

Remote Monitoring of COVID-19 Patients Following Discharge from a Tertiary Care Center

Ganesh Raam Kumarasamy^{1,2,3,4}, H el ene De Canni ere^{1,2}, Julie Vranken^{1,2}, David Ruttens⁵, Peter Karsmakers^{3,4}, Pieter Vandervoort^{2,6}

¹Hasselt University, Mobile Health Unit, Diepenbeek, Belgium

²Ziekenhuis Oost-Limburg, Future Health Department, Genk, Belgium

³KU Leuven, Declarative Languages and Artificial Intelligence, Leuven, Belgium

⁴KU Leuven, Advance Integrated Sensing, Geel, Belgium

⁵Ziekenhuis Oost-Limburg, Department of Pneumology, Genk, Belgium

⁶Ziekenhuis Oost-Limburg, Department of Cardiology, Genk, Belgium

Abstract

The COVID-19 pandemic has affected people, healthcare systems and caregivers on a global scale causing bottlenecks in hospital resources and overload of healthcare systems. The presence of disease sequelae in patients hospitalized due to COVID-19 warrants additional care and monitoring of these patients.

Remote monitoring techniques have been implemented in several domains of healthcare such as cardiology, cardiac rehabilitation and nephrology. Monitoring of vital signs using these technologies has allowed the tracking of patients with more granularity, resulting in better clinical outcomes such as reduction in hospitalizations. Therefore, we hypothesize that remote monitoring is beneficial in managing COVID-19 patients post-hospitalization, enabling home-based patient follow-up.

In this study, we investigated the use of remote monitoring on a COVID-19 patient cohort discharged from a tertiary care center. A post-hoc division of patients into two groups (alert-generating patients and non-alert generating patients) was performed. The longitudinal progression of sensor and questionnaire data was studied using linear mixed-effect models. The measured heart rate values were statistically significant in terms of the intercept ($p < 0.001$), indicating a difference between the two patient groups at baseline immediately post-discharge.

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 [1]. In Belgium, there have been almost 4.5 million cases of

COVID-19 resulting in more than 32,000 deaths [2].

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 recurrence of disease in patients and high mortality rates following hospitalization has highlighted the importance of monitoring patients post-discharge.

Remote monitoring is a useful tool to monitor progression of diseases outside the hospital. It has been used in multiple domains of healthcare including cardiology, cardiac rehabilitation, pregnancy, nephrology and medication monitoring [3][4][5]. Benefits of remote monitoring include increased monitoring granularity and improvement of clinical outcomes such as hospital length-of-stay and reduction in number of visits to the emergency department [6]. Therefore, remote monitoring can be leveraged for COVID-19 patients to facilitate discharge from hospitals and enable home-based patient follow-up.

Based on this hypothesis, this study was designed to explore remote monitoring for COVID-19 and patients discharged after hospitalisation due to COVID-19 were included in the study.

2. Materials and methods

2.1. Data collection and description

28 patients who were admitted to Ziekenhuis Oost-Limburg in Genk, Belgium due to COVID-19 and subsequently discharged from the hospital were included in this single-center, prospective, interventional study (EC-n o 20-0039U). Patients were provided with a pulse oximeter (to measure oxygen saturation (SpO₂) and heart rate [HR]) and a thermometer to measure core body temperature at home. Additionally, they were also asked to fill in questionnaires on their perceived well-being.

Patients were asked to measure the above parameters for a minimum of 5 days, 3 times per day. The remote monitoring platform of Ziekenhuis Oost-Limburg was used to register the patient data [7].

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

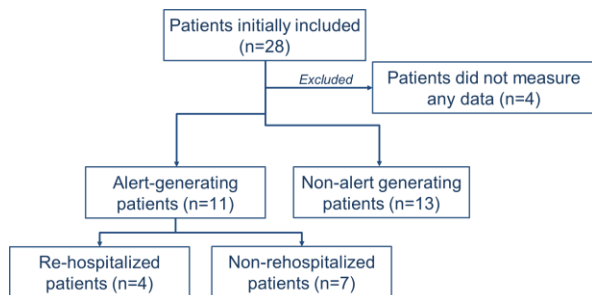


Figure 1 Overview of study cohort

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 collected.

Table 1 Overview of the data collected in the study

Data description	Parameter measured	Frequency of measurement
Sensor data	Heart rate	3x/day
	SpO ₂	3x/day
	Temperature	3x/day
Questionnaire data	General well-being score	3x/day
	Dyspnea score	3x/day
	Relative well-being score	1x/day

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)

A post-hoc division of patients into two groups was performed with patients assigned to the ‘alert-generating’ or the ‘non-alert generating’ group. 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

The criteria to define an alert were based on clinical guidelines used by pulmonologists in the remote monitoring pathway of COVID-19 to determine if patients had to be re-hospitalized or not. The creation of patient groups did not differentiate patients based on the number of alerts generated or the timestamp of alert generation.

2.2. Data processing

Data collected from patients was processed using the Numpy and Pandas libraries in Python 3.7. Preprocessing involved outlier detection and subsequent removal in temperature, SpO₂, dyspnea score and HR signals. The parameters were then 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 patient groups. Normality was tested using the Shapiro-Wilks test and the demographic data was found to not adhere to a normal distribution ($p < 0.05$). Therefore, the Welch’s t-test for independent groups was used for statistical differences across the demographic parameters. Histograms and boxplots of SpO₂ and temperature data were plotted to visually explore the underlying distributions of these signals (Figure 2 and Figure 3).

2.4. Linear mixed-effect models

During data collection, some patients collected data for more than the proposed study duration of 5 days. This, combined with the division of patients into two groups, necessitates the need for using mixed-effect models over traditional ANOVA-based techniques which consider time as a categorical variable. Mixed models have the additional advantage of allowing subject-specific slopes and intercepts to be modelled when testing for group-level differences. Therefore, linear mixed-effect models were fit on HR and ‘general well-being score’ data to check for statistically significant differences between groups over time. Since the SpO₂, temperature and ‘relative wellbeing’ score signals were used for post-hoc grouping of patients, no statistical analysis was performed on them. The ‘Statsmodels’ library in Python was used to implement the mixed-effect models. The limited memory implementation of the Broyden–Fletcher–Goldfarb–Shanno (L-BFGS) optimization algorithm was used for model fitting. Slopes and intercepts were included as fixed and random effects in order to account for subject-specific and group-specific variations.

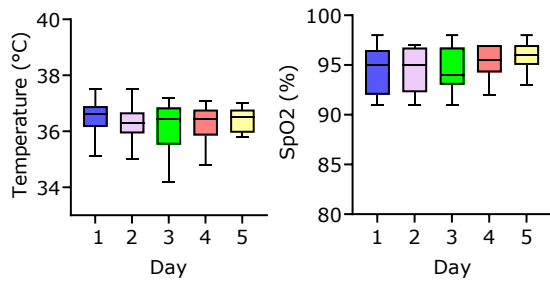


Figure 2 Boxplots of SpO2 and temperature data for non-alert generating patients

3. Results

3.1. Exploratory data analysis

Table 3 Summary of demographic information

Parameter	Alert-generating patients (n=11)	Non-alert generating patients (n=13)
Age (years) (p = 0.40)	53.45 ± 10.36	57.31 ± 10.45
BMI (kg/m ²) (p = 0.62)	32.24 ± 5.59	31.22 ± 3.36
Male	9 (82%)	9 (69%)
Days in hospital before discharge (p = 0.70)	6.69 ± 4.32	7.45 ± 4.62

A summary of the demographic information of the patient cohort is shown in Table 3. No statistically significant differences were found between the ages of the two patient groups (p = 0.40) and days of initial hospitalisation (p = 0.70). While the BMI of the two patient groups did not have a statistically significant difference (p = 0.62), both groups had a BMI of greater than 30, indicating the presence of obesity. The difference in length-of-stay between the groups was not statistically

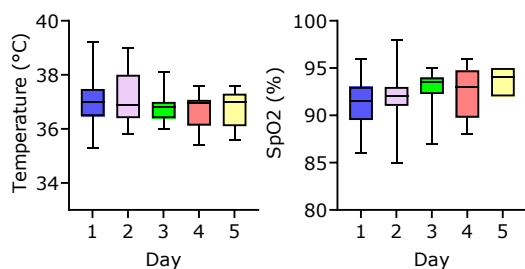


Figure 3 Boxplots of SpO2 and temperature data for alert-generating patients

significant, but the alert-generating group spent an average of 0.76 days longer at the hospital. Visual analysis of the boxplots showed a difference in the trends of the SpO₂ and temperature data for both groups.

3.2. Linear mixed-effect models

Linear mixed-effect models fitted for HR data did not show statistical significance for the random effects i.e., slopes and intercepts (p > 0.05). However, for the fixed effect of HR intercepts across the two groups, a statistically significant difference (p < 0.001*) was seen (Figure 4).

The linear mixed-effect models fitted for the ‘General well-being’ score did not show statistical significance differently across both groups (p > 0.05) for both slopes and intercept values (Figure 5). In addition, within-group differences between slopes and intercepts did not show statistical significance (p > 0.05).

● Alert-generating ■ Non-alert generating

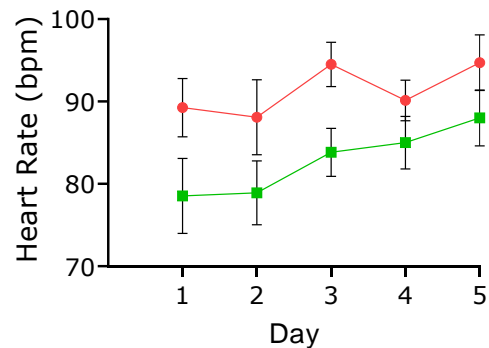


Figure 4 Longitudinal trend of Heart Rate data*

4. Discussion

4.1. Exploratory data analysis

Analysis of the BMI of both groups showed a mean value greater than 30 indicating the presence of obesity in both groups, confirming the presence of obesity as a risk factor for hospitalisation for patients with COVID-19. This corroborates the findings of the studies in [8], [9] and [10]. While the non-alert generating patient group spent almost one additional day at the hospital, this difference in the length-of-stay was not statistically significant.

A comparison of boxplots of SpO₂ data for both patient groups indicates a higher median value at discharge for the non-alert generating group, indicating relatively better disease status at discharge. The end-study SpO₂ values for the non-alert generating patients were higher as well indicating an improvement in disease status over the study duration.

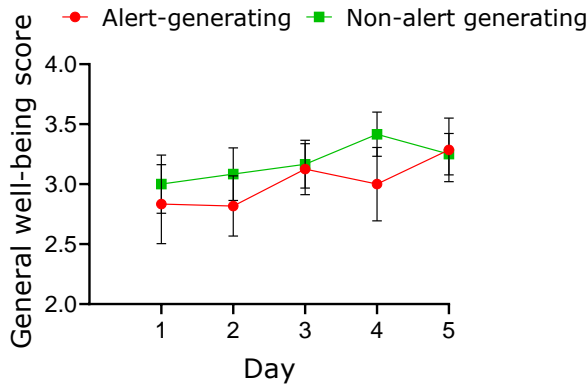


Figure 5 Longitudinal trend of General Well-being Score

This is expected since this patient group did not trigger any alerts and did not have adverse clinical outcomes during the study and is in line with existing literature that has reported a strong association between hypoxemia and worse clinical outcomes [11] [12]. With respect to the temperature data, it can be seen that the median and upper quartile values for the alert-generating patients is higher. This indicates the presence of fever (temperature $\geq 38^{\circ}\text{C}$) in these patients, especially during the first three days post-discharge. This is an important finding, highlighting the significance of the immediate period after discharge.

4.2. Linear mixed-effect models

Since the intercept of HR data was statistically significant, it can be inferred that the baseline HR at discharge was different between the two groups. The HR values for the alert-generating patients were higher, indicating worse health status at discharge. This is also validated by the triggering of alerts by this patient group in the immediate days post-discharge, attaching greater importance to remote monitoring during this period.

5. Conclusion

Sensor and questionnaire data were collected longitudinally from a cohort of COVID-19 patients following hospitalization. Patients were divided into two groups (alert-generating and non-alert generating patients) post-hoc based on the collected data. The two patient groups showed statistically significant differences in terms of the intercepts of the measured HR values. While other results were not statistically significant, trends showed differences in the two patient groups in terms of the SpO_2 signals and temperature values. The BMI of both groups was above 30, indicating the presence of obesity. Since patient alerts were generated within the first 5 days after discharge, this study highlights the importance of remote monitoring in the period immediately after discharge. Further investigation by means of larger cohort sizes is

necessary to confirm the findings of this study.

Acknowledgments

The authors would like to acknowledge Dr. David Ruttens for his help in data collection for this project. The authors would like to thank the assistants and nurses at the Department of Pneumology, Ziekenhuis Oost-Limburg as well as the scientific researchers of Future Health for their help in the data collection procedure.

References

- [1] COVID Live – Coronavirus Statistics - Worldometer [Internet]. United States of America: [publisher unknown]; 2020 January 01 [updated 2022 Sep 23; cited 2022 Sep 01]. Available from: www.worldometers.info/coronavirus/
- [2] Belgium Coronavirus Statistics - Worldometer [Internet]. United States of America: [publisher unknown]; 2020 January 01 [updated 2022 Sep 23; cited 2022 Sep 01]. From: worldometers.info/coronavirus/country/belgium/
- [3] Eisenkraft, Arik, et al.. "Continuous remote patient monitoring shows early cardiovascular changes in COVID-19 patients." *Journal of Clin. Med.* 10, (2021)
- [4] Boriani G, et al. "Effects of remote monitoring on clinical outcomes and use of healthcare resources in heart failure" *Europ. Jour. of Heart. Fail.* 2017 Mar;19(3):416-25.
- [5] Milan Manani S et al. "Remote monitoring in peritoneal dialysis: benefits on clinical outcomes and on quality of life." *Jour. of Neph.* 2020 Dec;33(6):1301-8.
- [6] Martirosyan M, Caliskan K, Theuns DA, Szili-Torok T. "Remote monitoring of heart failure: benefits for therapeutic decision making." *Exp. Rev. of Cardiovasc. Ther.*. 2017 Jul 3;15(7):503-15.
- [7] Gruwez H, et al. "Remote patient monitoring in COVID-19: a critical appraisal." *Eur. Resp. Jour.* 2022 Feb 1;59(2).
- [8] Malik P, et al. "Obesity a predictor of outcomes of COVID-19 hospitalized patients—a systematic review and meta-analysis." *Jour. of Med. Vir.* 2021 Feb;93(2):1188-93.
- [9] de Siqueira JV, et al. "Impact of obesity on hospitalizations and mortality, due to COVID-19: A systematic review." *Obes. Res. & Clin. Prac.* 2020 Sep 1;14(5):398-403.
- [10] Cottini M, et al. "Obesity is a major risk factor for hospitalization in community-managed COVID-19 pneumonia." *Mayo Clin. Proc.* 2021 Apr 1 pp. 921-931.
- [11] Xie J, et al. "Association between hypoxemia and mortality in patients with COVID-19." *Mayo Clin. Proc.* 2020 Jun 1, pp. 1138-1147.
- [12] Duan J, et al. "Correlation between the variables collected at admission and progression to severe cases during hospitalization among patients with COVID-19 in Chongqing." *Jour. of Med. Vir.* 2020 Nov;92(11):2616-22.

Address for correspondence:

Ganesh Raam Kumarasamy
Ziekenhuis Oost-Limburg, Kantoor M 9.16,
Schiepse Bos 6, 3600 Genk, Belgium
ganesh.kumarasamy@uhasselt.be