WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Convergence of Automation Technology toward the Healthcare

[1]Mohammad Ata ALshirah, [2]Rami Tayel Dalabeeh

[1,2]Royal Medical Services – Amman, Jordan
DOI: https://doi.org/10.55248/gengpi.2023.4121

INTRODUCTION

Data Healthcare is catching up with manufacturing in terms of Industry 4.0. We give a quick overview of Industry 4.0's history, key enabling technologies, and revolution in healthcare (dubbed Healthcare 4.0), as well as how it has changed the landscape of the whole healthcare value chain (Aceto, Persico et al. 2020). One or more health engineering application scenarios, such as primary care, preventive care, predictive technologies, hospitalization, home care, and occupational health, may be covered in the application scenarios. Instead of concentrating on single disciplinary approaches, solutions, and initiatives, we do so. In this paper, we offer cutting-edge research areas and issues, such as healthcare big data, automated medical manufacturing, and healthcare robots.

BACKGROUND: BASICS AND KEY TECHNOLOGIES

This section illustrates the definitions of some important terminologies that appear recently. These terms highlight the way healthcare in different aspects.

Artificial intelligence (AI) is the term used to describe algorithms or systems that have been built and given human-like cognitive abilities, such as the capacity to reason, deduce meaning, or learn from experience. This new technology is currently being used in a wide range of modern healthcare and medical systems, and it is on the increase as a solution to a number of issues that patients, hospitals, and the healthcare sector as a whole are facing (Ravì, Wong et al. 2016). In the study of complicated health or medical data for preventative or treatment strategies, such as diagnosis procedures, drug development, treatment protocol, personalized medicine, and patient monitoring and care (Amft, Palmer et al. 2015, Brüser, Antink et al. 2015), it approximates human cognition capacity.

Although AI is built on top of sophisticated statistics and machine learning (Jordanski, Radovic et al. 2016), allied domains like natural language processing (Agarwal, Baechle et al. 2017) are currently seeing revolutionary advancements. As a result, it has greatly sparked interest in a variety of scientific disciplines, including medicine and public health. Furthermore, AI-based tools are already visible in the health or applications for smart wearable and networked devices that are medically focused (Dehbandi, Barachant et al. 2016). This makes it possible for machines to detect, understand, learn, and act in order to carry out administrative and therapeutic tasks (Gaut, Steyvers et al. 2015, Hoogendoorn, Berger et al. 2016). AI has the potential to change public health, community health, and healthcare delivery in the future in order to improve people's quality of lives (Alshurafa, Sideris et al. 2016, Armananzas, Iglesias et al. 2016).

Big Data is a large corpus of information that is constantly growing exponentially. Due to its size and complexity, no traditional data management system can store or process this data adequately. Big data is a category of extraordinarily huge data. The following traits can be used to define big data:

- Volume
- Variety
- Velocity
- Variability

i. Volume: Big Data denotes to a massive enormousness taking into account its very name. The bulk of the data is a very imperative aspect in estimating the significance of the data (Khan, Yaqoob et al. 2014).

ii. Variety: Dissimilar causes and categories of data, both systematized and shapeless, are denoted as variety (McKinney Jr, Yoos II et al. 2017).

iii. Velocity: The word "velocity" denotes to the proportion at which data is produced. Actual prospective in the data is strongminded by how rapidly it is created and administered to fulfil requirements.

iv. Variability: This denotes to the unpredictability that the data might intermittently display, obstructing one's capability to professionally grip and accomplish the data.

THE ADVANTAGES OF BIG DATA IN HEALTH CARE

The benefits of being able to process big data in database management system (DBMS) are numerous, including:

i. Businesses can use external intelligence to help them make decisions.

Organizations are now able to fine-tune their business plans because to the availability of social data from search engines and websites like Facebook and Twitter.

ii. enhanced client services

New systems created using Big Data technology are replacing conventional consumer feedback systems. Big Data and natural language processing technologies are being employed in these new systems to read and assess customer feedback.

iii. Better operational efficiency Early detection of product/service risk, if any

iv. Improved operational effectiveness

Using big data technology, a staging area or landing zone for new data can be created before choosing whether data should be delivered to the data warehouse. By combining big data technology with data warehouses, a business can release infrequently utilized data. (Alexandru, Radu et al. 2018).

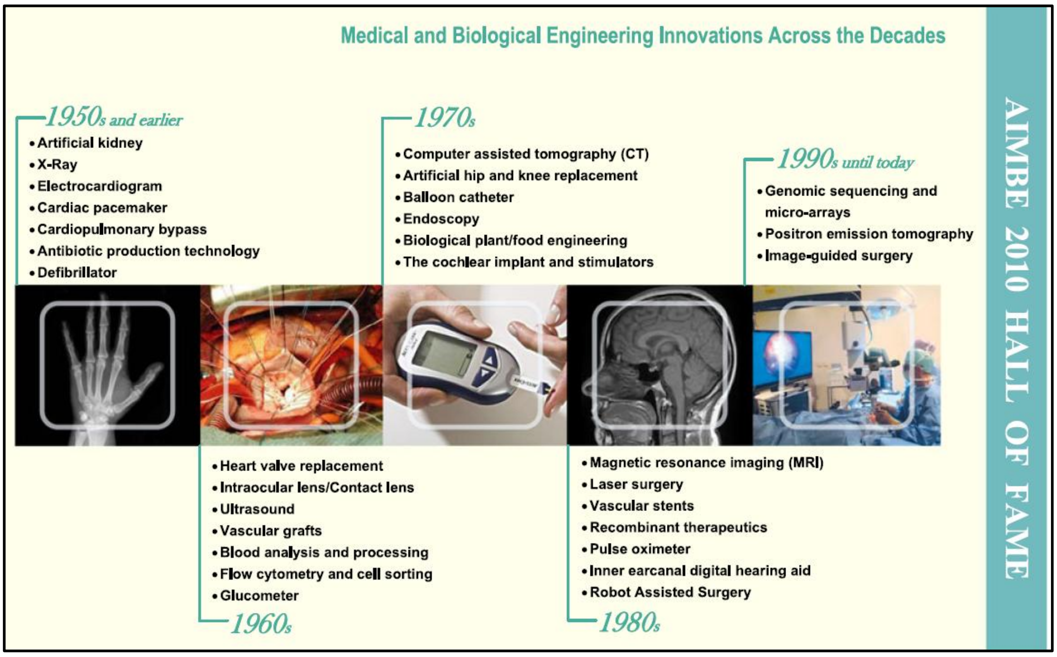
ASSOCIATION BETWEEN INDUSTRIAL TECHNOLOGY

REVOLUTIONS AND HEALTHCARE TECHNOLOGY REVOLUTIONS

Table I (Neuman, Baura et al. 2012) lists the significant developments in medical and biological engineering during the past 100 years that the American Institute of Medical and Biological Engineering has chosen for their Hall of Fame.

TABLE I

American Institute For Medical And Biological Engineering’s Hall Of Fame (Neuman, Baura et al. 2012)



Some fundamental modern medical tools were created and used in clinics during the first industrial revolution (Industry 1.0 and Healthcare 1.0), including the flexible tube stethoscope (1840s), piston syringe (1850s), and portable clinical thermometer (1860s). Although the passive, non-powered medical tools introduced in Healthcare 1.0 are simpler than the active, powered tools released later, their manufacture requires complex mechanical design and processing. It was made possible by the mechanical design and processing innovations of Industry 1.0 (Pang, Yang et al. 2018).

More sophisticated medical devices were created and used in clinics during the second revolution (Industry 2.0 and Healthcare 2.0), including X-ray imaging (1890s), sphygmomanometer (1890s), and electrocardiograph (1900s). In addition to mechanical engineering, these new medical technologies frequently make use of complex electrical and electronic engineering. Medical equipment entered the era of electricity thanks to Industry 2.0's introduction of electrical power.

Later, in the third revolution (Industry 3.0 and Healthcare 3.0), microelectronics, computer science, automation, and biomedical engineering advancements allowed for the development and adoption of more complex medical systems, including brightness mode ultrasonography (1960s), implantable pacemakers (1970s), X-ray computed tomography (1970s), magnetic resonance imaging (1980s), artificial hearts (1980s), Positron Emission Tomography (1980s), and many others. All of these medical systems require complex mechanical, electronic, software, and control algorithm designs. To build such systems, high-precision processing and quality control are necessary. It is impossible to make them a reality without the advanced production technology presented by Industry 3.0.

The aforementioned observation has confirmed the anticipated future of Healthcare 4.0, which is being rapidly realized thanks to key Industry 4.0 technologies like cyber physical systems (Wang 2018), IoT and services (Yang, Xie et al. 2014), AI, big data, robotics, bio-three-dimensional (3-D) printing, connected wearable devices, etc.

EMERGING RESEARCH TOPICS AND CHALLENGES: HEALTHCARE BIG DATA

For there to be any real improvement in the standard of care, it is imperative to make use of the vast amount of patient-related data. The vast amount of data collected by wearable technology is another source of big data in the healthcare industry (Ravi, Wong et al. 2016). Daily, a sizable amount of patient information is gathered. They include a lot of information regarding illnesses, their development, and their treatments. It is crucial to combine the use and analysis of a variety of organized and unstructured data from many sources in order to diagnose patient problems, match treatments with outcomes, and foresee potential health complications.

CONCLUSION

Healthcare 4.0 incorporates emerging technologies such as robots, cognitive computing, smart homes, and cyborg clinicians in order to best serve patients and medical staff. Healthcare robotics is growing and developing the capacity to understand human intentions and interact with environments and other agents, whether people or robots, thanks to AI and natural human-robot interface technology. This offers a potent instrument for the independent, assistive, and rehabilitation living of patients. The acceptance of healthcare robotics applications in clinical practice, the availability of high-quality training data from which to develop and maintain AI applications in robots, the issue of human safety during human-robot interaction, particularly in the uncertain and dynamic environments, and the associated legal issues, are major obstacles that must be overcome for the future adoption of healthcare robotics. Before healthcare robotics may be used more widely in the future in the aforementioned application scenarios, solutions at several levels (e.g., technological, legal, and political level) are needed.

Healthcare 4.0 and Industry 4.0 present educational institutions with additional challenges. Universities and professional institutions must develop programs to train the technicians, engineers, and other competent personnel needed to design, construct, evaluate, operate, and maintain these systems. To provide qualified employees for these duties, university programs like eHealth, biomedical engineering, and smart systems engineering are tentative beginnings in the right direction. To fulfill the Healthcare 4.0 goal, more specialized training that builds on top of health and biomedical backgrounds would be required. This would include knowledge of issues relating to privacy, security, and cognitive computing systems. Increased conversations on the ideals of Industry 4.0 and Healthcare 4.0 will undoubtedly lead to coordinated answers to some of the aforementioned problems.

REFERENCES:

Aceto, G., V. Persico and A. Pescapé (2020). "Industry 4.0 and health: Internet of things, big data, and cloud computing for healthcare 4.0." Journal of Industrial Information Integration**18**: 100129.

Agarwal, A., C. Baechle, R. Behara and X. Zhu (2017). "A natural language processing framework for assessing hospital readmissions for patients with COPD." IEEE journal of biomedical and health informatics**22**(2): 588-596.

Alexandru, A. G., I. M. Radu and M.-L. Bizon (2018). "Big Data in Healthcare-Opportunities and Challenges." Informatica economica**22**(2).

Alshurafa, N., C. Sideris, M. Pourhomayoun, H. Kalantarian, M. Sarrafzadeh and J.-A. Eastwood (2016). "Remote health monitoring outcome success prediction using baseline and first month intervention data." IEEE journal of biomedical and health informatics**21**(2): 507-514.

Amft, O., J. Palmer and B. Telfer (2015). "Guest Editorial-Body Sensor Networks: Novel Sensors, Algorithms, Platforms, and Applications." IEEE Journal of Biomedical and Health Informatics**19**(3): 783-783.

Armananzas, R., M. Iglesias, D. A. Morales and L. Alonso-Nanclares (2016). "Voxel-based diagnosis of Alzheimer's disease using classifier ensembles." IEEE journal of biomedical and health informatics**21**(3): 778-784.

Brüser, C., C. H. Antink, T. Wartzek, M. Walter and S. Leonhardt (2015). "Ambient and unobtrusive cardiorespiratory monitoring techniques." IEEE reviews in biomedical engineering**8**: 30-43.

Dehbandi, B., A. Barachant, D. Harary, J. D. Long, K. Z. Tsagaris, S. J. Bumanlag, V. He and D. Putrino (2016). "Using data from the Microsoft Kinect 2 to quantify upper limb behavior: a feasibility study." IEEE journal of biomedical and health informatics**21**(5): 1386-1392.

Gaut, G., M. Steyvers, Z. E. Imel, D. C. Atkins and P. Smyth (2015). "Content coding of psychotherapy transcripts using labeled topic models." IEEE journal of biomedical and health informatics**21**(2): 476-487.

Hoogendoorn, M., T. Berger, A. Schulz, T. Stolz and P. Szolovits (2016). "Predicting social anxiety treatment outcome based on therapeutic email conversations." IEEE journal of biomedical and health informatics**21**(5): 1449-1459.

Jordanski, M., M. Radovic, Z. Milosevic, N. Filipovic and Z. Obradovic (2016). "Machine learning approach for predicting wall shear distribution for abdominal aortic aneurysm and carotid bifurcation models." IEEE Journal of Biomedical and Health Informatics**22**(2): 537-544.

Khan, N., I. Yaqoob, I. A. T. Hashem, Z. Inayat, W. K. Mahmoud Ali, M. Alam, M. Shiraz and A. Gani (2014). "Big data: survey, technologies, opportunities, and challenges." The scientific world journal**2014**.

McKinney Jr, E., C. J. Yoos II and K. Snead (2017). "The need for 'skeptical'accountants in the era of Big Data." Journal of Accounting Education**38**: 63-80.

Neuman, M. R., G. D. Baura, S. Meldrum, O. Soykan, M. E. Valentinuzzi, R. S. Leder, S. Micera and Y.-T. Zhang (2012). "Advances in medical devices and medical electronics." Proceedings of the IEEE**100**(Special Centennial Issue): 1537-1550.

Pang, Z., G. Yang, R. Khedri and Y.-T. Zhang (2018). "Introduction to the special section: convergence of automation technology, biomedical engineering, and health informatics toward the healthcare 4.0." IEEE Reviews in Biomedical Engineering**11**: 249-259.

Ravì, D., C. Wong, F. Deligianni, M. Berthelot, J. Andreu-Perez, B. Lo and G.-Z. Yang (2016). "Deep learning for health informatics." IEEE journal of biomedical and health informatics**21**(1): 4-21.

Ravi, D., C. Wong, B. Lo and G.-Z. Yang (2016). "A deep learning approach to on-node sensor data analytics for mobile or wearable devices." IEEE journal of biomedical and health informatics**21**(1): 56-64.

Wang, Y. (2018). "Trust quantification for networked cyber-physical systems." IEEE Internet of Things Journal**5**(3): 2055-2070.

Yang, G., L. Xie, M. Mäntysalo, X. Zhou, Z. Pang, L. Da Xu, S. Kao-Walter, Q. Chen and L.-R. Zheng (2014). "A health-IoT platform based on the integration of intelligent packaging, unobtrusive bio-sensor, and intelligent medicine box." IEEE transactions on industrial informatics**10**(4): 2180-2191.