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IMPLICATIONS OF ARTIFICIAL INTELLIGENCE IN HEALTHCARE DELIVERY IN THE HOSPITAL SETTINGS: A LITERATURE REVEIW

Nada Khaled[1], Turki,A, Aidalina M.[3*]

[1]Master in Public Health Candidate, Department of Community Health, Faculty of Medicine, University Putra Malaysia.
[2]Master of Science (Health Service Management) Candidate, Department of Community Health, Faculty of Medicine, University Putra Malaysia.
[3]Department of Community Health, Faculty of Medicine, University Putra Malaysia.

**Corresponding author: Aidalina Mahmud; Email: aidalina@upm.edu.my*

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ABSTRACT

Background: Artificial intelligence use in healthcare is increasing over the years. The aim of this review is to determine the positive and negative implications of artificial intelligence in healthcare delivery in hospital settings.

Methods: Literature search was done using keywords “artificial intelligence”, “hospital” and “implications” from databases of Scopus, Science Direct, Google scholar and PubMed. The literature search was limited to articles published in English, available in open access and articles that are able to be retrieved in full text format.

Result: Artificial intelligence has positive influence on health care delivery especially in hospitals in terms of quality of care, efficiency and accuracy. On the other hand, artificial intelligence can also have negative implications in terms of ethical, privacy and de-humanization of care.

Conclusion: In conclusion, the positive implication of artificial intelligence and the wide range opportunities for technological development exceed the negative aspect, especially when the negative aspects are addressed appropriately or avoided.

Keywords: artificial intelligence, implications, hospital.

1.0 Introduction

Definition of Artificial Intelligence (AI)

Artificial intelligence (AI) is a part of computer science concerned with designing intelligent computer systems that exhibit the characteristics associate with intelligence in human behaviours, understanding, language learning, reasoning, solving problems (Barr et al,1981). It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable (John McCarthy, 2007).

Increase use of AI can bring major social and economic benefits. Artificial intelligence offers massive gains in efficiency, productivity and performance to most or all healthcare delivery processes. Artificial intelligence in the form of software that can be integrated into existing processes, therefore improving the processes and making more accurate decisions through better use of information. In the end AI can help reduce the associated operational costs.

In last 60 years, researchers aimed for AI to replicate human intelligence. This approach is called ‘Classical AI’. However, this was a limiting approach as it assumed human intelligence is the only form of intelligence. This approach also assumed human intelligence as the most that intelligence can be (Scott, 1993).

The involvement of healthcare delivery in AI started about 50 years ago. In 1970, William B Schwartz, a physician interested in the use of computing science in medicine argued, “computing science will probably exert its major effects by augmenting and, in some cases, largely replacing the intellectual functions of the physician” (Warwick, 2012).

Subsequently, there was a realization that conventional computing techniques were unsuitable for solving complex medical phenomenon. A more sophisticated computational model that simulated human cognitive processes, that is AI model, was required for clinical problem solving. Early efforts to apply AI in medicine consisted of setting up rules-based systems to help with medical reasoning. In 1976, the Scottish surgeon Gunn used computational analysis to diagnose acute abdominal pain (Shapiro, 1992). By the 1980s, AI research communities were well established across the world but especially in learning centers in the US. This development helped in expansion of the use of novel and innovative AI approaches to medical diagnoses. Much of this push was because medicine was an ideal testing ground for these AI applications. A significant number of AI applications in medicine at this stage were based on the expert system methodology (Topol, 2015). By the end of the 1990s, research in medical AI started to use new techniques like machine learning and artificial neural networks to aid clinical decision-making (Da Sim, 2001).

Artificial intelligence systems will be responsible for routine diagnostic and treatment processes. The intention is not to replace human clinicians but enable a streamlined high-quality healthcare delivery process. Of all the promising medical AI novelties that are being explored, robotics driven by AI will have an important role in the medical automation process. Robots embody AI and give it a form, while AI algorithms/programming provides intelligence to the robots. Robotic assistants have already been employed to conduct surgeries, deliver medication and monitor hospital patients but the most promising area for their use is in elderly care (Topol et al., 2015).

As more AI research is undertaken and AI systems become more trained and consequently intelligent, it is expected that these systems and machine will replace most of the human elements of clinical care if not all, while leaving the communication of serious matters and final decision making to human clinicians.

Subfield of artificial intelligence

There is no universally accepted classification of AI subfields relevant to health (Wahl, 2018). Nonetheless, there are several AI subfields that have been repeatedly cited by researchers as follows. The first is artificial neural networks (ANNs). This is the basis for deep learning models. In deep learning models, data is filtered through a cascade of multiple layers, with each successive layer using the output from the previous one to inform its results (Jennifer, 2018). Deep learning models can become more and more accurate as they process more data, essentially learning from previous results to refine their ability to make correlations and connections. Its classified into three broad categories includes supervised learning, unsupervised learning, and reinforcement learning.

The second AI subfield is the natural language processing (NLP). The natural language processing aims to bridge the divide between the languages that humans and computers use to operate. By using algorithms that allow machines to identify key words and phrases in natural language. The NLP has evolved to focus on managing and processing information from large datasets. One of the NLP approach is topic modeling that seeks to automatically identify the topics covered in documents by inferring relationships among prominently featured words. It emphasizes building a computer’s ability to understand human language and is crucial for large-scale analyses of content such as electronic medical record (EMR) data, especially physicians’ narrative documentation. To achieve human-level understanding of language, successful NLP systems must expand beyond simple word recognition to incorporate semantics and syntax into their analyses.

The third AI subfield is automated planning and scheduling that focuses on organising and prioritising the activities required to achieve a desired goal. It is also sometimes referred to as

AI planning. Some automated planning applications can be used to improve the efficiency of human procedures.

The fourth AI subfield is health informatics and electronic medical records (EMRs). Health informatics describes the acquisition, storage, retrieval and use of healthcare information to improve patient care across interactions with the health system. Health informatics can help shape public health programmes by ensuring that critical information is available for making sound policies and program decisions. Electronic medical records which are digital versions of patient and population health information are an important source of data for health informatics.

The fifth AI subfield is image and signal processing. This subfield is used to process large amounts of data from images and signals. Data produced by motion and sound are common examples of signals. Steps in image and signal processing algorithms typically include signal feature analysis and data classification using tools such as artificial neural networks (Wahl et al., 2018).

Use of AI in healthcare delivery

The health delivery system (HDS) is part of a health system; and it includes clinical services, and also preventive activities (Stevens, Kroneman, van der Zee, 2017). A consistent, correct care delivery process facilitates care that meets all of the desirable quality attributes: safe, effective, efficient, patient-centred, timely, and equitable. People should be able to count on receiving care that meets their needs and is based on the best scientific knowledge (Institute of Medicine, 2001).

Artificial intelligence is being employed in healthcare in many settings including hospitals, laboratories and research facilities. Artificial intelligence approaches employing machines to sense and comprehend data like humans has opened up previously unavailable or unrecognized opportunities for clinical practitioners and health service organizations (Shapiro, 1992). The main areas of using the artificial intelligence in healthcare delivery are in healthcare administration, clinical decision support, patient monitoring, and in healthcare interventions.

Healthcare administration

Information technology tools have been demonstrated to alleviate the burden on health services. Artificial intelligence and data mining techniques have been identified as among the most promising approaches to support healthcare administration by augmenting clinical care and lessening administrative demands on clinicians (Reddy, Fox, & Purohit, 2019). By undertaking repetitive and routine tasks like patient data entry and automated review of laboratory data and imaging results, AI can free time for clinicians to provide direct care for patients(Snyder et al., 2012). Linking machine learning algorithms to electronic health records can help clinicians and administrators to retrieve accurate and context-relevant patient information (Peyrou, 2018).

By using machine learning and concept-based information retrieval system, search accuracy and retrieval speed can be improved (Goldstein, 2017). Health services can also use optimized machine learning algorithms to support clinic scheduling and patient prioritization thus reducing waiting times and more efficient use of services (Huang, 1995). For example, AI techniques can help hospitals in predicting the length of stay of patients at the pre-admission stage, enabling more appropriate and efficient use of limited hospital resources.

Clinical decision support

Clinical decision support is defined as computer programs that use clinical data and knowledge to support decisions made by healthcare professionals (Reddy, 2019). Clinical decision support systems may help to reduce medical errors and increase healthcare consistency and efficiency and efforts to get clinical decision support systems into routine practice are increasing. They also have potential to help decision in treatment of difficult cases based in available large-scale data from previous cases that has the same situation.

Artificial intelligence in clinical decision support system research has been used since the early 1970s, for example, an AI framework employing sequential decision making could recommend alternate treatment paths, infer patient's health status even when measurements were not available and refine management plans as new information was received (Hauser, 2013).

One subfield of AI, the artificial neural networks, are now being trialled for medical diagnosis and appears to be capable of predicting and diagnosing medical conditions better than clinicians (Amato, 2013). Compared to traditional clinical decision support systems based on traditional software engineering, artificial neural networks are expected to have superior abilities in predicting many medical conditions such as cancer, cardiovascular disease and diabetes risk and artificial neural networks can be used for radiological and histopathological diagnosis.

Patient monitoring

The adoption of artificial intelligence in healthcare such as electronic health records and fitness monitoring devices has created remarkable access to automated data and the ability to better monitoring of patients (Saria, 2014).

Furthermore, the AI increases the efficiency of monitoring in other settings as well, such as improved monitoring and analysis of electrocardiographs, electroencephalographs, electromyograph and Doppler ultrasounds in hospital (Ramesh, Monson, & Drew, 2004). Artificial intelligence-enabled software can be used in intensive care units for cardiovascular and respiratory monitoring through the interpretation of vital signs. After a hospital visit, health services can use natural language processing-enabled virtual assistants to communicate appropriate health and medication information and schedule follow-up visits for patients. The use of such virtual health assistants has been found to increase medication compliance and reliable follow-up.

Healthcare interventions

Artificial intelligence programs based on Fuzzy logic, a form of many-valued logic, can be used to administer medication. For example, fuzzy controllers have been used to administer vasodilators for postoperative patients. Significant developments in computer vision and robotics in recent years promise speedier and less expensive diagnostic and treatment services. Computer vision has been used for several years for automated analysis of 3-dimensional medical images, but it is also now being used to assess a patient's condition through facial analysis. Elderly care presents the greatest opportunity for utilizing robots with artificial intelligence programs in healthcare as many of them live in the community but may have little support from family or care-givers. In these situations, robotic assistants can provide support for the elderly including reminding them about regular activities and guiding them through unfamiliar environments (Reddy et al., 2019).

Implications of AI use in healthcare: the decision criteria

In this review, the assessment of positive and negative implications of healthcare delivery in hospital setting involves consideration of financial quality and social implications. The assessment is based on the authors' interpretation of the results and conclusions of the original papers that were reviewed. Positive financial implication is when the use of AI is related to increase in productivity. Positive social implication when the use of AI can improve the quality of life of individuals such as in the case of robotic assistance. The other positive implication in the use of AI is that of quality in health care, when more accurate by decreasing the errors. Conversely, negative implications occur when there are ethical implications, lack of data privacy, inequity and access.

Aim of Manuscript

This paper aims to review the positive and negatives implications of artificial intelligence in healthcare delivery in the hospital settings.

2.0 Materials and Method

Literature search was done using keywords “artificial intelligence”, “hospital” and “implications” from databases of Scopus, Science Direct, Google scholar and PubMed. The literature search was limited to articles published in English, available in open access and articles that are able to be retrieved in full text format.

3.0 Result

The following table summarizes several examples of the AI used in the hospital setting and their brief descriptions.

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Table: Examples of the AI used in the hospital setting and their brief description.

No.	Author, year, title	Artificial intelligence sub-field	Brief description	Use
1	Gulshan, et al., 2016. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *Jama*, *316*(22), 2402-2410.	Deep learning	Diabetic Retinopathy and diabetic macular edema, in Retinal Fundus Photographs using neural networks (imaging analytics and diagnostics)	Decision making
2	Stahl & Coeckelbergh, 2016. Ethics of healthcare robotics: Towards responsible research and innovation. *Robotics and Autonomous Systems*, *86*, 152-161.	Robot	Ethical technological innovation	Patient monitoring and intervention
3	Jha & Topol, 2016. Adapting to artificial intelligence: radiologists and pathologists as information specialists. *Jama*, *316*(22), 2353-2354.	Deep learning	Radiology and pathology autodidact	Clinical decision support
4	Tang, et al., 2018. Canadian Association of Radiologists white paper on artificial intelligence in	Deep learning	Radiology image analysis	Clinical decision support

	radiology. *Canadian Association of Radiologists Journal*.			
5	Cohen.,et al., 2016. Methodological issues in predicting pediatric epilepsy surgery candidates through natural language processing and machine learning. *Biomedical informatics insights*, *8*, BII-S38308.	Machine Learning	Identify surgical candidates among paediatric epilepsy patients by means of Natural Language Processing and machine learning	Decision making
6	Bahl, et al., 2017. High-risk breast lesions: a machine learning model to predict pathologic upgrade and reduce unnecessary surgical excision. *Radiology*, *286*(3), 810-818.	Machine learning	Identifies high-risk breast lesions which are at low risk to upgrade into cancer.	Decision making
7	Malhotra & Shah, 2018. Telepsychiatry and Digital Mental Health Care in Child and Adolescent Psychiatry: Implications for Service Delivery in Low-and Middle-Income Countries. In *Understanding Uniqueness and Diversity in Child and Adolescent Mental Health* (pp. 263-287).	Information and communication technologies (ICT)	Tele-psychiatrics	Patient monitoring and intervention

8	Yamada & Kobayashi, 2017. Detecting mental fatigue from eye-tracking data gathered while watching video. In *Conference on Artificial Intelligence in Medicine in Europe* (pp. 295-304). Springer, Cham.	Eye-tracking	Mental fatigue	Patient monitoring
9	Busch, et al., 2012. Accurately predicting bipolar disorder mood outcomes—implications for the use of electronic databases. *Medical care*, *50*(4), 311.	Electronic databases	Bipolar	Patient monitoring Decision making Diagnosis
10	Liao, et al., 2019 Improving medication safety by cloud technology: progression and value-added applications in Taiwan. *International Journal of Medical Informatics*.	Cloud technology	Medication care delivery	Healthcare administration
11	Vemulapalli, et al., 2016 Non-obvious correlations to disease management unraveled by Bayesian artificial intelligence analyses of CMS data. *Artificial intelligence in medicine*, *74*, 1-8.	Bayesian networks	Management of chronic conditions.	Healthcare administration

12	Nelson, 2015. Practical implications of sharing data: a primer on data privacy, anonymization, and de-identification. In *SAS Global Forum Proceedings*.	Health Data Electronic Health Records (EHR)	De- identification system	Healthcare administration
13	Piette, et al., 2016. Patient-centered pain care using artificial intelligence and mobile health tools: protocol for a randomized study funded by the US Department of Veterans Affairs Health Services Research and Development Program. *JMIR research protocols*, *5*(2).	Reinforcement learning	Cognitive behavioural therapy (CBT) pain management	Healthcare intervention

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4.0 Discussion

Positive implications

Based on the articles reviewed, artificial intelligence seems to be able to enhance the quality of care. For example, deep learning AI was used in automated system for the detection of diabetic retinopathy (Gulshan et al., 2016). In their study, Gulshan demonstrated that deep neural networks can be trained, using large data sets and without having to specify lesion-based features, to identify diabetic retinopathy or diabetic macular oedema in retinal fundus images with high sensitivity and high specificity. This resulted in delivery of high quality results in a wider range of medical imaging tasks.

Another example of the use of AI in clinical decision-making was shown in the longitudinal study by Busch et al. (2016). Their study aimed to investigate the accuracy of predicting remission rate of bipolar disorder outcome by using information of limited clinical detail but feasible to collect electronically. The researchers concluded that by using electronic clinical data, predicting bipolar disorder remission was feasible and accurate.

Another example of the use of deep learning AI was in the study by Jha & Topol (2016), at the radiology and pathology department in the detection of disease such as lung and breast cancer. Based on the accuracy of the diagnosis, deep learning AI helped the physician in making accurate and efficient clinical decision. Overall, high quality of care with can be given to patients at a lower cost.

Artificial intelligence can also improve the quality of life of patients as a whole. In Japan, eye tracing data was used to develop a model to detect mental fatigue during natural situation, which improved the previous model. This new model detected fatigue during cognitive tasks for health monitoring for different age group, and results in improving the quality of life (Yamada & Kobayashi, 2018).

Given the availability of extensive digitized healthcare data it is now possible to use data-driven approaches to mine medical databases for novel insight. The study by Vemulapalli et al (2016) demonstrated the use of artificial intelligence based methods such as Bayesian networks can open up opportunities for creation of new knowledge in management of chronic conditions and enabling timely care intervention.

The wealth of data available in electronic database can also give positive implications as data can be shared in hopes that the quantity, diversity, and analytic potential of health-related data for research and practice will yield new opportunities for innovation in basic and translational science (Nelson, 2015).

Safety is very important in health care delivery especially in the hospital setting. The AI in the form of machine learning can help in ensuring safety of patients. This was demonstrated in the study by (Cohen et al., 2016). The study involved a series of structured experiments in a neurosurgery department. The study examined the effects of training data and classification algorithm in predicting candidacy for surgical intervention in pediatric epilepsy patients. The results showed that machine learning methods contributed to predicting pediatric epilepsy surgery candidates and reducing lag time to surgery referral. The researchers concluded that there is a positive implication of machine learning models has the potential in augmenting the decision making capacity of clinicians in neurosurgical applications.

Saving patients from unnecessary risks of surgery is also an important aspect of health care delivery in the hospital setting. A study by Bahl, et al. (2017) showed that AI machine learning model was able to predict pathologic upgrade among patients with high-risk breast lesions and hence reduce unnecessary surgical excision.

Medication safety can also be dealt with by the use of AI. For example, a study by Liao, et al (2019) which aimed to develop and implement an integrated cloud technology to ensure medication reconciliation during transitions of care and improve medication safety in aged societies, showed that cloud technology improved patient medication safety while also controlling overall drug expenditure.

Researchers are continually working on using AI in improving patient care. There is an ongoing study by Piette, Krein, Striplin, Marinec and Robert (2016). This study will evaluate an intervention that increases patients' access to effective CBT pain management services while allowing health systems to maximize program expansion given constrained resources. This study applies the principles from "reinforcement learning" (a field of artificial intelligence or AI) to develop an evidence-based, personalized CBT pain management service that automatically adapts to each patient's unique and changing needs (AI-CBT). AI-CBT uses feedback from patients about their progress in pain-related functioning measured daily via pedometer step counts to automatically personalize the intensity and type of patient support. The specific aims of the study are to (1) demonstrate that AI-CBT has pain-related outcomes equivalent to standard telephone CBT, (2) document that AI-CBT achieves these outcomes with more efficient use of clinician resources, and (3) demonstrate the intervention's impact on proximal outcomes associated with treatment response, including program engagement, pain management skill acquisition, and patients' likelihood of dropout.

Negative implications

There are health care providers who are concerned with the potential negative implications of the use of AI in medicine. For example, in the field of radiology, although AI applications currently focus on anomaly detection, segmentation, and classification of images, with availability of massive amounts of health data; it was stated in a paper by Tang et al (2018) that the radiology community must be educated on how to critically analyze the opportunities, pitfalls, and challenges associated with the introduction of new AI tools. Additionally, ethical reasoning should be developed to combine massive amounts of health data with AI in a private-public, multi institution, and trans-disciplinary environment.

Another negative implication of using AI in health care delivery is the de-humanization and ‘‘cold’’ care in term of autonomy, moral, social and ethical aspect (Stahl & Coeckelbergh, 2016). According to Stahl & Coeckelbergh, the use of AI may not only put humans out of job, but also remove the capacity for ‘‘warm human’’ care from the care process. It is highly doubtful that robots could ever be empathic or have emotions. The authors also reviewed the issues that raised by human–robot interaction in healthcare, such as the autonomy which is mean that the robot is designed to carry out tasks without continuous human guidance and assistance, surgical robots are remote controlled by the surgeon, yet health care research often aims to give more autonomy to the robot. The development of robotic technology could lead to replacement of human care workers, for instance if robotic care take over the work of the human nurse which raise the ethical implication. Robots as well do not have the capacity of moral reasoning or dealing with ethically problematic situations for dealing with complex ethical issues in healthcare. If robots are used as ‘‘social’’ companions and are given other roles which encourage social–emotional involvement of the humans (e.g. elderly people or children), elderly people are social isolated, and abandoned.

Another article also described the lack of human touch if AI is used such as in managing patients with psychiatric conditions. Malhotra and Shah (2006) argued that although the tele-psychiatic model provide telecommunication technology (ICT) to provide psychiatric services and treatment for mentally diseased patients across distances that increase reach and helps to establish geographic equity, still the specialist are unable to see a patient face-to-face (FTF) at the same time as providing video-consultation to a patient who is located remotely which can affect the accuracy of diagnosis and affect the treatment. The authors suggested that ideally be reserved only for difficult cases or where there has been poor response after several trials to treatment(Malhotra & Shah, 2006).

To summarize, the positive aspect of implication of artificial intelligence and the wide range opportunity of technological development has exceed the negative aspect, and even the later when its addressed appropriately it could be avoidable.

5.0 Limitations

This review did not cover several other aspects of potential positive and negative implications of using AI in the healthcare delivery in the hospital setting such as research, policy and legal aspects. The use of AI in health care is still “new” compared to other industries such as aerospace technology and the military. Additionally it is also assumed that there are studies on AI currently being conducted in the health care delivery and their results may not be available at present. Further studies should be done periodically to follow the progress of AI in health care.

6.0 Conclusion and recommendation

Artificial intelligence in healthcare delivery could improve health quality of life for people in hospital in the coming years, but only if this system and machines had gain the trust of doctors, nurses, and patients, and if policy, regulatory, and commercial obstacles are removed.

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