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Research and Applications

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Emotion sharing in remote patient monitoring of patients with chronic kidney disease

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ABSTRACT

Objective: To investigate the relationship between emotion sharing and technically troubled dialysis (TTD) in a remote patient monitoring (RPM) setting.

Materials and Methods: A custom software system was developed for home hemodialysis patients to use in an RPM setting, with focus on emoticon sharing and sentiment analysis of patients' text data. We analyzed the outcome of emoticon and sentiment against TTD. Logistic regression was used to assess the relationship between patients' emotions (emoticon and sentiment) and TTD.

Results: Usage data were collected from January 1, 2015 to June 1, 2018 from 156 patients that actively used the app system, with a total of 31 159 dialysis sessions recorded. Overall, 122 patients (78%) made use of the emoticon feature while 146 patients (94%) wrote at least 1 or more session notes for sentiment analysis. In total, 4087 (13%) sessions were classified as TTD. In the multivariate model, when compared to sessions with self-reported very happy emoticons, those with sad emoticons showed significantly higher associations to TTD (aOR 4.97; 95% CI 4.13–5.99; $P = < .001$). Similarly, negative sentiments also revealed significant associations to TTD (aOR 1.56; 95% CI 1.22–2; $P = .003$) when compared to positive sentiments.

Discussion: The distribution of emoticons varied greatly when compared to sentiment analysis outcomes due to the differences in the design features. The emoticon feature was generally easier to understand and quicker to input while the sentiment analysis required patients to manually input their personal thoughts.

Conclusion: Patients on home hemodialysis actively expressed their emotions during RPM. Negative emotions were found to have significant associations with TTD. The use of emoticons and sentimental analysis may be used as a predictive indicator for prolonged TTD.

Key words: remote monitoring, emoticon sharing, sentiment analysis, mHealth, mobile health, data collection

INTRODUCTION

Remote patient monitoring (RPM) has had significant impact on the healthcare system as it enhances clinicians' ability to monitor and manage patients when either of them are in a nonclinical setting.[1] It involves the use of information and communication technologies to collect health data from individuals in locations, such as at patients' homes, and to electronically transmit the information to healthcare professionals (clinicians, nurses, etc) for assessment and intervention.[2,3] One of the key utilities of RPM is to improve chronic care management,[4] where there is the necessity for healthcare professionals to be able to monitor the health conditions of patients with chronic disease on a regular basis, a feat which is difficult to achieve remotely without the use of technology.[5,6]

Prior studies on RPM systems typically consists of 3 main components: (1) tracking physiological parameters, such as respiration rate, heart rate,[7] blood pressure, and blood glucose level,[8] some of which are able to be captured by wearable sensors[9] while others rely on patients' self-input;[10] (2) a dashboard for clinicians to view data through a web or mobile interface, which enables healthcare professionals to monitor the patients' condition and provide timely intervention; and (3) a messaging function to provide reminders or alerts to both patients and clinicians. As technology advances, we are witnessing higher levels of sophistication and complexity in the RPM features (eg, personalized feedback, social health networks, etc) and their capabilities at enhancing clinical and health outcomes.[1,11]

Although patients' emotions correlate well with their sense of wellbeing, emotion sharing has been 1 of the lesser explored areas within RPM, despite the well-known clinical importance it plays in the management of chronic diseases.[5,12,13] In addition, the emotions of patients with chronic diseases and their sense of wellbeing can often change over time, and they are more prone to suffer from anxiety and depression.[14,15] As such, there is a need for healthcare professionals to be able to monitor and interpret the emotions of their patients.[13] However, in the typical clinical setting, it is often difficult to keep track and proactively procure the emotional statuses of patients in a nondisruptive manner, as patients may feel inconvenienced or frustrated if healthcare professionals were to frequently inquire about their emotional statuses outside of routine follow-up visits. In order to overcome these issues, alternative methods for collecting patients' emotions needs to be explored, and the most appropriate medium to do so is via a remote monitoring system.

Existing studies have shown that with the introduction of social media and computer-mediated communications (CMC), a number of methods have become available as means to either directly or indirectly gauge the emotions of an individual, with 1 example being the use of emoticons.[16–19] Emoticons are pictorial representations of facial expressions which are widely used in CMC as a means for providing socioe-motional context.[19] When studied empirically, it has been shown that the inclusion of emoticons helps readers better understand the level and direction of the emotional context surrounding CMC messages.[20] It is, therefore, worthwhile to explore the use of emoticons in an RPM setting and evaluate its effectiveness in facilitating emotion sharing between chronic patients and their healthcare professionals.

Another method for interpreting patient emotions is through sentiment analysis which involves the use of a broad range of techniques such as natural language processing (NLP) and machine learning (ML) to systematically quantify and extract sentiment measures (embedded views, attitudes, emotions, etc) from within CMC texts.[21,22] As sentiment measures can be viewed as a reflection of the health and emotional status of a patient, by analyzing the change in sentiment over time improvements or deterioration in patients' health can be recognised.[23] Based on prior studies, the analysis of sentiment when combined with clinical narratives can potentially offer higher levels of understanding and assist healthcare professionals in interpreting health statuses of their patients.[24,25] In this regard, ML approaches have long demonstrated their effectiveness and are the preferred method of choice to extract and derive deeper meanings from health-related CMC texts,[22] with the most common approaches including the use of random forest,[26–28] support vector machine,[28–31] neural network,[27,29,30] and naïve Bayes.[28,29,32]

In this study, we design and evaluate the use of emoticons and sentiment analysis in an RPM setting aimed towards patients on chronic home dialysis. Chronic dialysis refers to the long-term life-prolonging treatment modality for patients suffering from end-stage renal disease (ESRD), the most severe form of chronic kidney disease (CKD).[33] The dialysis procedure substitutes kidney function through the removal of accumulated metabolic waste products by a process of diffusion, as well as removal of excess fluids from the body by a process of ultrafiltration.[34] We selected patients undertaking home hemodialysis (HHD), a procedure that patients typically perform at least 3 times a week for 4 to 5 hours per session in the convenience of their own homes.[35] HHD offers a number of advantages over other forms of dialyses as it is associated with better patient survivals, better quality of life, and is more cost effective as compared to hemodialysis treatments provided to patients within healthcare facilities.[36] However, 1 of the major drawbacks of HHD is that patients often feel abandoned by the health system due to a lack of on-site presence and oversight by trained healthcare professionals, which may increase patients' anxiety,[37] and promote noncompliance (eg, violating dietary and fluid intake restrictions, skipping or shortening dialysis sessions, etc).[38–40]

HHD provides a great opportunity for a purpose-built RPM system to be implemented as it would be capable of abridging the disconnection between patients and healthcare professionals. Furthermore, due to the reliance of self-treatment where patients are required to complete each dialysis session without any clinical supervision, there is a higher risk for patients to experience an undesirable or troubled session outcome. We may label a dialysis session outcome as "technically troubled" based on a number of observations, such as when a patient accidentally removes too much bodily fluid beyond that of the recommended guidelines. Only by allowing patients to record their session parameters in real time via an RPM system, is it possible to provide faster forms of detection and intervention. By trialling our RPM system among HHD patients, we aim to explore the effectiveness of our 2 design features at extracting crucial emotional status data for healthcare professionals to interpret. Subsequently, by analyzing the emotion outcomes of emoticons and sentiment in comparison with occurrence rate of technically troubled dialysis (TTD), we aim to investigate the association of the 2 features in regard to poor health outcomes among patients with chronic diseases.

MATERIALS AND METHODS

We developed a custom RPM system for patients on HHD and evaluated its performance between January 1, 2015 and June 30, 2018 with specific focus on our emoticons and sentiment analysis features. The RPM system was implemented through the Regional Dialysis Centre in Blacktown Hospital in Western Sydney, New South Wales, Australia and is 1 of the largest home hemodialysis services in Australia.

The home hemodialysis remote monitoring system

The overall RPM system contains 3 main components: 1) the mobile application (app) for dialysis patients to input their data including personal messages and emotions, 2) a cloud database for the storage of data, and 3) a web dashboard for healthcare professionals to monitor and send feedback.

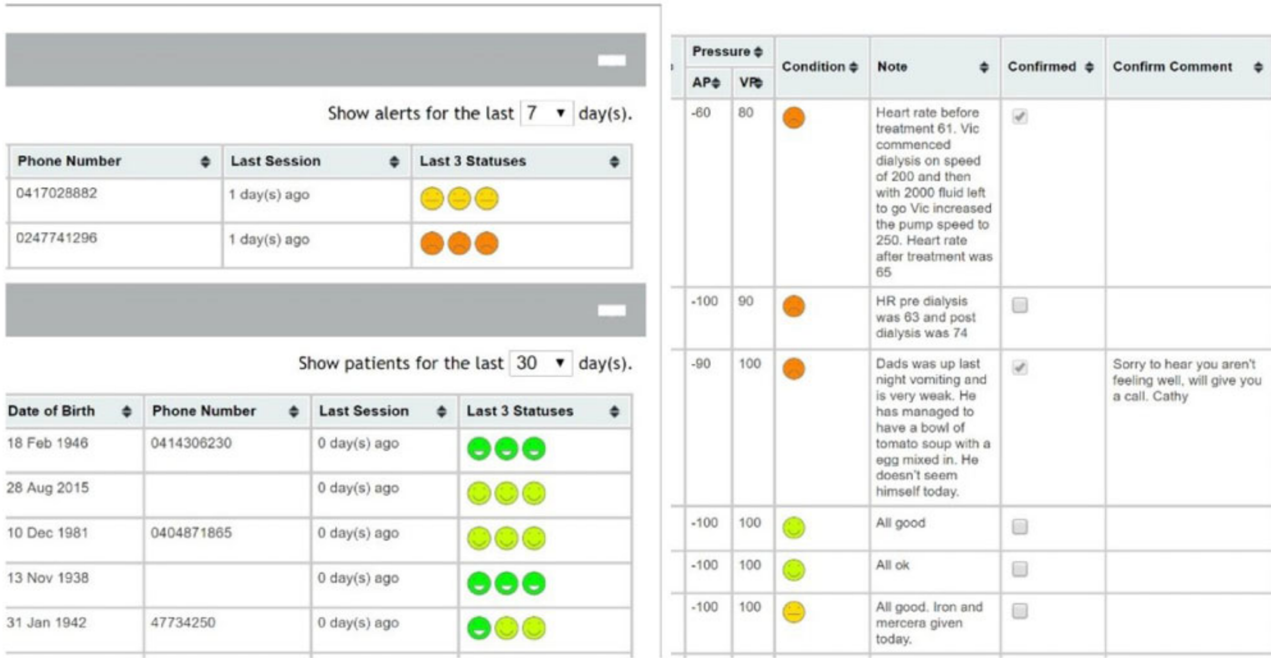

Figure 1. User interface of the web dashboard for clinicians/nurses to view their patients' data. The image on the left shows the home screen of the dashboard displaying recent dialysis sessions split by emoticons. The image on the right shows the detailed view of each patient's dialysis history.

The mobile app allows patients to record their hemodialysis data (eg, weight, blood pressure, ultra-filtration volumes, blood flows, venous and arterial pressures, session times, emotion, and an optional session note) during each dialysis session. It also enables patients to receive feedback as well as notifications on abnormal parameters or if they did not perform dialysis within a certain amount of time.

The web dashboard serves as the medium for healthcare professionals (nurses and clinicians) to monitor the condition of their patients per dialysis session. The home screen displays a list of recent patients that undertook hemodialysis and is separated into 2 display categories based on the 3 most recent self-reported health conditions. Through the dashboard, the health professional can browse through each individual patient's dialysis session history and tick to give indication that they have reviewed the data along with an optional free text input for any feedback or responses (Figure 1).

Emoticon and sentiment features

When using the app, at the end of each hemodialysis session, patients were asked to input their emotion status (as a general indication of how they are feeling) via a sliding scale with a corresponding emoticon representation (Figure 2). Based on the value selected in the sliding scale, the equivalent emoticon is submitted, as part of the self-health reporting exercise to the cloud database, as a way for the health professionals to obtain a general understanding of the patient's overall mood or emotion for each dialysis session. The emoticons are reported on a 5-point scale, with 0 = Very Happy, 1 = Happy, 2 = Neutral, 3 = Unhappy and 4 = Very Unhappy. In order to allow health professionals to quickly identify patients that are in need of care, the dashboard interface organizes the patients based on the 3 most recent emoticons submitted for their dialysis sessions.

In addition to the emoticon reporting feature, we also explored the use of sentiment analysis to extract and interpret patients' emotions from electronic texts. At the end of each session entry, there is an optional free text field for patients to write a note regarding the dialysis session. The content of the session note is entirely decided by the patient, and could range from any contextual information, such as the taking of additional medication or supplements, to reports on health conditions such as excessive bleeding or headaches, and it could even be general messages such as "it went well" or "feeling hungry". The session notes can be viewed by the healthcare professionals using the web dashboard and, if necessary, a personalized response message could be sent back to the patient (Figure 1).

In order to automatically identify priority session notes, we employed a machine learning algorithm using a naïve Bayes classifier. The classifier was trained on Twitter sentiment and movie reviews from the data set created by Pang et al.[41,42] The trained classifier was used to analyze and assign a sentiment classification of either positive, neutral, or negative to each session note. By implementing this feature, we aim to provide another perspective for health professionals to identify patients in need of follow-up.

Technically troubled dialysis (TTD)

We defined the outcome of a dialysis session as "technically troubled" (TTD) when the difference between the postweight and dry weight was greater than 5%, or the difference in ultrafiltration goal and dry weight was greater than 5%, or when the difference between arterial and venous pressure was greater than 1 standard deviation from the mean. The definition for TTD was derived by a nephrologist at the Regional Dialysis Centre based on the health parameters collected by our RPM system with reference to Kidney Health Australia-Caring for Australasians with Renal Impairment (KHA-CARI)[43] and European Dialysis and Transplant Nurses Association/European Renal Care Association (EDTNA/ERCA)[44] guidelines for care of adult renal patients.

Statistical analysis

Data collected during the period January 1, 2015 to June 30, 2018 were summarized and descriptive statistics were used to present

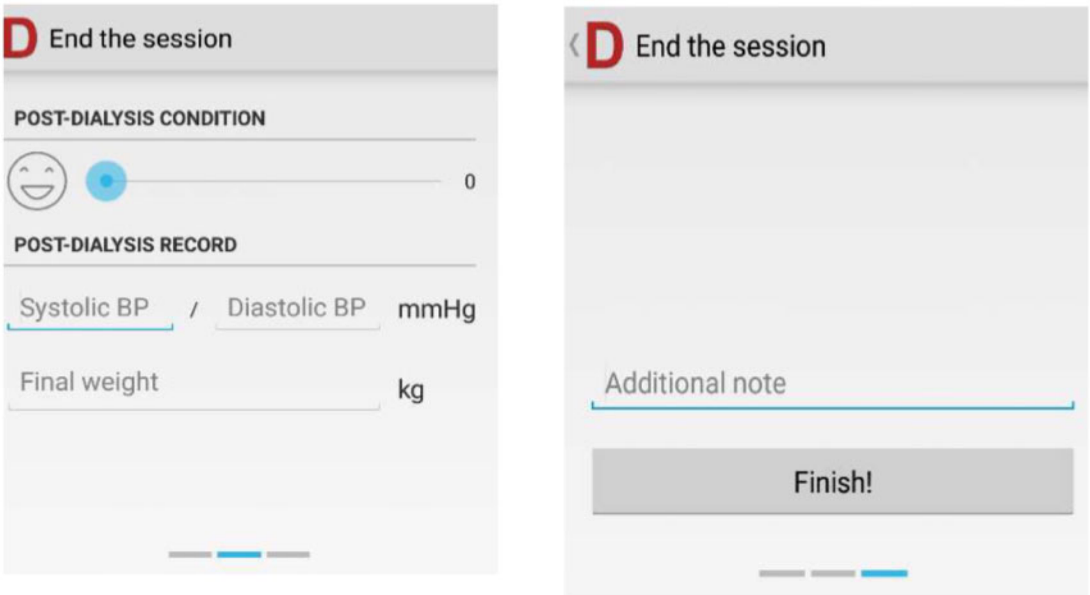

Figure 2. User interface of the post dialysis session input in the app. The patient inputs their emotion using the slider as shown in the left screen. Optional text input is shown on the right screen.

patient demographics and their health metrics. Our selection criteria included only patients who were active during this period (patients that recorded more than 10 dialysis sessions between January 1, 2015 to June 30, 2018). Logistic regression methods were used to assess the relationship between patients' emotions (emoticon and sentiment) and TTD. In multivariate analyses, stepwise backward selection of covariates, with a significance level of 0.05 for removal, was used to develop the multivariate models. The covariates analyzed included age, sex, app usage duration, weight, systolic/diastolic blood pressure (BP), arterial/venous pressure, dialysis duration, differences in presession and postsession weight and BP. All reported *P* values are 2-sided and a value less than 0.05 are considered statistically significant. Test for trend was performed for *P* overall values.

DATA ANALYSIS AND RESULTS

Descriptive statistics

During the period January 1, 2015 to June 30, 2018, 156 dialysis patients had used the app, with a total of 31 159 dialysis sessions recorded in the database. The median (interquartile range [IQR]) age at baseline (first date of app use) was 53 (41–61) years, and the gender distribution was 30% female, 70% male (Table 1). The median (IQR) number of dialysis session entry was 159 (80–315) per patient, and the median (IQR) app usage duration was 16 (9–29) months.

During this period, 122 patients (78%) made use of the emoticon feature. Of the 31 159 dialysis sessions, 25 800 (83%) contained a corresponding emoticon submission, and the distribution for very happy, happy, neutral, sad, and very sad was 8690 (33.7%), 14 120 (55%), 1978 (8%), 884 (3%) and 128 (1%), respectively (Table 2). In regard to session notes, 146 patients (94%) had written 1 or more session notes during the recording of their dialysis sessions. Of the 31 159 dialysis sessions, 9379 (30%) sessions had session notes. The distribution of sentiment among session notes were 1774 (19%) positive, 6077 (65%) neutral, and 1522 (16%) negative.

Table 1. Baseline demographics of patients

	N (% or IQR)
Patients	156
Age	
<40	32 (24.9%)
40–49	26 (18.6%)
50–59	46 (32.9%)
60–69	27 (19.3%)
70+	9 (6.4%)
Median (IQR)	52.6 (41.4–60.7)
Gender	
Female	47 (30.1%)
Male	109 (69.9%)
Number of session entries	
Median (IQR)	157.5 (67.5–307)
Usage duration (months)	
Median (IQR)	15 (7.5–28.5)
Emoticon Feature Use	
No	34 (21.8%)
Yes	122 (78.2%)
Session note use (sentiment)	
No	10 (6.4%)
Yes	146 (93.6%)
Have had TTD	
No	74 (47.4%)
Yes	82 (52.6%)
Have had prolonged TTD[a]	
No	33 (40.2%)
Yes	49 (69.8%)

[a]A TTD is considered as prolonged if the session directly before or after it was also a TTD.

Abbreviations: IQR, interquartile range; TTD, technically troubled dialysis.

Of the 156 patients, 82 (53%) had experienced 1 or more TTD sessions. In terms of recorded sessions, a total of 4087 (13%) sessions were classified as TTD, and among these sessions, 2764 (68%)

Table 2. Session summary

	N (%)
Sessions	31 159
Emoticon	
Very Happy	8690 (33.7%)
Happy	14 120 (54.7%)
Neutral	1978 (7.7%)
Sad	884 (3.4%)
Very Sad	128 (0.5%)
Missing	5359
Technically troubled dialysis	
No	27 072 (86.9%)
Yes	4087 (13.1%)
Session note	
No	21 780 (69.9%)
Yes	9379 (30.1%)
Sentiment outcome	
Positive	1774 (18.9%)
Neutral	6077 (64.8%)
Negative	1522 (16.2%)
Missing	21780
Presession blood pressure[a]	
Low	2832 (9.1%)
Normal	8855 (28.4%)
High	19 472 (62.5%)
Postsession blood pressure[a]	
Low	3807 (12.2%)
Normal	11 941 (38.3%)
High	15 411 (49.5%)

[a]Low BP: systolic < = 90 or diastolic < = 60, High BP: systolic > = 140 or diastolic > = 90.

Table 3. Comparison between normal and technically troubled dialysis in emoticons and sentiment

	Normal	Tech troubled dialysis
Sessions	27 072 (86.9%)	4087 (13.1%)
Prolonged TTD[a]		
No	–	1323 (32.4%)
Yes	–	2764 (67.6%)
Emoticon		
Very Happy	7740 (34.6%)	950 (27.5%)
Happy	12 161 (54.4%)	1959 (56.8%)
Neutral	1755 (7.9%)	223 (6.5%)
Sad	583 (2.6%)	301 (8.7%)
Very Sad	110 (0.5%)	18 (0.5%)
Missing	4723	636
Sentiment		
Positive	1535 (22.6%)	75 (6.1%)
Neutral	4292 (63.1%)	854 (69%)
Negative	974 (14.3%)	309 (25%)
Missing	20 542	2849

[a]A TTD session is considered “prolonged” if the session directly before or after it was also a TTD.

Abbreviation: TTD, technically troubled dialysis.

sessions were prolonged. The distribution of emoticons for TTD was 950 (28%) very happy, 1959 (57%) happy, 223 (7%) neutral, 301 (9%) sad, and 18 (1%) very sad. In regard to sentiment measures of session note, the distribution was 75 (6%) positive, 854 (69%) neutral, and 309 (25%) negative (Table 3).

Logistic regression

Two separate logistic regressions were performed to assess the effect of emoticons and sentimental analysis on TTD, with covariates included. Both emoticon and sentiment were found to be significantly associated with an increased risk of TTD (Table 4). When compared to sessions with self-reported very happy emoticons, those with sad emoticons showed a significantly higher risk of associated TTD (aOR 4.97; 95% CI, 4.13–5.99; $P = < .001$). Meanwhile, sessions with very sad emoticons revealed a similar albeit nonsignificant trend (aOR 1.83; 95% CI, 1.01–3.32; $P = .615$) compared to sessions with very happy emoticons. Similarly, for sentiment outcomes when compared to sessions with positive sentiments, the sessions that contained neutral and negative sentiments revealed significantly increased associations with TTD (aOR 2.67; 95% CI, 2.04–3.49; $P = < .001$) (aOR 1.56; 95% CI, 1.22–2; $P = .003$).

DISCUSSION

Overall, the RPM system for home hemodialysis experienced a relatively smooth operation at the Home Hemodialysis Service in Western Sydney. A considerable number of patients actively made use of the app, with the majority having regularly sent in emoticons and session notes (sentiment) for each of their dialysis sessions. In addition, a very high proportion of emoticon submissions in patients on HHD were of positive nature (very happy and happy, 88%), suggesting that patients are generally in a happy mood immediately after the completion of their hemodialysis session or that they prefer sharing positive emotions over negative ones.

We discovered that a large number of positive emoticons had come from TTD sessions, suggesting that a TTD session might not necessarily indicate and result in a negative sense of wellbeing from patients. One possible reason could be that patients feel reassured with the knowledge that their session data are viewed and checked by their healthcare professionals. Other reasons for this outcome could be that a TTD session was not associated with physical symptoms or consequences that could affect patients’ mood or sense of wellbeing or this could also be due to the patients’ own view of their health and the purpose of the emoticon feature.[45] From an informal meeting with patients, it was revealed that a number of them shared different interpretations on the intended usage of the emoticon-sharing feature. Some patients had often chosen to submit a positive emoticon even during complications because their overall mood was still relatively positive or that they simply were not aware that the session they just had was considered technically “troubled”. Other patients had submitted happy emoticons during such times in order to remain positive. When compared to the sentiment analysis outcomes, the emoticon distribution was skewed towards a more positive outlook.

However, based on the data collected, we found that when patients experience a TTD session, the subsequent session(s) is also likely to be a TTD session. Rather than being a one-off instance, a large majority of TTD sessions occurred in a consecutive, prolonged manner. A post hoc analysis, when comparing the emoticon distribution between singular TTD and prolonged TTD, revealed that 94% of all reported sad and very sad emoticons happened during the prolonged periods of TTD. This suggested that, despite the generally positive response sent from patients during TTD sessions, their mood tended to become much worse once this situation became prolonged. Based on this finding, it may be worthwhile to consider exploring patient reported negative emotions and TTD as a

Table 4a. Factors associated with technically troubled dialysis

	TTD		Univariate analysis			Multivariate analysis		
Predictor	No	Yes	OR (95% CI)	*P*	*P* (Overall)	OR (95% CI)	*P*	*P* (Overall)
Total Sessions	22 379	3451 (13.4%)						
Emoticon								
Very happy	7740	950 (10.9%)	1			1		
Happy	12 161	1959 (13.9%)	1.31 (1.21–1.43)	<.001	<.001	1.14 (1.04–1.25)	<.001	<.001
Neutral	1755	223 (11.3%)	1.04 (0.89–1.21)	<.022		1.09 (0.92–1.29)	<.001	
Sad	583	301 (34.1%)	4.21 (3.6–4.91)	<.001		4.97 (4.13–5.99)	<.001	
Very sad	110	18 (14.1%)	1.33 (0.81–2.2)	.562		1.83 (1.01–3.32)	0.615	
Age								
<40	3459	631 (15.4%)	1			1		
40–49	2695	626 (18.9%)	1.27 (1.13–1.44)	<.001		1.46 (1.27–1.67)	<.001	<.001
50–59	6295	1643 (20.7%)	1.43 (1.29–1.58)	<.001		2.11 (1.88–2.36)	<.001	
60–69	5071	266 (5%)	0.29 (0.25–0.33)	<.001		0.49 (0.41–0.57)	<.001	
70+	2865	20 (0.7%)	0.04 (0.02–0.06)	<.001		0.11 (0.07–0.18)	<.001	
Missing	1964	265 (11.9%)	0.74 (0.63–0.86)	.014		1.28 (1.08–1.52)	<.001	
Sex								
Female	5255	1941 (27%)	1			1		
Male	17 094	1510 (8.1%)	4.18 (3.88–4.5)	<.001		4.51 (4.13–4.91)	<.001	
App usage duration								
(Continuous)	22 379	3451 (13.4%)	1 (0.99–1)	.02		1.01 (1–1.01)	<.001	
Weight difference								
(Continuous)	22 379	3451 (13.4%)	1.47 (1.42–1.52)	<.001		1.43 (1.37–1.49)	<.001	
Blood pressure (pre-dialysis)								
Normal	2323	265 (10.2%)	1					
Low	6711	840 (11.1%)	0.91 (0.79–1.06)	.001	<.001			
High	13 315	2346 (15%)	1.41 (1.29–1.53)	<.001				
Blood pressure (post-dialysis)								
Normal	3223	290 (8.3%)	1			1		
Low	9049	1130 (11.1%)	0.72 (0.63–0.83)	<.001	<.001	0.39 (0.32–0.47)	<.001	<.001
High	10 077	2031 (16.8%)	1.61 (1.49–1.75)	<.001		1.69 (1.55–1.84)	<.001	
Session duration								
(Continuous)	22 379	3451 (13.4%)	1.06 (1.05–1.07)	<.001		1.03 (1.03–1.04)	<.001	

Abbreviation: TTD, technically troubled dialysis.

predictor for prolonged periods of TTD. Currently, the healthcare team at the Regional Dialysis Centre checks up on patients that have reported 2 or more negative emoticons in their 3 most recent recorded sessions. Ultimately, we may be able to provide a faster form of intervention by changing the workflow to performing a checkup on patients with just 1 self-reported negative emoticon if the session was also classified as a TTD.

Contrary to emoticon sharing, the overall distribution of the sentiment analysis outcomes was more balanced, with the majority of the session notes labeled "neutral" in sentiments. The distribution of sentiment for TTD showed a major decrease in positive sentiment emotions, with the majority having shifted towards the negative side. The difference in the distribution outcomes when compared to emoticons could be attributed to the usage purpose behind the sentiment analysis feature. The optional session note is a free text input which allows patients to write what they felt was important for their healthcare professionals to know. When inspecting the outcomes of each sentiment analysis with their corresponding session note texts, we found that a large majority were contextual-focused, where the primary intent of the session notes were to provide relevant information regarding that particular dialysis session. Some examples included "Zanidip and Avapro at start of treatment. Iron + Arenasp" and "Blood pressure dropped to 78 during dialysis. Reduced UF by 200ml to 1400. Machine was serviced yesterday." The reporting of personal health and the reporting of personal emotions at the end of each dialysis session were the next most frequently observed session note types. Some examples of self-reported health outcomes included messages such as "Feel sick after dialysis" or "finished with headache", and examples of report on personal emotions included simple phrases such as "Awesome. Hungry. Pizza?" or just a single word of "good" as the session note message.

Based on the usage data gathered, patients prefer to use emoticons over writing session notes. The emoticon feature requires only a swipe of the finger to input and is relatively easy to understand while session notes require manually typing 1 or more sentences. As such, the majority of dialysis sessions did not contain a corresponding session note. However, if viewed in regard to TTD sessions, a higher proportion of patients do spend the time to write session notes. When compared to the emoticon entered by the patients, the content of the session notes appears to be more valuable, as it was something which patients felt was necessary for their healthcare professionals to know. Nevertheless, the negative emotions derived from both emoticons and sentiment analysis have been shown to be significantly associated with TTD, highlighting the usefulness of both features. There is potential for such data to be incorporated into existing intervention curriculums in order to improve overall outcomes.

Table 4b. Factors associated with technically troubled dialysis

Predictor	TTD		Univariate analysis			Multivariate analysis		
	No	Yes	OR (95% CI)	P	P (Overall)	OR (95% CI)	P	P (Overall)
Total Sessions	7989	1384 (14.7%)						
Sentiment								
Positive	1155	367 (24.1%)	1			1		
Neutral	5155	922 (15.2%)	5.62 (4.43–7.12)	<.001	<.001	2.67 (2.04–3.49)	<.001	<.001
Negative	1679	95 (5.4%)	3.16 (2.54–3.93)	<.001		1.56 (1.22–2)	0.003	
Age								
<40	1367	406 (22.9%)	1			1		
40–49	650	249 (27.7%)	1.29 (1.07–1.55)	<.001		1.32 (1.06–1.64)	<.001	<.001
50–59	2151	590 (21.5%)	0.92 (0.8–1.07)	<.001		1.06 (0.9–1.25)	<.001	
60–69	1829	93 (4.8%)	0.17 (0.14–0.22)	<.001		0.33 (0.25–0.42)	0.001	
70+	1539	14 (0.9%)	0.03 (0.02–0.05)	<.001		0.1 (0.05–0.17)	<.001	
Missing	453	32 (6.6%)	0.24 (0.16–0.35)	.03		0.37 (0.24–0.55)	0.072	
Sex								
Female	1745	815 (31.8%)	1			1		
Male	6244	569 (8.4%)	5.13 (4.55–5.78)	<.001		5.04 (4.37–5.82)	<.001	
App usage duration								
(Continuous)	7989	1384 (14.7%)	1 (0.99–1)	.346		1.01 (1–1.01)	0.04	
Weight Difference								
(Continuous)	7989	1384 (14.7%)	1.86 (1.76–1.97)	<.001		1.86 (1.74–1.99)	<.001	
Blood Pressure (pre-dialysis)								
Normal	827	103 (11.1%)	1					
Low	2373	348 (12.8%)	0.85 (0.67–1.07)	.006	<.001			
High	4789	933 (16.3%)	1.33 (1.16–1.52)	<.001				
Blood pressure (post-dialysis)								
Normal	1123	131 (10.5%)	1			1		
Low	3093	411 (11.7%)	0.88 (0.71–1.08)	<.001	<.001	0.55 (0.41–0.73)	<.001	<.001
High	3773	842 (18.2%)	1.68 (1.48–1.91)	<.001		2.01 (1.73–2.32)	<.001	
Session duration								
(Continuous)	7989	1384 (14.7%)	1.05 (1.04–1.06)	<.001				

Abbreviations: CI, confidence interval; OR, odds ratio; TTD, technically troubled dialysis.

LIMITATIONS AND FUTURE WORK

The finding of our study should be interpreted with its limitations. One area for improvement would be to increase the accuracy of the sentiment analysis feature, as, during the early phase of the study, we were limited by the amount of data. As such, the algorithm used for classifying sentiment outcome was trained using separate data sources. However, with the current data collected, it is possible to for us to manually annotate the session note data and employ more advanced methods, such as deep learning neural networks, to train on the annotated data. Thus, we hope to provide a much more accurate outlook in regard to sentiment analysis as well as extract more meaningful semantics from the session notes in the future.

As the aim of our study was to investigate the use of emoticon sharing and sentiment analysis during RPM setting at an aggregated level, we did not explore individual patients' reasons for using different emoticons or sharing feelings through text notes. Our future work will include direct evaluation of patients' understanding, use, and interpretation of the emotion-sharing functions to have a comprehensive understanding of the phenomenon.

CONCLUSION

Overall, our study presented a novel RPM system designed to capture and convey patients' emotional statuses through the use of emoticons and sentiment analysis. Of the emotion-capturing features, 78% of all patients actively sent in emoticon representations of their emotions, and 94% have written 1 or more session notes for sentiment analysis. We have shown that HHD patients using our RPM system tend to display and report positive emotions after their dialysis session, even in situations where the hemodialysis session by itself may have been technically troubled, attesting to the benefits of RPM in this population on invasive life-sustaining treatments undertaken by patients in their home environments. When analyzed against the occurrence of TTD, our results showed that negative emotions are significantly associated with TTD and may potentially be a predictor to prolonged periods of TTD.

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AUTHOR CONTRIBUTIONS

RH and NL made substantial contributions to the conception and design of the work as well as interpretation of data; JK and KS supervised the research design and contributed to the writing and revision of the manuscript. MAN, MM, TB, and AA assisted in the data collection and patient communication process. KP aided in the statistical analysis and interpretation of the results. All authors give approval for the final version to be published and agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICT OF INTEREST STATEMENT

None declared.

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