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Use of Artificial Intelligence in Healthcare Delivery

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Abstract

In recent years, there has been an amplified focus on the use of artificial intelligence (AI) in various domains to resolve complex issues. Likewise, the adoption of artificial intelligence (AI) in healthcare is growing while radically changing the face of healthcare delivery. AI is being employed in a myriad of settings including hospitals, clinical laboratories, and research facilities. AI approaches employing machines to sense and comprehend data like humans has opened up previously unavailable or unrecognised opportunities for clinical practitioners and health service organisations. Some examples include utilising AI approaches to analyse unstructured data such as photos, videos, physician notes to enable clinical decision making; use of intelligence interfaces to enhance patient engagement and compliance with treatment; and predictive modelling to manage patient flow and hospital capacity/resource allocation. Yet, there is an incomplete understanding of AI and even confusion as to what it is? Also, it is not completely clear what the implications are in using AI generally and in particular for clinicians? This chapter aims to cover these topics and also introduce the reader to the concept of AI, the theories behind AI programming and the various applications of AI in the medical domain.

Keywords: artificial intelligence, healthcare delivery, medicine, machine learning, deep learning, intelligent agent and neural networks

1. Introduction

There has been an immense amount of discussion in recent years about the advent of artificial intelligence (AI) and the implication of its application in various domains. However, the concept of AI is not new and can be traced back to Ramon Llull's theory of a reasoning machine in 1300 CE and even Aristotle's syllogisms in 300 BC [1, 2]. However, it is only since the 1950s, clearer definitions and practical applications have been formulated [3, 4]. While

there was a lull in the development of AI in the 70s and 80s because of loss of interest and funding, there has been in the most recent period a dramatic revival in the research and development of AI programs. Countries like China have prioritised AI development by investing billions of dollars into AI industrial hubs [5]. Other nations and global corporations have also invested into AI programming and creation of innovative AI applications [6–8]. Building on this trend, institutions are now increasingly paying attention to application of AI in healthcare. AI is being used to improve the efficiency in delivery of healthcare and address previously intractable health problems [1, 9, 10]. The hundreds of AI-based healthcare applications being introduced into the market in recent years is a testimonial to this focus. Commentators have discussed how application of AI in healthcare is at the early stages and there is yet more to come [1, 4, 6]. However, is AI just hype and are entities investing into a bubble? To get an answer, we first need to understand what AI is and its approaches and tools. This chapter covers these issues and how they specifically apply to healthcare and what is next for the use of AI in healthcare?

2. Development and application of AI

2.1. Definition

So, what is AI? Because of the complexity involved in developing synthetic intelligence that is comparable to human intelligence, there are varying interpretations of what AI is and what goes into developing AI. Some authors even frown upon the term ‘AI’ and prefer the term ‘Computational Intelligence’ [11]. However, if we consider what is the objective of AI and what resources go into achieving the objective, an acceptable definition encompassing these components can be fashioned. The end objective of AI is to create systems that think and act rationally like humans [2, 4, 12]. These systems can also be termed as ‘intelligent agents’ [2, 4]. If the goal of the system is to demonstrate intelligence and developing these systems requires computer programming, a formal definition of AI would read as *‘a field of science concerned with the computational understanding of what is commonly called intelligent behaviour, and with the creation of intelligent agents that exhibit such behaviour’* [13]. Simpler definitions describe AI as ‘machines assuming human like capabilities’, ‘extension of human intelligence through computers’ and ‘making computers do things which currently humans do’ but a more accurate description would be ‘the science of making intelligent machines’ [1, 2, 4, 14].

2.2. Intelligent agent

AI theory can be best understood through the *intelligent agent* concept [11]. An intelligent agent incorporates the skills required to pass the Turing Test, which assesses whether a machine can think like a human? [2, 3]. So an intelligent agent should be skilled in perception, practical reasoning and have an ability to take action to achieve its goals. The agent utilises the environment, it operates within, to both receive input and take action (**Figure 1**). Some key inputs that feed into an agent and potentially, which it can draw itself are current observations about the environment, prior knowledge about the environment, past experiences

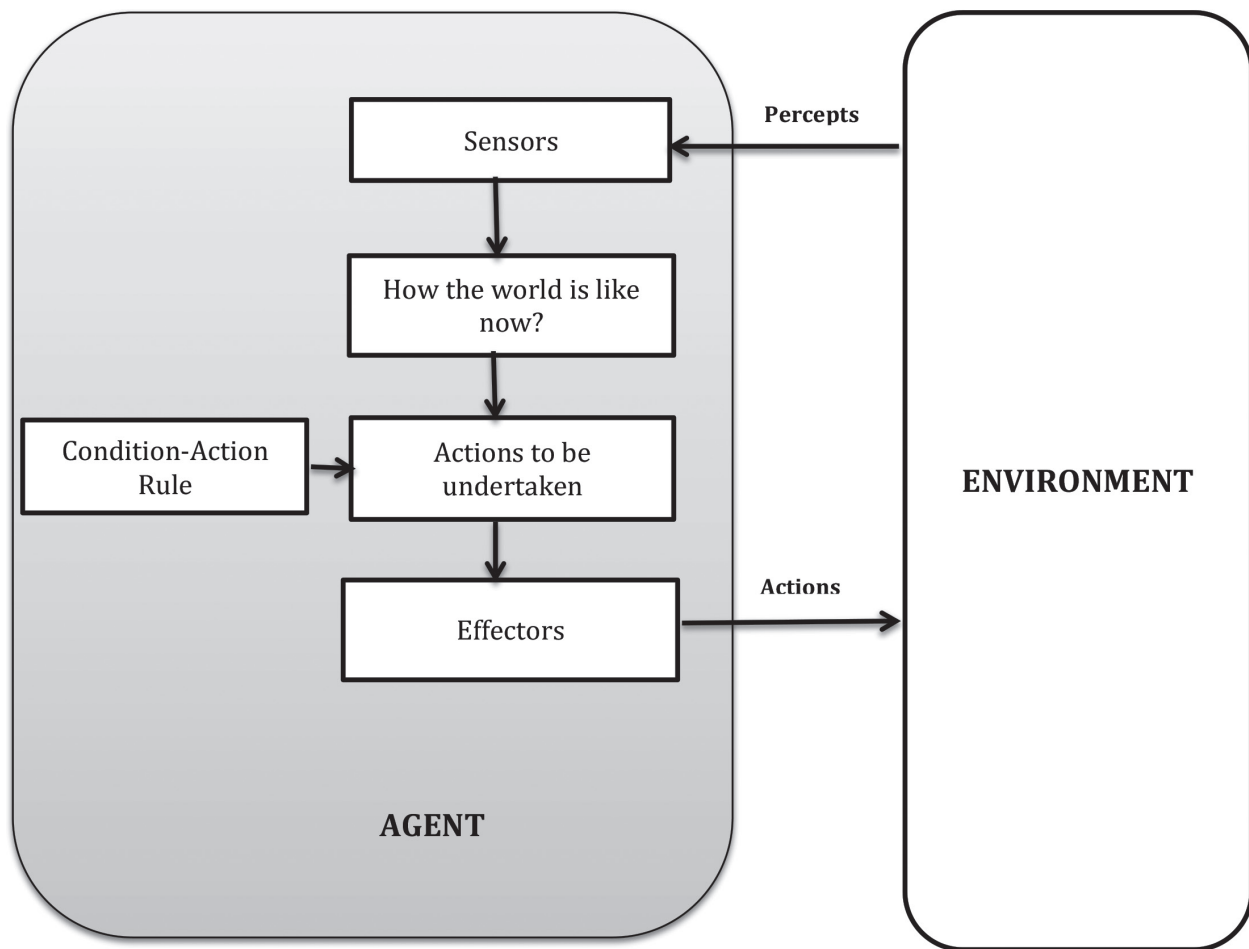


Figure 1. Concept of an intelligent agent.

that it can learn from and the objectives it needs to achieve. The agent perceives the environment through sensors and acts on the environment through effectors. When an intelligent agent is comprised of a computational core with physical actuators and sensors, it is termed a ‘robot’ [11]. When an agent is a program acting in a pure computational environment, it is an ‘infobot’ and when an advice providing program is coupled with a human expert, it is a ‘decision support system’.

2.3. What makes up AI?

In the past, researchers aimed for AI to replicate human intelligence [2]. 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 assumes human intelligence is the most intelligence can be. Intelligence mainly comprises of learning and reasoning [3, 13]. Constructing intelligence does not have to be defined by the limitations human intelligence poses. An apt analogy to discuss here is flight. While bird flight may be a source of inspiration for constructing aeroplanes, the aeroplane structure is not replicating the anatomic structure of a bird. So in constructing AI, it is more important to incorporate the vital characteristics of intelligence than merely replicate human intelligence.

Learning is an essential characteristic of intelligence [2, 4, 11]. Learning involves acquiring new knowledge, developing new skills through instruction or practise and knowledge representation and experimentation. If AI comprises learning, it has to demonstrate all the aforementioned features. A very common process through which AI systems achieve learning objectives is by *Machine Learning*. Machine learning is the modelling of different aspects of the learning process by computers [15]. Key goals of machine learning are for algorithms¹ to self-learn and improve through experience. The algorithms for machine learning typically fall into two categories: supervised and unsupervised categories [16]. Supervised learning involves an algorithm working with labelled training data. Categorisation of data and programming of the relationship between input and output data occurs in supervised learning. On the other hand, unsupervised learning allows the algorithm to identify a hidden pattern in a stack of data. Here the algorithm is run to check what patterns can be identified in the data and what outcomes may occur?

Reasoning and knowledge representation are the other aspects of AI [11]. In AI, reasoning involves manipulation of data to produce actions. Unlike traditional programming, the emphasis in AI is on what is to be computed rather than how it is to be computed? Structuring of this computation happens through design-time reasoning, offline computation and online computation. Earlier forms of AI involved algorithms based on the step-by-step reasoning model used to address predicated problems [2]. However, these models were not useful for uncertain situations or when there was incomplete information. AI reasoning models have now evolved to respond to these situations by drawing upon concepts from probability and economic theories. To resolve problems-certain or uncertain, AI systems require widespread knowledge about the relevant environment and then be able to represent this knowledge in a computable form [11]. For this to occur, AI uses a *Representation and Reasoning System* (RRS). An RRS is comprised of a programming language to communicate with a computer, a method to allocate meaning to the language and after input a process to figure out the answers. Knowledge is represented in different forms, but the most widely used method is Frames [2]. Frames are files in the computer where information is stored in slots. To enable AI knowledge representation and reasoning, programming languages and computational resources are two important properties. Different programming languages are used in AI, but the most popular are low-level programming languages such as Lisp, Python, C++ and Fortran. In the past, stand-alone computers and their limited processing power had restricted the advancement of AI. In recent years, AI reasoning and knowledge representation has immensely benefited from the rapid technological advances in computing power and wireless technology. These advances have helped in the deployment of sophisticated algorithms designed to resolve problems that could not have been addressed by AI applications in the past.

2.4. AI tools

AI systems employ several tools to automate problem-solving tasks. These tools are based on AI principles, some of which were discussed in the previous sections. The tools are used to

¹In computer science, an algorithm is an explicit description of how to solve a class of problems? [2–4].

create AI applications to resolves issues across various disciplines and industries. Some commonly utilised tools are discussed in this section.

Search in AI system mirrors real-life problem solving but draws upon computing power to resolve the problems [17]. Search problems are classified based on the amount of information that is available to the search process. This information may relate to the whole of the problem area or a specific component of the problem. AI through an independent search planning process analyses multiple options and identifies an optimal solution. AI adopts a faster and better process to search and optimisation than conventional techniques [17, 18]. The search process that separates AI from conventional techniques is its process remembers past results, learns and refines its performance in relation to past searches, plans its path forward and answers search queries akin to human intelligence. One such example of AI search and optimisation tool is *Evolutionary Computation*. Evolutionary Computation is the umbrella term for algorithms based on natural evolutionary processes that incorporate mechanisms of natural selection and survival of the fittest principle [1, 10]. Foremost of the evolutionary computation algorithms are the *Genetic Algorithms*. Genetic Algorithms are a category of stochastic search and optimisation algorithms based on Darwin's natural biological evolution. These algorithms use a population-based search process to create random solutions for the problem at hand. These solutions are termed chromosomes. The chromosomes are comprised of random values derived from various control values. The variations in the values are utilised for the search process. The population of chromosomes is then assessed for an objective function. This population of solutions then evolves from one generation to another to arrive at an acceptable solution. The ideal solutions are retained and the mediocre ones disposed of. Through a process of repetition, improvements and generation of new solutions would occur.

In their quest to replicate biological intelligence, AI researchers inspired by the biological nervous system have developed *Artificial Neural Networks (ANNs)* [1, 19]. Artificial Neural Networks attempt to simulate nerve cell (neurons) networks of the brain. This approach of copying biological neuronal networks to function independently differs from conventional computing process that primarily seeks to support human brain computation. A very simple base algorithm structure (see **Figure 2**) lies behind the artificial neural networks but it can be adapted to a range of problems. The artificial neurons, which are computer processors, are interconnected with each other and are capable of performing parallel computations for data processing and knowledge representation [19]. These neural networks are capable of learning from historical examples, examining non-linear data, and managing imprecise information. ANNs are categorised into two main categories: *Feedforward Neural Networks* and *Recurrent Neural Networks*. In feedforward network the signal passes in only one direction and in recurrent neural networks, feedback and short-term memories of previous inputs are enabled. In both categories, application of deep learning, which is a class of machine learning that uses a cascade of multiple layers of non-linear processing units, enhances the problem-solving capabilities of the neural networks. So we have deep feedforward and deep recurrent neural networks increasingly being used to resolve real-world problems through language modelling, analysis of unstructured data and strategy formulation.

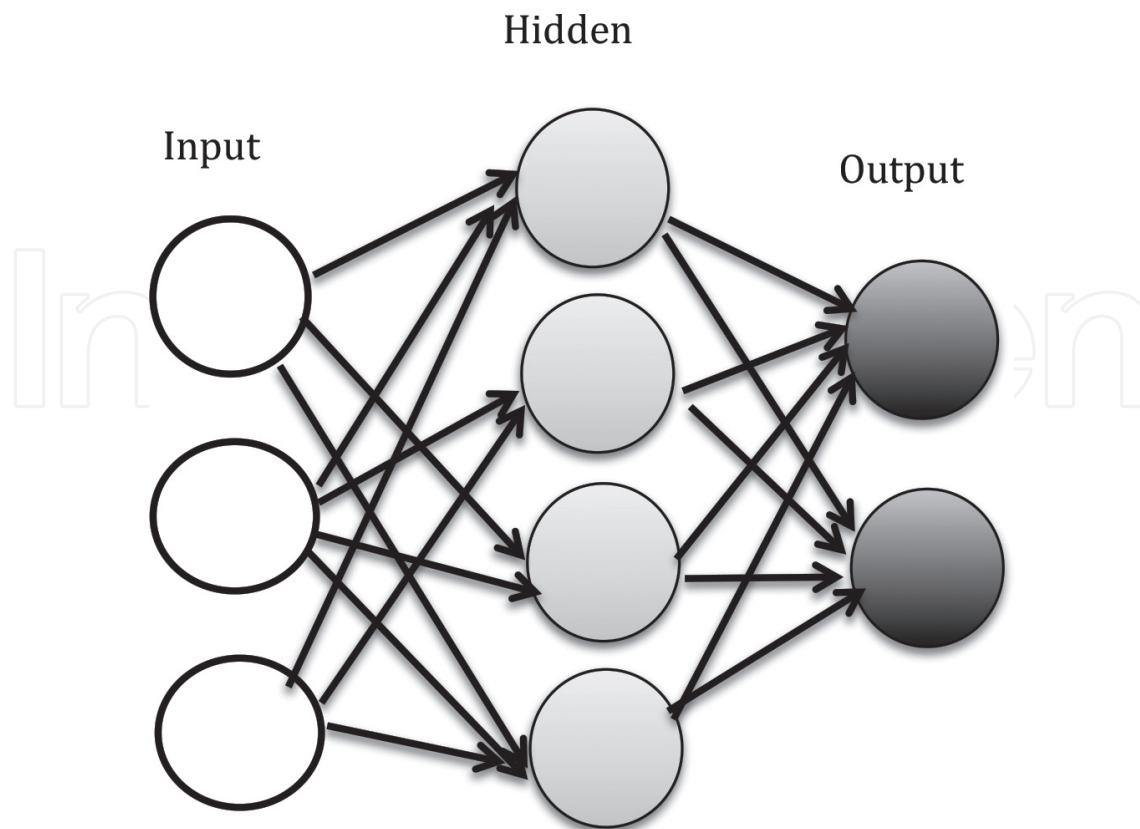


Figure 2. Schematic representation of an artificial neural network.

Logic is important to reasoning, which in turn is a key component of intelligence. Classical logic is based on the assumption that only two truth-values (false and true) exist [2]. This assumption is called *bivalence*. On the other hand, *Fuzzy Logic* reflects real world phenomenon, where everything is a matter of degree [1, 2, 10]. A fuzzy logic can be viewed as a fuzzy extension of a multi-valued logic i.e. instead of recognising everything is black and white, it recognises there are shades of grey. Fuzzy logic uses continuous set membership from 0 to 1 in opposition to Boolean logic, which relies on sharp distinctions such as 0 for false and 1 for true. Fuzzy applications utilise a structure of series of 'if-then' rules for modelling. This approach by fuzzy logic permits ambiguity and can be used in AI systems for indeterminate reasoning.

Another important AI technique is *Natural Language Processing*. Natural language processing (NLP) is concerned with the use of software programming to understand and manipulate natural language text or speech for practical purposes [20]. With NLP, the process of language analysis is decomposed into various stages mirroring theoretical linguistic distinctions as outlined by syntax, semantics and pragmatics [4, 20]. NLP enables machines to read and understand human language. NLP can also be utilised to gather and analyse unstructured data such as free text. In recent years, progress in NLP specifically in the field of syntax has led to development of effective grammar characterisation and chart parsing. Development of numerous conceptual tools has led to formation of systems and interface subsystems to use

for experiments. Part-of-speech identification and word sense disambiguation have become standard processes in NLP. Other current applications of NLP include information retrieval, machine translation and text mining.

Use of *Hybrid Artificial Intelligent Systems* (HAIS), which are a combination of AI techniques, is becoming popular because of its capabilities to address real world complex problems that individual AI techniques cannot address [21]. By combining different AI learning and adaptation techniques, HAIS overcomes the limitations associated with a particular technique. HAIS may involve a combination of agents and multi-agent systems, fuzzy systems, artificial neural networks, optimisation models and so forth. By combining symbolic and sub-symbolic techniques, complex issues involving indistinctness, ambiguity and vagueness can be resolved by HAIS. The synergy in HAIS also allows it to adjust to common sense, mine knowledge from raw data, use human like reasoning, and learn to adapt to a changing environment.

3. AI in healthcare

AI lends itself to healthcare delivery very well. In fact, in the recent years there has been an exponential increase in the use of AI in clinical environments [1, 6, 21–24]. With modern Medicine facing a significant challenge of acquiring, analysing and applying structured and unstructured data to treat or manage diseases, AI systems with their data-mining and pattern recognition capabilities come in handy. Medical AI is mainly concerned with the development of AI programs that help with the prediction, diagnosis and treatment or management of diseases. In contrast to non-AI medical software application, which relies on pure statistical analysis and probabilistic approaches, medical AI applications utilise symbolic models of diseases and analyse their relationship to patient signs and symptoms [1, 25–27]. For example, diagnostic AI applications gather and synthesise clinical data and compare information with predefined categories such as diseases to help with diagnosis and treatment. Medical AI applications have not just been used to support diagnosis but also treatment protocol development, drug development and patient monitoring too [1].

3.1. History of use of AI in healthcare

Discussion of the use of AI in medicine coincides with the advent AI in the modern era. This is not surprising as AI systems initially intend to replicate the functioning of the human brain [2]. In 1970, William B Schwartz, a physician interested in the use of computing science in medicine, published an influential paper in the *New England Journal of Medicine* titled '*Medicine and the computer: the promise and problems of change*' [28]. In the paper he argued '*Computing science will probably exert its major effects by augmenting and, in some cases, largely replacing the intellectual functions of the physician*'. By the 1970s there was a realisation that conventional computing techniques were unsuitable for solving complex medical phenomenon [2, 4]. A more sophisticated computational model that simulated human cognitive processes, that is AI models, 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. However, serious

clinical problems are too complex to lend them to simple rules-based problem solving techniques. Problem solving in medicine then progressed to construction of computer programs based on models of diseases. It was not just with the field of general medicine, that AI was being explored to assist with problem solving. In 1976, the Scottish surgeon Gunn used computational analysis to diagnose acute abdominal pain [1]. This was achieved through clinical audits of structured case notes through computers, whereby diagnosis through this route proved to be about 10% more accurate than the conventional route. By the 1980s, AI research communities were well established across the world but especially in learning centres in the US [1, 2, 4, 13]. 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 [1, 25, 29–31]. By the end of the 1990s, research in medical AI had started to use new techniques like machine learning and artificial neural networks to aid clinical decision-making. The next section explores current application of AI in various aspects of healthcare.

3.2. Application of AI techniques in healthcare

The wide acceptance of AI in healthcare relates to the complexities of modern medicine, which involves acquisition and analysis of the copious amount of information and the limitation of clinicians to address these needs with just human intelligence. Medical AI applications with their advanced computing ability are overcoming this limitation and are using several techniques to assist clinicians in medical care.

AI is being used for all the three classical medical tasks: diagnosis, prognosis and therapy but mostly in the area of medical diagnosis [9, 32]. Generally, the medical diagnosis cycle (**Figure 3**) involves observation and examination of the patient, collection of patient data, interpretation of the data using the clinician's knowledge and experience and then formulation of a diagnosis and a therapeutic plan by the physician. If we can compare the medical diagnostic cycle (**Figure 3**) to the concept of an intelligent agent system, the physician is the intelligent agent, the patient data is the input and the diagnosis is the output. There are several methods, through which AI systems can replicate this diagnostic cycle and assist clinicians with medical diagnosis. One such approach is the use of *Expert Systems*. Expert systems are based on rules clearly outlining the steps involved in progressing from inputs to outputs [2]. The progression occurs through the construction of a number of IF-THEN type rules. These rules are constructed with the help of subject experts like clinicians who have interest and experience in the particular domain. The success of the expert system relies on the explicit representation of the knowledge area in the form of rules. The core of the expert system is the inference engine, which transforms the inputs into actionable outputs.

Commonly, the application of the expert system approach in medical software programming is seen in *Clinical Decision Support Systems* (CDSS). Simply put, CDSS are software programs that enable clinicians to make clinician decisions [33, 34]. CDSS provides customised assessment or advice based on analysis of patient data sets. An early version of CDSS was the MYCIN program developed in the 1970s. MYCIN was a CDSS focusing on the management

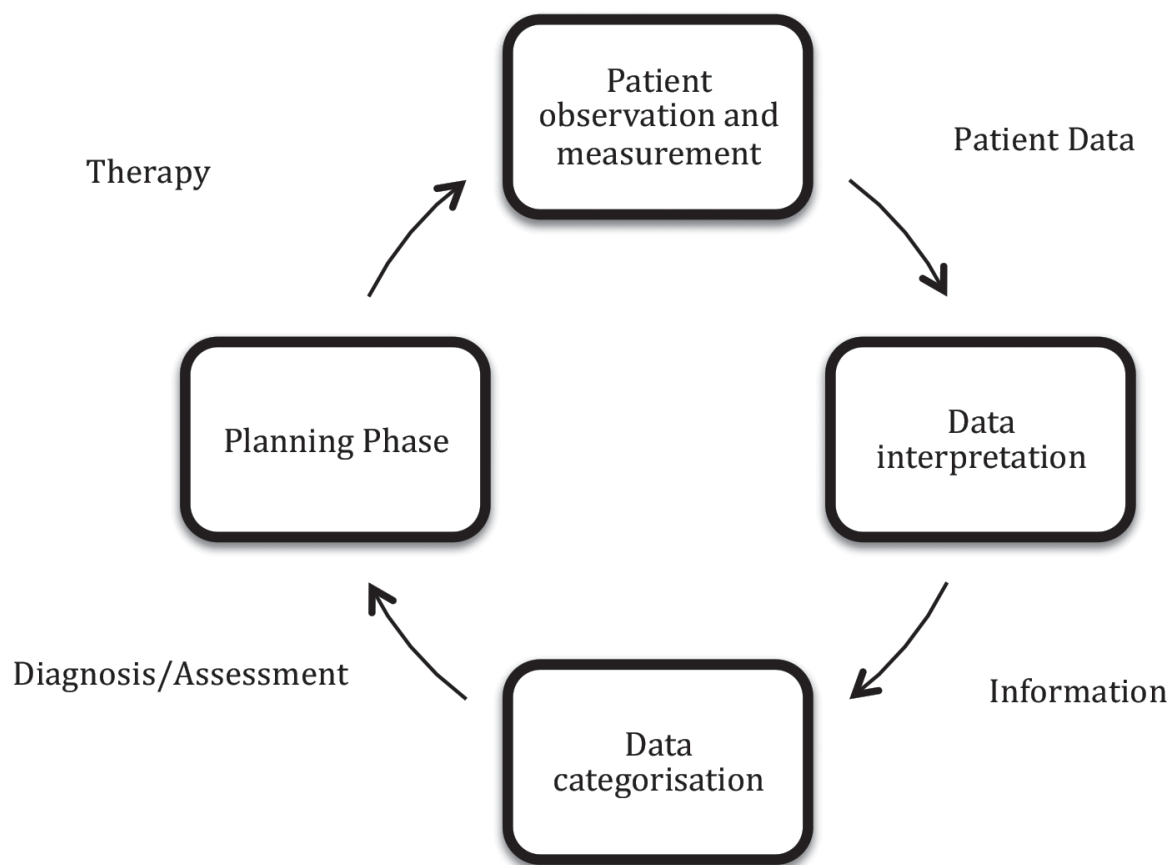


Figure 3. Medical diagnostic-therapeutic cycle.

of infectious disease patients. Infectious disease knowledge was represented in the form of production rules, which are conditional statements as to how observations can be inferred appropriately. However, MYCIN had less emphasis on diagnosis and more on the management of patients with infectious diseases. In a later evaluation of the MYCIN system, it was found it compared favourably with the advice provided by infectious disease experts. MYCIN paved the way for the development of knowledge-based systems and the commercialisation of rule-based approaches in medicine and other fields. Another CDSS that was initially developed around the same time period as MYCIN but continues to be used is the QMR system [35]. The QMR system utilises a customised algorithm modelled on the clinical reasoning of one single University of Pittsburgh internist. Hence the system was initially called INTERNIST-I. By considering historical and physical findings, QMR system generates the differential diagnosis. Utilising a large database that categorises disease findings into 'evoking strengths', 'importance' and 'frequencies' domains, the system generates the differential diagnosis. Heuristic rules drove the system to produce a list of ranked diagnoses founded on disease knowledge domains in-built into the system. Where the system was unable to make a determined diagnosis it probed the user with further questions or provided advice about further tests until a determination of the condition was made. While MYCIN and QMR systems offered diagnostic support, other forms of CDSS can provide alerts and reminders and advice about patient treatment and management. These systems operate by

creating predictive models and multi-dimensional patient view through aggregation of data from multiple sources including knowledge and patient information databases. As treatment and management of diseases have evolved, CDSS architecture is now utilising multi-agent systems [26]. Each of the multiple agents performs distinct tasks and operations in various capacities or different locations but transmit data to a central repository so aggregated data can be used for knowledge discovery.

Unlike experts systems where a serial or sequential data processing approach is utilised, ANN processing utilises a parallel form of data processing analogous to the brain [19]. In ANNs, the processing elements, otherwise called as neurons, process data simultaneously while communicating with each other. The processing elements are arranged in layers and the layers, in turn, are connected to each other. The links between the processing elements are associated with a numerical weight. The memory and adaptation of ANNs are adjusted by changing the weights, which leads to the amplification of the effects of afferent connection to each processing element. As a result of this architecture, ANNs can be trained to learn from experience, analyse non-linear data and manage inexact information. These abilities have led to ANN techniques being one of the most popularly utilised AI techniques in medicine [1]. ANNs in addition to medical diagnosis have been used for radiology and histopathology analysis. In radiology, gamma camera, CT, ultrasound and MRI all create digital images, which can be manipulated by ANNs and used as inputs. The digitised inputs are then transmitted through the hidden and output layers to produce desired outputs (see **Figure 2**). Using the Backpropagation approach, a learning algorithm, ANNs have successfully identified orthopaedic trauma from radiographs [36]. When ANNs and radiologists interpret the same radiological images separately, research has identified good diagnostic agreement [1, 36]. ANNs have also been used for analysis of cytological and histological specimens too [1, 25]. For example, ANNs has been used to screen abnormal cells from slide images for haematology and cervical cytology. Further, ANNs have also been used to interpret ECGs and EEGs through waveform analysis. For this to occur, a multi-layered neural network is trained with waveform data from both people with the disease and without [1]. Evaluation of the waveform interpretations by ANNs has identified excellent pattern approximation and classification abilities and comparable in interpretation to clinicians.

Data Mining acts as the foundation for machine learning. Data mining is the process for identifying previously unknown patterns and trends in large databases and then utilising the same to create predictive models [37, 38]. Data mining involves multiple iterative steps (**Figure 4**) that includes retrieval of data sets from data warehouses or operational databases, cleaning of data to remove discrepancies, analysis of data sets to identify patterns that represent relationships amongst the data, validation of the patterns with new data sets and culminating in knowledge extraction [39]. Use of data mining has become hugely popular in healthcare largely because of the generation of data too voluminous and complex to be processed by conventional computational techniques. The potential application of data mining in healthcare can be huge but practically data mining has been used in evaluating the effectiveness of medical treatments, analyse epidemiological data to identify disease outbreaks and act as an early warning system, analyse hospital records to identify acute medical conditions and help with interventions, quality assessment of medical interventions and predicting survival

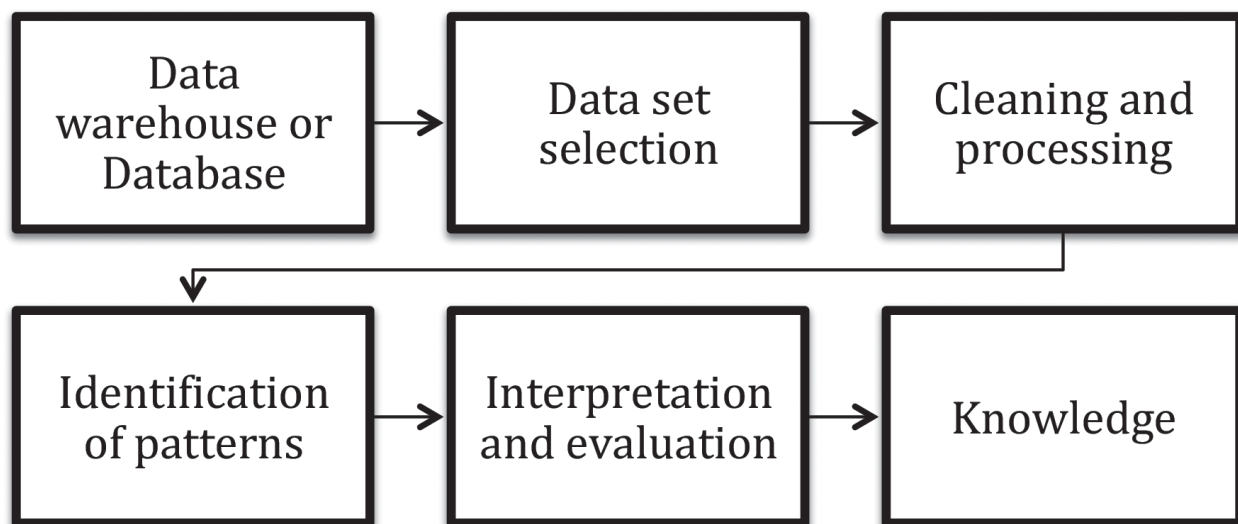


Figure 4. Data mining process. Adapted from Huang et al. [39].

time for chronic disease and cancer patients [8, 38–40]. Data mining medical data faces two main issues: heterogeneity of data sometimes with incomplete recording or filing of data and complexity of the requested outputs [27]. Fuzzy logic, which we discussed in an earlier section, with its proficiency to represent assorted data, strength in adapting to change in the user environment and its distinctive expressiveness can support data mining in addressing these issues. Thus data mining utilising fuzzy logic has been used for a range of situations in healthcare including prediction of the prognosis of cancer and assessing the satisfaction of clinicians for patient information management systems.

There are an estimated 5 billion mobile phone subscriptions in the world [41]. Many mobile phones now have memories and processing power equivalent to the capacity of mini-computers [42]. So it is natural to see mobile communication devices being harnessed to deliver healthcare. The use of wireless communication devices to support delivery of healthcare is called *Mobile Health* or in a popular terminology: *mHealth* [41]. Mobile health applications are being used in many areas of healthcare delivery including education and awareness, point-of-care support and diagnostics, patient monitoring, disease surveillance, emergency medical response and patient information management [41, 43–46]. The rapid development in mHealth has coincided with the increase in AI research and development of AI techniques. Consequently, there has been an increased application of AI techniques in mHealth. The move has worked well as characteristics of an intelligent agent system lend themselves to the objectives of mHealth. The intelligent agent perceives the environment and autonomously acts upon it. In case of multi-agent systems, the agents can communicate between themselves, dynamically manage data and resource and handle the complexity of solutions through decomposition, modelling and reorganisation of relationships. These abilities mean agent-based mobile applications can be used for remote monitoring of patients especially elderly and chronic disease patients, support clinical decision-making and provide remote training for health workers. The application of AI has not been restricted to mobile communication devices but has been extended to other smart devices. When these smart devices are

connected to each other to create a cyber-physical smart pervasive network, it is termed as the *Internet of Things* (IoT) [47, 48]. IoT is being used across for many purposes including prediction of natural disasters, water scarcity monitoring and intelligent transport systems but in health care, the concept is being used to design smart homes to assist senior citizens to accomplish their daily living activities while preserving their privacy and to remotely monitor their health conditions and medicine intake [48]. An IoT powered by AI and set up to address the healthcare need of senior and incapacitated patients is called as *Ambient Assisted Living* (AAL) [49]. As the main aim of AAL is to extend the independent living of elderly individuals in their homes, automation, security, control and communication are key aspects of AAL modular architecture. The system also includes sensors, actuators and cameras to collect different types of data about the individual and home. The constituent system sets up a smart home environment where activities and the health condition of the resident are not only tracked but also predicted [50].

In addition to the examples discussed above, AI techniques have been successfully used in other areas of medicine. Genetic algorithm techniques have been used to predict outcomes in acutely ill and cancer patients, to analyse mammograms and MRI images and fuzzy logic techniques have been used in diagnosing various cancers, characterise ultrasound and CT scan images and predict survival in cancer patients and administer medication and anaesthetics [1, 6].

Of all the AI applications that have been developed over the past many decades, IBM's Watson is one of the well-recognised applications. IBM Watson is a cognitive computing technology that groups together the competencies of reading, reasoning and learning to reply to questions or investigate original connections [40]. IBM Watson aggregates huge volumes of structured and unstructured data from multiple sources into a single repository called Watson corpus. IBM incorporates machine learning and NLP techniques to process and analyse data to undertake problem solving. The technology of IBM Watson has been extended to the medical domain to assist medical scientists and clinicians in improving patient care [31, 51–53]. Some of the published examples of the use of IBM Watson in health care include automated problem list generation from electronic medical records, drug target identification and drug repurposing, interpretation of genetic testing results, oncological decision making support, and to support the roll-out of government healthcare programs.

3.3. Future trends and application of AI in healthcare

As more AI research is undertaken and AI systems become more trained and consequently intelligent, it is foreseeable that these agents replace some of, if not all, the human elements of clinical care [6]. While leaving the communication of serious matters and final decision making to human clinicians, AI systems can take responsibility for routine and less risky diagnostic and treatment processes. The intention here 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 provide intelligence to the robots [2]. 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 [31]. Mobile robotic assistants are already being used to assist the elderly people in their day-to-day activities either in their home or in aged care settings [51]. The robotic assistants mainly undertake tasks that remind them of their routine activities including medication intake or guidance in their environments. With advances in AI and robotics, the employment of robotic assistants in elderly care is only bound to grow.

While the conventional thinking is that robots act as a vessel for a silicon-based artificial brain, there is emergence of a school of thought that imagines the use of biological brains in robots [2]. With advances in science now allowing the culture of biological neurons, the potential use of a biological brain in a robotic frame through which it can sense the world and move around is not inconceivable. This *Cyborg* model presents a true blurring of the boundaries between human and artificial intelligence and the imaginable development of a hybrid human-artificial intelligence health worker that can revolutionise healthcare delivery.

3.4. Challenges

While the application of AI in delivery of healthcare has very promising potential, challenges—both technical and ethical—exist. AI research is largely led and driven by computer scientists without medical training and it has been commented that this has led to a very technologically focused and problem oriented approach in the application of AI in healthcare delivery [24]. Contemporary healthcare delivery models are very dependent on human reasoning, patient-clinician communication and establishing professional relationships with patients to ensure compliance. These aspects are something AI cannot replace easily. Use of robotic assistants in healthcare has raised issues about the mechanisation of care in vulnerable situations where human interaction and intervention is probably more appealing [6]. There is also the reluctance of clinicians in adopting AI technologies that they envisage will eventually replace them. Yet there is no qualm in them using technologies that automate and speed up laboratory diagnostic process [1]. This has led to some suggesting a model of co-habitation [6]. This is a model that accommodates both the AI and human elements in healthcare delivery and anticipates the inevitable automatising of significant components of medical processes while preserving the human aspects of clinical care like communication, procedures and decision-making.

4. Conclusion

Healthcare delivery has over years become complex and challenging. A large part of the complexity in delivering healthcare is because of the voluminous data that is generated in the process of healthcare, which has to be interpreted in an intelligent fashion. AI systems with their problem solving approach can address this need. Their intelligent architecture, which incorporates learning and reasoning and ability to act autonomously without requiring constant human

attention, is alluring. Thus the medical domain has provided a fertile ground for AI researchers to test their techniques and in many instances; AI applications have successfully solved problems with outcomes comparable to that of human clinicians. As healthcare delivery becomes more expensive, stakeholders will increasingly look to solutions that can replace the expensive elements in patient care and AI solutions will be sought after in these situations. However, cold technology cannot totally replace the human elements in patient care and a model that incorporates both technological innovations and human care has to be investigated.

Notice

The chapter was submitted to a double blind review and it is in line with COPE Ethical Guidelines.

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