysis is encouraged is lower costs and resources occupy (Agar et al., 2019; Walker et al., 2014). By reducing costs and resource utilization, more attention can be paid to the quality of service to enhance patient motivation and reduce mortality.

Simultaneously, many factors with negative influence also appeared which could aggravate noncompliance. For example, social isolation, self-operation, and family burden are the main obstacles patients need to confront. Cafazzo et al. (2009) proved self-cannulation and family burden are primary barriers for patients to adopt home hemodialysis. Lack of confidence and fear of frequent needling themselves conquer the perception of pain and become one of the most important inhibitors of compliance behavior. Complex dialysis therapy is also hard for family members which would increase the burden and fear to bear responsibility which would be completed by care providers in traditional treatment. This opinion is confirmed again by Walker and Hanson in 2015. In addition, they highlighted another important obstacle, social isolation. Many patients mentioned that being alone is the reason why they refused to choose home hemodialysis.

Although many passive indicators exist in the digital environment, compared with center hemodialysis, the implementation of remote patient monitoring systems displayed better adherence, and the global trends in home hemodialysis will not change (Agar et al., 2019; Berman et al., 2011). More research can focus on improving services to increase satisfaction and acceptability to reach a better outcome and adherence.

2.4 Prediction Methodology

There are several prediction methods already applied to measure the performance of different algorithms used to predict noncompliance behavior. Logistic Regression (LR) and Random Forest (RF) are two of the most popular classification methods during analyzing the relationships or independent of different factors with compliance (Leggat et al., 1998; Saran et al., 2003; Wang et al., 2020a; Kutner et al., 2002; Haas et al., 2019).

LR is widely used in classification or prediction in the medical field and provides easier implementation with effective training. Saran et al. (2003) utilized logistic regression to identify predictors of non-compliance (e.g., race, age, gender, and depression) and discover the associations between facility practice patterns and compliance. Logistic Regression was also mentioned by Kutner et al. (2002) which was implemented to prove the influence of non-compliance by smoking and successfully ensure the negative impact of smoking after comparing and analyzing the results.

RF is a supervised machine learning algorithm which ensure high performance in high dimensional dataset. Both Haas et al. (2019) and Wang et al. (2020a) applied RF technique to help them develop predictive models. RF brings many benefits including addressing variables with missing values and providing comparative analysis using different datasets (Haas et al., 2019). Wang et al. (2020a) stated that RF shows higher effective in identifying biomarkers to predict the outcome of treatments.

Cox proportional hazards model(Cox, 1972) is another common method that is also suitable in medical statistics. The model is always used to justify the correlations between the survival time of patients and factors which have been identified to predict. Both Saran et al. (2003) and Leggat et al. (1998) utilized cox proportional hazards models in survival analysis which focus on estimate death and hospitalization risk associated with different measures of non-compliance like race and country. The result showed that black is more likely to drop out a session compared with white which has 88% of compliance.

2.5 Current Problem

Compared with traditional settings, remote treatment collects more digital and accurate information from patients like medical parameters, emotional records, and messages. With the popularity of HHD, the electronic communication service has been implemented in most applications to replace face-to-face consultation. Bauer and Moessner (2012) stated that communication could improve understanding of treatment and assessing symptoms by patients' behaviors to support monitoring. The importance of analyzing patient-provider communication has also been emphasized by many researchers but there is little evidence that communication can refine self-management and clinic interventions to affect adherence (Roter and Hall, 2009; de Jong et al., 2014). Most research just cites patients' messages to prove and justify points (Walker et al., 2015; Cases et al., 2011; Diefenbach-Elstob et al., 2017). Message content usually regards as an argument or example to increase the persuasiveness of opinions. However, communication can be considered as a new factor to discover the impact to adherence. Although Roter and Hall (2009) proposed a general pattern to classify communication as a symbol of different levels of compliance to better understanding the relationship between adherence, few studies focus on analyzing a specific aspect of communication like message frequency to discover whether these messages imply patients' emotions and attribute changes that would impact compliance. In addition, communication factor analysis may also help solve the controversial indicators and provide a new direction to upgrade clinic services and patient's satisfaction as messages information grouped variables like education levels and emotions together which allow considering and analyzing more factors at the same time.

2.6 Multi-modal Communication Theory

Multimodality is a basic feature of human language which means multiple signal channels are used simultaneously when communication (Taglialatela et al., 2015). Louwerse et al. (2012) proved the synchronized behavior in multimodal communication. The relevance evidence of this opinion like unintentional synchronization behavior (e.g., body posture, gesture, and movement) has been found by Richardson and Dale (2005) and Shockley et al. (2003) which means person's behavior can be impacted by another one during communication. In addition, much research emphasized the influence of emotional expression and interaction (Knutson, 1996; Van Kleef, 2009; Mehu, 2015). They mentioned that emotion should also be regarded as a communication signal as both emotional expressions and reactions could change people's perceptions and behaviors. The combine of emotional and symbolic 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. A suitable communication strategy can improve effectiveness of consultations which would impact patients' satisfactions and adherence (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, communication is an important aspect that affects patient compliance, and it is necessary to conduct more research on communication factors such as the amount of information and emotions.

Combined with the mentioned before, there are two hypotheses are proposed in the study to better access the relationship between communication factors and patients' compliance. Both number of messages and emotions factors would be evaluated by different methods.

Hypothesis 1: The number of text messages can be used to predict remote monitoring patients' non-compliance behavior.
Hypothesis 2: The emotion conveyed by messages imply remote monitoring patients' compliance.

CHAPTER 3

Method

3.1 Design artifact of RPM

Employing the multi-model communication and the existing RPM literature as our kernel theory, 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 3.1 below.

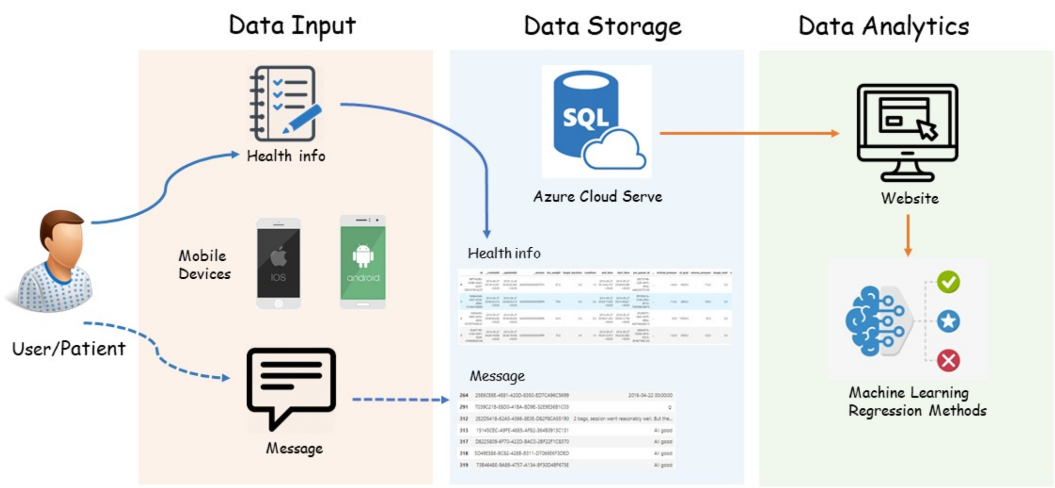

FIGURE 3.1: RPM System Artifact

3.2 Prototype and context of study

With the above meta-design, we have developed an RPM system for patients undergoing hemodialysis at home to receive better remote treatment (named as HHD system thereafter). There are three main components included in the HHD system, including application, cloud server, and Web app. The first component is conducted on the mobile device, which means patients have to install the HHD app on their own phones. Basic functions display on the dashboard to help patients record their sessions like recording weights or blood pressures data and providing feedback. Data of sessions would be uploaded instantly with an internet connection. The cloud server which builds on Window Azure services is the second component. It provides a safe platform place to store patients' data in the database. This information can be analyzed at any time through the website which is the last component hosted by Azure to ensure privacy and security.

The feature of sharing messages was designed to enhance the connection and mutual attention between health care professionals and patients. Patients are able to enter messages after each session to share their feeling and opinions with clinicians. The purpose of this function is to ensure effective communication between patients and professionals 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 emotion is another factor that would improve the prediction results.

3.3 Data Source

My Home Hemodialysis is a mobile application that has been implemented in several hospitals like Black hospital for ESRD patients to achieve better remote treatment. About 7 years of data came from 338 remote monitoring patients have been collected. From 2014 May to 2021 March, 53768 sessions were recorded and available for further analysis. To increase the reliability and accuracy of results, incorrect data has been removed after data cleaning, include inactive users and unusual durations. Inactive users would be considered as virtual users who are researchers or clinical nurses. This situation always occurs as researchers and nursers would also create accounts on the app and simply played around for a few days to better understand or test some functions on the app. This part of users is not included in our research area, so the users with less than ten sessions would be deleted. The second condition is unusual duration which means too long or too less time in sessions. Normally, a dialysis session lasts 6 to 7 hours, but parts of durations in the data are not in this period. It usually caused by patients forgetting to click “End Session” after starting a session entry. Therefore, unusual duration data would be treated as a normal session (6-7 hours) and for patients who has a low entry would be removed.

Therefore, patients who recorded less than 30 sessions with unusual duration (less than 3 hours or more than 6 hours per session) would be considered as virtual users and removed. After data cleaning, there are 226 patients with 49131 sessions left and a total of 17518 records were stored after integrating sessions by week for further analysis. The final dataset includes 7 attitudes which have been displayed in Table 3.1.

Attribute (Original)	**Feature Name**	**Type**	**Description**
user_id	user_id	String	Unique identifier of patients
session_id	session_id	String	Unique identifier of sessions
start_time	week	Numeric	Week of the dialysis session performed
session_id, start_time	session_count	Numeric	Number of dialysis session per week
session_id, start_time	average_count	Numeric	Average number of weekly sessions per patient
note	note	String	Messages patients wrote after each session
session_id, start_time	noncompliance	Categorical	1 refers for noncompliance behavior. 0 refers to the noncompliance behavior.

TABLE 3.1: Description of Data Attributes

3.4 Noncompliance Behavior Definition

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 accept hemodialysis three times a week and each session takes 3 to 4 hours (Sockrider and Shanawani, 2017).

Skipping sessions is a classic character that has been utilized in most research to distinguish concompliance behaviour for hemodialysis and the majority of patients take three sessions per week (Kimmel et al., 1998; Ibrahim et al., 2015; Kutner et al., 2002; Leggat et al., 1998). In this study, the definition of non-compliance behaviour is attendance time less than three in a week. The number of weekly sessions would be counted and mark the weeks with less than three sessions.

3.5 Prediction Method Design

Compared with previous prediction methods, a new prediction algorithm was developed based on the outcomes of statistics and sentiment analysis. Apart from the number of weekly sessions, both number of weekly notes and emotions were taken into consideration in the new method. Finally, there are three components utilized to predict noncompliance behavior. Weekly session number means the number of sessions for each patient in a week which is also the criteria for classifying noncompliance. The weekly note is similar to weekly sessions which counted the number of online messages posted by patients after each session in a week. The sentiment score is the last component which is measured by VADER lexicon to extract emotions from weekly notes. Four weeks of record data of different patients were utilized to measure the deviations and make predictions. Four weeks reference duration has been proved by Dietrich et al. (2021) and is widely used in many compliance analysis research (Varghese et al., 2021; Moffatt et al., 2019). Dietrich et al. (2021) stated that four weeks is the shortest and most significant monitoring period to detect a deviation in patients' behavior.

Independent variables are the number of messages, weekly sessions, and emotional changes. Compliance is a dependent variable that has two values (Yes or No) depending on the number of weekly sessions. Three machine learning algorithms (Logistic Regression, Random Forest, Decision Tree) would be implemented to evaluate the performance and sentiment analysis method would be applied to evaluate and identify the emotions in the text messages.

CHAPTER 4

Evaluation

4.1 Sentiment Analysis Method

To compare the performance of sentiment analysis methods (E.g., SentiWordNet, VADER, and AFINN), a 10% sample of the total dataset was manually labeled to calculate the accuracy of different methods.

4.1.1 SentiWordNet

SentiWordNet is created based on WordNet which is a lexical database of semantic relations between words in more than 200 languages. The largest dictionary allows the SentiWordNet method can consider more relations that exist in sentences and achieve better performance. SentiWordNet method is also widely used in medical areas such as drug review and healthcare (Baccianella et al., 2010). In this method, each synset has 3 emotion scores, positivity, negativity, and objectivity. And the sum of these 3 scores is 1.

4.1.2 VADER

VADER (Valence Aware Dictionary and sEntiment Reasoner) lexicon which is a dictionary and rule-based sentiment analysis tool focused on adjusting sentiment expressed in social media had been finally implemented to measure the emotion score of each note (Hutto and Gilbert, 2014) This method consists of four components: neg, pos, neu, and compound score. The sum of neg, pos, and neu is equal to 1. A larger score in one of these components means a higher likelihood of being inclined toward the corresponding emotion finally. 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.

4.1.3 AFINN

The AFINN dictionary is one of the simplest and most popular dictionaries that can be widely used for sentiment analysis which contains more than 3,300 words with polarity scores. AFINN ranges from -5 to 5 which means sentiment scores greater than 0 are classified in the positive group, neutral are scores equal to 0, and other scores less than 0 are classified in the negative group. In addition, this method has already been proved to be useful in many fields, including social media and medicine (Tighe et al., 2015).

4.2 Evaluation Method

4.2.1 Logistic Regression

LR is one of the most popular linear regression and statistical models, which is easy to implement and provides good performance for linearly separable classes. It is a powerful supervised machine learning algorithm that is widely used to handle classification problems in multiple fields, including medicine (Peng et al., 2002).

4.2.2 Decision Tree

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. In addition, decision trees are a top-down learning method that does not require normalization. It is easy to implement and meets the requirements for training on large data sets (Quinlan, 1999).

4.2.3 Random Forest

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 averaging is utilized to increase the accuracy and stable prediction. Similar to the decision tree, random forest can also handle large datasets efficiently and is easy to implement. However, random forest can also control overfitting by using multiple trees (Breiman, 2001).

4.3 Evaluation and Optimization

To evaluate and optimize the performance of the prediction method, Area Under Curve of Receiver Operating Characteristics Curve (AUC-ROC) would be applied. AUC-ROC was measured based on the confusion matrix Table 4.1. It is a performance measurement for machine learning classification issues with multiple classes. In this study, we have two classes with four different combinations of predicted and actual values: True Positive (T_p), True Negative (T_n), False Positive (F_p), and False Negative (F_n).

	Actual = YES	Actual = NO
Predicted = YES	T_p	F_p
Predicted = NO	F_n	T_n

TABLE 4.1: Confusion Matrix

T_p refers to the prediction result is compliance at that week and it is true.
T_n refers to the prediction result is compliance at that week but it is false.
F_p refers to the prediction result is noncompliance at that week and it is true.
F_n refers to the prediction result is noncompliance at that week and it is false.

AUC-ROC which is an evaluation metric for binary classification problems has two parts. ROC represents a probability curve and AUC is the degree of reparability. Both are plotted with True Positive Rate (TPR) against False Positive Rate (FPR) and the formulas were displayed in Formulas 4.1. The value of AUC-ROC denotes the ability of models to differentiate different classes. Higher AUC (close to 1) means better distinction can be completed by the model. The value of AUC less than 0.5 means the classifier is not able to distinguish between two different classes.

$$\begin{aligned} TPR &= \frac{T_p}{T_p + F_n} \\ FPR &= \frac{F_p}{F_p + T_n} \end{aligned} \tag{4.1}$$

The cross-validation (CV) method would be also implemented to access the performance of final prediction methods. CV is a widespread strategy for algorithm selection that split data into k groups and runs k times. Each time just one group would be used to evaluate, and others are applied to training. Finally, the cross-validation accuracy is the mean of results from k times. Compared with other evaluation algorithms, CV ensures the greatest possible amount of data for training and reduces the risk of overfitting as the training sample is independent (Arlot and Celisse, 2010). After applying CV method, the mean of accuracy and standard deviation can be calculated to better compare the performance of different methods (Formula 4.2). As the square root of the variance, the standard deviation is a statistic that represents the dispersion of a dataset compared to its mean. A volatile stock represents a higher standard deviation, while lower value means data are clustered around the mean value which means more reliable.

$$\begin{aligned} \mu &= \frac{1}{N}\sum_{i=1}^{N} x_i \\ \sigma &= \sqrt{\frac{\sum(x_i-\mu)^2}{N}} \end{aligned} \tag{4.2}$$

μ = the accuracy mean

N = the size of the accuracy

σ = accuracy standard deviation

x_i = each value from the accuracy

CHAPTER 5

Experiments and Results

5.1 Statistical Analysis

5.1.1 Descriptive statistics

After data cleaning and processing, there are 226 patients with 17518 weekly records left in the dataset. The gender distribution was 28.3% female and 71.7% male. The average count of weekly sessions is 2.8 and 224 (99.1%) patients experienced at least one non-compliance behaviour during treatments (Table 5.1).

Patient Details	N (% or IQR)
Patients	226
Gender	
Male	162 (71.7%)
Female	64 (28.3%)
Weekly Sessions	
Average	2.8
Compliance	
Yes	2(0.9%)
No	224 (99.1%)
Session Note	
Yes	216 (95.6%)
No	10 (4.4%)

TABLE 5.1: Demographic of Patients

Session Details	N (% or IQR)
Weekly Session	17518
Session Note	
Yes	7938 (45.3%)
No	9580 (54.7%)
Weekly Note	
0	9580 (54.7%)
1	3606 (20.6%)
2	2128 (10.0%)
3	2255 (12.9%)
>3	320 (1.8%)

TABLE 5.2: Weekly Session Summary

5.1.2 Text messages

Among the 17518 weekly sessions, 7938 (45.3%) records have online notes. The average weekly note number is 0.87 and the majority of weekly sessions have less than 3 messages (Table 5.2). In terms of the messages, 216 (95.6%) wrote more than one message after dialysis sessions to share their opinions or situation.

5.2 Hypothesis Analysis

Hypothesis Testing 1:

H0 (Null Hypothesis): The number of weekly notes does not associate with noncompliance.

H1 (Alternative Hypothesis): The number of weekly notes can be used to predict remote monitoring patients' non-compliance behavior.

Hypothesis Testing 2:

H0 (Null Hypothesis): The emotion conveyed by message does note associate with noncompliance.

H1 (Alternative Hypothesis): The emotion conveyed by messages imply remote monitoring patients' compliance.

5.3 Sentiment Analysis

There are three most popular sentiment methods in healthcare (SentiWordNet, VADER, and AFINN) utilized to make comparisons and discover which one is most suitable for this study. To better compare the methods of different types of messages, all messages are divided into two groups according to whether have emojis, which means that emoji-only messages are divided into emoji group and other messages are moved to the normal group. 10% samples (1650 rows) were random selected from the database and manually labelled to access the accuracy of different methods.

	SENTIWORDNET	**VADER**	**AFINN**
NON-EMOJI DATASET (1610 ROWS)	0.806	0.858	0.791
EMOJI DATASET (40 ROWS)	0.341	0.854	0.878
TOTAL (1650 ROWS)	0.795	0.857	0.793

TABLE 5.3: Sentiment Analysis Results

As shown in Table 5.3, VADER displayed the best performance in the non-emoji dataset and AFINN achieved the highest accuracy in the emoji group. With comprehensive consideration of all samples, the VADER lexicon is more suitable than other sentiment methods for this study. Therefore, the VADER lexicon was finally applied to measure emotion scores which be regard as variables in noncompliance prediction. The outcome and distribution of three emotion groups were displays in Table 5.4.

	Compliance		**Mean (95% CI)**	**P-Value**
Predictor	Yes (0)	No (1)		
Sessions	14300 (86.6%)	2209 (13.4%)		
Emotion				
Positive	5097 (90.0%)	566 (10.0%)	0.100 (0.092, 0.108)	< .0.01
Neutral	7475 (85.7%)	1243 (14.3%)	0.143 (0.135, 0.150)	< .0.01
Negative	1728 (81.2%)	400 (18.8%)	0.188 (0.171, 0.205)	.759

TABLE 5.4: Sentiment Analysis Results Analysis

From table 5.4 which displays the distribution of three groups with 95% confidence intervals, we can discover that patients' emotions have influence on their behaviors. Patients with negative emotions have a higher proportion to display noncompliance behavior in the further treatment. Otherwise, positive emotions bring a lower possibility of nonadherence.

5.4 Evaluation Model Analysis

There are three machine learning methods applied to evaluate the performance of the model established in this study. LR is easy to implement and provides good performance for linearly separable classes with few parameters need to be tuned. RF ensembles a number of categorical decision trees for classification and regression which might provide a higher accuracy with stable prediction. DT is the last method which is a non-parametric supervised learning method for classification and regression. It is easy to implement with few parameters need to be tuned. AUC-ROC was considered the optimistic metric to optimize parameters. The final optimal parameters for these methods are displayed in Table 5.5.

Methods	Optimal Parameters	
Logistic Regression	penalty='l2'	multi_class='ovr'
	dual=False	Solver='liblinear'
	tol=0.0001	C=1.0
	fit_intercept=True	intercept_scaling=1
	class_weight='balanced'	random_state=42
	max_iter=100	verbose=0
	warm_start=False	n_jobs=None
	l1_ratio=None	
Random Forest	n_estimators=100	criterion='gini'
	max_depth=None	min_samples_split=2
	min_samples_leaf=1	min_weight_fraction_leaf=0.0
	max_features='sqrt'	max_leaf_nodes=None
	min_impurity_decrease=0.0	bootstrap=True
	oob_score=False	n_jobs=None
	random_state=42	verbose=0
	warm_start=False	class_weight='balanced'
	ccp_alpha=0.0	
Decision Tree	criterion='gini'	splitter='best'
	max_depth=None	min_samples_split=2
	min_samples_leaf=1	min_weight_fraction_leaf=0.0
	max_features=None	random_state=42
	max_leaf_nodes=None	min_impurity_decrease=0.0
	class_weight='balanced'	ccp_alpha=0.0

TABLE 5.5: Optimal Parameters

5.5 Result

	LR	**RF**	**DT**
Basic Model	0.663 (0.017)	0.646 (0.020)	0.642 (0.019)
Model 1 (with weekly note)	0.717 (0.016)	0.769 (0.015)	0.765 (0.015)
Model 2 (with emotion score)	0.638 (0.017)	0.769 (0.011)	0.719 (0.009)
Model 3 (summary)	0.723 (0.016)	0.805 (0.011)	0.764 (0.012)

TABLE 5.6: Accuracy Result

After applying 10-fold cross-validation, the values of mean accuracy with standard deviation were displayed in Table 8. There are totally four different models measured by three machine learning algorithms. Basic model excludes all communication factors including weekly note and emotion score which aims to be considered as a control group to make comparison. Model 1 takes the number of weekly notes into consideration and model 2 add the emotion scores. The purpose of these two models is to confirm the impact of different factors in communication on noncompliance and whether can be utilized to prediction. Model 3 considered all variables mentioned in this study. Apart from the number of weekly sessions, both number of weekly notes and emotions were taken into consideration in the Model 3. Four weeks reference duration is considered as benchmark to make analysis and predictions.

Both weekly sessions and sentiment were shown to be significantly correlated with noncompliance and were able to make predictions (Table 5.6). Compare with basic method which exclude communication factors in prediction, our method is able to improve the accuracy in three machine learning method and random forest achieved the best performance. Sentiment analysis based on previous performance to measure deviation combined with all sentiment scores calculated by VADER further improved the accuracy of predictions. The best outcome is 80.5% (0.011) when consider all variables and using last four weeks datasets as a reference to measure deviations and compare changes. In addition, a higher associated relationship can be observed between negative emotion and noncompliance behavior. Patients with negative sentiment messages (mean 0.188; 95% CI, 0.171-0.205; $p = .759$) are more likely to appear noncompliant than other patients with positive notes (mean 0.100; 95% CI, 0.092, 0.108; $p = <.001$) (Table 5.4).

Random forest method has the best performance among all models in this study. Meanwhile, Model 3 achieved the best outcomes considering all communication variables when applying the RF method. More details have been displayed in Figure 5.1. Therefore, we are able to identify noncompliance by taking communication factors into consideration in the RF model. Both statistical analysis and machine learning algorithms proved that two hypotheses proposed based on multi-modal communication theory are valid.

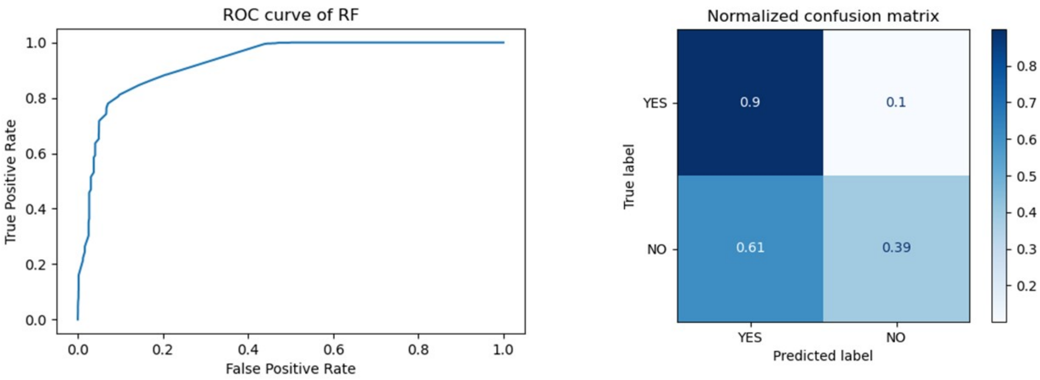

FIGURE 5.1: Random Forest Results

5.6 Contribution

In this study, the impact of two communication factors (the number of text messages and emotion changes) is successfully confirmed by fitting machine learning methods and analyzing the accuracy results. This is future research based on previous studies which proved that communication between patients and health professionals is important and it is necessary to have more studies on communication factors and patients' compliance. The result of this study might solve part of the problems and provide a new direction to improve quality of life, isolation, and compliance. A mechanism was put forward to make predictions of noncompliance under the RPM method with higher prediction accuracy to help clinicians better identify noncompliance behavior or detect potential problems in advance and modify treatment strategies timely to avoid poor outcomes. In addition, more suggestions about how to upgrade health services and recommendations about communication strategies after further research on problems cause the emotional changes based on online messages to help health providers establish a better environment for patients to accept RPM by increasing their satisfaction and reducing nonadherence.

CHAPTER 6

Discussion

The purpose of this study was to explore the impact of app-mediated communication on patient behavior in RPM by analysing data from the HHD app. A mechanism was put forward to make predictions of noncompliance under the RPM method. To access the hypothesis of online emotion communication proposed based on the multi-modal communication theory, two regression analyses were implemented to make comparisons. Previous method without emotional factors ensures the possibility to make predictions based on the number of weekly sessions. The new method created in this study which take communication factors into consideration that exist in messages has been proved to have a significant influence on patients' non-compliance behaviours.

A prediction method was established to provide help for the RPM system to improve their service including better monitoring patients' attitudes and enabling to discover noncompliance behavior in advance. The dataset collect from HHD was transformed into binary classification problems and three machine learning algorithms (SVM, RF, and DT) were implemented to compare and evaluate the outcomes of different prediction models. Four weeks reference durations are considered as benchmark to make analysis and predictions.

From the results, weekly note number combined with number of weekly sessions which is one important standard criterion to distinguish noncompliance behavior have been proved as parts of the prediction mechanism. It is possible to use previous session records to predict patients' behavior in advance. Compared with other machine learning methods, LR displays the best performance which reached the highest accuracy of 76.9% with a low standard deviation of 0.015.

We also discovered that patients' noncompliance behavior in the RPM method is highly correlated with communication. Sentiment has been confirmed to be a significant factor that would impact patients' behavior. The sentiments explored in messages are classified into three groups: positive, negative, and neutral. Compared with other groups, negative emotion has a higher possibility bring worse results like skip dialysis sessions. In addition, sentiment scores would also significantly improve the accuracy of prediction in all machine learning methods applied 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 emotion scores peaked at 80.5% (0.011) when the reference duration is four weeks.

CHAPTER 7

Conclusion and Future Work

Overall, this study confirms the impact of sentiment conveyed by online communications on RPM patients' behaviors, and communication is another important factor need to be considered during prediction. A new method has been posted for healthcare professionals to make predictions based on patients' previous attitudes. Of the sentiment analysis, 95.6% of total patients wrote more than one messages after dialysis sessions to share their opinions and status. Compare with positive or neutral sentiment, patients with negative emotions have higher possibility to show noncompliance in the future. When made the predictions, our results displayed that the accuracy of predictions have be improved after subjoining sentiment scores calculated from online messages. Random Forest (RF) is the most suitable method which achieved highest accuracy (80.5%, 0.011) when the reference duration is four weeks.

This study has a few limitations need to be noted. First, the data distribution is quite unbalanced which would impact the result of the prediction results although weight-balanced method was used to reduce the influence. Second, due to the lack of relevant attributes, the number of sessions per week was the only criterion used for classification. More relevant information, such as Interdialytic Weight Gain (IDWG) could improve the accuracy of the classification which is directly related to the final outcomes.

As the purpose of the study is to explore the impact of sentiment that exists in communication on RPM patients' behavior, less analysis about the reason of individual patients for expressing different emotions or feeling through online messages. Further work will focus on having a deeper understanding of patients' feelings and potential reasons cause the noncompliance behavior. More evaluation would be processed on special situations like sentiment suddenly changed or unusual conditions.

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