Remote monitoring of COVID-19 patients following early discharge from a tertiary care center

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Abstract

The COVID-19 pandemic has affected most people in some or the other way. For those who have been unfortunate to have been hospitalised owing to the disease, the presence of illness sequelae warrants extra attention, care and monitoring [1].

Remote monitoring techniques have been implemented in several domains of healthcare such as cardiology, cardiac rehabilitation, pregnancy, medication intake and adherence monitoring [2]. Monitoring of vital signs using these technologies has allowed to track the health of patients with more granularity while improving symptoms and clinical outcomes. Therefore, remote monitoring can be of tremendous benefit in the case of COVID-19 by alleviating clinical burden on hospitals and healthcare staff.

In this study, we investigated the use of remote monitoring on a COVID-19 population discharged early from a tertiary care center. The longitudinal progression of sensor and questionnaire data was studied using linear mixed effect models. The changes of heart rate were statistically significant in terms of the slope, indicating a difference between alert-generating and non-alert generating patients.

1. Introduction

To say that SARS-CoV-2 or COVID-19 (as referred to colloquially) has had a tremendous impact on our lives for the past two-and-a-half years would be an understatement. The world has witnessed a total of just over 600 million COVID-19 cases leading to almost 6.5 million deaths. In Belgium alone, there have been almost 4.5 million cases of COVID-19 resulting in more than 32,000 deaths.

The challenge in combating COVID-19 at the beginning of the pandemic was primarily due to lack of information about the disease and its progression. However, the occurrence of multiple waves of the disease and a mounting toll of deaths has highlighted the importance of illness sequelae from the illness and due to hospitalisation.

Remote monitoring is a useful tool that has been used in multiple domains of health and care including cardiology, cardiac rehabilitation, pregnancy and medication monitoring. The primary benefits of remote monitoring lie in the preventive and diagnostic aspects [3].

2. Materials and methods

2.1. Data description

28 patients who were admitted to Ziekenhuis Oost-Limburg in Genk due to COVID-19 and subsequently discharged early from the hospital were included in this single-center, prospective, interventional study (EC-n° 20-0039U). Patients were provided with a pulse oximeter (to measure SpO2 and heart rate) and a thermometer to measure core body temperature. In addition to this, they were also asked to fill in questionnaires on their perceived well-being. All data was to be filled in three times a day for a minimum of 5 days via a remote monitoring platform of the hospital.

An overview of the study cohort is shown in Figure 1. 4 patients were excluded from the study owing to difficulties association with handling the measurement technologies.

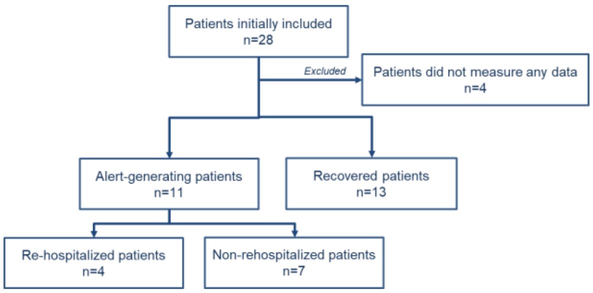

Figure 1 Overview of study cohort

A summary of the data collected in this study is shown in Table 1. Table 2 explains the scales and ranges of the different questionnaire parameters that were collected.

Table 1 Overview of the data collected in the study

Data description	Parameter measured
Sensor data	Heart rate
	SpO2
	Temperature
Questionnaire data	General well-being score
	Dyspnea score
	Relative well-being score

Table 2 Description of the questionnaire data collected

Parameter	Range
General well-being score	1 (poor) to 5 (outstanding)
Dyspnea score	1 (no breathlessness) to 10 (highest breathlessness)
Relative well-being score	1 (worse than yesterday) to 3 (better than yesterday)

The subjects were assigned into two groups based on the sensor and questionnaire data - alert-generating and non-alert generating patients. An alert was defined as the simultaneous occurrence of at least two of the following conditions:

- SpO2 value < 90%
- Temperature ≥ 38°C
- Relative well-being score < 3

These conditions for triggering an alert were based on the criteria used by physicians in the remote monitoring pathway of COVID-19 patients to determine whether patients had to be re-hospitalized or not.

The demographic information of the study cohort is shown in Table 3.

Table 3 Summary of demographic information

Parameter	Alert-generating patients (n=11)	Non-alert generating patients (n=13)
Age (years)	53.45 ± 10.36	57.31 ± 10.45
BMI (kg/m^2)	32.24 ± 5.59	31.22 ± 3.36
Male	9 (82%)	9 (69%)
Days in hospital prior to discharge	6.69 ± 4.32	7.45 ± 4.62

2.2. Data processing

Discrete data collected from patients was converted from wide to long format and subsequently processed using scientific libraries in Python including Pandas and Numpy. This involved outlier detection and removal of outliers in temperature, SpO2 and HR signals. The parameters were averaged to obtain a single value per day for further processing.

2.3. Exploratory Data Analysis

As a part of exploratory data analysis, demographic information of patients was compared between the two groups using a two-sample t-test for independent groups. Since the questionnaire data were found to not adhere to a normal distribution (p-value of Shapiro-Wilks test > α), non-normality of data was assumed and Welch's t-test was performed. Histograms and boxplots of all data were plotted to visually explore the underlying distributions of data.

2.4. Linear mixed effect models

During the data collection procedure, some patients collected data for more than the proposed study duration. This combined with the fact that the dataset consists of different levels in terms of patient groups necessitates the need for using mixed effect models. Since ANOVA-based techniques consider time as a categorical variable, they are not suitable for this dataset. Therefore linear mixed effect models were fit on this data to determine for statistically significant differences between groups for sensor and questionnaire data over time.

The 'Statsmodels' library in Python was used to implement the mixed effect models on the Heart Rate and General well-being score data. The limited memory implementation of the Broyden–Fletcher–Goldfarb–Shanno (L-BFGS) optimization algorithm was used to fit the model on the data. Slopes and intercepts were included as random effects in order to account for subject-specific variations of these parameters within groups.

3. Results

3.1. Exploratory data analysis

There were no statistically significant differences between the alert-generating and non-alert generating groups with regard to their demographic information ($p>0.05$). The average BMI of both groups was higher than 30, indicating a presence of obesity in both groups. Visual analysis of the boxplots shows a difference in the trends of the SpO2 and temperature data for both groups. Since this data was used for the post-hoc grouping of patients, no statistical analysis was performed on these parameters.

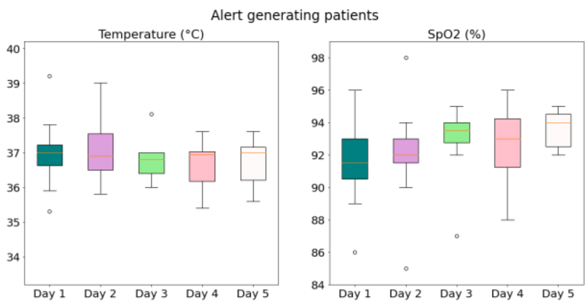

Figure 2 Boxplots of SpO2 and temperature data for alert-generating patients

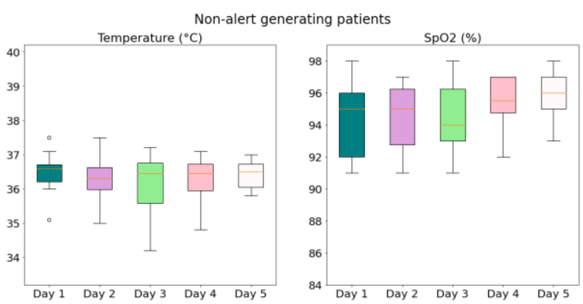

Figure 3 Boxplots of SpO2 and temperature data for non-alert-generating patients

3.1. Linear mixed effect models

The linear mixed effect models fitted for the 'General well-being' score did not show statistical significance in terms of the parameter varying with time differently across both groups. Subject-specific random slopes and intercepts did not also show statistical significance.

Linear mixed effect models fitted for heart rate data did not show statistical significance for the random effects (random slopes and random intercepts). However, for the fixed effect of HR varying over time differently across the two groups, there was a statistically significant difference ($p<0.001$).

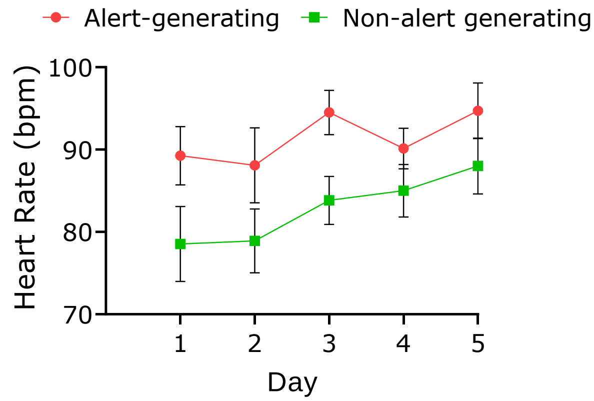

Figure 4 Longitudinal trend of Heart Rate data

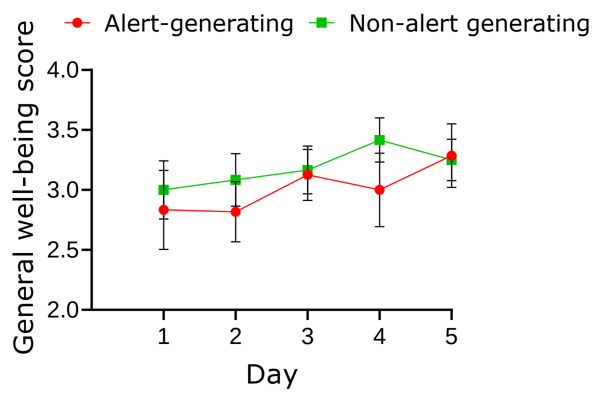

Figure 5 Longitudinal trend of General Well-being Score

4. Discussion

Analysis of the BMI of both groups showed a mean value greater than 30 indicating the presence of obesity in both groups. This is important since it can indicate the presence of obesity being a risk factor for hospitalisation in case of COVID-19 patients.

A comparison of boxplots of SpO2 data for both groups indicates a higher baseline value for the non-alert generating group as well as a higher end value. With regard to the temperature data, it can be seen that the median and upper quartile values for the alert-generating patients is higher.

Since the fixed effect of the slope of HR data was statistically significant, it can be inferred that the progression of HR was difference for both groups across the duration of the study. While the HR of both patients increased, the slope for the non-alert-generating patients was steeper. This suggests either an improvement in disease status leading to greater activity levels of patients or worsening of disease status resulting in increase in resting heart rate values.

5. Conclusion

Sensor and questionnaire data were collected longitudinally from a cohort of COVID-19 patients discharged early from a hospital. The alert-generating and non-alert-generating patients did not differ significantly in terms of their demographic information ($p>0.05$). The only statistically significant difference between the two groups of patients was in the slope of the HR data.

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