****

**Minimizing the influence of coronavirus in a built environment**

**MICROBE**

O3/A2. Literature Review

**Project No: 2020-1-LT01-KA203-078100**

**Literature Review**

Research in the areas of large-scale screening, diagnostics, monitoring, analysis and COVID-19-based categorizations of people by symptoms have wrought much honor and recognition to numerous scientists and practitioners for their achievements. Their applications for accomplishing such work includes wearable technologies, early warning systems, biometric monitoring technologies, IoT based systems, Internet of Medical Things and other tools pertinent to the COVID-19 pandemic.

Modern healthcare methods and systems have suffered a never before experienced crisis by the emergence of the COVID-19 pandemic. Remote monitoring became a primary means of healthcare provision for safeguarding millions of Americans as a result of the resource constraints, when this pandemic hit its first peak ([Hollander and Carr, 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b32)).

Symptomatic people, as researchers have discovered, often indicate a drop in heart rate variability, although their resting heart rate and breathing rate rise. So long as measurements could capture such changes in a person, health can be treated as much as a week prior to a potential reporting of such disturbing symptoms. As many as 72% of the people suffering from COVID-19 most often report feeling fatigue. The other symptoms frequently reported by patients were headaches by 65%, body aches by 63%, a loss of taste and smell sensations by 60% and coughing by 59%. Researchers have discovered that as few as 55% of people ailing with COVID-19 reported having a fever, which is alarming, because merely temperature screening may be insufficient to denote such an infection ([Terry, 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b80)).

Clinical care as well as the research in this field are bound to adopt remote monitoring permanently. The needs for convenience and security have opened opportunities for greater use of Telehealth and remote real-time monitoring of vital signs. Measurements of vital signs can be taken safely and conveniently within people’s homes by employing biometric monitoring technologies (BioMeTs). BioMeTs can serve a number of clinical requirements for adequate responses to the COVID-19 pandemic. It can be applied for assisting initial physical evaluations of people, contributing to the triage of patients indicating COVID-19 symptoms and even for monitoring patients after their discharges from a hospital to lessen the risk of readmission. BioMeTs currently come in numerous versions for remote collections of vital signs for many days. The signs collected include body temperature, heart rate, BP, blood oxygen saturation (SpO2) and respiratory rate. These are needed for the overall care of people suffering from COVID-19. A number of research studies employ wearables like WHOOP, Oura Ring and smartwatches. These are in appropriate positions to undertake investigations regarding the use of BioMeTs measurements, not only for early detection of the illness but also as a means for predicting the possible severity of it ([Manta et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b54)).

While people are isolated during this pandemic, there is the potential of discretely applying Doppler radar for data on breathing-related information. This adapted, battlefield radar for biomedical purposes has the ability to view people’s bodies beneath their clothing in order to record their breathing frequency rates, heart rates, tidal volume and pulse pressure. The aim of such testing is finding ways to ease lockdowns meant to restrict coronavirus infections. Furthermore such technology for sensing respiration in an inconspicuous manner is capable of monitoring pulse, heart rate variability and respiratory rates. Thereby early-stage symptoms of COVID-19 can be easily captured ([Islam et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b34)).

The spread of coronavirus infections can also be greatly curtailed by the use of wearable technology. This technology can gather numerous sorts of data including heart rate, blood pressure, body temperature, ECG, lung sound, levels of blood oxygen saturation (SpO2) and the like ([Ding et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b18)).

The physiological stress on the body caused by the COVID-19 virus rises. This generally causes a rise in heart rate as well. Wearable remote monitoring systems, once upgraded, could offer healthcare solutions that are cost-effective and timely. Furthermore these offer an entire range of help over the course of managing COVID-19 illnesses for patients, covering early warning systems for preventative purposes, diagnosis, treatment and, finally, rehabilitation ([Islam et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b34)).

Health monitoring must track the primary metrics of people. The IoT based system has been recommended by [Tamilselvi et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b79) for this purpose. The system is fully capable of tracking body temperature, heart rate, eye movement and percentage of oxygen saturation. Furthermore this system offers integrated heartbeat, SpO2, temperature and eye blink sensors to handle the gathering of data. The Arduino-UNO has also been recommended as a processing device.

Physicians must identify clinically meaningful changes in vital signs when they monitor for COVID-19 or any other changes in health status. Various technologies are potentially able to assist in such efforts to denote health deviances from their normal variations. Deviances can be due to biological variability, time of day, food and drink, age, a person’s exercise or underlying physiological conditions ([Li et al., 2017](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b51), [Izmailova et al., 2019](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b35), [Buekers et al., 2019](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b9)).

The accuracy of a wearable is not the only consideration involving the product. People are not likely to use a product if wearing it is uncomfortable. To name two examples, sticky adhesives and bulky smart clothing will simply never be adopted by all people, whether they are patients or not ([Manta et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b54)).

Management of the medical and logistical aspects of the COVID-19 crisis evidently required a real-time, command and control tool for hospitals. The requirement for maximizing the efficiency of hospitals is a system capable of integrating clinical data on patients, medical staff status, inventories of critical clinical resources and asset allocations into one dashboard. The development of the CoView™ System addressed such a goal. It was able to join together defense concepts, big data analytics and health care protocols. Decision-makers can use this system to respond efficiently and optimally, because this system provides needed evidence pertinent to the status of all COVID-19 patients at all hospitals and admission facilities. The system is capable of analyzing aggregated data from patient monitors and electronic charts by employing artificial intelligence algorithms. It then permits appropriately alerting medical staffs regarding a worsening health among certain patients on an individual basis or analyzing treatment procedures at specific hospitals. High-level experts acting as professional advisors are able to monitor every hospital for its current situation along with its schedules of treatments and their effectiveness. Thereby such experts can assist hospital staffs everywhere in the country as required. Hospital occupancy, patient conditions, logistics and other similar factors must enter into a centralized, real-time review to establish the status of hospitals. Effective decision-making and resource allocations fundamentally rely on this sort of overview ([Abbo et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b1)).

One monitoring technology used for measuring breathing and heart rates involves thermal imaging techniques ([Hu et al., 2018](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b33)). Others include breathing dynamics ([Pereira et al., 2015](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b64)) and respiration rate ([Lewis et al., 2011](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b50)). A recommendation offered by [Jiang et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b36) involves use of a portable non-contact method. It is meant to screen the health conditions of people by analyzing respiratory characteristics even while people are wearing their face masks. This is possible with the application of a device mainly consisting of a FLIR one thermal camera and an Android phone. Its use includes monitoring possible COVID-19 patients by inspecting them in practical scenarios such as in hospitals or for pre-inspections at schools. Health screenings were performed by [Jiang et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b36) by virtue of combining the RGB and thermal videos, which they acquired from the dual-mode camera and from deep learning architecture. A respiratory data capture technique was first accomplished by [Jiang et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b36) on people wearing face masks by employing facial recognition. Next, they applied a bidirectional GRU neural network with an attention mechanism to the respiratory data to arrive at a final health screening result. Respiratory health status can be recognized to an 83.7% accuracy rate on the real-world dataset, as the results of validation experiments indicate regarding the [Jiang et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b36) model.

When it comes to predicting respiratory symptoms over the course of COVID-19 progression, [Dhanapal et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b17) recommend a Pervasive computational model with wearable devices system. Breathing rate, inhale–exhale rate, temperature ratio and shortness of breath the focus of the information examined. Deep-learning computational models depict and process the difference between normal and abnormal breathing conditions. This recommended approach gathers data on how far away people are from the sensory devices, regardless of the cloth used to construct the facemask, the angles of measurement and other information, which is appropriate for classification purposes. The results of the recommended system are at a 94% rate of accuracy. Their precision, rate of recall and F1-measure display as averages in the performed experiments. Automatic encoders obtain possible traits by virtue of the machine-learning algorithms. These are possible due to the simplicity of large-scale screening and monitoring as well as their being requirements ([Dhanapal et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b17)).

The three levels of severity of the COVID-19 viral infection, according to the categorizations by the latest clinical research, are mild, moderate and severe. Different respiratory symptoms are observable at each level, ranging from, e.g., the dry cough occurring in mild infections, to shortness of breath in moderate illnesses and onward to the severe dyspnea and respiratory distress, when the respiratory frequency > 30 breaths/min, which is also known as tachypnea, in cases of severe illness ([Cascella et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b10)). Despite the three categories, actually, all such breathing deviations progress to abnormal articulation variations. Subsequently, the employment of automatic speech and voice analysis for assistance in diagnosing COVID-19 are expected to have great interest, since these are non-invasive and inexpensive ([Han et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b27)). Cases of intelligent speech analysis relevant for COVID-19 diagnosis among patients have been the focus of [Han et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b27) for developing potential, future use. Currently [Han et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b27) have already built audio-only based models from an analysis of patient speech recordings for automatic categorization of patient health states by four aspects: illness severity, sleep quality, fatigue and anxiety. Such experimentation by [Han et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b27) indicate a 69 percent average rate of accuracy relevant to the severity of illness, derived from the number of hospitalization days.

The class of CIoT that is specific for the medical industry is the Cognitive Internet of Medical Things (CIoMT). It holds a key position in smart healthcare. The availability of remote data on patients in real time to medical personnel include physiological data like body temperature, blood pressure, heart rate, glucose level, EEG, ECG, oxygen level and such as well as psychological data like speech, expression, and such. The IoMT delivers such data remotely ([Yang et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b86)). Real-time communications of medical data are possible via Internet, and all hospital units caring for COVID-19 patients have extensive interconnections with Internet, making information transmittals both cost and time efficient. Real-time clinical parameters are available due to the assistance from CIoMT sensors, including the Electroencephalogram (EEG) sensor, Electrocardiogram (ECG) sensor, Blood pressure sensor, Pulse Oximeter, Electromyography (EMG) sensor and others. Such data is useful when assessing the severity an illness and when employing predictive analysis. Thereby, by monitoring feedback on patients, it becomes possible to prescribe effective treatments of the disease ([Swayamsiddha and Mohanty, 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b78)).

Next, the COVID-19 time series can be forecast a hybrid intelligent approach, as [Castillo and Melin (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b11) explain, by a combination of fractal theory and fuzzy logic. The complexity of dynamics in the time series of countries around the world can be measured by the mathematical concept of fractal dimension. [Castillo and Melin (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b11) provide a key contribution by proposing the hybrid approach, which combines the fractal dimension and fuzzy logic, that then facilitates fast and precise COVID-19 time series forecasting. Use of the information in a short window assists decision-makers in taking immediate actions needed in the fight against the pandemic according to this proposed approach. Meanwhile this same approach is also beneficial in the use of the longer window, such as the 30-day one, for long-term decisions, as per the study by [Castillo and Melin (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b11). Self-organizing maps were applied by [Melin et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b57) for their analysis of the spatial evolution of the global coronavirus pandemic. The clustering abilities of these self-organizing maps served as the basis in this [Melin et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b57) analysis to spatially group countries. Such groupings form in terms of similarities relevant to their coronavirus cases. These have enabled the use of similar strategies to benefit similarly behaving countries in managing the virus and curtailing its contagion.

The central objective for the study by [Dansana et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b16) was a classification of X-ray images in three categories — those of people ill with pneumonia, ill with COVID-19 and healthy people. The two algorithms used were convolution neural networks and decision tree classification. [Dansana et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b16) were able to infer highly satisfactory performances by the fine-tuned version of the VGG-19, Inception\_V2 and decision tree model. These indicated a 91% rate of increase in training and validation accuracy compared to that of the Inception\_V2 (78%) and the decision tree (60%) models.

Clinical trials applying marketable wearables for identifying and screening COVID-19 have been enacted recently by an entire array of universities like, e.g., Stanford University, Florida Atlantic University, McMaster University, Central Queensland University and University of California San Francisco; scientific research institutes like, e.g., Scripps Research Institute; hospitals like, e.g., Cleveland Clinic and companies like, e.g., AVA Sensors and NEC XON. These studies examined different physiological parameters of people like, e.g., temperature, heart and respiratory rates, heart rate variability, activity and sleep levels, oxygen saturation, sleep measures, galvanic skin response, electrodermal activity, electrocardiogram, blood pressure and others.

Some of the health metrics that consumer devices can measure quite easily include, e.g., respiration rate, heart rate and heart rate variability. These are notable for their ability to foresee early symptoms of potential illnesses. An additional feature is the ability of mobile applications accompanying wearable devices to gather data on related, self-reported symptoms and demographics. Such consumer devices can play valuable roles in the battle against the COVID-19 pandemic ([Natarajan et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b61)). Two approaches for assessing COVID-19 were considered by [Natarajan et al. (2020)](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b61). These were a symptom-based approach and a physiological signs-based technique. Illness usually raises the respiration rate and heart rate; whereas, heart rate variability generally drops. An early diagnosis of this condition is possible by recording a history of such measurements. Such a history aids in tracking the progress of the illness as well ([Natarajan et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b61)). The digital infrastructure for remote patient monitoring has come into prominence during the recent COVID-19 pandemic. The clear-cut need is for harnessing and leveraging it. Tests and related vaccines are implemented slowly, making clear the deficiencies in disease detection and in the monitoring of health at both the individual level and for the entire population. The assistance for accomplishing these tasks can come from wearable sensors. Numerous physiological parameters can be accurately measured remotely due to the developed, integrated sensor technology. Such measurements have proven beneficial for tracking the progress of a viral disease. This technology has a wide range of impact. For example, a person who is under quarantine at home may suddenly require better care, and this technology can be brought into play. Another example might involve an entire community under threat of an oncoming outbreak of illness that vitally needs immediate intervention ([Seshadri et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596" \l "b72)).

Physiological metrics have been correlated with daily living and human performance pertinent to the functionality of this technology. Nonetheless, this technology must translate into predictions of COVID-19 cases. People wearing devices that are joined to predictive platforms could receive alerts regarding changes in their metrics whenever they correspond with possible COVID-19 symptoms. Depersonalized data gathered on the basis of neighborhoods or zip codes, especially during a second wave, could prove valuable for public health officials and researchers for tracing and alleviating the spread of this virus. Once certain persons are identified with a COVID-19 diagnosis, others with whom they have associated, such as families, coworkers and persons encountered in businesses and other facilities, can also be engaged into remote monitoring. Thereby very needed data regarding the speed of disease transmission and the beginning of its pertinent symptom manifestations can be detected ([Seshadri et al., 2020](https://www.sciencedirect.com/science/article/pii/S0952197620303596#b72)).

The H2020 ROCK project conducted in Vilnius city during which the ROCK Video Neuroanalytics and related infrastructure were developed involved studies of passers-by at eight sites in the city (Kaklauskas et al., 2019). We analyzed the Vilnius Happiness Index (see https://api.vilnius.lt/happiness-index) with ROCK Video Neuroanalytics in real-time, also conducted different other activities (see https://Vilnius.lt/en/category/rock-project/). The ROCK Video Neuroanalytics consists of framework containing a Database Management Dystem, a Database, Sensor Network, a Model Database Management System, a Model Database and a User Interface. The kinds of states stored in the ROCK Video Neuroanalytics Database are emotional states (happy, sad, angry, surprised, scared, disgusted or a neutral state), affective states (boredom, interest and confusion) and physiological states (average crowd facial temperature, crowd composition by gender and age groups as well as heart and breathing rates), arousal and valence. These are the MAPS data assembled in the Sensor Network. The subsystems contained within the Model Database are the Data Mining Subsystem, Recommendations Model, Decision Support and Expert Subsystem and Correlation Subsystem. Meanwhile the Database consists of the developed Video Neuroanalytics as well as the Historical, Recommendations, Decision Support and Expert Subsystem Databases. Remote data generated from affective, emotional and physiological parameter measurement devices base the compilation of a Sensor Network. Such remote data consist of MAPS data, sex, age (as per FaceReader 8), temperature (as per Infrared Camera FLIR A35SC), breathing rate (as per Sensor X4M200) and numbers of passersby (as per the H.264 Indoor Mini Dome IP Camera).

A dependency was discovered in the pre-COVID-19 and post-COVID-19 periods in an entire array of studies, including the research by Speth et al. (2020), Karadaş et al. (2020), Nalleballe et al. (2020), Altable and de la Serna (2020), Groarke et al. (2020) and Mishra and Banerjea (2020). These two periods linked with neurological and neuropsychiatric manifestations like apathy, confusion, anxiety and mood disorders; neurological problems and symptoms that include stress and mood as well as anxiety levels indicating depression. Therefore, the research conducted by these same authors on potential COVID-19 infection includes supplemental analyses on emotional and affective states.

A study pertinent to elderly age by Speth et al. (2020) discovered baseline depressive mood and anxiety levels during the pre-COVID-19 period, which positively associated with more depressive moods and anxiety during the COVID-19 period. Headaches, stress, stroke, itch, cerebrovascular dysfunction and BBB disruption are all examples of COVID-19-caused symptoms stemming from numerous neurological problems (Kempuraj et al., 2020). A study involving 239 patients of which 133 were males and 106 were females, all with COVID-19 diagnoses, was performed by Karadaş et al. (2020). Of the 239 patients, 83, or 34.7% involved neurological findings. COVID-19 causes harm to the nerve and muscle systems. Typical neurological symptoms include headache, muscle pain, sleep disorder, impaired consciousness, smell and taste impairments, dizziness and cerebrovascular diseases (Karadaş et al., 2020).

Then, in 2020, a study was conducted by Nalleballe et al. (2020) on 40,469 COVID-19 positive patients. Its finding was that 22.5% of patients displayed neuropsychiatric symptoms associated with COVID-19. A handful of minor studies corresponded with this same finding. These had been performed by Mao et al. (2020) and Helms et al. (2020). There appears to be a potentially strong relationship between coronavirus infections and psychosis. COVID-19 patients display neuropsychiatric symptoms, which customarily include anxiety, mood disorders, headache, sleep disorders, encephalopathy, stroke, seizures and neuromuscular complications (Nalleballe et al., 2020). Neuropsychiatric symptoms appear from the start of a COVID-19 illness whether it is mild, moderate or severe. The kinds of neuropsychiatric symptoms include anxiety, panic attacks, depression, mental confusion, acute confusional syndrome, psychomotor excitement, psychosis and, possibly, suicidal inclinations. The importance of these symptoms appearing in COVID-19 cases is that patients suffer these in addition to the customary symptoms of fever, cough and dyspnea. The suffering of such an illness further causes apathy, anorexia and muscular pain (Altable and de la Serna, 2020).

Morbidity and mortality have outcropped significantly during the ongoing COVID-19 pandemic due to neurological complications. A large number of hospitalized patients indicate neurological symptoms in addition to a respiratory insufficiency. Such symptoms appear as a wide range of maladies from a headache and loss of smell, to confusion and disabling strokes (Groarke et al., 2020). Coronavirus-caused neurological maladies constitute clear-cut pathogenic symptoms. The damage caused by neurological impairments can extend from general, cognitive and motor dysfunctions up to a wide spectrum of CNS anomalies like anxiety and other kinds of audio-visual incapacities (Mishra and Banerjea, 2020).

**References:**

Abbo, A. R., Miller, A., Gazit, T., Savir, Y., & Caspi, O. (2020). Technological Developments and strategic management for overcoming the COVID-19 challenge within the hospital setting in Israel. Rambam Maimonides Medical Journal, 11(3).

Altable, M., & de la Serna, J. M. (2020). Neuropsychiatry and COVID-19: An Overview. Qeios.

Buekers, J., Theunis, J., De Boever, P., Vaes, A. W., Koopman, M., Janssen, E. V., ... & Aerts, J. M. (2019). Wearable finger pulse oximetry for continuous oxygen saturation measurements during daily home routines of patients with chronic obstructive pulmonary disease (COPD) over one week: Observational study. JMIR mHealth and uHealth, 7(6), e12866.

Cascella, M., Rajnik, M., Aleem, A., Dulebohn, S., & Di Napoli, R. (2022). Features, evaluation, and treatment of coronavirus (COVID-19). StatPearls.

Castillo, O., & Melin, P. (2020). Forecasting of COVID-19 time series for countries in the world based on a hybrid approach combining the fractal dimension and fuzzy logic. Chaos, Solitons & Fractals, 140, 110242.

Dansana, D., Kumar, R., Bhattacharjee, A., Hemanth, D. J., Gupta, D., Khanna, A., & Castillo, O. (2020). Early diagnosis of COVID-19-affected patients based on X-ray and computed tomography images using deep learning algorithm. Soft Computing, 1-9.

Dhanapal, J., Narayanamurthy, B., Shanmugam, V., Gangadharan, A., & Magesh, S. (2020). Pervasive computational model and wearable devices for prediction of respiratory symptoms in progression of COVID-19. International Journal of Pervasive Computing and Communications.

Ding, X., Clifton, D., Ji, N., Lovell, N. H., Bonato, P., Chen, W., ... & Zhang, Y. T. (2020). Wearable sensing and telehealth technology with potential applications in the coronavirus pandemic. IEEE reviews in biomedical engineering, 14, 48-70.

Groarke, J. M., Berry, E., Graham-Wisener, L., McKenna-Plumley, P. E., McGlinchey, E., & Armour, C. (2020). Loneliness in the UK during the COVID-19 pandemic: Cross-sectional results from the COVID-19 Psychological Wellbeing Study. PloS one, 15(9), e0239698.

Han, J., Qian, K., Song, M., Yang, Z., Ren, Z., Liu, S., ... & Schuller, B. W. (2020). An early study on intelligent analysis of speech under COVID-19: Severity, sleep quality, fatigue, and anxiety. arXiv preprint arXiv:2005.00096.

Helms, J., Kremer, S., Merdji, H., Clere-Jehl, R., Schenck, M., Kummerlen, C., ... & Meziani, F. (2020). Neurologic features in severe SARS-CoV-2 infection. New England Journal of Medicine, 382(23), 2268-2270.

Hollander, J. E., & Carr, B. G. (2020). Virtually perfect? Telemedicine for COVID-19. New England Journal of Medicine, 382(18), 1679-1681.

Hu, M., Zhai, G., Li, D., Fan, Y., Duan, H., Zhu, W., & Yang, X. (2018). Combination of near-infrared and thermal imaging techniques for the remote and simultaneous measurements of breathing and heart rates under sleep situation. PloS one, 13(1), e0190466.

Islam, M., Mahmud, S., Muhammad, L. J., Nooruddin, S., & Ayon, S. I. (2020). Wearable technology to assist the patients infected with novel coronavirus (COVID-19). SN computer science, 1(6), 1-9.

Izmailova, E. S., McLean, I. L., Hather, G., Merberg, D., Homsy, J., Cantor, M., ... & Wagner, J. A. (2019). Continuous monitoring using a wearable device detects activity‐induced heart rate changes after administration of amphetamine. Clinical and translational science, 12(6), 677-686.

Jiang, Z., Hu, M., Fan, L., Pan, Y., Tang, W., Zhai, G., & Lu, Y. (2020). Combining visible light and infrared imaging for efficient detection of respiratory infections such as COVID-19 on portable device. arXiv preprint arXiv:2004.06912.

Kaklauskas, A., Zavadskas, E. K., Bardauskiene, D., Cerkauskas, J., Ubarte, I., Seniut, M., ... & Velykorusova, A. (2019). An affect-based built environment video analytics. Automation in Construction, 106, 102888.

Karadaş, Ö., Öztürk, B., & Sonkaya, A. R. (2020). A prospective clinical study of detailed neurological manifestations in patients with COVID-19. Neurological Sciences, 41(8), 1991-1995.

Kempuraj, D., Selvakumar, G. P., Ahmed, M. E., Raikwar, S. P., Thangavel, R., Khan, A., ... & Zaheer, A. (2020). COVID-19, mast cells, cytokine storm, psychological stress, and neuroinflammation. The Neuroscientist, 26(5-6), 402-414.

Lewis, G. F., Gatto, R. G., & Porges, S. W. (2011). A novel method for extracting respiration rate and relative tidal volume from infrared thermography. Psychophysiology, 48(7), 877-887.

Li, X., Dunn, J., Salins, D., Zhou, G., Zhou, W., Schüssler-Fiorenza Rose, S. M., ... & Snyder, M. P. (2017). Digital health: tracking physiomes and activity using wearable biosensors reveals useful health-related information. PLoS biology, 15(1), e2001402.

Manta, C., Jain, S. S., Coravos, A., Mendelsohn, D., & Izmailova, E. S. (2020). An evaluation of biometric monitoring technologies for vital signs in the era of COVID‐19. Clinical and translational science, 13(6), 1034-1044.

Mao, L., Wang, M., Chen, S., He, Q., Chang, J., Hong, C., ... & Hu, B. (2020). Neurological manifestations of hospitalized patients with COVID-19 in Wuhan, China: a retrospective case series study. MedRxiv.

Melin, P., Monica, J. C., Sanchez, D., & Castillo, O. (2020). Analysis of spatial spread relationships of coronavirus (COVID-19) pandemic in the world using self organizing maps. Chaos, Solitons & Fractals, 138, 109917.

Mishra, R., & Banerjea, A. C. (2020). Neurological damage by coronaviruses: a catastrophe in the queue!. Frontiers in immunology, 2204.

Nalleballe, K., Onteddu, S. R., Sharma, R., Dandu, V., Brown, A., Jasti, M., ... & Kovvuru, S. (2020). Spectrum of neuropsychiatric manifestations in COVID-19. Brain, behavior, and immunity, 88, 71-74.

Natarajan, A., Su, H. W., & Heneghan, C. (2020). Assessment of physiological signs associated with COVID-19 measured using wearable devices. NPJ digital medicine, 3(1), 1-8.

Pereira, C. B., Yu, X., Czaplik, M., Rossaint, R., Blazek, V., & Leonhardt, S. (2015). Remote monitoring of breathing dynamics using infrared thermography. Biomedical optics express, 6(11), 4378-4394.

Seshadri, D. R., Davies, E. V., Harlow, E. R., Hsu, J. J., Knighton, S. C., Walker, T. A., ... & Drummond, C. K. (2020). Wearable sensors for COVID-19: a call to action to harness our digital infrastructure for remote patient monitoring and virtual assessments. Frontiers in Digital Health, 8.

Speth, M. M., Singer‐Cornelius, T., Oberle, M., Gengler, I., Brockmeier, S. J., & Sedaghat, A. R. (2020). Mood, anxiety and olfactory dysfunction in COVID‐19: evidence of central nervous system involvement?. The Laryngoscope, 130(11), 2520-2525.

Swayamsiddha, S., & Mohanty, C. (2020). Application of cognitive Internet of Medical Things for COVID-19 pandemic. Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 14(5), 911-915.

Tamilselvi, V., Sribalaji, S., Vigneshwaran, P., Vinu, P., & GeethaRamani, J. (2020, March). IoT based health monitoring system. In 2020 6th International conference on advanced computing and communication systems (ICACCS) (pp. 386-389). IEEE.

Terry M., (2020). Fitbit COVID-19 study suggests wearables can detect disease before symptoms arrive BioSpace. Available online: <https://www.pharmalive.com/fitbit-covid-19-study-suggests-wearables-can-detect-disease-before-symptoms-arrive/>

Yang, T., Gentile, M., Shen, C. F., & Cheng, C. M. (2020). Combining point-of-care diagnostics and internet of medical things (IoMT) to combat the COVID-19 pandemic. Diagnostics, 10(4), 224.