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Digital Epidemiological Surveillance, Smart Telemedicine Diagnosis Systems, and Machine Learning-based Real-Time Data Sensing and Processing in COVID-19 Remote Patient Monitoring

Mark Woods
mark.woods@aa-er.org
The Center for Artificial Intelligence-enabled
Healthcare Delivery at CLI, Nashville, TN, USA
(corresponding author)
Renata Miklencicova
rmiklencicova@gmail.com
Faculty of Mass Media Communication,
University of SS. Cyril and Methodius,
Trnava, Slovak Republic

ABSTRACT. Employing recent research results covering digital epidemiological surveillance, smart telemedicine diagnosis systems, and machine learning-based real-time data sensing and processing in COVID-19 remote patient monitoring, and building our argument by drawing on data collected from Accenture, Amwell, Black Book Market Research, CMA, CFPC, Deloitte, HBR, Kyruus, PwC, RCPSC, Sage Growth Partners, and Sony, we performed analyses and made estimates regarding machine learning algorithms and deep neural network-driven Internet of Things in remote patient monitoring. The precision rate as regards diagnosis can be optimized through deep learning algorithms and smart networked medical devices. Deep neural network-driven Internet of Things and wearable devices are pivotal in patient-oriented medical real-time analytics and smart healthcare. Artificial intelligence-powered diagnostic tools and machine learning-based real-time data sensing and processing have been integrated into big healthcare data analytics. Descriptive statistics of compiled data from the completed surveys were calculated when appropriate.

Keywords: COVID-19; remote patient monitoring; telemedicine diagnosis; big data

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1. Introduction

The massive volume of COVID-19 treatment data necessitate cutting-edge machine learning techniques (Andronie et al., 2021) for inspecting personalized therapeutic consequences in assessing new patients (e.g., hospitalization prediction) by use of artificial intelligence-based diagnostic algorithms. (Alimadadi et al., 2020) Big healthcare data is sensitive and entails instantaneous processing. (Farouk et al., 2020) Internet of Things gathers physical and physiological patient data in remote medical services. (Chanak and Banerjee, 2020)

2. Conceptual Framework and Literature Review

The precision rate as regards diagnosis can be optimized through deep learning algorithms (Gray-Hawkins and Lăzăroiu, 2020) and smart networked medical devices throughout clinical decision support systems by use of healthcare big data. (Deperlioglu et al., 2020) Internet of Medical Things will improve medical care service, and monitor and provide treatment to patients from remote locations through healthcare sensors. (Yu et al., 2020) Machine learning algorithms can identify potential cases of COVID-19 accurately, its early detection reducing mortality rates. (Otoom et al., 2020) Deep neural network-driven Internet of Things and wearable devices are pivotal in patient-oriented medical real-time analytics and smart healthcare through coherent sensing and data collection. (Patan et al., 2020) Internet of Things is instrumental in enhancing medical-related decision and training. (Usak et al., 2020) Internet of Medical Things and integrated biosensors advance personalized medicine and continuous status assessment in remote patient monitoring through detecting health condition alteration and abnormal situation. (Bedón-Molina et al., 2020) Healthcare monitoring and prediction systems are decisive when users are remotely located. (Khan and Algarni, 2020) Artificial intelligence-powered diagnostic tools and machine learning-based real-time data sensing and processing (Lyons and Lăzăroiu, 2020) have been integrated into big healthcare data analytics in relation to pattern identification, modeling, and prediction. (Ibrahim et al., 2020)

3. Methodology and Empirical Analysis

Building our argument by drawing on data collected from Accenture, Amwell, Black Book Market Research, CMA, CFPC, Deloitte, HBR, Kyruus, PwC, RCPSC, Sage Growth Partners, and Sony, we performed analyses and made estimates regarding machine learning algorithms and deep neural network-driven Internet of Things in remote patient monitoring. Descriptive statistics of compiled data from the completed surveys were calculated when appropriate.

4. Study Design, Survey Methods, and Materials

The interviews were conducted online and data were weighted by five variables (age, race/ethnicity, gender, education, and geographic region) using the Census Bureau's American Community Survey to reflect reliably and accurately the demographic composition of the United States.

Data sources: Accenture, Amwell, Black Book Market Research, CMA, CFPC, Deloitte, HBR, Kyruus, PwC, RCPSC, Sage Growth Partners, and Sony.
Study participants: 5,800 individuals provided an informed e-consent.

The data was weighted in a multistep process that accounts for multiple stages of sampling and nonresponse that occur at different points in the survey process. All data were interrogated by employing graphical and numeric exploratory data analysis methods. Multivariate analyses, and not univariate associations with outcomes, are more likely to factor out confounding covariates and more precisely determine the relative significance of individual variables. Results are estimates and commonly are dissimilar within a narrow range around the actual value.

Test data was populated and analyzed in SPSS to ensure the logic and randomizations were working as intended before launching the survey. To ensure high-quality data, data quality checks were performed to identify any respondents showing clear patterns of satisficing (e.g., checking for high rates of leaving questions blank). Sampling errors and test of statistical significance take into account the effect of weighting. Question wording and practical difficulties in conducting surveys can introduce error or bias into the findings of opinion polls. The sample weighting was accomplished using an iterative proportional fitting process that simultaneously balanced the distributions of all variables. Stratified sampling methods were used and weights were trimmed not to exceed 3. Average margins of error, at the 95% confidence level, are +/-2%. The design effect for the survey was 1.3. For tabulation purposes, percentage points are rounded to the nearest whole number. The cumulative response rate accounting for non-response to the recruitment surveys and attrition is 2.5%. The break-off rate among individuals who logged onto the survey and completed at least one item is 0.2%.

Confirmatory factor analysis was employed to test for the reliability and validity of measurement instruments. Addressing a significant knowledge gap in the literature, the research has complied with stringent methodology, reporting, and data analysis requirements. The precision of the online polls was measured using a Bayesian credibility interval.

Flow diagram of study procedures

5. Statistical Analysis

This survey employs statistical weighting procedures to clarify deviations in the survey sample from known population features, which is instrumental in correcting for differential survey participation and random variation in samples. Descriptive analyses (mean and standard deviations for continuous variables and counts and percentages for categorical variables) were used. Descriptive statistical analysis and multivariate inferential tests were undertaken for the survey responses and for the purpose of variable reduction in regression modeling. Independent *t*-tests for continuous variables or chi-square tests for categorical variables were employed.

⬇

AMOS-SEM analyzed the full measurement model and structural model. Mean and standard deviation, *t*-test, exploratory factor analysis, and data normality were inspected using SPSS. To ensure reliability and accuracy of data, participants undergo a rigorous verification process and incoming data goes through a sequence of steps and multiple quality checks. Descriptive and inferential statistics provide a summary of the responses and comparisons among subgroups.

⬇

An Internet-based survey software program was utilized for the delivery and collection of responses. Non-response bias and common method bias, composite reliability, and construct validity were assessed. Panel research represents a swift method for gathering data recurrently, drawing a sample from a pre-recruited set of respondents. Behavioral datasets have been collected, entered into a spreadsheet, and cutting-edge computational techniques and empirical strategies have been harnessed for analysis. Groundbreaking computing systems and databases enable data gathering and processing, extracting meaning through robust deployment.

Flow diagram of statistical parameters and reproducibility

6. Results and Discussion

Remote diagnosis can be provided by Internet of Medical Things by sensing users' health status in conformity with and sharing clinical data. (Jiang et al., 2020) The efficient deployment and utilization of data fusion (Lăzăroiu and Harrison, 2021) enable accurate evaluation in remote patient monitoring, optimizing preventive care for chronic diseases by use of machine learning-based automated diagnostic systems and artificial intelligence-enabled wearable medical devices. (Alshehri and Muhammad, 2021) Sensor technologies and implantable surgical devices enable real-time treatment monitoring and the collection of heterogeneous patient physiological parameters so that diagnostics can be swiftly tracked. (Kelly et al., 2020) (Tables 1–10)

Table 1 Supporting comprehensive virtual care through digital interoperability across the healthcare system (%, relevance)

Physician payment for virtual care services is a major barrier for expanding the use of digital tools.	84
Consumer demand and the drive to improve access will make virtual care more common in the healthcare system.	83
Virtual care can transform the way care is delivered to patients and the way physicians work.	80
Improving access, making care more equitable, the democratization of health information and the promise of reducing costs have added to the focus on virtual care.	77
Virtual care can mitigate part of the increase in the demand for home- and facility-based continuing care as the population ages.	77
Costs to government might expand if patients currently without a family physician were better able to access regular care with the aid of virtual tools.	76
The ease of access to physicians through virtual means will allow frivolous or nonessential medical care to grow in volume.	73

Sources: CMA; CFPC; RCPSC; our survey among 5,800 individuals conducted March 2021.

Table 2 Which of the following would you do virtually if given the choice? (%)

Health and wellness advisories	21
Remote monitoring of ongoing health issues through at-home devices	19
Routine appointments	17
Mental health appointments	13
Appointments with medical specialists from chronic conditions	12
Appointments with medical specialists for diagnosis or acute care	11
Diagnoses for illnesses, diseases and disorders	7

Sources: Accenture; our survey among 5,800 individuals conducted March 2021.

Table 3 How willing would you be to share the information tracked in your apps or devices for the following reasons? (%, relevance)

	Chronic disease	No chronic disease
Blinded/Anonymous contribution to an organization that does healthcare research	51	42
Blinded/Anonymous contribution to a device developer to improve device/program	53	44
Share with emergency services if experiencing a sudden emergency situation	69	55
Alert myself and share with family if in danger due to a fall or other health emergency situation	66	60
Share with my doctors to help them provide better care to me	77	65

Sources: Deloitte; our survey among 5,800 individuals conducted March 2021.

Table 4 Consumer attitudes towards specialized remote health monitoring devices (%, yes)

Do you think a remote health monitoring device provided by your doctor would help you better manage your chronic condition and collaborate with your doctor?	91
When thinking about managing your chronic condition and sharing information with your doctor, would you trust a consumer wearable device that is not designed specifically for your chronic condition even though it may have health tracking capabilities (e.g., Fitbit, Apple Watch, etc.)?	35
If a doctor gave you or the person you care for a specialized remote health monitoring device (ex: smart watch, smart wristband, health wearable) that was only used for your chronic condition, would you wear it?	77
If your doctor doesn't provide a remote health monitoring device to help you manage your chronic condition, would you switch to a doctor that does?	45
Do you find it difficult (with or without a monitoring device) to continuously track vitals/measurements for your chronic condition (glucose levels, blood pressure, heart rate, blood clots, temperature, etc.) in order to share them with your doctor?	34
When thinking about all the signs and symptoms that may indicate a problem with your chronic condition, have you ever stressed about not noticing or misreporting one of them?	41
Has a doctor ever recommended or given you or someone you care for a remote health monitoring device (e.g., smart watch, wristband, health wearable) that was specifically designed to help monitor a chronic condition?	26
Do you think you would physically visit the doctor's office less if you or the person you care for could share health information about your chronic condition via a remote health monitoring service/device?	51
Have you or someone you care for ever had a health emergency/scare that resulted from not continuously tracking vitals, getting measurements or taking medications related to your chronic condition?	33
Given the COVID-19 pandemic, would you feel safer if you had a wearable device provided by your doctor that was designed to help you monitor your chronic condition?	68

Sources: Sony; our survey among 5,800 individuals conducted March 2021.

The Internet of Medical Things-based health monitoring system can optimize the duration of human body networked nodes and carry out energy-saving technologies. (Wei et al., 2020) The heterogeneity in the massive quantities of health data produced by Internet of Medical Things platforms should be reduced for the adequate deployment of big data processing methods. (Sárez Rubí and de Lira Gondim, 2020) The reliability, sharing, and adjustability of cloud computing technology are pivotal in the Internet of Medical Things. (Sun et al., 2020) The Internet of Things devices can gather real-time data as regards patient health conditions and lifestyle parameters. (Ismail et al., 2020)

Table 5 Virtual care and digital technology are instrumental in the delivery of healthcare (%, relevance)

COVID-19 is shaping the experience, behavior, and expectations of patients and physicians alike.	88
By rapidly accelerating telehealth adoption and the proliferation of telehealth use cases, COVID-19 has profoundly altered the trajectory of virtual care.	86
COVID–19 has had a dramatic impact on telehealth adoption and usage among both consumers and providers.	84
The increased telehealth usage has been largely driven by a shift to scheduled visits.	83
The need to provide ongoing care to existing patients and the need to provide safe care to those suspected of having COVID–19 have driven providers to rapidly scale virtual care.	82
COVID-19 has pushed physicians to embrace virtual care and led them to branch out from established use cases and leverage telehealth for a broader range of visit types and specialty care.	83
The pressures brought on by COVID-19, coupled with the regulatory changes that created more flexibility for physicians, have had a significant impact on traditional barriers to telehealth adoption.	82

Sources: Amwell; our survey among 5,800 individuals conducted March 2021.

Table 6 Artificial intelligence applications that could change healthcare (%, relevance)

Applications and key drivers for adoption	92
Robot-assisted surgery (technological advances in robotic solutions for more types of surgery)	89
Virtual nursing assistants (increasing pressure caused by medical labor shortage	87
Administrative workflow (easier integration with existing technology infrastructure)	86
Fraud detection (need to address increasingly complex service and payment fraud attempts)	82
Dosage error reduction (prevalence of medical errors, which leads to tangible penalties)	85
Connected machines (proliferation of connected machines/devices)	85
Clinical trial participation (patent cliff; plethora of data; outcomes-driven approach)	82
Preliminary diagnosis (interoperability/data architecture to enhance accuracy)	84
Automated image diagnosis (storage capacity; greater trust in artificial intelligence technology)	83
Cybersecurity (increase in breaches; pressure to protect health data)	83

Sources: HBR; our survey among 5,800 individuals conducted March 2021.

Table 7 Telehealth offers individuals an option to seek care without exposing themselves to the risk of infection

48%	would switch their physician in order to have access to virtual care.
51%	would like more access to virtual behavioral or mental health services for anxiety, depression and social isolation.

Sources: Sage Growth Partners; Black Book Market Research; our survey among 5,800 individuals conducted March 2021.

Table 8 Appointment types patients would use virtual care for in the future (%)

Wellness check-ins, such as an annual or routine appointment checkup	69
COVID-19 related symptoms, such as shortness of breath, cough, or fever	65
Consult or follow-up related to a prior surgery or procedure	68
Care for a chronic condition, such as diabetes, COPD, or hypertension	66
Acute need, such as the onset of sudden symptoms, pain, or discomfort	64
Mental/Behavioral health needs	62

Sources: Kyruus; our survey among 5,800 individuals conducted March 2021.

Table 9 Willingness to use telehealth by type of visit (%, yes)

	Physicians	Consumers
Prescription renewal	96	76
Chronic care check-ins	95	58
Post-discharge/Surgery follow-up	77	46
Urgent care	60	42
Initial meeting with doctor	54	36

Sources: Amwell; our survey among 5,800 individuals conducted March 2021.

Table 10 Perceived advantages of using advanced computers or robots with artificial intelligence for healthcare (%, relevance)

Healthcare would be easier and quicker for more people to access	95
Faster and more accurate diagnoses	93
Will make better treatment recommendations	92
Like having your own healthcare specialist, available at any time	89
Fewer mistakes than doctors or healthcare professionals	87
Can perform surgery and diagnostic tests much more accurately than humans	86

Sources: PwC; our survey among 5,800 individuals conducted March 2021.

Through Internet of Medical Things, a real-time detection and monitoring system (Throne and Lăzăroiu, 2020) can gather symptom data from users to determine possible COVID-19 cases, supervise the treatment response of recovered individuals, and grasp its nature by acquiring and inspecting pertinent data. (Otoom et al., 2020) The convenience and effectiveness of medical diagnosis are optimized through medical image processing methods and cloud-based automated clinical decision support systems. (Wang et al., 2021) Internet of Things devices can sense healthcare patient data and medical condition remotely through smart healthcare devices and applications. (Saba et al., 2020)

7. Conclusions, Implications, Limitations, and Further Research Directions

The precision rate as regards diagnosis can be optimized through deep learning algorithms and smart networked medical devices in COVID-19 prevention, screening, and treatment. Deep neural network-driven Internet of Things and wearable devices are pivotal in patient-oriented medical real-time analytics and smart healthcare in remotely monitoring and caring for confirmed or suspected COVID-19 patients. Artificial intelligence-powered diagnostic tools and machine learning-based real-time data sensing and processing have been integrated into big healthcare data analytics in the diagnosis and treatment of COVID-19 patients. This article focuses only on digital epidemiological surveillance, smart telemedicine diagnosis systems, and machine learning-based real-time data sensing and processing in COVID-19 remote patient monitoring. Limitations of this research also include a convenient sample, small sample size, and cross-sectional data collection, thus limiting generalizability. Certain variables were dichotomized because of small cell sizes throughout the analysis. The sample size and the richness of the cohort study dataset enable the control for numerous potential confounders in the multivariable analysis, and provide novel data on the topic. More data gathered either cross-sectionally or longitudinally that utilize larger study populations are required to check and support the conclusions drawn in this study. Further research should consider artificial intelligence-enabled wearable medical devices, clinical and diagnostic decision support systems, and Internet of Things-based healthcare applications in COVID-19 prevention, screening, and treatment.

Mark Woods, https://orcid.org/0000-0002-7782-0045
Renata Miklencicova, https://orcid.org/0000-0002-7818-1652

Research method
Cross-sectional design employing self-report questionnaires.

Data analysis
The gathered data were entered into a spreadsheet and analyzed.

Software information
To process and inspect the collected data, IBM SPSS 24 and AMOS 20 tools were used.

Data and materials availability
All research mentioned has been published and datasets used and inspected during the current study are available from respective outlets. All raw, results,

and key source data supporting the conclusions, statistics, models, and codes generated or used, together with the details of the study design and the procedures for information analysis, are provided with this article. Note: The publisher is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing content) should be directed to the corresponding author for the article. Other modeling input assumptions are available on reasonable request.

Compliance with ethical standards

Ethical approval
All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent
The ethical consequences of this research have been carefully considered. Best practices have been respected so as to inform the participants and protect the data and integrity of the interviewees whose participation was voluntary and who were given a plain language document with information as regards the research. The data have been processed in a way that ensures appropriate security of personal data against unauthorized or unlawful processing, accidental loss, destruction or damage, employing appropriate technical or organizational measures. All the information provided by the interviewees has been anonymized for confidentiality reasons. Study participants were informed clearly about their freedom to opt out of the study at any point of time without providing justification for doing so. If a participant began a survey without completing it, that was withdrawal of consent and the data was not used. To prevent missing data, all fields in the survey were required. Any survey which did not reach greater than 50% completion was removed from subsequent analysis to ensure quality. Throughout the research process, the total survey quality approach, designed to minimize error at each stage as thus the validity of survey research would be diminished, was followed. At each step in the survey research process, best practices and quality controls were followed to minimize the impact of additional sources of error as regards specification, frame, non-response, measurement, and processing. Only participants with non-missing and non-duplicated responses were included in the analyses. Individuals who completed the survey in a too short period of time, thus answering rapidly with little thought, were removed from the analytical sample.

Animal studies statement verification
This article does not require animal studies verification.

Code availability

This project has employed statistical analytical techniques standard in all statistical packages.

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Author contributions

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication. The authors take full responsibility for the accuracy and the integrity of the data analysis.

Conflict of interest statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Disclosure by the editors of record

The editors declare no conflict of interest in the review and publication decision regarding this article.

Transparency statement

The authors affirm that the manuscript represents an honest, accurate, and transparent account of the research being reported, that no relevant aspects of the study have been left out, and that any inconsistencies from the research as planned (and, if significant, registered) have been clarified.

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