E-health Strategies

Technology, Telehealth & Wearables in the Coronavirus Pandemic: A literature review

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Abstract

COVID-19 brought a worldwide pandemic that critically hit the medical system. One of the biggest concerns is that the rapid spread of COVID-19 would exceed the hospitalization ability of a country. To relieve pressure on hospitals and lower the population transmission, E-health technologies are widely used during this pandemic. Remote consultation, remote monitoring via technologies like Telehealth and wearables largely enrich the healthcare services. Additionally, the data which E-health equipment collected could be used in prediction models. This would help policy makers in the decision-making process, and as a consequence, lower the number of infection and mortality. In the present study, E-health is divided into Telehealth, wearables, and prediction models. By conducting a literature review on those three sectors, the question "How does E-health act in COVID-19 pandemic?" will be answered.

Keywords: E-health, Telehealth, wearables, prediction model, COVID-19, healthcare services

1. Introduction

The whole world has been suffering with COVID-19 during the past 2 years. The coronavirus has affected almost 228 countries and territories claiming the lives of approximately 63 million people all over the world.[1] Therefore, the importance of an early prediction of the virus tends to prove essential for its prevention.

The importance of Telehealth has rapidly grown as a result of the coronavirus (COVID-19) pandemic, particularly as many physical clinics have closed.

Social distancing is necessary to stop the spread of the coronavirus pandemic. Utilizing Telehealth is one way to avoid the need for social distance. Employees who need to be quarantined may still be able to work due to Telehealth. [2]

Furthermore, during the COVID-19 pandemic, telemedicine, which is defined as the delivery of healthcare services (such as illness diagnosis, treatment, prevention, research, and education) at a distance utilizing telecommunications technology, has quickly gained popularity.

The use of telemedicine has increased due to developments in communication technology and better health literacy, and a number of medical and surgical specialties have reported positive outcomes from their use of telemedicine.

After reviewing several pieces of literature, it is divided into three major categories. The first category covered Telehealth-based COVID-19 control. The second category concentrated on COVID-19 and Telehealth's technological features. The third category covered different prediction models that have been implemented during the pandemic.

2. Telehealth

2.1. Control

During the COVID-19 pandemic, Telehealth was used to monitor and manage each disease. The following subsections cover the functions of Telehealth and how it is integrated into the management of each disease.

2.1.1 Diabetes

It is becoming more and more obvious that individuals with diabetes see Telehealth as a desirable and workable substitute for in-person care. In a diabetes care center, the switch from in-person to Telehealth was fast and met with high patient satisfaction. [3]

In order to manage diabetes, systems have been developed to organize many types of objective and subjective data, including:

- Patient-collected physiological data, including blood sugar levels, continuous glucose levels, and blood pressure.
- laboratory data, including hemoglobin levels.
- behavioral data, including dietary intake and exercise patterns.

- medication dosages, allergies, and other history.
- subjective symptoms of hypoglycemia or other complaints.
- Information about relevant events, such as hospital stays, scheduled ophthalmologist visits, vaccinations, and missed clinic appointments.

These data allow a practitioner or a doctor to get in touch with the patient immediately or on a regular basis as scheduled [4].

Telehealth has the potential to significantly alter the way diabetes is handled by increasing the effectiveness of care and the standard of care for all people with this condition.

2.1.2 Mental disorder

In this pandemic situation, stress levels are significantly increased in both symptomatic and asymptomatic COVID-19 patients. Telemedicine makes mental health services more available by enabling patients to receive care in the privacy of their own homes while avoiding stigma. Telemedicine can effectively treat a variety of mental health issues, such as anxiety, depression, and substance use disorders, among others, especially in the primary healthcare setting. In mental health care, in order to reduce the danger of doctors or patients contracting an infection while still delivering care, Telehealth may be an alternative, particularly in areas with a shortage of psychiatrists and other mental health specialists [5].

2.1.3 Cancer

The fast adoption of Telehealth in cancer care and other disciplines has been prompted by the COVID-19 pandemic. Many of the changes made to standard clinical practice may persist after the pandemic. This is meant to serve as a helpful manual for cancer doctors and others in setting up and raising the standard of consultations provided through Telehealth. With the aid of Telehealth and digital tools, cancer professionals may now help regions that might not have access to local cancer specialists, care models, or specialty services [6].

2.2 Medical procedure

During the COVID-19 pandemic, medical practices involve the urgent and non-urgent usage of telemedicine.

Different surgical procedures can be considered as urgent which is an important procedure. Although telemedicine use in surgery has proven to be practical, the field encountered an unique circumstance during the COVID-19 pandemic, in which Telehealth became a key method of providing medical care. During the COVID-19 pandemic, surgeons employed Telehealth at significantly higher rates than in the prior, with significant variance between specialties.

Of the 4405 active surgeons, 2588 (58.8%) employed Telehealth in a patient care setting. Surgeons who saw at least one new patient in 2020 were considered to be active. 1182 active surgeons (26.2%) used Telehealth specifically for new patient visits [7].

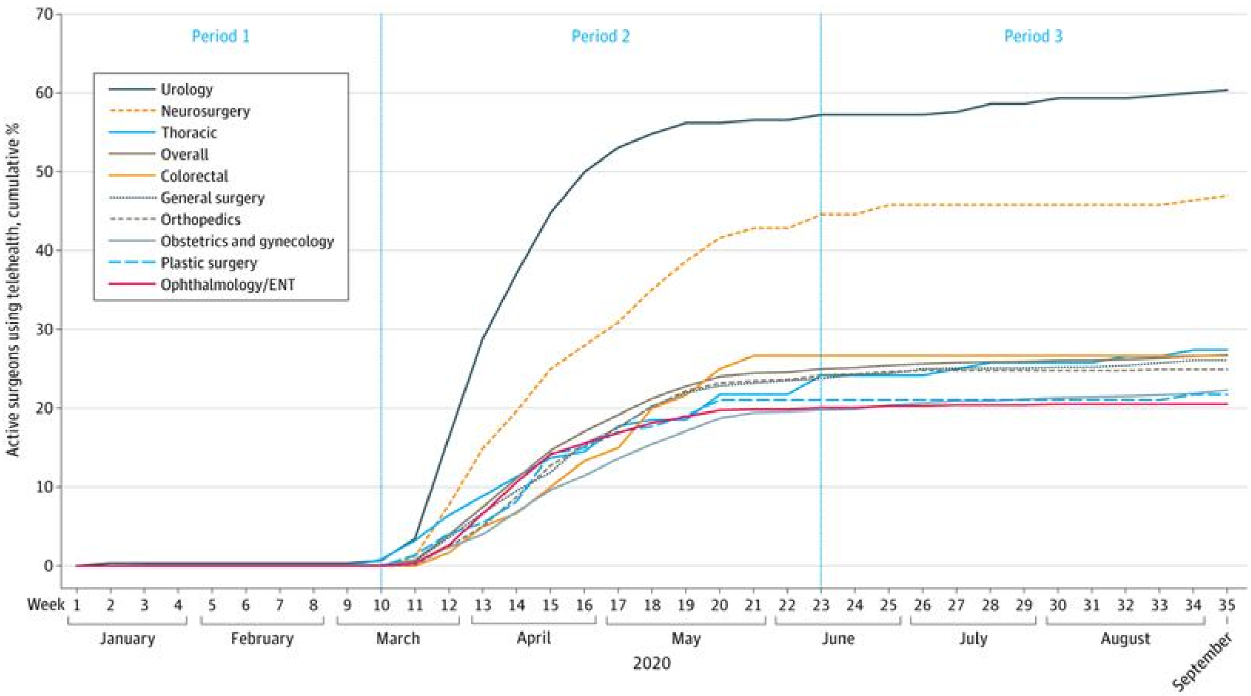

Figure. 1: *By surgical specialty, the use of surgeon Telehealth in new patient visits in 2020 [4]*

For non-urgent medical procedures, we can highlight the following Telehealth solutions that were used during the COVID-19 pandemic:

- Telemonitoring: The ability to measure, store, and transmit specific patient information at any given time is referred to as Telemonitoring.
- Tele-management: To monitor COVID-19 patients in home quarantine who are at risk of poor health with illness development, a Telehealth model was created while taking the medical personnel shortage into account. By providing ongoing monitoring of outpatients, Tele-management combines teleconsultation with telemonitoring services
- Screening: In order to provide services in areas with restricted access to expertise during the COVID-19 pandemic, screening strategy includes contacting specialists from centers throughout the world.
- Tele-dentistry: Instead of having direct face-to-face interactions with patients, tele dentistry uses information technology to facilitate dental care, counseling, and education remotely. Tele dentistry can be integrated into standard dental practice because it has so many uses, including remote triaging of COVID-19 patients for dental care and reducing the unneeded exposure of healthy or uninfected

patients by reducing their visits to already overloaded dental offices and hospitals. [8]

- Tele-consultation: A tele-consultation is an electronic exchange of information between a health professional and a patient or other health professional for the purpose of providing medical services. In order to support vulnerable patients and stop spread and infection, teleconsultation is a highly effective strategy with a high percentage of satisfaction.

3. Wearables

Wearables are devices that help in monitoring the vital signs such as temperature, heart rate in medical patients. The widespread use of wearables are also being used now by common people who use it as a tool to pre-detect an alarming situation and get prepared beforehand for any case of medical emergencies. For example, Fitbit smartwatches are designed to (i) Collect the data of users' personal health and exercise; (ii) Providing real-time data; (iii) promoting self-management.

3.1 Rise of Wearables during COVID-19

The different types of sensors used, their placement in the body and the use of AI technology with e-health wearables were studied based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analyses) based guideline. The different types of sensors that were used for detecting the symptoms of COVID-19 were:

(i) Temperature Sensors- Monitoring fever proved to be pretty important during the time of covid. A device called TempTraq[9] which is used to detect the infant's temperature and send the data via Bluetooth to a smartphone app is a notable example. This monitors temperature for around 48 hours.[10]

(ii) Pulse Oximeters- This is one of the main wearable devices that was used during the time of COVID-19 in order to measure the SpO2 (blood oxygen) level. [11] This device could estimate the level of oxygen and could give an alert if the SpO2 level is low. The measuring sites are the fingers, toes, and ear lob.[10]

(iii) Respiratory Rate- The Respiration Rate (RR) is one of the features that help in detecting the severity of a respiratory disease. Devices such as Wearable strain gauge sensor [12], accelerometers are used to study the respiratory movement.[10]

(iv) Cough and Lung Sound Monitoring- People having dry cough was one of the symptoms during the time of COVID-19. The monitoring proved to not only prevent covid but also from spreading it to other people when one person coughs. Cough signals were acquired with an audio sensor when the vibration caused by the cough is detected.[10]

(v) ECG (Electrocardiogram) for Monitoring COVID-19 Patients- ECG is used to measure the activity of the heart. Wearable-based-tele-ECG monitoring was used in order to reduce staff-patient contact. Adhesive ECG patches [13] with a sensor system, a microelectronic circuit with a recorder and memory storage with an internal battery were used to measure ECG for several days as a wearable small sized wireless patch.[10]

(vi) BP Monitoring- Blood Pressure (BP) monitoring is one of the most important features that help in preventing cardiovascular diseases. A very commonly used cuff-based sphygmomanometer is used for measuring the BP. Continuous and regular monitoring of the BP is vital and the unobstructive BP monitoring wearables such as BP watches help to do that. [14,10]

3.2 Future of Wearables

The future of wearables is bright and it can take over from a lot of other technologies in the future. Anticipating medical emergencies before they happen might be the way to go forward hereafter, direct communication between the wearable and the user's doctor's office, monitor and detect hypertension, blood flow hemodynamics[15] is to be observed and reported where the distribution of pumping of blood throughout the body is studied, the user health hazards should be anticipated, a wearable sensor in pulmonary artery where a patient with a cardiac condition may have a wearable technology sensor implanted in their pulmonary artery that collects and communicates real-time data to their doctor.[16] [17]

4 Prediction models

The prediction models, which represent the technology of artificial intelligence and big data, work with Telehealth and wearables to construct an IT-infrastructure against COVID-19. In the aspects of prevention, diagnosis, treatment, protection, and management aims, data can be the driving force to integrate the components.[18]

4.1 Methodology

In this sector, Scopus is used to search for papers. Search terms would include: COVID-19, prediction, model. First, the search result is sorted by the number of citations. However, this would lead to a higher possibility of showing papers that are written in 2020. Thus, the second step is limiting the result by year. The third step is to sort the result by relevance. In each step, the top 30 papers are chosen. After excluding duplicate and irrelevant research, a total number of 26 papers are shown in ***Table 1***. The models can be divided into two main categories: mathematical model and computational model.

4.2 Mathematical models

Mathematical models are based on mathematical equations. Moreover, the model can be derived only by mathematical equations. It is also analytical. This category would include SIR-based models, which use differential equations; Time series models, for example Holt, ARIMA and Prophet. Mathematical model is considered more pure, and suitable for static situations. However, it lacks the ability to fit reality situations, which normally are nonlinear and dynamic. For example, the main theory of the SIR model is to divide the population into Susceptible, Infected, and Recovered. It assumes that the recovered ones will gain immunity from the infection. As a result of that, the recovered ones (or the vaccinated) will not be infected again. But the Omicron variant of COVID-19 may lead to more significant immune escape from the immunity protection elicited by previous COVID-19 infection, which would make the division more complicated.[19] Furthermore, it is hard for SIR to fit the reality when non pharmaceutical interventions will affect the spreading of COVID-19.[20]

4.3 Computational models

Computational models are derived by running a simulation. By simulating, it can adjust the parameters in the model and study from different simulation results.[21] This category would include Artificial neural network, decision tree and agent-based models.

4.3.1 Agent-based models

Compared with mathematical models, agent-based models are a relatively new approach in the pandemic prediction area. Its strategy is based on different characteristics of individuals and programmed rules, which distinct it from the mathematical model that considers a homogenous population.[22]

4.4 Hybrid models

In ***Table 1***, there are hybrid models that combine mathematical and computational models. The computational model can be used in data preprocess. Because the COVID-19 data could be imperfect. [23] It could also be that turning Mathematical models (like SIR) output into time-series data. Then the computational data can make use of the time-series data.[24]

5 Discussion

This section tried to identify and emphasize three key elements: (1) Telehealth's difficulties and issues; (2) reasons for interest in the topic's advantages and importance.

5.1. Challenges

The necessity of providing Telehealth that satisfies patients' needs during a pandemic has created various challenges.

Despite the fact that the quality and accessibility of low-cost technologies improved during the pandemic, patients frequently mentioned how their Telehealth programs were affected by equipment breakdown, shortages of equipment, connection issues, device incompatibility with readily available software, and restricted functionality.[25]
Poor patient engagement as well as provider difficulty to reach patients or decreased consultation confidentially were identified as Telehealth challenges.
Utilizing Telehealth raises additional security issues during the COVID-19 pandemic. On the internet, it is more challenging to preserve patient information protection and privacy. Many patients might not feel at ease having their data transmitted online, and security breaches can be one of their worries regarding Telehealth. [26]

Furthermore, there are some challenges that have appeared in the wearable: technology false-positive findings pose a danger, necessitating more time and effort to correctly analyze the data, privacy and security concerns, as most data may be shared if the digital network's security is breached.
Also, regulatory issues are preventing E-health from progressing to the next level of innovation. One of them happening in the wearables sector is that before a gadget can be approved, it must go through a series of complicated and time-consuming procedures. Prediction models can predict the trends and outbreaks of COVID-19 infected cases. Thus, promote policymaking to protect people from the pandemic. But the decision-making process is affected by political reasons, which would cause a slow reaction.[27]
Ethical problems could also arise because many models use data like race and geography.[28] Then the policy actions may “recognize and address these inequities”.[29]

5.2. Motivations

Whenever possible, limiting in-person contact during the pandemic has slowed the spread of COVID-19 and preserved more sensitive patients. The capacity to use Telehealth in the future can shield patients from additional dangers of healthcare facility visits such infections and stop the spread of the flu and other diseases.

Additionally, Telehealth proved incredibly cost-effective for facilities, providers, and patients during the pandemic. Travel expenses, administrative tasks, and more expensive care alternatives, such as emergency rooms and hospital stays, can all be avoided by avoiding the need to visit a medical facility.

The advantages related to the wearable technology are capable of monitoring with little input from users, implemented easily and works efficiently in patients remote settings, hence providing a noninvasive assessment of patients, ability to offer objective physiological parameter readings that may correlate with practical wireless network systems and serve as a platform for real-time input to patients and clinicians, provide a key early-warning system for diseases.

6 Conclusion

The COVID-19 pandemic's recent and quick use of E-health, as well as the uncertainties surrounding the pandemic, are likely to increase E-health's potential.

The COVID-19 pandemic has accelerated the development and adoption of E-health, prompting a shift toward its usage for clinical assessment of the virus as a vital step. In this paper, in order to maximize the effectiveness and quality of the technologies used, particularly in respect to their involvement in the control, implementation, and prediction models during the COVID-19 pandemic, the relationship between COVID-19 and Telehealth is discussed. Although there are challenges like ethical, political, patient privacy, and variance equipment problems, E-health and related technology will still continuously evolve. Not only because of the emerging variants of Covid-19 and potential threat like Monkey pox, but also for its advantages and potential. To enable E-health with the ability of prevention, diagnosis and treatment during a pandemic, co-operation among various software, equipment, and prediction models are needed.

Category	Title	Year	Citation	Data Type	Prediction	Model	Ref
SIR-based model	Forecasting COVID-19 epidemic in India and high incidence states using SIR and logistic growth models	2021	54	Time-series data of COVID-19	Daily COVID-19 cases in the future	SIR	[30]
	SIRVD-DL: A COVID-19 deep learning prediction model based on time-dependent SIRVD	2021	1	Time-series data of COVID-19, and vaccination	Daily COVID-19 cases in the future	SIRVD-DL	[24]
	Data-based analysis, modeling and forecasting of the COVID-19 outbreak	2020	565	Time-series data of COVID-19	Daily COVID-19 cases in the future	SIRD	[31]

	Data-driven prediction of COVID-19 cases in Germany for decision making	2022	2	Time-series data of COVID-19	Daily COVID-19 cases in the future	SEIR	[32]
Computational model	COVID-19 cases prediction by using hybrid machine learning and beetle antennae search approach	2021	74	Time-series data of COVID-19	Daily COVID-19 cases in the future	ANFIS	[33]
	Predicting mortality risk in patients with COVID-19 using machine learning to help medical decision-making	2021	39	Symptoms, Pre-existing Conditions, Demographics	COVID-19 mortality risk	Support Vector Machine (SVM), Artificial Neural Networks, Random Forest, Decision Tree, Logistic Regression, and K-Nearest Neighbor (KNN)	[34]
	COVID-19 mortality rate prediction for India using statistical neural networks and gaussian process regression model	2021	10	Time-series data of COVID-19 death cases, COVID-19 Confirmed Case(dependent) and Death Cases(independent)	mortality rate	Statistical Neural Networks (Radial Basis Function Neural Network (RBFNN), Generalized Regression Neural Network (GRNN)), and	[35]

						Gaussian Process Regression (GPR)	
	Prediction of the number of COVID-19 confirmed cases based on K-means-LSTM	2021	1	Demographic data, weather data, Time-series data of COVID-19	Daily COVID-19 cases in the future	K-means-LSTM	[36]
	A Machine Learning Algorithm Predicts Duration of hospitalization in COVID-19 patients	2021	3	laboratory data, Demographics, Social history, Vitals, Clinical observations, Comorbidities	Duration of hospitalization in COVID-19 patients	Ensemble-based model	[28]
	Machine Learning Applied to Clinical Laboratory Data in Spain for COVID-19 Outcome Prediction: Model Development and Validation	2021	7	Clinical Laboratory Data	e severity of infection and mortality	XGBoost	[37]

	COVID-19 Pandemic Prediction for Hungary; A Hybrid Machine Learning Approach	2020	203	Time-series data of COVID-19	Daily COVID-19 cases and mortality rate in the future	Adaptive network-based fuzzy inference system (ANFIS) and multi-layered perceptron-imperialist competitive algorithm (MLP-ICA)	[23]
	COVINet: a convolutional neural network approach for predicting COVID-19 from chest X-ray images	2020	16	chest X-ray images	diagnosis	convolutional neural network	[38]
	Real-time Prediction of the Daily Incidence of COVID-19 in 215 Countries and Territories Using Machine Learning: Model Development and Validation	2021	8	Time-series data of COVID-19, Google Trends data	Daily COVID-19 cases in the future	Random tree regression	[39]

	Machine Learning–Based Prediction of Growth in Confirmed COVID-19 Infection Cases in 114 Countries Using Metrics of Nonpharmaceutical Interventions and Cultural Dimensions: Model Development and Validation	2021	10	Time-series data of COVID-19, Nonpharmaceutical interventions, Hofstede cultural dimensions	Daily COVID-19 cases in the future	random forest and adaptive boosting (AdaBoost) regression	[20]
Agent-based model	An agent-based model to evaluate the COVID-19 transmission risks in facilities	2020	103	Transmission process data	Daily COVID-19 cases in the future		[22]
Other Mathematical models	Development and Validation of a Web]Based Severe COVID-19 Risk Prediction Model	2021	3	demographic, clinical, and laboratory data	Severe COVID-19 Risk	Multivariable logistic regression	[40]
	Modeling and prediction of COVID-19 in Mexico applying mathematical and computational models	2020	90	Time-series data of COVID-19	Daily COVID-19 cases in the future	Gompertz and Logistic models	[41]
	Real-time forecasts of the COVID-19 epidemic in China from February 5th to February 24th, 2020	2020	528	Geography, Clinical	Daily COVID-19 cases in the future	phenomenological model	[42]

	Machine-learning-based COVID-19 mortality prediction model and identification of patients at low and high risk of dying	2021	15	clinical	low and high risk of dying	partial least square (SIMPLS)	[43]
	A novel reliability-based regression model to analyze and forecast the severity of COVID-19 patients	2022	0	clinical	severity of COVID-19 patients	Reliability-based regression	[44]
	An Efficient COVID-19 Prediction Model Validated with the Cases of China, Italy and Spain: Total or Partial Lockdowns?	2020	28	Time-series data of COVID-19	Daily COVID-19 cases in the future	Verhulst equation	[45]
	A new COVID-19 prediction scoring model for in-hospital mortality: experiences from Turkey, single center retrospective cohort analysis	2020	9	Laboratory and clinical data	in-hospital mortality	prediction scoring model	[46]
Time-series model	Prediction of COVID-19 growth and trend using machine learning approach	2021	4	Time-series data of COVID-19	Daily COVID-19 cases in the future	Holt's winter model	[47]
	Application of machine learning time series analysis for prediction COVID-19 pandemic	2020	10	Time-series data of COVID-19	Daily COVID-19 cases in the future	Naïve method and ARIMA	[48]

	Determining an effective short term COVID-19 prediction model in ASEAN countries	2022	0	Time-series data of COVID-19	Daily COVID-19 cases in the future	Holt’s and ULFR	[49]
	COVID 19 Prediction Model Using Prophet Forecasting with Solution for Controlling Cases and Economy	2022	0	Time-series data of COVID-19	Daily COVID-19 cases in the future	Prophet	[50]

Table. 1 *Summary of the results of studies in predicting covid-relevant situation*

Data type means what kinds of data the models use as input; prediction means a specific field that can be predicted; model means the core model to predict

Reference

[1] “COVID-19 CORONAVIRUS PANDEMIC” https://www.worldometers.info/coronavirus/

[2] Schulz T, Long K, Kanhutu K, Bayrak I, Johnson D, Fazio T. (2022). Telehealth during the coronavirus disease 2019 pandemic: Rapid expansion of Telehealth outpatient use during a pandemic is possible if the programme is previously established. doi:10.1177/1357633X20942045

[3] Andrews, Elizabeth & Berghofer, Kendall & Long, Julie & Prescott, Amber & Caboral-Stevens, Meriam. (2020). Satisfaction with the use of Telehealth during COVID-19: An integrative review. International journal of nursing studies advances. doi:10.1016/j.ijnsa.2020.100008.

[4] Klonoff D. C. (2009). Using telemedicine to improve outcomes in diabetes--an emerging technology. https://doi.org/10.1177/193229680900300401

[5] Arafat, M. Y., Zaman, S., & Hawlader, M. (2021). Telemedicine improves mental health in COVID-19 pandemic.
https://doi.org/10.7189/jogh.11.03004

[6] Burbury, K., Wong, Z.-W., Yip, D., Thomas, H., Brooks, P., Gilham, L., Piper, A., Solo, I. and Underhill, C. (2021), Telehealth in cancer care: during and beyond the COVID-19 pandemic. Intern Med J, 51: 125-133.
https://doi.org/10.1111/imj.15039

[7] Chao GF, Li KY, Zhu Z, et al. Use of Telehealth by Surgical Specialties During the COVID-19 Pandemic.
doi:10.1001/jamasurg.2021.0979

[8] Al Kawas, S., Al-Rawi, N., Talaat, W. et al. Post COVID-19 lockdown: measures and practices for dental institutes. BMC Oral Health 20, 291 (2020). https://doi.org/10.1186/s12903-020-01281-6

[9] TempTraq Available online: https://www.temptraq.com/Home

[10] Channa A, Popescu N, Skibinska J, Burget R. The Rise of Wearable Devices during the COVID-19 Pandemic: A Systematic Review. Sensors. 2021; 21(17):5787. https://doi.org/10.3390/s21175787

[11] PO3M iHealth: Wireless Pulse Oximeter. Available online: https://ihealthlabs.com/

[12] Ding X., Clifton D., Ji N., Lovell N.H., Bonato P., Chen W., Yu X., Xue Z., Xiang T., Long X., et al. Wearable sensing and Telehealth technology with potential applications in the coronavirus pandemic. IEEE Rev. Biomed. Eng. 2020;14:48–70.
doi: 10.1109/RBME.2020.2992838.

[13] Kabir MM, Perez-Alday EA, Thomas J, Sedaghat G, Tereshchenko LG. Optimal configuration of adhesive ECG patches suitable for long-term monitoring of a vectorcardiogram. J Electrocardiol. 2017 May-Jun;50(3):342-348.
doi: 10.1016/j.jelectrocard.2016.12.005.

[14] Poon C.C., Wong Y.M., Zhang Y.T. M-health: The development of cuff-less and wearable blood pressure meters for use in body sensor networks; Proceedings of the 2006 IEEE/NLM Life Science Systems and Applications Workshop; Bethesda, MD, USA. 13–14 July 2006; pp. 1–2.

[15] Regina Bailey. (2021). What Is Hemodynamics?
https://www.thoughtco.com/what-is-hemodynamics-4175323

[16] The future of medical wearables. https://www.medicalalertadvice.com/articles/the-future-of-medical-wearables-2022-and-beyond/

[17] A. Hedayatipour and N. Mcfarlane, "Wearables for the Next Pandemic," in IEEE Access, vol. 8, pp. 184457-184474, 2020.
doi: 10.1109/ACCESS.2020.3029130.

[18] Asadzadeh, A., Mohammadzadeh, Z., Fathifar, Z. et al. A framework for information technology-based management against COVID-19 in Iran. BMC Public Health 22, 402 (2022). https://doi.org/10.1186/s12889-022-12781-1

[19] Wang Y, Zhang L, Li Q, et al. The significant immune escape of pseudotyped SARS-CoV-2 variant Omicron. Emerg Microbes Infect. 2022 Dec;11(1):1–5. DOI:https://doi.org/10.1080/22221751.2021.2017757

[20] Yeung AY, Roewer-Despres F, Rosella L, Rudzicz F. Machine Learning-Based Prediction of Growth in Confirmed COVID-19 Infection Cases in 114 Countries Using Metrics of Nonpharmaceutical Interventions and Cultural Dimensions: Model Development and Validation. J Med Internet Res. 2021 Apr 23;23(4):e26628.
doi: 10.2196/26628.

[21] "Computational models - Latest research and news". www.nature.com.

[22] Erik Cuevas, An agent-based model to evaluate the COVID-19 transmission risks in facilities, Computers in Biology and Medicine, Volume 121, 2020, 103827, ISSN 0010-4825. https://doi.org/10.1016/j.compbiomed.2020.103827.

[23] Pinter, G.; Felde, I.; Mosavi, A.; Ghamisi, P.; Gloaguen, R. COVID-19 Pandemic Prediction for Hungary; A Hybrid Machine Learning Approach. Mathematics 2020, 8, 890. https://doi.org/10.3390/math8060890

[24] Zhifang Liao, Peng Lan, Xiaoping Fan, Benjamin Kelly, Aidan Innes, Zhining Liao, SIRVD-DL: A COVID-19 deep learning prediction model based on time-dependent SIRVD, Computers in Biology and Medicine, Volume 138, 2021, 104868, ISSN 0010-4825.
https://doi.org/10.1016/j.compbiomed.2021.104868.

[25] Lori Uscher-Pines, Jessica Sousa, Ateev Mehrotra, Lee H Schwamm, Kori S Zachrison. (September 2021). Rising to the challenges of the pandemic: Telehealth innovations in U.S. emergency departments.
https://doi.org/10.1093/jamia/ocab092

[26] Supplemental Health Care. (Jan 5, 2022). The Pros and Cons of Telehealth Expansion.
https://www.shccares.com/blog/the-pros-and-cons-of-Telehealth-expansion

[27] Sebhatu, A., Wennberg, K., Arora-Jonsson, S., Lindberg, S.I. Explaining the homogeneous diffusion of COVID-19 nonpharmaceutical interventions across heterogeneous countries (Open Access) (2020) Proceedings of the National Academy of Sciences of the United States of America, 117 (35), pp. 21201-21208. Cited 58 times. doi: 10.1073/pnas.2010625117

[28] Ebinger J, Wells M, Ouyang D, Davis T, Kaufman N, Cheng S, Chugh S. A Machine Learning Algorithm Predicts Duration of hospitalization in COVID-19 patients. Intell Based Med. 2021;5:100035. doi: 10.1016/j.ibmed.2021.100035. Epub 2021 May 27. PMID: 34075366; PMCID: PMC8156835.

[29] Tsai, T.C., Arik, S., Jacobson, B.H. et al. Algorithmic fairness in pandemic forecasting: lessons from COVID-19. npj Digit. Med. 5, 59 (2022). https://doi.org/10.1038/s41746-022-00602-z

[30] Malavika B, Marimuthu S, Joy M, Nadaraj A, Asirvatham ES, Jeyaseelan L. Forecasting COVID-19 epidemic in India and high incidence states using SIR and logistic growth models. Clin Epidemiol Glob Health. 2021 Jan-Mar;9:26-33. doi: 10.1016/j.cegh.2020.06.006. Epub 2020 Jun 27. PMID: 32838058; PMCID: PMC7319934.

[31] Anastassopoulou, C., Russo, L., Tsakris, A., & Siettos, C. (2020). Data-based analysis, modelling and forecasting of the COVID-19 outbreak. PloS one, 15(3), e0230405. https://doi.org/10.1371/journal.pone.0230405

[32] Refisch, L., Lorenz, F., Riedlinger, T., Taubenböck, H., Fischer, M., Grabenhenrich, L., Wolkewitz, M., Binder, H., & Kreutz, C. (2022). Data-driven prediction of COVID-19 cases in Germany for decision making. BMC medical research methodology, 22(1), 116. https://doi.org/10.1186/s12874-022-01579-9

[33] Zivkovic, M., Bacanin, N., Venkatachalam, K., Nayyar, A., Djordjevic, A., Strumberger, I., & Al-Turjman, F. (2021). COVID-19 cases prediction by using hybrid machine learning and beetle antennae search approach. Sustainable cities and society, 66, 102669. https://doi.org/10.1016/j.scs.2020.102669

[34] Pourhomayoun, M., & Shakibi, M. (2021). Predicting mortality risk in patients with COVID-19 using machine learning to help medical decision-making. Smart health (Amsterdam, Netherlands), 20, 100178. https://doi.org/10.1016/j.smhl.2020.100178

[35] Dhamodharavadhani, S., Rathipriya, R., & Chatterjee, J. M. (2020). COVID-19 Mortality Rate Prediction for India Using Statistical Neural Network Models. Frontiers in public health, 8, 441. https://doi.org/10.3389/fpubh.2020.00441

[36] Vadyala, S. R., Betgeri, S. N., Sherer, E. A., & Amritphale, A. (2021). Prediction of the number of COVID-19 confirmed cases based on K-means-LSTM. Array (New York, N.Y.), 11, 100085. https://doi.org/10.1016/j.array.2021.100085

[37] Domínguez-Olmedo, J. L., Gragera-Martínez, Á., Mata, J., & Pachón Álvarez, V. (2021). Machine Learning Applied to Clinical Laboratory Data in Spain for COVID-19 Outcome Prediction: Model Development and Validation. Journal of medical Internet research, 23(4), e26211. https://doi.org/10.2196/26211

[38] Umer, M., Ashraf, I., Ullah, S., Mehmood, A., & Choi, G. S. (2022). COVINet: a convolutional neural network approach for predicting COVID-19 from chest X-ray images. Journal of ambient intelligence and humanized computing, 13(1), 535–547. https://doi.org/10.1007/s12652-021-02917-3

[39] Peng, Y., Li, C., Rong, Y., Pang, C. P., Chen, X., & Chen, H. (2021). Real-time Prediction of the Daily Incidence of COVID-19 in 215 Countries and Territories Using Machine Learning: Model Development and Validation. Journal of medical Internet research, 23(6), e24285. https://doi.org/10.2196/24285

[40] Woo, S. H., Rios-Diaz, A. J., Kubey, A. A., Cheney-Peters, D. R., Ackermann, L. L., Chalikonda, D. M., Venkataraman, C. M., Riley, J. M., & Baram, M. (2021). Development and Validation of a Web-Based Severe COVID-19 Risk Prediction Model. The American journal of the medical sciences, 362(4), 355–362. https://doi.org/10.1016/j.amjms.2021.04.001

[41] Torrealba-Rodriguez, O., Conde-Gutiérrez, R. A., & Hernández-Javier, A. L. (2020). Modeling and prediction of COVID-19 in Mexico applying mathematical and

computational models. Chaos, solitons, and fractals, 138, 109946. https://doi.org/10.1016/j.chaos.2020.109946

[42] Roosa, K., Lee, Y., Luo, R., Kirpich, A., Rothenberg, R., Hyman, J. M., Yan, P., & Chowell, G. (2020). Real-time forecasts of the COVID-19 epidemic in China from February 5th to February 24th, 2020. Infectious Disease Modelling, 5, 256–263. https://doi.org/10.1016/j.idm.2020.02.002

[43] Banoei, M. M., Dinparastisaleh, R., Zadeh, A. V., & Mirsaeidi, M. (2021). Machine-learning-based COVID-19 mortality prediction model and identification of patients at low and high risk of dying. Critical care (London, England), 25(1), 328. https://doi.org/10.1186/s13054-021-03749-5

[44] Bakhtiarvand, N., Khashei, M., Mahnam, M., & Hajiahmadi, S. (2022). A novel reliability-based regression model to analyze and forecast the severity of COVID-19 patients. BMC medical informatics and decision making, 22(1), 123. https://doi.org/10.1186/s12911-022-01861-2

[45] Sanchez-Caballero, S., Selles, M.A., Peydro, M.A., & Pérez-Bernabeu, E. (2020). An Efficient COVID-19 Prediction Model Validated with the Cases of China, Italy and Spain: Total or Partial Lockdowns? Journal of Clinical Medicine, 9.

[46] Doganci, S., Ince, M. E., Ors, N., Yildirim, A. K., Sir, E., Karabacak, K., Eksert, S., Ozgurtas, T., Tasci, C., Dogan, D., Ozkan, G., Cosar, A., Gulcelik, M. A., Aydin, K., Yildirim, V., & Erdol, C. (2020). A new COVID-19 prediction scoring model for in-hospital mortality: experiences from Turkey, single center retrospective cohort analysis. European review for medical and pharmacological sciences, 24(19), 10247–10257. https://doi.org/10.26355/eurrev_202010_23249

[47] Gothai, E., Thamilselvan, R., Rajalaxmi, R. R., Sadana, R. M., Ragavi, A., & Sakthivel, R. (2021). Prediction of covid-19 growth and trend using machine learning approach. Materials today. Proceedings, 10.1016/j.matpr.2021.04.051. Advance online publication. https://doi.org/10.1016/j.matpr.2021.04.051

[48] Chaurasia, V., Pal, S. Application of machine learning time series analysis for prediction COVID-19 pandemic. Res. Biomed. Eng. 38, 35–47 (2022). https://doi.org/10.1007/s42600-020-00105-4

[49] Sharif, O., Hasan, M. Z., & Rahman, A. (2022). Determining an effective short term COVID-19 prediction model in ASEAN countries. Scientific reports, 12(1), 5083. https://doi.org/10.1038/s41598-022-08486-5

[50] Bhalerao, S., Chavan, P. (2022). COVID 19 Prediction Model Using Prophet Forecasting with Solution for Controlling Cases and Economy. In: Hassanien, AE., Elghamrawy, S.M., Zelinka, I. (eds) Advances in Data Science and Intelligent Data Communication Technologies for COVID-19. Studies in Systems, Decision and Control, vol 378. Springer, Cham. https://doi.org/10.1007/978-3-030-77302-1_8