Case Report

Remote Patient Monitoring for Global Emergencies: a case study in COVID-19 patients

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Remote Patient Monitoring for Global Emergencies: A Case Study in COVID-19 Patients

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Abstract: Background: The COVID-19 pandemic has highlighted the critical need for telehealth and remote patient monitoring in healthcare delivery. Despite the growing use of on-body wearable sensors for continuous monitoring and predicting adverse events, such as hospitalizations or falls, their widespread adoption within the healthcare ecosystem remains a significant challenge. While the pandemic has accelerated the acceptance of these technologies, achieving widespread integration requires their sustained incorporation into routine healthcare practices beyond emergency situations. In this study, we extend the application of our previously developed remote patient monitoring system, originally designed for the geriatric frail population, to COVID-19 patients. Our objective is to assess whether the metrics obtained from this system, which includes physical activity and indoor localization sensors, along with vital sign monitoring, can provide additional insights into the recovery trajectory of individuals affected by COVID-19. **Objective:** The objective of this case study is to demonstrate that remote patient monitoring systems, can be adapted to diverse patient cohorts during emergencies. We aim to illustrate the ease of deployment, particularly when these systems are already integrated into the existing healthcare ecosystem. **Methods:** From November 2020 to July 2021, 73 patients were recruited through the UCLA Center for Smart Health after being consented to participate in the study for two weeks. The research concentrated on an exploratory analysis, focusing on the detailed examination of characteristics and behaviors of COVID-19 patients as captured by the remote patient monitoring system. We collected day-to-day changes in the following sensor measurements: daily activity, daily energy expenditure, indoor localization, Sp02, respiratory rate, heart rate, and temperature. **Results:** Out of the 73 patients satisfying the inclusion criteria, 41 successfully adhered to using the monitoring technology, with only 22 providing substantial watch data (>4 hours). Among the participants, 39 used the pulse oximeter, 37 used the thermometer, and 36 utilized respiratory monitoring at night. The study demonstrated an overall increase in patients' activity levels towards the end of the study, with many beginning to leave their homes after two weeks. Additionally, respiratory rates shifted towards healthier lower levels, and oxygen saturation improved. Fatigue and headache were identified as the most prevalent symptoms, followed by cough and loss of smell. **Conclusions:** The conclusion highlights the critical importance of monitoring patients outside of hospital settings, especially during pandemics when patient travel to hospitals or home visits by healthcare professionals could increase the risk of disease transmission. Studies demonstrating the benefits and efficacy of remote monitoring in home settings can better prepare healthcare professionals for future pandemic events. Continuous monitoring of a wide range of patient metrics, from activities to vital signs, and integrating this data into electronic health records would not only improve accuracy and reduce the burden of data collection but also pave the way for enhanced home care, offering higher quality care at a lower cost.

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Keywords: COVID-19; remote sensing technology; physical activity; health care delivery models; wearable sensors; indoor localization; bluetooth low energy beacons; smartwatches

Introduction

In late 2019, an outbreak of coronavirus disease 2019 (COVID-19) emerged and spread rapidly worldwide. As of May 5th, 2020, where we began this study, there were more than 3.6M confirmed cases and >250,000 deaths attributed to COVID-19 worldwide; with over 69,000 deaths alone in the United States. These numbers have reached 7M deaths worldwide including 1.2M in United States only (1,2). Despite the development of multiple vaccines, the virus and its new variants continue to wreak havoc in the public health sector. While the mortality rate for COVID-19 was reported to be around 2%, the number was significantly increased among older patients with underlying coexisting conditions. Notably, in hospitalized patients, the death rate approached 15%. Individuals who were at mild to moderate risk, such as those with cancer, could demonstrate significant clinical deterioration within 24-48 hours.

In recent years during COVID-19 pandemic, we observed the implementation of policies such as "shelter in place" aimed at preventing the unnecessary strain on the healthcare system, measures that may become necessary in the face of another pandemic. Some high-risk patients were instructed to "weather the storm" at home without adequate monitoring, despite the potential for rapid deterioration in their health (3). Over the past decade, the emergence of commercially available, affordable, and lightweight sensors has significantly accelerated the adoption of remote patient monitoring systems within the healthcare system for continuous and comprehensive patient tracking. Even prior to the COVID-19 pandemic, substantial evidence indicated that continuous monitoring of vital signs, such as pulse oximetry and heart rate, was associated with reduced mortality (4,5). This aligns with numerous studies conducted during the pandemic, which explored the use of pulse oximetry and other wearable devices for continuous vital sign monitoring (4,6,7). During the COVID-19 pandemic, numerous studies evaluated the use of technology for patient management and assessed its effectiveness in reducing hospitalizations (3,6,8–11). While some initiatives were labeled as Remote Patient Monitoring, they often focused more on telehealth, e-visits, and the utilization of patients' existing technologies, such as smartphones to connect to healthcare professionals. These studies demonstrated encouraging results, indicating that technology can significantly enhance patient management (6,8,9).

In a series of studies, we had introduced and documented the development and implementation of our remote patient monitoring system and its clinical validation within older patient populations at-risk of various health conditions (12–15). This platform, known as Sensing At-Risk Population (SARP), encompasses activity monitoring through smartwatches, indoor localization using stationary beacons, and the collection of additional physiological data via wireless sensors. Data is securely and automatically transmitted to a HIPAA-compliant cloud infrastructure. For this study, we expanded the capabilities of our system to serve as a monitoring hub and to support additional devices tailored to the needs of COVID+ patients. We incorporated commercially available Bluetooth-enabled thermometers, pulse oximeters, and respiratory distress monitors. These additions enabled us to capture relevant information for monitoring and assessing COVID+ cases. The primary objective of this study was to enhance existing outpatient COVID+ clinical trials, which incorporates the variables that our system captures as secondary or exploratory endpoints. By leveraging our platform, we aimed to minimize COVID+ patients' exposure while collecting crucial vital information. Our intention was to gather this data within a natural environment, shedding light on the diverse array of symptoms presented by COVID+ patients, thus contributing to a better understanding of this disease and the ongoing pandemic using the emerging remote patient monitoring systems.

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Methods

Design, Setting and Participants

Study design and participants Patient recruitment occurred from November 2020 to March 2021 at University of California, Los Angeles (UCLA) Health center. We emphasized that participation in the study would not affect their care at UCLA and was entirely separate from their medical treatment. Participation would conclude either after a two-week period or if the patient was admitted to the hospital during that timeframe.

Eligible participants were individuals aged 18 or older with a COVID-19 diagnosis who were not hospitalized or had known exposure to a COVID-19 positive case. They required the ability to manage their condition at home, access to home WiFi, proficiency in either English or Spanish, and a willingness to provide informed consent by signing the approved form (IRB #20-001565) from the University of California, Los Angeles, titled "Early Detection of Health Improvement and Decline through Remote Health Monitoring in COVID-19 Positive Patients.

Inclusion and Exclusion Criteria

Wearable device compatibility (ability to wear a watch), willingness to host the remote monitoring system for a 2-week period, age 18 or older, current UCLA Health patient, confirmed positive COVID-19 lab result or known exposure to COVID-19.

To ensure the meaningfulness of the activity data, we imposed an additional inclusion criterion requiring a minimum daily wear time of the smartwatch of at least 4 hours. However, the utilization of the Remote Patient Monitoring (RPM) kit was not limited solely to the smartwatch; it also included a thermometer and pulse oximeter for spot checks, along with a respiratory monitor capable of continuous data capture. Data collection was conducted either continuously or at specific intervals from these devices. For analysis, we included individuals with measurements taken on more than 7 distinct days and calculated the mean value of the metric for each day.

Exclusion Criteria: Clinical diagnosis of movement disorders (e.g., Parkinson's Disease), failure to meet inclusion criteria.

Sensing At-Risk Population (SARP)

Sensing At-Risk Population (SARP) is a Remote Patient Monitoring system (RPM) developed by UCLA's Center for SMART Health, designed to cater to patients beyond the confines of healthcare institutions. Its primary purpose is to monitor vulnerable, at-risk populations by simulating the measurement of Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL) (16) through cost-effective sensor technology. SARP has been employed to generate prognostic data and predictive models for mortality and functional decline (12–15).

The core components of SARP encompass hardware, including an Android Smartwatch and readily available proximity BLE Beacons, and clinically validated software featuring activity recognition and indoor localization algorithms. Additionally, SARP incorporates a remotely triggered adaptive smart questionnaire mechanism, data visualization tools, and algorithms for assessing frailty, all within a HIPAA-compliant infrastructure (17).

Activity features were derived from three groups of parameters using smartwatches and BLE beacons: (1) activity recognition (e.g., sitting time, standing time), (2) indoor localization (e.g., time in bed, time in the bathroom), and (3) raw acceleration quantification (Mean Absolute Deviation in Accelerometer signal: MAD). By combining these attributes, we created features such as sitting time in bed and energy expenditure during walking or while in bed (12,13).

To ensure fair comparisons among patients with different watch wear times, we normalized features by dividing the time spent on activities or in locations by the total wear time (uptime). Energy-related features were also normalized by uptime to yield energy intensity and by the total daily value to calculate energy percentage.

Bluetooth Low Energy (BLE) beacons are used in the SARP system to estimate indoor patient locations by measuring the Received Signal Strength Indicator (RSSI) values via smartwatches (18–

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20). Patients were instructed to place a BLE beacon in each designated indoor location: the kitchen, bathroom, bedroom, dining room, and TV/sitting room. If the system does not detect any beacons, it infers that the patient is outside, indicating they are not at home.

Data Collection

For this study, SARP was modified to integrate a series of FDA-cleared Bluetooth-enabled devices, including pulse oximeters, thermometers, and Ultra-Wideband (UWB) radar technology for monitoring respiratory characteristics. Numerous studies have demonstrated the utility of such metrics for patient assessment, with subsequent research validating the accuracy of Bluetooth-enabled devices for home or remote monitoring (5,7,9,10,21–24). However, discussing the efficacy of these devices is beyond the scope of this paper; we assume their outputs are reliable given that all the devices used have FDA clearance. Nevertheless, it is worth noting that some studies suggest UWB radar may overestimate respiratory rates at low levels and underestimate them at high levels, as indicated in (25,26).

Bluetooth-enabled devices were used to augment an established system, gathering extra patient data remotely. This information was securely uploaded to a HIPAA-compliant cloud system, enhancing the infrastructure for remote patient monitoring. Bluetooth-enabled devices used for capturing vital signs complemented the existing SARP infrastructure by remotely gathering additional vital data from patients. The data from these devices were collected and uploaded to a HIPAA-compliant Azure IoT cloud infrastructure. By incorporating additional Bluetooth devices, we dynamically expanded the capabilities of our remote monitoring system to accommodate varying patient needs. Specifically, for this project, pulse oximeters and thermometers were used to detect COVID-19 symptoms, such as shortness of breath and fever, enabling us to make testing recommendations for patients. Additionally, SARP integrated an FDA-cleared Bluetooth device equipped with radar, a microphone, and a light sensor to monitor respiration and detect conditions such as hypoventilation, hyperventilation, and impaired lung function. The respiration monitoring device was recommended to be positioned adjacent to the patient's bed to observe breathing patterns, primarily during nighttime or when the patient was present in the room.

We recorded the day-to-day changes in the following sensor measurements and compiled the assessments shown in the Table 1:***Position:*** Lying down, Sitting, Standing, Walking

2. ***Active:*** Active (Walking), Active (Not Walking), Non-Active
3. ***Steps:*** Total daily steps. Total distance traveled
4. ***Indoor Localization:*** Bedroom, Bathroom, Kitchen, Dining Room, Family Room, Office
5. ***Sleep Quality:*** Duration and Toss and Turn
6. ***Heart Rate:*** ever hour + during walking speed measurements
7. ***Temperature*** with Infrared technology
8. ***SpO***$_2$ Oxygen Saturation with pulse oximetry
9. ***Breath per Min (BrPM)*** with UWB radar Technology
10. ***Respiration Waveform*** (Inhalation/Exhalation Patterns) with UWB radar Technology

Table 1. Patient Assessments from Sensor Measurements.

Summary Sensor Assessments
• Percent of time out of bedroom
• Percent of time out of house
• Percent of time walking
• Total daily steps
• Walking Speed
• Counts of activities and locations

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• Total Active time
• Total Energy
• Weighted total activity score
• Hourly Temperature
• Hourly SpO_2
• Hourly average BrPM
• Respiratory rate and chest displacement
• Early Warning Score

As described in (12), active/non-active is determined by an empirical threshold of 0.02 m/s^2 (2 cm/s^2) imposed on the MAD value of an accelerometer signal in every 10 seconds. The threshold translates to 1 meter of displacement of the hand in 10 seconds (hand wearing the smartwatch with accelerometer). Furthermore, the energy expenditure is estimated to be proportional to the Mean Absolute Deviation (MAD) of accelerometer magnitude signal.

Exploratory Analysis

The primary objective of this study was to conduct an observational analysis aimed at developing predictive models for forecasting adverse COVID-19 outcomes, including hospitalization within 24 or 48 hours. Given the absence of adverse events among the participants, the research emphasis shifted towards an exploratory analysis, concentrating on the delineation of characteristics and behaviors of COVID-19 patients as captured by the remote patient monitoring system.

All the analysis were performed using Python Programming Language (version 3.11.3) libraries Pandas (version 2.2.1), Numpy (version 1.25.2), Scipy (version 1.11.1), Scikit-learn (version 1.3) and Searborn library (version 0.12.2) was used for statistical data visualization.

Activity and Energy

Energy intensity, as detailed in the SARP section, was analyzed for all individuals on their first day of the study (baseline) and their last day using a box plot. The plot displays the median line, representing the central tendency, and the overall distribution of energy intensity values. It is important to note that these observations were made after applying the inclusion criteria, which only considered days where patients had more than 4 hours of watch wear time.

Using Bluetooth beacons, the time each patient spent in specified locations within their home was calculated to better form a daily storyline of their activity patterns. The goal was to assess whether patients spent less time in the bedroom as the study progressed and whether they spent more time outside their residence. The percentage of time spent in each location was calculated by dividing the duration in that location by the total uptime (watch wear time) for that day. A heatmap was generated to visualize the average percentage of time spent in each location longitudinally over a 2-week period.

It is important to note that data was analyzed after applying inclusion criteria, and some participants were in the study for fewer than 2 weeks. For each day of the study, the time spent in each location was averaged across the number of patients observed on that particular day. Given that the start and end dates varied across patients, the analysis was conducted by calculating each patient's individual day. For example, "Day 1" represents the average time percentage spent in each location for all patients on their respective first day, which may differ chronologically between patients.

Vital Signs

The distributions of SpO2, pulse rate, respiratory rate, and temperature were visualized using kernel density estimate (KDE) plots. The KDE plots depict patients' baseline (the first day of data

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collection) and their final day (the last available day of the study). For each patient, the mean value of observations was used for both the baseline and the final day. A minimum interval of 7 days between the baseline and final day was enforced to exclude patients with only a few days of data, as their differences could not accurately represent longitudinal trends. It is important to note that the KDE visualization may include out-of-bounds values due to the edge effect, where Gaussian distribution-based estimation extends beyond the actual data range. When the observations are close to the edges of the data range, the KDE which is formed by centering around each data point, may extend beyond the boundary. This can be addressed by truncating the graph and clipping x-axis out of bound values, although this is merely a visualization adjustment. Alternatively, the edge effect can be mitigated by smoothing the KDE curve through bandwidth adjustment. In the Seaborn library, the default bandwidth value is determined by Scott's rule (set to 1) (27) and automatically adapts to the data characteristics (28). While increasing the bandwidth reduces sensitivity to individual observations and produces a smoother curve, the authors opted not to adjust the bandwidth due to the limited number of observations and the need to maintain the graph's sensitivity to changes.

Self-Reported Survey

Daily self-reported surveys, collected using the SARP app provided to patients on tablets, were integrated with sensor data. The purpose of this integration was to later align the data with potential complications, including cardiovascular issues or hospitalizations, to retrospectively investigate whether any early indications could have been inferred from the observational data. This analysis aimed to identify potential early warning signs and develop timely interventions.

Results

Demographic Characteristics

Out of 176 interested patients who were approached by our team, 73 met the eligibility criteria and were enrolled to utilize our remote patient monitoring kit, SARP as detailed in Table 2. Of these, 41 patients successfully connected to and complied with the system.

Table 2. Sociodemographic characteristics of the patient cohort.

Characteristics	# of patients
	N=73 (%)
Race	
White	42 (57.5)
Black or African American	6 (8.2)
Asian	3 (4.1)
Hawaiian/other Pacific Islander	1 (1.4)
Other	21 (28.8)
Ethnicity	
Not Hispanic or Latino	44 (60.3)
Hispanic or Latino	26 (35.6)
Unknown or not reported	3 (4.1)
Sex	
Female	38 (52.0)
Male	31 (42.5)
Prefer not to say	4 (5.5)
Highest Education Level	
High school diploma	6 (8.2)
Some college	19 (26.0)
Bachelor's degree	28 (38.3)

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Graduate degree	18 (24.7)
Employment Status	
Employed	44 (69.8)
Unemployed	10 (13.7)
Self-employed	8 (11.0)
Retired	4 (5.5)
Marital Status	
Married	34 (46.6)
Divorced	2 (2.7)
Widowed	2 (2.7)
Single	29 (45.3)
Separated	2 (2.7)
Age	
20-30	14 (19.2)
30-40	15 (20.5)
40-50	17 (23.3)
50-60	14 (19.2)
60-70	9 (12.3)
70-80	3 (4.1)
80-90	1 (1.4)
Weight (lbs)	
110-150	20 (27.3)
150-190	17 (23.3)
190-230	24 (32.9)
230-270	9 (12.3)
270-310	2 (2.8)
310-360	1 (1.4)
Not reported	1 (1.4)
Height (feet)	
3-4	1 (1.4)
4-5	15 (20.5)
5-6	56 (76.7)
Not reported	1 (1.4)
Total # of patients	73

To reiterate, the SARP RPM included a smartwatch, thermometer, pulse oximeter and a respiratory rate monitoring device. We established an additional inclusion criterion that mandated a minimum daily wear time for the smartwatch of at least 4 hours.

Activity and Energy

There were 22 patients with substantial watch data (> 4 hours per day) with average usage (SD) of 10.1 (4.3) days of watch wear time. 39 patients used Pulse Oximeter to check the SpO_2 and Heart Rate with average usage (SD) of 10.1 (4.7) days of utilizing the device. The number of patients who used thermometer decreases to 37 with average (SD) usage period of 9.7 (4.8) days. The number of patients with respiratory data is 36 with average (SD) of 11.4 (4.7) nights of continuous monitoring of breathing rate per minute.

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Box plot in Figure 1 shows that the overall energy levels of patients increased on the last day of the study compared to the first day. Both the mean intensity and the variability of energy levels showed an upward trend. The figure indicates an overall improvement in the physical activity of COVID-19 patients over time, though with varying degrees of recovery across the patients.

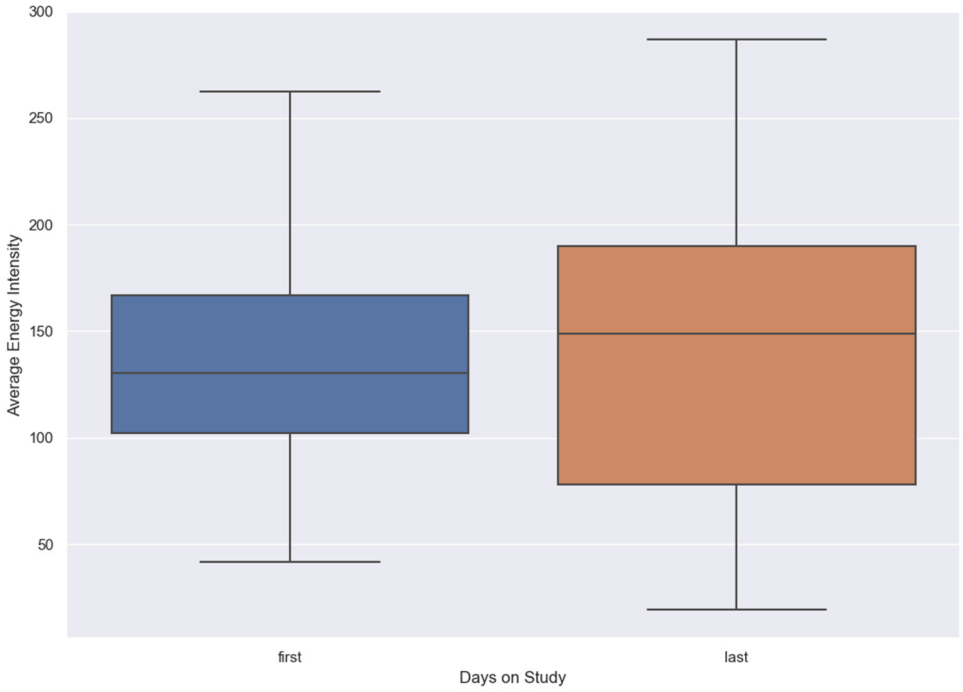

Figure 1. Average Energy Intensity: First Day vs. Last Day.

By analyzing the heatmap of patient activities shown in Figure 2, it is evident that towards the end of the study, patients were expending less energy in the bedroom and more in other areas outside the home. The fading color in the bedroom area towards the end of the study suggests a decrease energy expended in that location. Similarly, there is a noticeable decline in activity within other home settings, such as the TV/sitting area, as captured by indoor localization beacons. This trend likely reflects patients' gradual recovery and increased mobility, allowing them to engage more in activities outside their homes.

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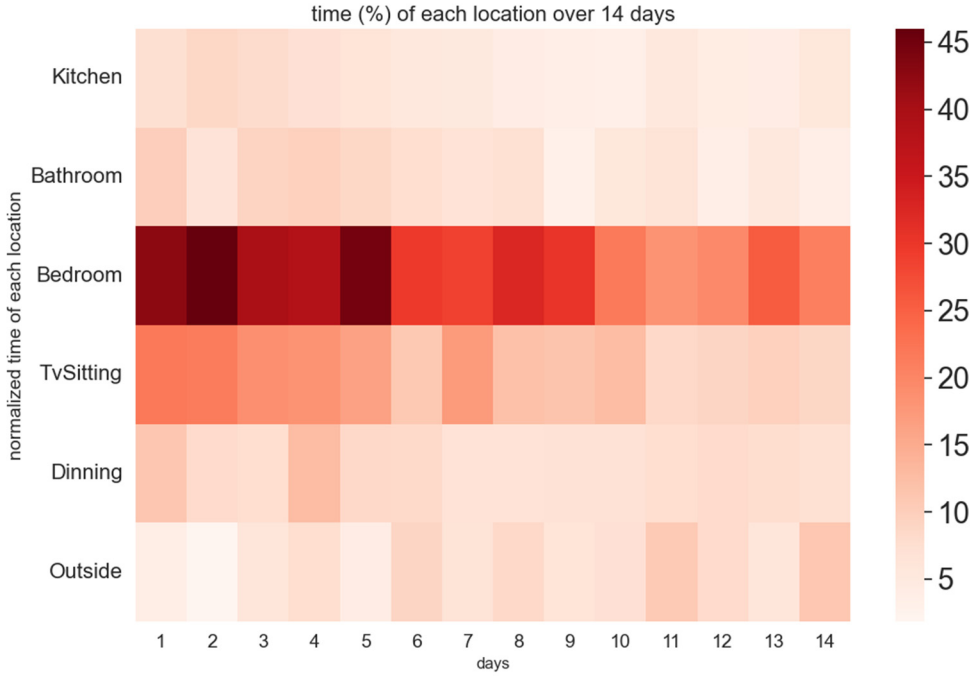

Figure 2. Heatmap of patients activities during the 2 week study.

Vital Signs

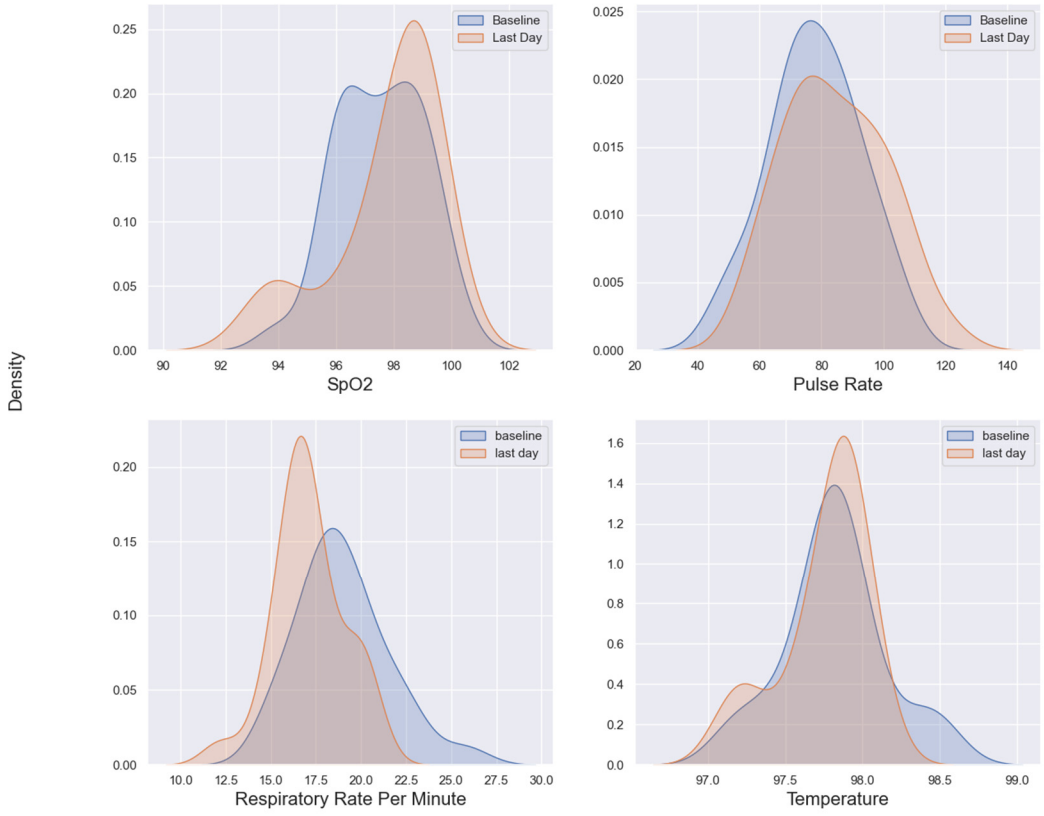

Figure 3. Biomarkers: First Day vs. Last Day.

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Investigating Figure 4 kernel density estimation graphs for four vital signs shows that the distribution for SpO2 has shifted slightly to the right from baseline to the last day, indicating an overall improvement in oxygen saturation levels by the end of the study. The of the last day's SpO2 distribution is higher than the baseline, suggesting more patients reached higher SpO2 levels on the last day.

The pulse rate distribution on the last day shows a slight shift to the right compared to the baseline. This suggests that patients' pulse rates tended to increase slightly by the end of the study. The distribution also appears to broaden slightly, indicating greater variability in pulse rates among patients on the last day.

On the respiratory rate subgraph, there is a noticeable shift in distribution towards lower rates on the last day compared to the baseline. This may indicate that, on average, patients had a lower respiratory rate by the end of the study, potentially reflecting improved respiratory function. The last day's distribution is narrower, suggesting reduced variability in respiratory rates, with most patients converging around healthier respiratory measures.

The temperature distributions however remain relatively similar in both baseline and the last day, with only slight difference.

Self-Reported Survey

Figure 4 illustrates the prevalence of symptoms reported by patients at least once during the two-week observation period.

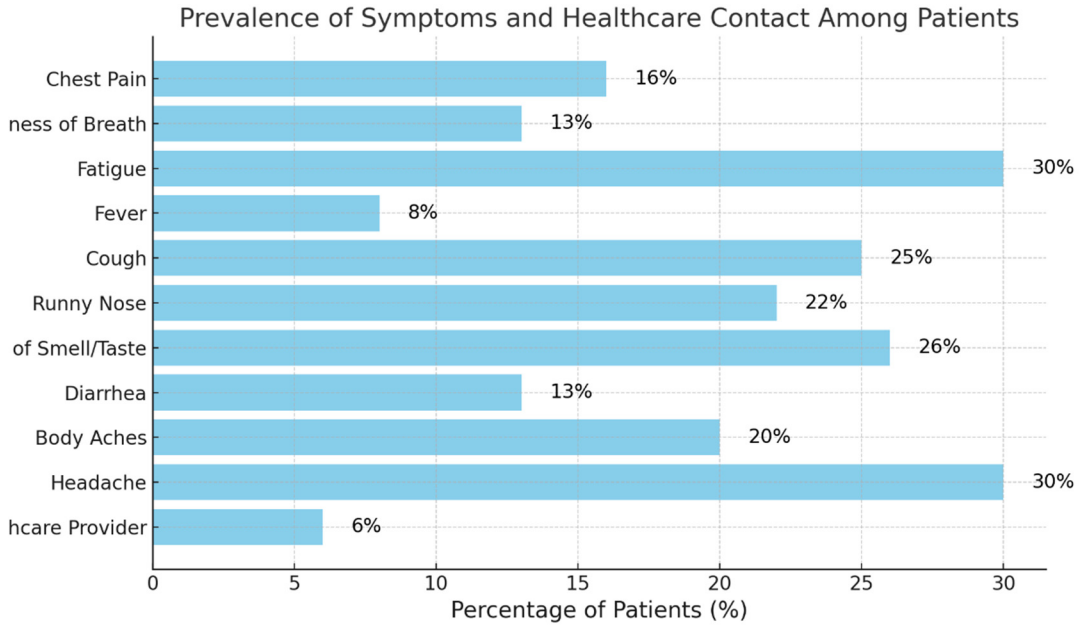

Figure 4. prevalence of symptoms.

Figure 4 indicates that fatigue and headache were the most prevalent symptoms amongst COVID-19 patients followed by cough and loss of smell. Despite these symptoms, only 6% of patients contacted a healthcare provider, suggesting either mild severity or potential difficulties to seeking medical advice. Since there was a direct contact number for the patients in the study and the ease of contacting them, it would be safe to assume the mild severity was the main reason. This underscores the need for careful monitoring of common COVID-19 symptoms.

Discussion

Our analysis of activity and indoor location suggests that a positive trend in data from wearable and remote monitoring devices is aligned with recovery of COVID-19 patients over the study period.

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Figure 1 shows an increase in overall energy levels, with both the mean energy intensity and variability rising from the first to the last day, indicating an overall improvement in physical activity. Figure 2 offers additional insights, revealing that patients progressively expended less energy in the bedroom and other indoor locations, such as the TV/sitting area, as the study progressed. This decline in indoor activity suggests that patients were recovering and becoming more mobile, with greater energy expenditure in locations outside their homes. The shift in activity distribution likely reflects improved physical health, as indicated by the higher intensity color in the heatmap corresponding to outdoor locations toward the end of the study.

Our study results are consistent with a systemic scoping review of studies published between 2019 and 2022, in which the smartwatches or fitness trackers were reported as the preferred type of wearable technologies for early and pre-symptomatic detection (29–32). Much of the published literature is focused on using wearables for early detection (33,34). These studies do show that wearables can track heart rate and heart rate variability with improvement over the course of 7 days (35). Moreover, SpO2 and activity tracking from wearable device might be able to help identify COVID-19 patients at risk for sudden death (36) based on a systematic review. However, the best results are looking at physiological features in a multi-modal approach where one can achieve sensitivity as high as 90% and specificity as high as 80% (37). Our study asked about self-reported symptoms and the importance of combining symptoms with sensor data that has been shown to allow for better predictive models (38). The use of wearables and remote monitoring has also been explored in managed Long COVID (39).

The prevalence of fever among COVID-19 patients varies across studies and cohorts, with a high percentage observed in hospitalized patients (40). However, in non-hospitalized patients, fever is less frequently observed or may be entirely absent. In studies such as (41), fever was recorded for fewer than 2 days throughout the course of illness, primarily in frail patients, even after lowering the temperature threshold from 100.4°F to 100°F. Body temperature in our cohort never exceeded 98.6°F. Figure 3 indicates that patients' body temperatures were relatively stable throughout the study with a marginal increase by the last day. Both distributions of body temperatures in baselines and last day are tightly clustered indicating consistent body temperatures across patients. This suggests that either the cohort did not exhibit fever, or the Non-contact Infrared Thermometers (NCIT) used were not sufficiently sensitive, despite being FDA-cleared. This aligns with an FDA study (42) highlighting misleading labeling of FDA-cleared devices during COVID-19, showing that NCITs may fail to reliably detect fevers when used on adults and may not meet the accuracy specifications advertised in manufacturers' instructions for use. Notably, 8% of patients in the study reported fever in the self-reported surveys (Figure 4), indicating that the subjective experience of fever was prevalent in at least 8% of the cohort.

Figure 3 of vital signs in overall, suggests that by the end of the study, patients generally showed signs of physiological improvement, with higher SpO2 levels, slightly elevated pulse rates, and lower respiratory rates. Such trends indicate a recovery or improvement in the monitored patients' vital signs.

Study Limitations

Patient compliance with wearing a smartwatch and using the Bluetooth-enabled thermometer and pulse oximeters was one of the main challenges of this study, and we anticipate this to be a common obstacle in similar studies that aim to utilize wearable technology for patient monitoring. In contrast, the UWB respiration monitoring device required no patient interaction and could monitor respiration passively. However, the accuracy of this device could be compromised if more than one person was in the bedroom or if the patient left the room. To mitigate this, we ensured that only the results from patients who lived alone in the monitored bedroom were included in the analysis. While setting up the devices was designed to be straightforward—requiring only a tablet and a simple app we provided to connect all devices to the patients' home internet in one step—it is reasonable to assume that certain patients, particularly those less familiar with technology, may have found the setup process challenging.

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Conclusions

The COVID-19 pandemic demonstrated the importance of telehealth and remote monitoring of at-risk patients. A recent cost-utility analysis estimates that daily pulse oximetry use with a follow-up after three weeks could reduce the mortality rate to 6 per 1,000 patients, compared to 26 per 1,000 without at-home monitoring. Various studies suggest that remote patient monitoring in COVID-19 patients could potentially reduce hospitalizations and deaths by as much as 80% and yield cost savings of around $12,000 per patient (10,43). This underscores the growing importance of utilizing technology for continuous at-home monitoring, which can enhance the quality of care while significantly reducing costs.

In this study, we demonstrated that affordable remote monitoring devices can effectively track individuals over time, revealing trends in their health status. However, a significant challenge in remote and home monitoring systems is ensuring participant adherence. Our study found that only 41 out of 73 individuals consistently used all the provided devices. This finding aligns with previous research, which suggests that patients are more likely to engage in remote monitoring or mHealth when they perceive an immediate personal benefit. Additionally, patients tend to prefer passive sensing methods over more demanding active monitoring that requires their ongoing participation. This study also generated novel data specific to COVID-19, comparing self-reported symptoms with objective monitoring data.

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Conflicts of Interest: The SARP system is protected by a patent (US Patent 10937547) (15) in which RR and AN are listed as co-inventors. RR and AN are cofounders of InvistaHealth LLC. Other authors have declared no potential conflict of interest regarding the publication of this paper.

Abbreviations

RPM	Remote Patient Monitoring
SARP	Sensing At-Risk Patients
MAD	Mean Absolute Deviation

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