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Telehealth-Based Information Retrieval and Extraction for Analysis of Clinical Characteristics and Symptom Patterns in Mild COVID-19 Patients

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Abstract: Clinical characteristics of COVID-19 patients have been mostly described in hospitalised patients, yet most are managed in an outpatient setting. The COVID-19 pandemic transformed healthcare delivery models and accelerated the implementation and adoption of telemedicine solutions. We employed a modular remote monitoring system with multi-modal data collection, aggregation, and analytics features to monitor mild COVID-19 patients and report their characteristics and symptoms. At enrolment, the patients were equipped with wearables, which were associated with their accounts, provided the respective in-system consents, and, in parallel, reported the demographics and patient characteristics. The patients monitored their vitals and symptoms daily during a 14-day monitoring period. Vital signs were entered either manually or automatically through wearables. We enrolled 162 patients from February to May 2022. The median age was 51 (42–60) years; 44% were male, 22% had at least one comorbidity, and 73.5% were fully vaccinated. The vitals of the patients were within normal range throughout the monitoring period. Thirteen patients were asymptomatic, while the rest had at least one symptom for a median of 11 (7–16) days. Fatigue was the most common symptom, followed by fever and cough. Loss of taste and smell was the longest-lasting symptom. Age positively correlated with the duration of fatigue, anorexia, and low-grade fever. Comorbidities, the number of administered doses, the days since the last dose, and the days since the positive test did not seem to affect the number of sick days or symptomatology. The i-COVID platform allowed us to provide remote monitoring and reporting of COVID-19 outpatients. We were able to report their clinical characteristics while simultaneously helping reduce the spread of the virus through hospitals by minimising hospital visits. The monitoring platform also offered advanced knowledge extraction and analytic capabilities to detect health condition deterioration and automatically trigger personalised support workflows.

Keywords: COVID-19; telemedicine; mHealth; wearables; IoT

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1. Introduction

An outbreak of acute respiratory syndrome emerged in humans in Wuhan, China, on 12 December 2019. The causative virus was subsequently identified and named severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), and human-to-human transmission was confirmed. On 11 March 2020, the World Health Organization (WHO) declared the

outbreak of SARS-CoV-2 as a pandemic [1]. Individuals infected with SARS-CoV-2 developed coronavirus disease 2019 (COVID-19), leading to elevated rates of hospitalisation and admission to intensive care units (ICUs) [2]. This new disease imposed an overwhelming burden on healthcare infrastructures. The range of COVID-19 infection severity spans from mild symptoms affecting the upper respiratory tract to severe pneumonia, necessitating intensive care unit (ICU) treatment due to respiratory failure. Most COVID-19 cases suffer from mild symptoms and can be managed in an outpatient setting; however, approximately 5–15% deteriorate and require hospitalisation for treatment, with advanced age and underlying health conditions amplifying the likelihood of severe illness [3]. The median duration from initial symptom onset to the severe stages is estimated to be around 8 days [2,4]. Even though COVID-19 outpatients account for up to 80%, their clinical characteristics and symptomatology are much less documented compared to ICU and non-ICU hospitalised patients.

During the COVID-19 pandemic, with social distancing measures and lockdowns in place, there was a surge in demand for remote healthcare services. Telemedicine platforms could allow patients to consult with healthcare professionals (HCPs) without the need for in-person visits. The mass-produced wearables and portable sensors and the telemedicine tools for diagnostics, monitoring, and management could enhance control over the COVID-19 pandemic. The potential benefits of employing these telemedicine methods during a pandemic have been previously discussed and reviewed [5–8]. The healthcare delivery models underwent significant changes, leading to a rapid implementation of telemedicine solutions providing healthcare services to COVID-19 patients [9,10]. Indeed, a case study described the impact of the COVID-19 pandemic on telemedicine in one large health system. The study reported the feasibility and impact of video-enabled telemedicine use among patients and healthcare providers. It showed that telemedicine visits for urgent and non-urgent care visits increased, with most of the urgent care visits being COVID-19 related [11].

Hence, the COVID-19 pandemic led to a rapid surge in the adoption of telemedicine for both urgent and non-urgent care consultations, expanding beyond COVID-19-related care to include a wide range of medical issues. Patients sought virtual consultations for routine check-ups, mental health support, and various non-emergency conditions. Telemedicine systems also provided easy access to health services for chronic patients with heart diseases, diabetes, pulmonary arterial hypertension, and kidney transplant recipients [12–16]. Telehealth services guaranteed the uninterrupted delivery of care and treatment for both hospitalised and non-hospitalised patients during the pandemic and the corresponding restrictive measures implemented in various countries while minimising the transmission of the virus within hospital settings [5,17,18].

In Greece, a study revealed that patients encountered obstacles in accessing medical care at hospitals due to pandemic-related restrictions. This resulted in difficulties both in consulting with specialists and in scheduling appointments. Half of the outpatient participants in the study reported challenges in communicating with hospitals to arrange appointments or access medical services overall [19].

In view of the above, we employed the i-COVID telemedicine platform to remotely monitor COVID-19 patients with mild symptomatology for 14 days [20]. Our aim was to support the patients in terms of professional medical monitoring while providing insight into the characteristics and symptomatology of COVID-19 outpatients. At the same time, we aimed to assess whether the healthcare services provided via the platform could reduce the number of visits to the hospital, thereby limiting the risk of virus transmission and the strain on healthcare facilities.

We initially present the study protocol (Section 2.2), followed by a brief overview of the monitoring system, the processes of data flow and information retrieval, data privacy, and finally, its implementation methodology (Sections 2.3–2.6). We then proceed with the presentation of the remotely monitored patients' health data results, as collected by the

platform (Sections 3.1–3.4). Finally, in Section 4, we discuss our results in terms of the clinical findings, platform employment, and related works.

2. Materials and Methods

2.1. Study Approval

This prospective, observational study was approved by the Ethics Committee of the 'Evangelismos Hospital', Athens, Greece (473/7-10-2021). After signing an informed consent form, the patients were enrolled in the study and registered on the platform as users.

2.2. Study Protocol

We enrolled adult patients between February and May 2022 with a positive real-time polymerase chain reaction (RT-PCR) nasopharyngeal swab test. The patients were considered outpatients if they presented with mild symptoms and did not require hospitalisation. If the patient had persisting or worsening symptoms and required hospitalisation, remote monitoring was discontinued, and the patient was excluded from the study. Patients were monitored via the platform for 14 days. At enrolment, the following were reported: age, sex, height, weight, days since the positive test, days of symptoms, symptoms, vaccination status, medications, smoking status, comorbidities, and medications. The patients reported their vitals daily (body temperature, heart rate, blood pressure, oxygen saturation levels, respiratory rate) and their symptoms. Vital signs were entered either manually or automatically through wearables.

2.3. System Overview

On a technical level, we evaluated a modular, cloud-based eHealth solution that was tailored to the specific requirements of COVID-19 monitoring and according to the operational scenarios that needed to be supported (Figure 1), as set by the HCPs of the hospital. In this direction, several adjustments of a pre-existing internet-of-things (IoT) platform [21–23] were performed to support end-users and HCPs in the context of the COVID-19 pandemic. The overall system followed a flexible and highly efficient architectural design, built using a microservices approach and implementing the various operations as cloud functions and containers. These are fully extensible, modular, and can be dynamically provisioned, contributing in that way to the efficiency and scalability of the solution [20–22]. A user-friendly user interface, designed for people with limited computer use skills, and support of multiple platforms (web, Android, iOS) facilitate user acceptance.

In the context of this usage scenario, seven main components were utilised and categorised into 4 modules to form the architecture of the proposed platform (Figure 1). The "*User Management*" component (in the "*Communication, User Interaction*" module) was responsible for the patients' enrolment and for the creation and management of the system users (patients, HCPs, supervisors, and administrators). Within this component, user profiles, informed consent, and authentication processes were managed while ensuring that users could securely access and use the platform. The "*Data Retrieval and Synchronisation*" component (in the "*Health Data Management*" module) was designed and deployed to interface with various data sources, such as wearable devices and medical sensors (these devices are described later in the manuscript). This component was collected from multiple sources of data related to vital signs and symptoms, as well as the symptoms reported by the patients and other manually entered data. The "*Data Storage and Processing*" component (in the "*Health Data Management*" module) was utilised to organise, manage, and store all the collected data. A cloud-based approach was used to accommodate all the collected data, including data aggregation tools that create an abstraction layer to facilitate internal operations and improve data exchange effectiveness with external systems. The "*Health Data Analysis and Visualisation*" component (in the "*Data mining, AI, Analytics*" module) supported the visualisation and analysis of the collected data while it provided tools for HCPs to monitor the patients' health status and visualise trends and patterns through graphical

interfaces for better data interpretation. The "*Alerts and Notifications*" component (in the "*Data mining, AI, Analytics*" module) could automatically trigger alerts and notifications to the HCPs when the patients' measurements' were outside of normal ranges. The "*Data Governance*" component (in the "*Health Data Management*" module) monitored and enforced the security measures to protect sensitive health data that are circulated and stored in the platform. This component was responsible for data encryption, role-based access control, and compliance with data privacy regulations. Finally, the "*Interoperability and Integration for Internet of Medical Things*" module ensured the platform's (and its sub-systems/other modules) compatibility with other health systems (within or outside the platform) by using well-approved standards like fast healthcare interoperability resources (FHIR), logical observation identifiers names and codes (LOINC), and international classification of diseases—tenth revision (ICD-10) standards for data types and vocabularies.

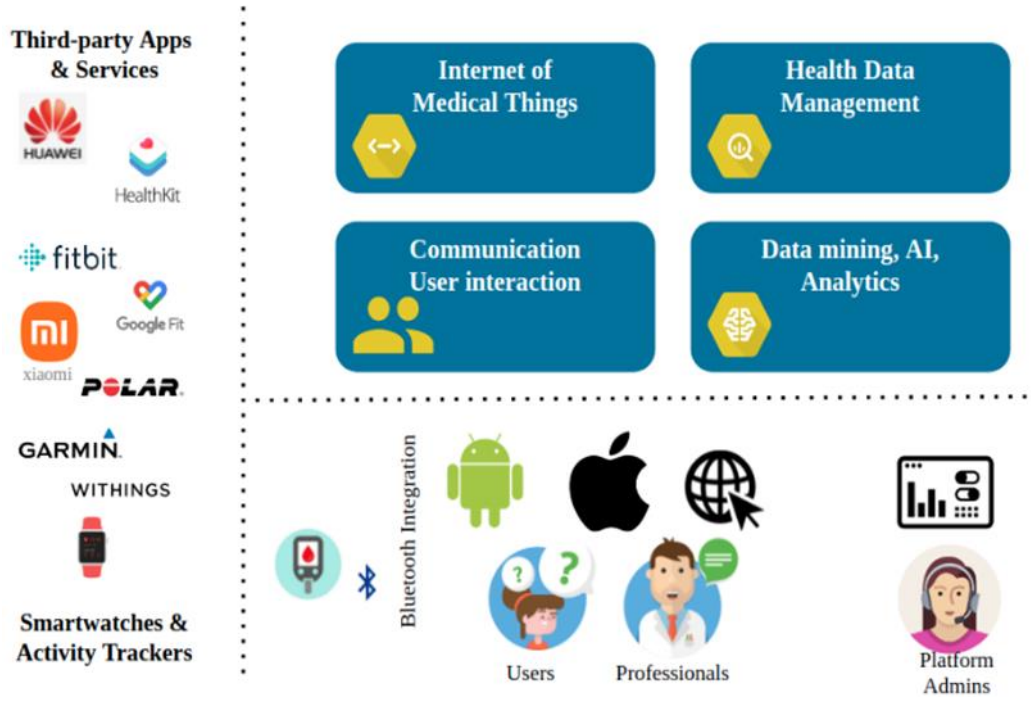

Figure 1. i-COVID system overview: a modular, cloud-based eHealth solution capable of supporting modern health monitoring and teleconsultation services.

The platform enabled the provision of vital signs monitoring services, incorporating a personal health record (PHR) for COVID-19 patients [20]. The platform was adapted to meet the study's requirements for remote monitoring of COVID-19 patients with mild symptoms. The main users of the platform were the patients and the physicians who participated in the study. All the patients enrolled in the study were registered on the platform, which they could also access via a mobile application. To enable continuous patient monitoring with minimal interference, the solution harnesses the capabilities of sensors and wearable devices, facilitating real-time health data exchange.

Furthermore, the support of rich multimedia data content facilitated the bidirectional communication between patients and HCPs. All information that the patient should be aware of, the therapeutic plan, the suggested nutrition, and measurements schedule, along with any other multimedia material that the professionals considered useful for the patients and may have contributed to the improvement of their recovery process, was modelled into the system. This content was delivered promptly to the patients through mobile applications (both for Android and iOS devices) to improve their engagement with the system and adherence to the therapeutic and monitoring plans.

Additional features, which were tailored to the requirements of the study, enhanced communication among different entities involved. Patients could engage in teleconsultation sessions via cross-platform videoconferencing, exchanging text messages and rich multimedia content seamlessly within the end-user applications. Physicians could communicate via video and chat with patients, analysing patient health records during the consultation. In the cases requiring actions from the patient (such as the medication intake, the measurement of a biosignal, or the response to a questionnaire), application notification reminders were sent to the patients' smartphones. Furthermore, personalised dashboards containing content from professionals and the system were provided for each patient.

2.4. Data Flow and Information Retrieval

Data interoperability is at the core of the system design, as part of the "*Data Retrieval and Synchronisation*" component, keeping in pace with the evolution of the system with newer features and supporting more usage scenarios. A flexible data model based on FHIR [24] and its extensions was adopted across all system elements to support all types of health-related data. LOINC and ICD-10 standards were also used as vocabularies for the respective data types. The platform incorporates a cloud-native NoSQL database for data storage, which accommodates the aforementioned data models. With the implementation of data aggregation and querying components, an abstraction data layer was created. This facilitated the internal operation of the system and improved the effectiveness of data exchange with external systems.

The i-COVID platform utilises several information retrieval techniques to handle health data effectively and to deliver accurate information to HCPs and patients. This health data retrieval functionality has two aspects: (a) application-level integration, where the system communicates with sensors, such as oximeters, spirometers, blood pressure measurement devices, etc. via Bluetooth; (b) platform-level integration, where the acquisition of measurements takes place via services from the cloud platforms of the device manufacturers, such as AppleWatch, Fitbit, Garmin, Polar, Withings, etc. Both approaches follow well-established standards, and data aggregation and federation mechanisms were in place to address the respective data harmonisation challenges. These challenges are not only related to the different data formats, models, and vocabularies but, most importantly, to the nature of the retrieved data with different granularities varying from single measurements to continuous time series and aggregated data on the manufactures' platforms. Figure 2 presents the data flow of the system employed.

At the application level, the data retrieval processes were difficult to be implemented since they required the development of specific Bluetooth modules/drivers for communicating and controlling each one of the biosignal measurement devices according to the manufacturers' protocols. Even though this required tremendous effort for cross-device validation and testing, the operational processes were considerably simplified since the system had total control of the process (e.g., synchronisation periodicity and error identification).

At the platform level, the system communicated with the manufacturers' cloud platforms to obtain user-consented data without being device-specific. Integration focused on retrieving diverse data types and harmonising them, considering the diversity of application programming interfaces (APIs) and the data granularity variations. The retrieved data's completeness and whether these data should be considered for analysis and decision-making were uncertain since the system had no direct access to the devices and data synchronisation was performed through "abstraction layers" on the manufacturers' platform. Furthermore, the different API approaches for data retrieval of each platform (e.g., push vs. pull or hybrid using push notification to pull the data) introduced additional complexity and required highly configurable and extensible data retrieval modules. An example of data completeness uncertainty was when patients' data were recorded from a wearable device at noon on the previous day, and a notification was received the next day from the manufacturer that new data were available and should be synchronised. In cases where APIs still returned incomplete data, what should be the conclusion in the system

about these data? To address these retrieval, aggregation, and harmonisation challenges, and avoid the inefficient "regular polling" of the APIs, which in most cases leads to communication errors due to API throttling from the manufactures' platforms, a hybrid approach was used in the system, with three main aspects:

1. Use of smart checkpoints for the synchronisation of each data type, which were moved in time according to the manufacturer's API, the data type, and the configurations of the usage scenario from the healthcare organisation;
2. Limited API polling, which was dynamically adapted to the synchronisation status of each patient, also taking into consideration the checkpoints;
3. In cases where the two previous approaches could not resolve the retrieval status, notifications were sent to the users through the app to act and initiate the synchronisation process manually.

The system incorporated functionalities for visualising and reporting on the collected data both to the physicians and the patients to perform certain actions such as taking additional biosignal measurements or contacting their physicians. Furthermore, the physicians were able to export the aggregated data for individual patients or anonymise it in cohorts to perform additional analysis according to the study. By following this approach, the study results, the identified patterns, and the models that were produced through the analysis of the data would be incorporated as future modules for the assessment of risk and pathway mining.

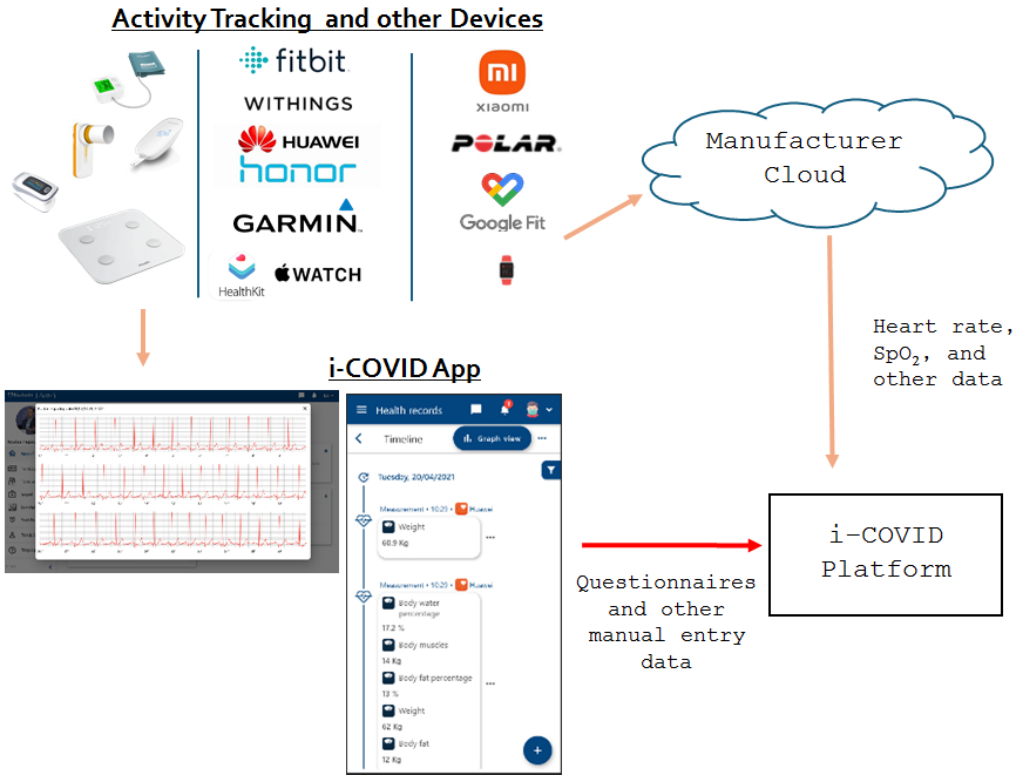

Figure 2. Data flow of the i-COVID System.

2.5. Data Privacy

Recognising the importance of privacy, a comprehensive privacy policy was formulated. This policy aimed to apprise users of the purpose behind processing their personal data, elucidating the technical security measures implemented by the system to protect this information, clarifying the methods and duration of data storage, and outlining users' rights as stipulated in the General Regulation on Personal Data Protection 2016/679. In the realm of collecting personal and medical data, anonymisation algorithms were deployed to uphold data confidential-

ity. Regarding the data anonymisation for the cohort analysis, the techniques of (a) data interruption, (b) data reduction, and (c) k-anonymisation were used and aligned with the COVID-X project anonymisation guidelines (https://rebrand.ly/COVID-X_Anonymization_Guide; accessed on 1 June 2022) for further data analysis.

In this context, the platform supports state-of-the-art technologies and a robust, serverless, health insurance portability and accountability act (HIPAA) compliant architecture based on microservices, allowing for a highly customisable and scalable solution capable of supporting a wide range of use cases. Access to all data was facilitated through a role-based, identity, and access management mechanism. This ensured that the mandated levels of security and privacy were maintained while offering the necessary flexibility in content delivery.

2.6. Implementation Methodology

For the COVID-19 patients, biosignal measurements were recorded using wearable and medical devices or by manual data entry. Crucial for the overall solution's effectiveness was the seamless integration of the platform and end-user applications with specific devices. The COVID-19 patients performed self-assessments (questionnaires, symptom reporting) daily, following the physician's instructions through the platform. All the above data were merged in the platform's PHR for each patient. Physicians had access to the patients' PHR through the platform's information retrieval tools to monitor their healthcare status during the 14-day monitoring period. The tools' core functionality lies within health data aggregation from different sources, data harmonisation, and the ability to identify incomplete or partially synchronised data. Furthermore, the tools facilitated the search, selection, and analyses of the data of a specific patient within the PHR records. They also facilitated semantic search (enhanced search capability) in ontologies and vocabularies incorporated into the system to retrieve more relevant results by understanding the meaning behind the search queries. The physicians had the ability to observe the patients' data in an aggregated form using data visualisation tools (ex. Graphs) and to receive automated notifications from the platform when the measurements of their patients were out of the normal range. In detail, the monitoring platform incorporated data mining mechanisms, facilitating the effective aggregation of multimodal datasets for visualisation within the application. It could also generate reports for individual patients, groups, or populations and unify various datasets for consumption by system-level analysis mechanisms. This process identified events related to patients' health conditions, prompting notifications to physicians who could then take the appropriate actions. Additionally, the platform offered data aggregation and extraction for further analyses using third-party tools employed by the physicians.

2.7. Statistical Analysis

Anonymisation was performed using the aforementioned techniques during the data extraction process. All collected data extracted from the monitoring platform were processed for statistical analyses. Data are presented as N (%), mean ± SD or SEM for normally distributed variables, or median (interquartile range) for variables with skewed data. When multiple measurements were taken in a day, the worst measurement over 24 h was used for analysis purposes. Graphs were generated thereafter to depict the vital signs' progression over the 14-day monitoring period, the prevalence of symptoms within the study population, and their onset and progression within the 14-day monitoring period. Spearman's correlation coefficient was used to test correlations. The IBM SPSS statistical package, version 22.0 (IBM Software Group, New York, NY, USA), and GraphPad Prism, version 8.0 (GraphPad Software, San Diego, CA, USA), were used for data analysis. Statistical significance was set at $p < 0.05$.

3. Results

From the healthcare provision aspect, more than 300 in-person visits were replaced with teleconsultations, ensuring patient safety regarding the contamination of the virus. In addition, more than 100 working hours per month were reserved for the HCPs during the study period.

3.1. Study Population

We enrolled 162 Caucasian adult patients from February to May 2022 with a positive RT-PCR nasopharyngeal test who presented with mild symptoms and did not require hospitalisation. The median age of our cohort was 51 (42–60) years, with the youngest being 19 and the oldest 81. Forty-four percent were male, 54% were smokers, and 22% had at least one comorbidity (under medication), with a BMI of 23.7 ± 4.3. Three-quarters (73.5%) of the study population were fully vaccinated, mainly with the Pfizer vaccine (3–4 doses), followed by the single-dose Johnson & Johnson vaccine, while six patients were unvaccinated (3.7%). The median days from the last vaccine dose administered were 120 (88–160) days, and only 3.7% had been priorly infected without requiring hospitalisation. Patients were enrolled 3 (1–11) days after their positive test. The patients typically reported experiencing symptoms prior to enrolment for a median duration of 3 (2–5) days. The patients were instructed to remain enrolled in the study for 14 days. Several patients recorded a shorter or longer period (5 to 25 days), and the median time enrolled in the study was 14 (13–15) days. Usually, the patients recorded on the platform until complete symptom resolution from COVID-19. Demographics and characteristics of the study population are given in Table 1.

Table 1. Demographics and characteristics of the study population.

Characteristic	Data
Patients, N	162
Age, years (median, IQR)	51 (42–60)
Sex, N (%)	
Male	72 (44.4)
Female	90 (55.6)
Smoking status, N (%)	
Yes	87 (53.7)
No	75 (46.3)
Comorbidities, N (%)	35 (21.6)
Hypertension	33
Hyperlipidemia	33
Coronary artery disease	5
Diabetes	4
Thyroid disease	4
Asthma	4
Chronic obstructive pulmonary disorder	2
BMI, kg/m^2 (mean ± SD)	23.7 ± 4.3
Vaccination status, N (%)	
4 doses	1 (0.6)
3 doses	113 (69.8)
2 doses	37 (22.8)
1 dose	5 (3.1)
Unvaccinated	6 (3.7)
Vaccine type, N (%)	
Pfizer	142 (87.6)
Moderna	5 (3.1)
Johnson & Johnson	5 (3.1)
AstraZeneca	4 (2.5)
Days since the last vaccine dose (median, IQR)	120 (88–160)
Previous infection, N (%)	6 (3.7)
Days from positive test prior to enrolment (median, IQR)	3 (1–11)
Days of symptoms prior to enrolment (median, IQR)	3 (2–5)
Days of monitoring (median, IQR)	14 (13–15)

Data are expressed as percentages of total related variable (%), mean ± SD, or median (IQR) for skewed data.

3.2. Vitals Signs

The patients reported their vitals (temperature, heart rate, blood pressure, oxygen saturation, respiratory rate) and their symptoms daily. Vital signs were measured and entered either manually using medical devices or automatically through wearables. If oxygen saturation measurements were ≤94% or the respiratory rate was >22, an alert was generated by the system to inform the HCPs. The patient was then contacted by the HCPs, and if there were persistently low oxygen levels, a deterioration in symptoms, or any other cause for concern, the patient was instructed to present to the hospital for further assessment. During the monitoring period, one patient had persistent hypoxia and fever, resulting in hospitalisation and discontinuation of the protocol.

During the 14-day monitoring period, over 2500 biosignals were recorded. As seen in Figure 3, the heart rate was within normal values and decreased steadily over the monitoring period (Figure 3A). The diastolic and systolic blood pressures remained constant and within a normal range (Figure 3B,C). Oxygen saturation levels (SpO_2) steadily increased over the monitoring period (Figure 3D). The overall oxygen saturation levels were 98% (97–98), with the lowest measurement at 94%. With regard to the respiratory rate, it decreased over time (Figure 3E). Overall, the respiratory rate was 15 (14–17), with the highest measurement at 22. During the first days, body temperature was higher, indicative of fever, which eventually returned to normal values (Figure 3F). When multiple measurements were taken through wearables, the worst value over the 24-h day was used.

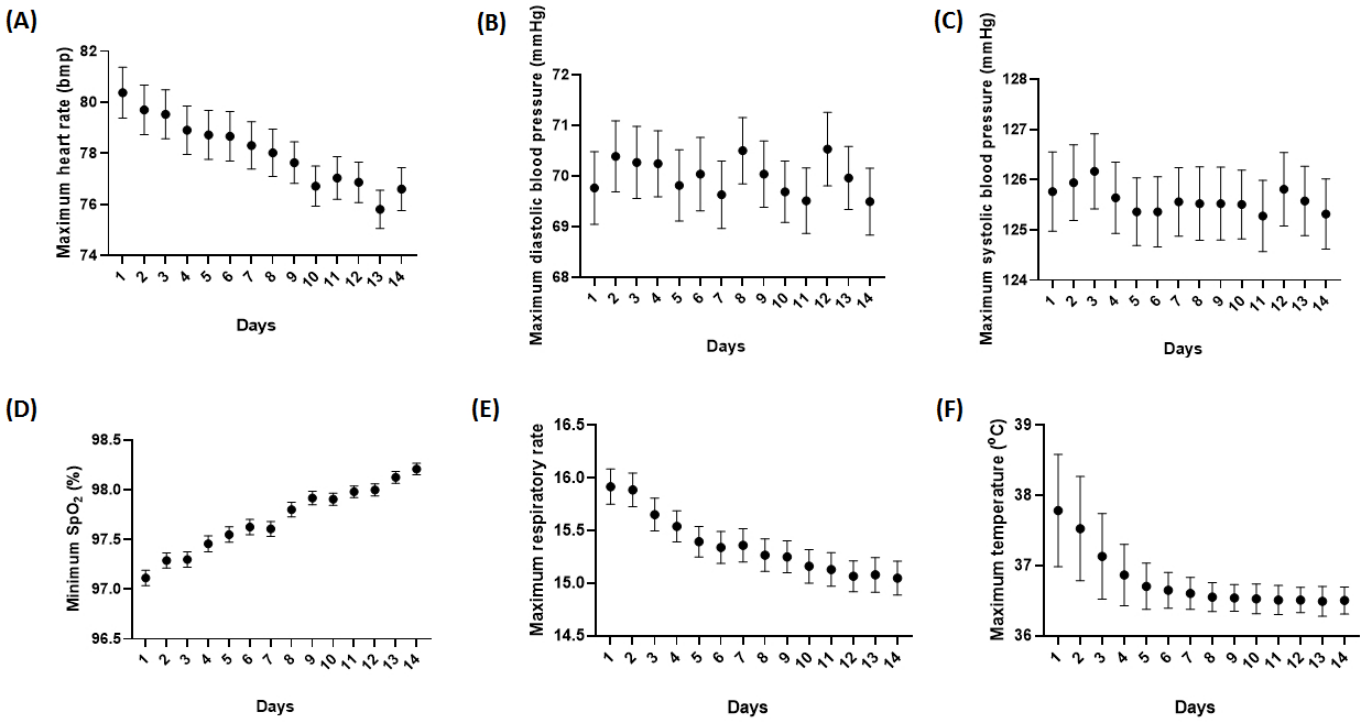

Figure 3. Vital signs were measured daily for the 14-day monitoring period. The mean and standard error mean (SEM) of 162 enrolled patients are shown over the monitoring period. (**A**) Heart rate, (**B**) diastolic blood pressure, (**C**) systolic blood pressure, (**D**) oxygen saturation levels (SpO_2), (**E**) respiratory rate, and (**F**) body temperature.The worst measurement over 24 h was used.

3.3. Symptomatology

Thirteen patients (8%) were asymptomatic, while the rest had at least one symptom for a median of 11 (7–16) days. Patients experienced a median of three (2–4) symptoms during the 14-day monitoring period. Fatigue was the most common symptom (N = 93),

followed by fever (N = 90) and cough (N = 60). In Figure 4, the symptoms are given as a percentage of the total patients enrolled.

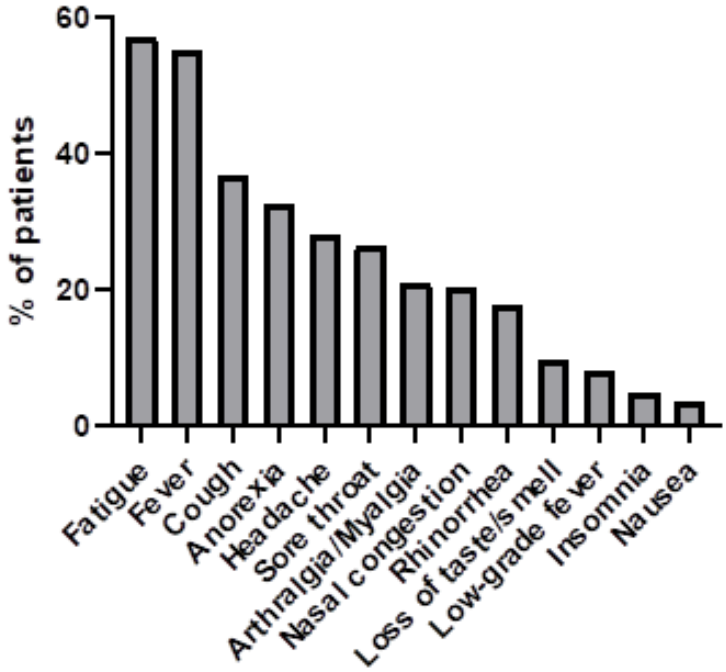

Figure 4. COVID-19 symptoms. One hundred and sixty-two mild COVID-19 patients were enrolled in the study. Symptoms experienced are depicted as a percentage of total patients.

Loss of taste and smell, fatigue, and fever were the first symptoms experienced by the patients. These were followed by rhinorrhoea, nasal congestion, and arthralgia/myalgia. All symptoms appeared in the first week of monitoring, apart from insomnia, whose onset was in the second week of the monitoring period. Loss of taste and smell (N = 16) was the longest-lasting symptom [11 (7–16)], followed by fatigue [9 (6–15)] and anorexia [8 (6–9); N = 53]. In Figure 5, the onset, progression, and duration of symptoms are depicted.

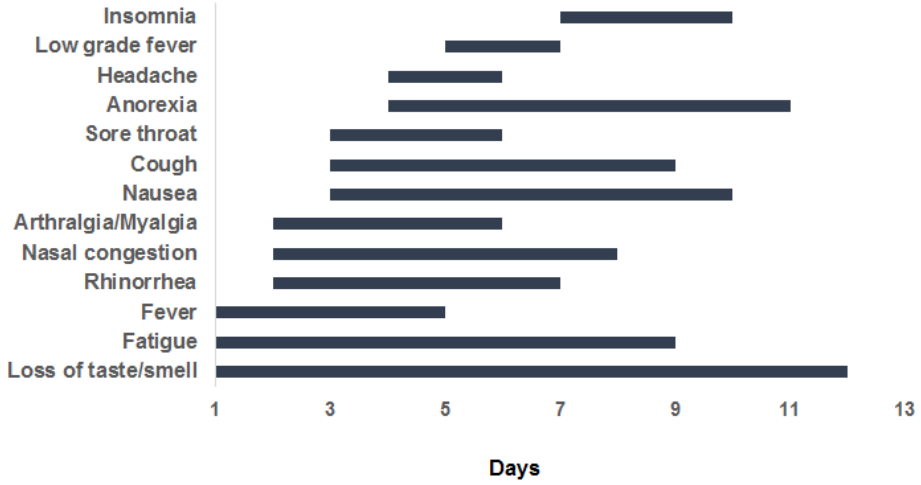

Figure 5. COVID-19 symptom onset and progression. One hundred and sixty-two mild COVID-19 patients were enrolled. The onset and progression of the symptoms within the 14-day monitoring period are depicted as bars. Day 1 denotes the day of enrolment in the study.

3.4. Correlation of Characteristics and Symptomatology

Age positively correlated with the duration of fatigue (r = 0.304, $p < 0.0001$), anorexia (r = 0.197, $p = 0.012$), and low-grade fever (r = 0.239, $p = 0.002$). Female patients had more days of headache compared to males (r = 0.190, $p = 0.016$), whereas patients with higher BMI had fewer days of anorexia (r = −0.218, $p = 0.006$). Comorbidities, the number of administered doses, the days since the last dose, and the days since the positive test did not seem to affect the number of sick days or symptomatology.

4. Discussion

In this prospective observational study, we employed the i-COVID web application to remotely monitor COVID-19 patients with mild symptoms. We managed to remotely monitor 162 patients with mild COVID-19 in a period of 3 months. Patients were followed for 14 days, and in the majority, there was complete symptom resolution by then. Our first aim was to provide close monitoring of COVID-19 patients who presented initially with mild symptoms over a 14-day period/symptom resolution to reduce hospital visits. We also aimed to describe the clinical characteristics and symptoms observed in patients who received outpatient care. We were able to complete our goals, as one patient who had persistent symptoms was recognised by the system and was referred to the hospital for further action. Taken into consideration that approximately 80% of COVID-19 cases worldwide are managed in outpatient settings, we hypothesised that the clinical characteristics and symptomatology, in terms of their onset, duration, and correlations with demographics, presented in the current study may apply to most COVID-19 outpatients.

The majority of large-scale studies that have determined symptom duration among patients with COVID-19 who did not require hospitalisation and have identified potential risk factors associated with prolonged symptom duration rely on retrospective medical record review studies with data from the electronic health records of the patients [25,26]. Other means of symptom reporting have been visits to outpatient clinics or remotely via telephone and video visits [27,28]. The results of these studies have shown that the median symptom duration in outpatients is 15 days and that the most common presenting symptoms are fever and cough. A large prospective study in France described the clinical features of nearly 1500 COVID-19 cases with outpatient management. They reported that dry cough and fever were reported in 90% of patients, while myalgia, headache, and asthenia in 60%, followed by shortness of breath and anosmia and ageusia in 30% of cases [29]. This was a "call-study"; patients were asked to contact the emergency medical system with their questions and in the event of worsening symptoms. After an initial assessment, patients with less severe symptoms received a follow-up telephone call within the following 12 h.

The study by Knight et al. described the initial symptoms, clinical course, and outcomes, such as emergency department (ED) visits, hospitalisations, and time to resolution of viral shedding in 106 patients in a virtual outpatient clinic setting in the USA [30]. The authors utilised a 24 h remote patient monitoring program using an interactive care plan. Their results showed that the most common initial symptoms patients reported were cough, fever, and fatigue, while the longest-lasting symptoms were cough, fatigue, and fever. Most patients recovered at home, highlighting the role of frequent telehealth visits in preventing ED visits and lowering the ED burden.

Indeed, telemonitoring during the COVID-19 pandemic has been suggested as a safe strategy to monitor patients at home [31]. One of the first controlled studies demonstrating the safety and effectiveness of home monitoring in COVID-19 was performed in the Netherlands. In this study, 55 patients with home monitoring were compared to 110 matched patients discharged without home monitoring. The authors demonstrated the potential of home monitoring to reduce hospital admissions during a 28-day follow-up by safely surveying clinical symptoms and vitals. They suggested further investigation of their results in larger patient groups with confirmed COVID-19 diagnosis [32]. In the USA, researchers were able to implement a remote patient monitoring (RPM) program

quickly and effectively by repurposing an existing third-party application. Their program provided a safe and satisfying experience for patients while minimising COVID-19 exposure and in-person healthcare utilisation. Hence, the authors concluded that RPM appears to be an effective approach for managing COVID-19 symptoms at home [17]. In Korea, COVID-19-positive asymptomatic and mildly symptomatic patients were isolated and accommodated at government-sponsored facilities called living and treatment support centres (LTSCs). The patients were monitored by healthcare staff at least twice a day by implementing information and communications technology (ICT)-based remote patient management systems [10]. Other, mostly retrospective, studies have included COVID-19 patients following hospital discharge. These have demonstrated the potential of RPM in reducing hospital stay and facilitating discharge, hence relieving the burden on bed demand whilst allowing for a safe follow-up and preserving good care [18,33–36]. A viewpoint reviewing the benefits of remote monitoring in the hospital and home settings concluded that enhanced monitoring at home could potentially improve safety and value; however, the empirical evidence of the benefits of this approach is limited [37]. Two rapid, mixed-method studies were not able to find evidence that RPM for COVID-19 had been effective. They found that many patients required support and preferred human contact. They suggested that when designing and implementing RPM services, barriers to implementation, delivery, and engagement should be considered [38,39].

Taking all these into consideration, we employed the i-COVID platform to remotely monitor COVID-19 patients presenting with mild symptoms in an effort to reduce hospital visits and prospectively report the clinical characteristics and symptomatology of COVID-19 outpatients. The platform design was based on user requirements and related scientific work [18]. Its development relied on three main pillars: (i) easy access to health services and ensuring continuous care throughout the pandemic by endorsing teleconsultations and virtual visits while relieving hospitals and reducing the in-hospital spread of the virus; (ii) automated and remote health status monitoring and coaching for COVID-19 patients, minimising the risk of spread and enabling more efficient treatment supervision and personalised care through multimedia content, automated reminders, and the acquisition of biosignals; (iii) data collection and analysis of COVID-19 patients' data to advance research and understanding of the disease and its impacts [20]. To the best of our knowledge, this is the first report on remote monitoring to also present, apart from symptoms, the quantitative data of mild COVID-19 outpatients.

In this paper, several aspects of the information retrieval and extraction methodologies can be assumed to be particularly original or tailored to the specific context of telemonitoring COVID-19 patients. The platform's ability to harmonise data from various devices and manufacturers, using specific APIs and maintaining data granularity, addresses a major challenge of the healthcare domain relative to data integration. This information retrieval approach ensures that the data retrieval process is robust and uniform across all the platforms or devices used. Another significant component of the platform is the use of wearable devices and IoT technology for continuous real-time health monitoring. The system's ability to integrate data from these devices seamlessly into the PHR not only enables real-time data retrieval but also supports immediate response and intervention. This is particularly crucial when managing patients with infectious diseases like COVID-19, whose condition may rapidly change. The adoption of a flexible data model that expands upon established health IT standards (like FHIR) is a state-of-the-art approach in the context of telehealth solutions for COVID-19. Although FHIR is designed to enable interoperability and easy data exchange between health information systems, the i-COVID platform's specific adaptation to extend this framework adds a layer of customisation that enhances data retrieval and application in real-world scenarios. In addition, the implementation of automated alerts and notifications based on specific data patterns detected through continuous monitoring of the patients can be assumed to be a significant advancement in the data retrieval process. This method upgrades the simple data collection to proactive patient care while detecting early signs of deviation from the normal range for specific

biosignals important in monitoring COVID-19 progression. Another state-of-the-art feature relative to patients' data retrieval is the development of advanced data visualisation tools tailored to the telehealth context, which can assist the HCPs in better assessing the health status of COVID-19 patients remotely. The above visualisation tools not only provide a better understanding of the patient's data but also support the HCPs in delivering a quick, informed, and evidence-based decision, which was essential during the pandemic.

The analysis of the data collected and extracted from the platform showed that our mild COVID-19 patients experienced at least one symptom for a median of 11 days, which was higher than the isolation period in place during that period. Fatigue was the most common symptom, followed by fever and cough. Loss of taste and smell was the longest-lasting symptom. Age positively correlated with the duration of fatigue, anorexia, and low-grade fever. Comorbidities, the number of administered vaccine doses, the days since the last dose, and the days since the positive test did not seem to affect the number of sick days or symptomatology. The vital signs of the patients, which were recorded daily and monitored closely by the HCPs, were within normal range throughout the monitoring period. Only one patient had a persistent fever and low SpO_2 levels, so the HCPs decided that this patient should be hospitalised. In our study, we noticed that the vast majority of our enrolled patients remained active on the platform and entered their vitals and symptoms, as instructed, for 14 days. We noticed that only three patients did not continue recording after the 1st week, whereas one patient recorded data for 25 days. It seemed that patients, after being symptom-free for more than 2 days, did not feel the need to continue being monitored through the platform. Moreover, 82% of patients were below 65 years of age. Only 13 patients were above 75, and these were facilitated by a younger person at home to handle the platform.

Overall, it seemed that the i-COVID web application platform allowed HCPs to track patients' vital signs, collect health data, and manage mild COVID-19 patients from a distance. It incorporated roles for all participating stakeholders, along with end-user hardware in the form of smart devices for the patients. Its main users were the COVID-19 patients and the HCPs. The COVID-19 patients experienced advantages such as uninterrupted care and simplified access to a comprehensive range of healthcare services through a single mobile application, offering state-of-the-art features for continuous, efficient, and personalised care. Moreover, the i-COVID solution enabled healthcare professionals to efficiently monitor a larger number of patients, both existing and new, while it increased loyalty from patients toward healthcare professionals. Using wearable and medical devices, specific biosignals were recorded for each patient registered as a user. The measurements were automatically transmitted to the platform's mobile application and stored in the user's personal health record, which also included information such as medical test results, medications, and allergies, which were accessible to the clinicians, enabling them to make well-informed decisions and offer personalised care to their patients.

Telemedicine played a pivotal role in managing the COVID-19 pandemic. It provided a means for HCPs to remotely assess and treat patients, reducing the risk of virus transmission and alleviating strain on healthcare facilities. Telemedicine facilitated timely consultations, monitoring of symptoms, and even triage, enabling patients to receive medical attention while minimising physical contact. Additionally, telemedicine enhanced access to healthcare services, particularly for individuals in remote or underserved areas. Through telemedicine platforms, patients can seek medical advice, receive prescriptions, and access mental health support, contributing significantly to pandemic response efforts. Our study emphasised the advantages of utilising telemedicine as a means of care for mild COVID-19 patients. The ability to monitor and assess patient data in real-time via our platform allowed clinicians to provide reassurance regarding the recovery process and expected outcomes, ultimately reducing the strain on hospitals and gaining insights into the disease. We believe that the ease of use of the platform also facilitated improved follow-up and monitoring, which might have been challenging with a traditional office-based protocol, given the extended duration of patients' symptoms.

While the initial push for telemedicine was driven by the urgent need to adapt to the challenges posed by the pandemic, the changes it brought about are likely to have a lasting impact on how healthcare is delivered in the future. The integration of telemedicine into mainstream healthcare represents a shift towards more patient-centred and technology-driven healthcare models.

5. Conclusions

In this study, we prospectively described the clinical characteristics and symptom profiles of mild COVID-19 patients as collected via their monitoring through the i-COVID platform. Adverse outcomes and loss to follow-up were minimal, while all patients but one recovered at home. Our study added to the important role of telemedicine in preventing hospital visits and lowering their burden. Compared to previous reports, we found a higher incidence of fatigue and loss of taste/smell. We consider our findings to offer practical guidance for patients that is applicable to everyday practice, particularly concerning symptom expectations. Recognising initial clinical characteristics and symptoms could play a pivotal role in identifying high-risk patients much earlier in the disease progression, potentially allowing for vital early interventions.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

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