IoT and AI in Remote Patient Monitoring: Applications, Clinical Effectiveness and Challenges

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Abstract

Smart healthcare provides patients with access to high-quality health services in safe environments regardless of geographical barrier. Remote patient monitoring helps the patients receive adequate monitoring from their clinicians in remote health offices with continuous medical data analysis and real-time diagnosis. This approach is expected to replace the casual healthcare management of some diseases and takes the Internet of Things technology as backbone of the patient monitoring systems with integrated Artificial Intelligence for clinical decision support. The purpose of this paper is to explore the applications of remote monitoring systems, its clinical effectiveness and the associated challenges.

1 Introduction

Technology has dramatically transformed the face of the healthcare sector. Innovative advancements make delivering of healthcare services at a distance become feasible in modern medical field.

Telemedicine, adopted in 1969, refers to the provision of medical care without physical patient-doctor attendance (Bashshur et al., 2011; Weinstein et al., 2014). Meanwhile telehealth, introduced later in 1978, has an expanded scope, covering telemedicine and additional nonphysician aspects of healthcare such as telenursing and telepharmacy (Weinstein et al., 2014) as well as public health with health education and disease epidemiology (Bashshur et al., 2011). The rising power of the Internet and electronic processing in the late 20th, and mobile communications and network technologies in early 21st century coined the concepts of e-health (1999) and m-health (2003) respectively (Bashshur et al., 2011). m-health evolved from the traditional desktop platforms of original e-health (Bashshur et al., 2011) and its main drivers are considered the existence of mobile applications, smart sensors and devices (Weinstein et al., 2014).

Remote patient monitoring (RPM) is a service of telemedicine based on m-health to collect patients' medical measurements and make appropriate interventions in case of deteriorating health. It is believed to benefit patients in rural areas, patients with disability or chronic diseases, at the same time, alleviate the shortage of clinicians and excess hospital capacity by implementing autonomous and cost-effective remote health monitoring solutions (Riazul et al., 2015). The novel technology – Internet of Things (IoT) plays a vital role in providing the functionality of data collection and the medium of data transmission for these systems. And emerging Artificial Intelligence (AI) possibilities help to handle the huge amount of patient's health-related data with reduced intervention of medical staffs.

This paper includes a brief outline of how remote healthcare has evolved in the introduction, following by sections to discuss RPM system's infrastructure and the possible implementations, its clinical effectiveness, and the current challenges considering security and privacy, clinical adoption and trust.

2 Remote Patient Monitoring systems

2.1 The IoT-based network

The core idea of the IoT in healthcare relies in smart objects with the ability to measure medical data keep communicating and interacting with each other (Michalakis & Caridakis, 2017). Riazul et al. (2015) explained that smart objects consist of medical gadgets, sensors, diagnostic and imaging devices, which are considered the primary parts of IoT healthcare architectures. Smart sensors can appear in either wearable devices (non-invasive) or minimally invasive implant devices. Invasive devices are to directly monitor patients' biomedical parameters. Despite its accuracy of measurement, efforts have been made to shift from invasive methods to painless non-invasive approaches (Lee et al., 2018; Kamišalić et al., 2018).

A typical remote healthcare monitoring system consisting of three tiers (different communication layers) was presented by Negra et al., (2016), Mohsin et al. (2018) and Kakria et al. (2015). Health data of the patient is continuously captured by multiple wireless sensors in Tier-1 before being transmitted to mHealth devices (smartphones, laptops, digital assistants, etc.) via small area network protocols in Tier-2. Data is then sent to the remote medical station through the Internet in Tier-3. This tier is considered server side which the medical database resides, the healthcare providers get access to the patient health information, and the AI applications are performed. Meanwhile, Azimi et al. (2018), Elmisery et al. (2019) and Greco et al. (2020) emphasized the use of cloud computing for server side in the similar IoT architecture with new concept of edge computing (processes are performed by devices in local network, near the deployed sensors to improve response times and optimize the data traffic).

2.2 Applications

Numerous common implications of medical sensors are to measure glucose level, electrocardiogram (ECG), blood pressure, body temperature, oxygen saturation, electromyogram (EMG), heart rate, electrodermal activity (EDA), and respiration rate (Riazul et al., 2015; Majumder et al., 2017; Kamišalić et al., 2018). Other than physiological signs, mini motion sensors such as accelerometers and gyroscopes are deployed to capture activity related signals (Majumder et al., 2017; Kamišalić et al., 2018).

Remote medical monitoring applications of IoT networks are mainly developed towards elderly care at home, disease management, post-discharge rehabilitation and assisted quality of living for people with disabilities (Negra et al., 2016). Accessing to real-time sensed data of monitored patients helps healthcare providers early detect and diagnose various cardiovascular, pulmonary, respiratory and neurological illnesses (Majumder et al., 2017). Moreover, continuous motion monitoring is useful for activity recognition such as fall detection, gait pattern and posture assessment, and sleep quality study (Majumder et al., 2017).

These analyses could be carried out with reduced medical staffs' interference using several basic to advanced ways which are primitive mathematical transformations and rule sets, statistical approaches, and machine learning models (Kamišalić et al., 2018).

2.3 The role of AI

The applications of AI involve in Tier-3 of the remote healthcare monitoring model. AI satisfies the need of transforming massive volume of raw inputs into meaningful knowledge by performing intelligent data analysis. Machine learning, a subset of AI, has been received rising interest in enhancing IoT-based remote healthcare systems (Kamišalić et al., 2018). An emerging trend towards edge machine learning is noticed (Azimi et al., 2018, Elmisery et al., 2019; Greco et al., 2020), which implements model training on the cloud and decision making on the edge.

Machine learning is grouped into three categories, including supervised learning, unsupervised learning and reinforcement learning. Supervised machine learning trains algorithms to classify data and predict outcomes using labeled datasets. It applies regression analysis to calculate calorie expenditure, and classification methods to assess sleep quality, recognize illnesses, detect activities and identify stress (Kamišalić et al., 2018). In unsupervised learning, the model discovers the patterns on its own by grouping similar data together into clusters (called clustering) from unlabeled data. This analysis is used to (1) build patient's profile based on grouped activity related data and physiological signs, then (2) detect anomalies in real-time streams of patients' sensed data and (3) remove invalid or false data (Kamišalić et al., 2018). Automated anomaly detection is of prime importance in healthcare analytics due to its potential of saving human life. With regards to reinforcement learning, the intelligent agent learns from experimental trials and feedback and then is able to take suitable actions to maximize reward in a specific situation. Many of its applications are seen in boosting remote healthcare systems' efficiency, for example, enhanced routing protocol for wireless sensor networks (Kiani, 2017), optimized the number reserved connections and transmission scheduling decision (Niyato et al., 2009).

3 Clinical effectiveness of RPM

Several researches were conducted to study the impact of RPM on patients with heart failure after hospital discharge using wearable devices (Ong et al., 2016; Olivari et al., 2018), patients with cardiac implanted devices (Morgan et al., 2017; López-Liria et al., 2020), patients with type-2 diabetes (Salehi et al., 2020) and clinical outcomes in general (Noah et al., 2018).

The research by Ong et al. (2016) was to implement telephone health coaching calls along with RPM system require human resources to do the data analysis. In another effort to reduce clinician intervention, Olivari et al. (2018) used a RPM system integrated decision support. López-Liria et al. (2020) undertook a five-year study which data gathered from adults implanted with pacemakers is accessible to clinicians via a website for medical assessment. Similarly, the study by Morgan et al. (2017) also aimed at patients with cardiac electronic devices, however, had a larger population of more than 800 participants for both groups of RPM and casual care, and a shorter period of study of around 3 years. Four studies yielded unfavorable clinical results, RPM was equally useful as casual care and did not reduce the frequencies of rehospitalizations and emergency visits in post-discharge and device implanted heart patients. The similar view was found in the study by Noah et al. (2018), they argued that patients with heart failure may not be ideally suitable with RPM.

However, beneficial aspects of RPM were found, that it is safe and effective in early detection of health issue and in reducing clinical visits (Morgan et al., 2017; López-Liria et al., 2020), and helps improve quality of life (Olivari et al., 2018, Morgan et al., 2017) of patients with heart failure. The review by Salehi et al. (2020) showed positive impact of RPM systems in reducing HbA1c among type 2 diabetic patients. Promising outcomes were witnessed in patients with Parkinson's disease undergoing rehabilitation training, including improvements of their gait speed and balance; and in patients with hypertension due to effective reduction of blood pressure (Noah et al., 2018).

RPM approach is still in its immaturity phase and has showed both limited and optimistic clinical outcomes.

4 Challenges

4.1 Data Security and Privacy issues

Malasinghe et al. (2019) pointed out that a major weakness of RPM solutions is inadequate evaluation of remote health systems' capacity to ensure the privacy and security of patients' sensitive medical data. Elmisery et al. (2019) also revealed that serious security flaws were identified in healthcare IoT devices. Indeed, many studies of RPM systems totally ignored the judgement of security, for example, the real-time monitoring system for remote cardiac patients of Kakria et al (2015). Sensing networks can easily face malicious attacks; thus, the lack of advanced protection possibly falsifies the system's functionality and poses significant threats to patients' health status (Malasinghe et al., 2019).

Many attempts have been done to overcome the privacy and security vulnerabilities of RPM systems. Some examples are data integrity enhancement using smart contracts based on blockchain technology (Griggs et al., 2018; Jamil et al., 2020), improved security with intrusion detection using reinforcement learning on big sensed data (Otoum et al., 2019) and biometric authentication using finger vein (Mohsin et al., 2018).

4.2 Adoption issues

RPM systems are believed to possess state-of-the-art architectures and intelligent supports that can bring positive impacts on medical outcomes. However, this modern approach still has not significantly proved its clinical success over casual care management. Thorough evaluation on whether RPM works well for certain patient populations or not is needed before making the decision of implementing one in clinical setting.

The lack of interoperability is another problem preventing healthcare providers from implementing RPM systems. Two systems are interoperated when they are able to communicate and exchange services and can work together as a combined system (Noura et al., 2019). However, researchers and providers take different approaches to build IoT solutions from various options of devices, platforms, APIs and infrastructures; thus, limit the ability for systems to work together. Noura et al. (2019) argued that businesses might bear a financial burden when changing to another IoT solution. In the context of RPM, this means that the hospitals offering RPM services heavily rely on the particular chosen system, and face a threat of high cost once the current implementation is no longer effective. Existing non-interoperable medical devices and established architecture may not compatible with the new system, resulting in additional investment of new components and services. While researchers have worked on building the bridge between different IoT systems and have introduced a number of solutions focusing on device and network layers, taking advantages of semantic web technology and internetworking API can open new directions for future studies (Noura et al., 2019).

4.3 Regulatory issues

Besides strong belief of beneficial contributions of machine learning models in remote healthcare systems, Beniczky et al. (2021) worried about their unclear performance benchmarks and the possibility of these models become unnoticeably malfunctioning due to incorrect datasets and missing data. Furthermore, Minsen et al. (2020) presented that still none of standardized law or regulation has been adopted to control the use of machine learning in medical devices. And those gadgets are only assessed based on their compliance to regulatory requirements for medical devices in general (Minsen et al., 2020). Meanwhile, medical regulatory bodies are not purely equipped for assessing algorithms to ensure the safety and effectiveness of learning models that are continuously trained by new and updated data (Beniczky et al., 2021).

5 Conclusion

The blended implementation of IoT and AI in remote healthcare systems actively assists independent living of at-risk patients through real-time surveillance of health and physical well-being. RPM has promising applications for a wide range of illnesses and rehabilitation programs; however, healthcare providers should carefully consider the effectiveness before starting RPM program on any particular group of patients. The question of how to thoroughly evaluate machine learning performance remains unanswered, and other aspects of RPM architectures still open for future work such as protection for data security and privacy, and a standard for semantic interoperability. RPM has received growing interests for further development, especially amidst utter devastation of Covid-19 in healthcare sector. RPM will be the solution for current and future healthcare systems where social distancing is the key to stop the transmission of deadly viruses.

References

Azimi, I., Takalo-Mattila, J., Anzanpour, A., Rahmani, A. M., Soininen, J. P., & Liljeberg, P. (2018). Empowering Healthcare IoT Systems with Hierarchical Edge-Based Deep Learning. In (pp. 63-68): ACM.

Bashshur, R., Shannon, G., Krupinski, E., & Grigsby, J. (2011). The Taxonomy of Telemedicine. *Telemed J E Health, 17*(6), 484-494. doi:10.1089/tmj.2011.0103

Beniczky, S., Karoly, P., Nurse, E., Ryvlin, P., & Cook, M. (2021). Machine learning and wearable devices of the future. *Epilepsia, 62*(S2), S116-S124. doi:10.1111/epi.16555

Elmisery, A. M., Elmisery, A. M., Rho, S., Rho, S., Aborizka, M., & Aborizka, M. (2019). A new computing environment for collective privacy protection from constrained healthcare devices to IoT cloud services. *Cluster computing, 22*(S1), 1611-1638. doi:10.1007/s10586-017-1298-1

Greco, L., Percannella, G., Ritrovato, P., Tortorella, F., & Vento, M. (2020). Trends in IoT based solutions for health care: Moving AI to the edge. *Pattern Recognit Lett, 135*, 346-353. doi:10.1016/j.patrec.2020.05.016

Griggs, K. N., Ossipova, O., Kohlios, C. P., Baccarini, A. N., Howson, E. A., & Hayajneh, T. (2018). Healthcare Blockchain System Using Smart Contracts for Secure Automated Remote Patient Monitoring. *J Med Syst, 42*(7), 1-7. doi:10.1007/s10916-018-0982-x

Jamil, F., Ahmad, S., Iqbal, N., & Kim, D. H. (2020). Towards a Remote Monitoring of Patient Vital Signs Based on IoT-Based Blockchain Integrity Management Platforms in Smart Hospitals. *Sensors (Basel), 20*(8), 2195. doi:10.3390/s20082195

Kakria, P., Tripathi, N. K., & Kitipawang, P. (2015). A Real-Time Health Monitoring System for Remote Cardiac Patients Using Smartphone and Wearable Sensors. *Int J Telemed Appl, 2015*, 373474-373411. doi:10.1155/2015/373474

Kamišalić, A., Fister, J. I., Turkanović, M., & Karakatič, S. (2018). Sensors and Functionalities of Non-Invasive Wrist-Wearable Devices: A Review. *Sensors (Basel), 18*(6), 1714. doi:10.3390/s18061714

Kiani, F. (2017). Reinforcement Learning Based Routing Protocol for Wireless Body Sensor Networks. In (pp. 71-78): IEEE.

Lee, H., Hong, Y. J., Baik, S., Hyeon, T., & Kim, D. H. (2018). Enzyme‐Based Glucose Sensor: From Invasive to Wearable Device. *Adv Healthc Mater, 7*(8), e1701150-n/a. doi:10.1002/adhm.201701150

López-Liria, R., López-Villegas, A., Leal-Costa, C., Peiró, S., Robles-Musso, E., Bautista-Mesa, R., Catalán-Matamoros, D. (2020). Effectiveness and Safety in Remote Monitoring of Patients with Pacemakers Five Years after an Implant: The Poniente Study. *Int J Environ Res Public Health, 17*(4), 1431. doi:10.3390/ijerph17041431

Majumder, S., Mondal, T., & Deen, M. J. (2017). Wearable Sensors for Remote Health Monitoring. *Sensors (Basel), 17*(1), 130. doi:10.3390/s17010130

Malasinghe, L. P., Malasinghe, L. P., Ramzan, N., Ramzan, N., Dahal, K., & Dahal, K. (2019). Remote patient monitoring: a comprehensive study. *Journal of ambient intelligence and humanized computing, 10*(1), 57-76. doi:10.1007/s12652-017-0598-x

Michalakis, K., & Caridakis, G. (2017). *IoT Contextual Factors on Healthcare.* Paper presented at the GeNeDis 2016, Cham.

Minssen, T., Gerke, S., Aboy, M., Price, N., & Cohen, G. (2020). Regulatory responses to medical machine learning. *Journal of Law and the Biosciences*. doi:10.1093/jlb/lsaa002

Mohsin, A. H., Zaidan, A. A., Zaidan, B. B., Albahri, A. S., Albahri, O. S., Alsalem, M. A., & Mohammed, K. I. (2018). Real-Time Remote Health Monitoring Systems Using Body Sensor Information and Finger Vein Biometric Verification: A Multi-Layer Systematic Review. *J Med Syst, 42*(12), 1-36. doi:10.1007/s10916-018-1104-5

Morgan, J. M., Kitt, S., Gill, J., McComb, J. M., Ng, G. A., Raftery, J., Cowie, M. R. (2017). Remote management of heart failure using implantable electronic devices. *Eur Heart J, 38*(30), 2352-2360. doi:10.1093/eurheartj/ehx227

Negra, R., Jemili, I., & Belghith, A. (2016). Wireless Body Area Networks: Applications and Technologies. *Procedia computer science, 83*, 1274-1281. doi:10.1016/j.procs.2016.04.266

Niyato, D., Hossain, E., & Camorlinga, S. (2009). Remote patient monitoring service using heterogeneous wireless access networks: architecture and optimization. *IEEE journal on selected areas in communications, 27*(4), 412-423. doi:10.1109/JSAC.2009.090506

Noah, B., Keller, M. S., Mosadeghi, S., Stein, L., Johl, S., Delshad, S., Spiegel, B. M. R. (2018). Impact of remote patient monitoring on clinical outcomes: an updated meta-analysis of randomized controlled trials. *NPJ Digit Med, 1*(1), 20172-20172. doi:10.1038/s41746-017-0002-4

Noura, M., Noura, M., Atiquzzaman, M., Atiquzzaman, M., Gaedke, M., & Gaedke, M. (2019). Interoperability in Internet of Things: Taxonomies and Open Challenges. *Mobile networks and applications, 24*(3), 796-809. doi:10.1007/s11036-018-1089-9

Olivari, Z., Giacomelli, S., Gubian, L., Mancin, S., Visentin, E., Di Francesco, V., Stafylas, P. (2018). The effectiveness of remote monitoring of elderly patients after hospitalisation for heart failure: The renewing health European project. *Int J Cardiol, 257*, 137-142. doi:10.1016/j.ijcard.2017.10.099

Ong, M. K., Romano, P. S., Edgington, S., Aronow, H. U., Auerbach, A. D., Black, J. T., Fonarow, G. C. (2016). Effectiveness of Remote Patient Monitoring After Discharge of Hospitalized Patients With Heart Failure: The Better Effectiveness After Transition–Heart Failure (BEAT-HF) Randomized Clinical Trial. *JAMA Intern Med, 176*(3), 310-318. doi:10.1001/jamainternmed.2015.7712

Otoum, S., Kantarci, B., & Mouftah, H. (2019). Empowering Reinforcement Learning on Big Sensed Data for Intrusion Detection. In (pp. 1-7): IEEE.

Riazul Islam, S. M., Daehan, K., Humaun Kabir, M., Hossain, M., & Kyung-Sup, K. (2015). The Internet of Things for Health Care: A Comprehensive Survey. *IEEE access, 3*, 678-708. doi:10.1109/ACCESS.2015.2437951

Salehi, S., Olyaeemanesh, A., Mobinizadeh, M., Nasli-Esfahani, E., & Riazi, H. (2020). Assessment of remote patient monitoring (RPM) systems for patients with type 2 diabetes: a systematic review and meta-analysis. *Journal of diabetes and metabolic disorders, 19*(1), 115-127. doi:10.1007/s40200-019-00482-3

Weinstein, R. S., Lopez, A. M., Joseph, B. A., Erps, K. A., Holcomb, M., Barker, G. P., & Krupinski, E. A. (2014). Telemedicine, Telehealth, and Mobile Health Applications That Work: Opportunities and Barriers. *Am J Med, 127*(3), 183-187. doi:10.1016/j.amjmed.2013.09.032