ARTIFICIAL INTELLIGENCE AND ELECTRONIC HEALTH RECORDS (HER) SYSTEM

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ABSTRACT

A recommendation system that is assisted by type-2 fuzzy ontologies is shown in the article. By tracking the user's vitals and suggesting meals and medications, the system keeps tabs on the user's health. Data extraction for patient risk variables is the initial step of the system. After then, it uses the patient's wearable sensors to figure out their health status. And lastly, it provides diabetic-specific medications for an intelligent medical cabinet and food for an intelligent fridge. In this ontology, the goal is to provide decision-making knowledge based on patient information using Protégé Web Ontology Language (OWL)-2 tools. This recommendation system is based on fuzzy logic and the Semantic Web Rule Language (SWRL). In order to gauge the extent of progress, the proposed ontology's performance was assessed following each round of development. This technology can alleviate the strain on hospitals caused by chronic patients, aid doctors in retrieving physiological data for diagnosis, and provide long-term care for elderly people with chronic conditions without requiring them to see doctors every day.

KEYWORDS: AI; HER; Fuzzy; Patients; SWRL

INTRODUCTION

The development of a CDSS for paediatric abdominal pain in an emergency department is being pursued due to a significant need for process organisation, as stated in [1]. There is consistent, intense strain on emergencies. Abdominal discomfort, particularly in youngsters with appendicitis, piqued the curiosity of the writers. It is difficult to diagnose appendicitis in youngsters. Within the Health Care Systems Research Network (HCSRN), the CDSS was developed to aid in the management of paediatric patients with acute abdominal discomfort. When possible, the system incorporates previous diagnoses, medications, test results, and other medical records. "Risk for appendicitis" is precisely identified and allocated at intervention locations. A summary and specific management suggestions are provided by the system, which may be put into the clinical note. Two major HCSRN health systems are now running the system, and they both have a track record of effectively creating, deploying, and assessing CDSS systems. The knowledge gained from HCSRN locations was invaluable to the research group. Organisations not part of the network might not have been able to accomplish the collaborative problem-solving strategy. Finding the sweet spot between reaching enrolment goals and enrolling the right people is still a big issue [2].

In this instance, fuzzy logic provides the basis for the rules for building CDSSs, and fuzzy sets may be defined using statistical information. Using statistical data that describes the relationship between input factors and output classes is suggested in [3]. The strategy is grounded in the philosophy of possibilities. The objective was to acquire fuzzy partitions that are well-suited for

medical applications and are especially helpful for classification tasks. In order to calibrate their model, the authors of this technical article performed field investigations. When using CDSSs on an individual patient level, it is more appropriate to use potential measures to encode the membership of patient features to distinct classes in order to characterise the results. A single, most trustworthy class is also the most common output of DSSs.

In [4], the authors suggested doing a research on the topic of imaging CDSS selection and deployment. To aid radiologists in making sure they can comprehend and participate in the imaging CDSS implementation process, the tool is offered as a procedure. The writers provided an intelligent analysis of the system's evidence and regulations, and they went into depth on the effectiveness of imaging CDSS. In addition, they demonstrated a variety of factors to think about when choosing a CDSS vendor, offered advice on how to configure CDSS so that it works with the department's objectives, and provided guidance on how to execute and manage changes. After imaging CDSS was put into place, a number of studies showed that the rise of imaging utilisation decreased and the appropriateness of advanced imaging requests improved. A number of recent changes to healthcare policy have prompted calls for new CDSS. Careful deployment of CDSS can significantly effect incorrect imaging use, according to the study. Use of CDSS necessitates meticulous preparation; otherwise, it risks becoming an administrative roadblock to delivering excellent patient care. To ensure long-term, mutually beneficial relationships with referring doctors and to promote the radiologist's worth as a clinical consultant rather than a clinical commodity, radiologists should carefully consider how CDSS is set up.

The main emphasis of [3] was on ensuring the privacy of patients using clinical decision support systems. With the ever-increasing data utilised by clinical decision systems, safeguarding patient privacy has become a critical concern. The authors put forth a novel patient-centered CDSS. With the system's privacy protections in place, doctors can more accurately assess their patients' illness risks. You may train a Bayesian classifier system using the historical data of previous patients that are kept in the cloud. All patient medical data remains secure and private. In order to categorise and calculate the illness risk for new patients, the algorithm employs training data.

The potential benefits of a CDSS in conjunction with Traumatic Brain Injury (TBI) Prediction Rules were of particular interest to the writers of [5]. The capacity of prediction rules and guidelines to safely influence care is their paramount relevance. This study set out to answer the question, "Will there be a decrease in the rate of cranial CT (Computed Tomography) use for children with minor blunt head trauma at very low risk of TBIs without increasing the rate of missed TBIs?" by implementing the two age-based PECARN TBI (Paediatric Emergency Care Applied Research Network) clinical prediction rules through a multifaceted intervention centred around computerised CDSS. The second step of the study aimed to find out if CT use would decrease if CDSS supplied risk data for traumatic brain injury to all children with mild blunt head trauma. There was no increase in the rate of missed injuries after implementing TBI prediction rules and providing risks of TBI through computerised CDSS. The authors found that CT use rates for children with minor blunt head trauma and those at very low risk of TBI decreased modestly but variably. However, there was inconsistency in the reduction of CT rates.

The study aims to inform the design of health information technology by identifying decision complexity and its elements in combination with cognitive methods. This information is reported

in reference [6]. Giving physicians helpful cognitive support was crucial. The writer zeroed emphasis on these specific enquiries:

HOW DOES THE DIFFICULTY OF DECISIONS FACED BY ID SPECIALISTS RELATE TO CERTAIN FACTORS?

HOW CAN ID SPECIALISTS HANDLE COMPLEXITY IN THEIR MINDS?

Researchers consulted with a number of doctors for their findings. The technique involved a systematic assessment of individual interviews and a structured documentation process of coding. The ID specialists involved in the study had an average of 18.5 years of expertise. Two women and eight men made up the ID specialists' ten-person panel. In order to assist ID specialists with the identification of procedure complexity elements, cognitive methods were used. The research proved that there is a way to improve the administration of complicated therapeutic tasks by rethinking the paradigm of evidence-based medicine. Based on their evaluation of the practice guidelines, the reviewers generally believed that experienced clinicians had some room to use their clinical judgement when evaluating patients. When clinical decision support systems contain guidelines, however, doctors quickly accept suggestions based on rules. ID specialists handle decision complexity through several means. This decision-making complexity is influenced by a number of cognitive elements, as mentioned in:

- 1. The patient's condition does not align with the expected trend,
- 2. Miscommunication regarding the circumstances, and
- 3. Societal and psychological demands.

For a number of reasons, the writers of [7] were able to explain the many aspects and possibilities of sentiment analysis within the framework of healthcare and medicine. A wide range of medical professionals, including therapists, nurses, and specialists in several fields, work together to provide patients with therapy. Because of their function in medical records, it is crucial to determine a physician's personal views and beliefs. Other medical staff will be able to use them to get a full picture of a patient's health. Contrary to the outcomes of tests, reports and papers convey observations or experiences in an unstructured manner. On the flip side, there is usually a certain format for reporting exam results. That is why you need to be very careful when drawing conclusions from tests or observations. Clinical data assessment and patient health status monitoring are two areas where they shine. Practitioners find automated decision support easier. Despite the often-objective tone of professional documentation, patients' medical issues nonetheless have a significant influence on their daily lives.

Importantly, sentiment analysis aids in determining the impact of such written content. In methods dealing with sentiment analysis, sentiment lexicons are common [8–10].

Recognising emotion phrases and patterns of expressions in natural language texts is greatly aided by the work of the authors of [11]. Both rule-based and machine-learning-based methods exist for extracting sentiment from medical online data. Writing on technical subjects, the writers anticipated that their work would resemble clinical tales. Clinical narratives and medical social media are going to be the focus of their investigation because of the language and sentiment expressions used there. In order to carry out the experiment, they consulted a variety of data

sources that had thousands of entries. They studied and contrasted the word usage of the following six text kinds within a quantitative framework:

1. A NURSE'S LETTER; 2. POST-DISCHARGE REPORTS; 3. MEDICINE EVALUATIONS; 4. MEDICAL BLOGS; AND 5. INTERVIEWS ON SLASHDOT.

There are several potential applications for this study. Clinical decision-making might benefit by collecting and considering uncertainty, attitudes, and implicit emotion. Building a sentiment vocabulary that is particular to a certain topic and creating techniques to evaluate sentiment based on context are two potential solutions to the problem of sentiment analysis.

Oncology has been one area where the [12] a CDSS with components for machine learning and natural language processing—has shown encouraging results. As far as cancer therapy goes, 99% of Watson's suggestions are on par with what doctors would do. In addition, Quest Diagnostics and Watson worked together to provide the AI Genetic Diagnostic Analysis. Knowledge interchange, clinical care environment CDSS installation, and approaches for standardising data and knowledge representation all require more effort.

Finally, one example is Deep Surv, a recommender system that anticipates the impact of treatment choices on a patient's risk using a neural network and makes personalised treatment recommendations based on the patients' variables [13]. In general, CDSS technology is still a prime example of an AIA's usefulness in healthcare. Their level of development is the most advanced, however there is room for improvement.

INTERNET-ENABLED HOUSES

In order to function, a smart home relies on a network of interconnected devices, usually connected to either the internet or a local area network (LAN). The Internet of Things (IoT) allows for the remote monitoring and access of various devices, such as sensors, RFID (Radio Frequency Identification), and other appliances that are linked to the network. As a new paradigm, it seeks to improve household ease, security, comfort, and leisure by responding to consumers' perceived demands. For both the elderly and medical technology, they are crucial. Many academics are captivated by the allure of smart houses. An essential part of people's everyday lives, human activity recognition in smart homes has been the subject of several studies. Activity recognition [14], gesture recognition [15], home behaviour analysis [16], and emotion recognition [17] are all examples of successful uses of human activity recognition. Another area that has been studied in relation to smart homes is living support. People with cognitive impairments, such dementia, benefit greatly from these systems' support features [18]. A new protocol called Ergo was introduced to handle smart houses for assisted living by the authors of [19]. An historic house constructed in 1938 that was transformed into a smart home using sensing technology has already made use of the established protocol. It monitors a resident's various appliances and their motions to forecast their wellbeing.

While the writers of [20] were thinking about ways to help MS patients in their smart homes, the authors of [21] investigated how different types of expressive speech affected the accuracy of automated speech recognition and then used their findings to help the elderly.

A system that integrates fog and cloud computing with Internet of Things (IoT) and big data

analytics is suggested by the authors of [22] for smart houses. Problems arise when trying to design quick systems that can process massive amounts of unstructured data collected from smart homes.

COMPUTING IN FOGS ENTAILS

Cloud computing is crucial because it enables computationally expensive applications to access vast amounts of data stored in the cloud, which in turn delivers analytics in near real-time.

In order to enable activity models to automatically change and adapt according to users' specifics, a technique was suggested in [23] that combines knowledge-driven reasoning with data-driven reasoning. In this instance, the authors were able to infer an initial activity model by knowledge-driven reasoning. Stage two involves training the model using data to create an activity model that can adapt to different user actions. The study's findings demonstrated that compared to the baseline activity model, the learnt activity model produces noticeably better recognition rates.

A home ambient intelligence system called RUDO [24] was developed to assist blind individuals residing with sighted individuals. The system's unified user interface makes it easier for visually impaired persons to do tasks such as using a computer, typing in Braille on a standard keyboard, etc. RUDO makes these folks more self-reliant and sets the stage for them to dive headfirst into it. We have seen that smart home technology is the subject of several patents. A device telemetry circuit was created by the authors of [25] to identify electrical irregularities in many smart home devices. The development of systems and techniques for informing users of the status of smart home security detection systems is detailed in [26]. Upon receiving identifying information from an electronic device, a controller device verifies if it is from an authorised user's device and sends an operational status message to the device. This process occurs after the sensor has detected and received the identifying information.

A key aspect of smart homes is their focus on large data [27]. That is why data mining and machine learning are so intriguing when applied to smart home prediction, detection, and assistance. Fitting in with users' present and future lives, (2) the simplicity of administering smart home technology, (3) interoperability across systems, and (4) cost are five obstacles that smart houses, which are gaining popularity among both the scientific community and end consumers, are trying to overcome [28]. (5) confidentiality and safety; (4) dependability its exorbitant price tag, lacklustre usability, rigidity, and overall user engagement all work against its widespread adoption. Research into new smart home solutions has advanced, but their uptake has not kept pace with customer demand, therefore researchers are looking for other approaches.

DATA MINING FOR HEALTHCARE

"Big data" describes extremely big and diverse data collections that are expanding at a dizzying rate. Volatility, variety, validity, value, validity, variability, virality, and visualisation are the 10 V's that define it [29]. Big data in medicine is unique from data in other fields and from more conventional clinical epidemiology. Research, public health, safety monitoring, diseases, and clinical decision support are some of the areas that use big data technologies for predictive modelling. Medical big data may be found in many places: electronic health records, clinical registries, biometric data, administrative claim records, patient reported data, medical imaging, biomarker data, prospective cohort studies, and so on. Dimensions of data change and grow more

complicated when they confront big size, diverse sources, different scales, incongruities, incompleteness, and complexity.

Much of the published research on big data in medicine is on its potential benefits, risks, opportunities, and obstacles. The use of big data has proven useful in every area of public health. "Definitive extents and databases on the occurrence of many diseases" [30] and "monitoring population health in real-time" are also within this capability's purview. Some of the health fields that make use of big data include public health, environmental health, epidemiology, infectious diseases, sleep science, maternal and child health, safety and occupational health, healthy food and nutrition, smart homes, and safety and occupational health. Optimism and proof of big data's usefulness in public health study and action abound.

The potential of big data in infectious disease surveillance on a worldwide scale was investigated by the writers of [31]. With hybrid systems improving traditional surveillance methods, and greater chances for accurate infectious disease models and forecasts, they believe that big data will greatly increase the granularity and timeliness of accessible epidemiological information.

Although there is no direct relationship between the two, data mining finds extensive use in the big data setting. It is well-known that data mining algorithms perform better with massive amounts of data. Machine learning and computational interpretation of huge data are introduced to the modern plastic surgeon, for instance, by the authors in [32]. The medical field has great promise for the application of big data analytics. As a result, it is essential to highlight a few obstacles for healthcare big data applications [33]: (1) there is a lack of proof of the practical advantages of big data analytics; (2) there are numerous methodological issues, including data quality, data instability and inconsistency, observational study limitations, validation, analytical issues, and legal issues. The use of big data analytics in clinical practice is essential. According to the authors of [130], cardiology is one area where big data research in health informatics has not yet become popular, although it might be very useful for both research and clinical cardiology. The beneficial effect of big data on the quality of decision making has been shown in several research, for example [131–135]. Concerning the use of big data, particularly in data gathering methods, the authors of [137] brought up important concerns regarding patient privacy.

EXPLORATION AND ORGANISATION

While there are a plethora of healthcare technology and potential applications, we focused on five critical AIA applications because of their breadth of use. We found that AI in healthcare is primarily concerned with using data mining techniques to diagnose and treat a variety of issues. Because of this, AI can now provide suggestions and forecasts. To be more specific, a data mining algorithm is trained to anticipate a new example's decision variable. Additionally, it is capable of associating collections of frequently used items and producing prediction-ready association rules with a predetermined level of confidence.

The healthcare industry is full of optimism about artificial intelligence, yet there is still reluctance to really apply technology in patients' everyday lives and in hospital settings. The development of AI systems for healthcare does come with its fair share of ethical concerns. There are legitimate worries regarding safeguards for personal information, secrecy, and even intimacy. The issue of patients' free and informed consent also presents difficulties. While there are many benefits to

utilising big data in healthcare and AI, such as improved decision-making through analysis of massive amounts of data, there are also some concerns around privacy and security, especially with regard to sensitive information. These pose risks to the widespread use of data mining and big data in smart homes. Also, even if we know that data mining techniques and ontologies are utilised, it is not always easy to explain why AI systems generate recommendations and conclusions. The AI black box, or lack of transparency, becomes an issue in light of this. AI applications have the potential to enhance healthcare quality in hospitals and also offer efficient support to patients facing daily challenges, even when they are not in the hospital. One use of AI in healthcare is the mitigation of adverse occurrences and medical mistakes. However, the security of AI in healthcare is jeopardised by a phenomenon known as automation complacency. In the event of recurrent usage, doctors, particularly those with full schedules, may follow the advice of AI systems and even give them complete decision-making authority. We should not place too much emphasis on these systems. When an AI system consistently confirms doctors' findings, they may subconsciously start excluding other options. Negative outcomes are possible, but we must weigh them against the possibility of positive ones [34-50].

Another big problem with AI in healthcare is that it can't always produce outcomes that people can understand. As an example, a typical source of incorrect diagnoses, particularly in the case of pneumonia, is the interpretation of imaging studies. So, AI has been used to interpret automated chest radiographs using deep learning and machine learning algorithms, although there are a lot of drawbacks [38]. Our assessment is far from comprehensive, but their findings may point to many more areas that need investigation, particularly in gathering sufficient empirical data to warrant widespread field implementation. Serving patients in such a complicated setting necessitates AIA, which introduces a level of unpredictability that is either ignored or difficult to replicate in clinical informatics research [51-63].

A new design for future studies that would use sophisticated systems to direct primary healthcare delivery. Especially for complicated instances (e.g., chronic care) with comorbidities needing coordination, our approach can assist in integrating numerous AIA technologies around patient demands in various healthcare contexts, as shown in Figure 1. This allows for a more accurate portrayal of patient concerns in AIA design by directly linking AIA technology, features, and applications to health outcomes. The healthcare system is just one part of a patient's lifespan that allows for continuous monitoring and diagnosis of health conditions. This is how the data is created, collected by AIA, and then used in smart system applications [64-69].

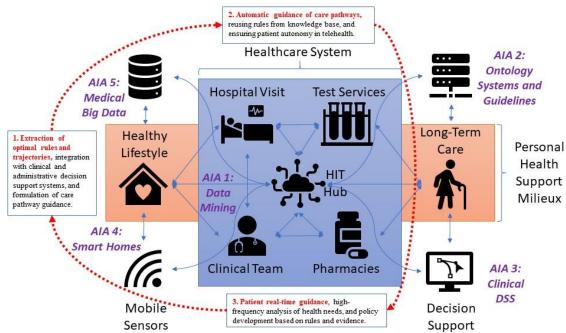


Figure 1. Patient-centric framework for healthcare artificial intelligence and analytics (AIA). Source: Inspired by [39], based on [40].

Based on the Expanded Chronic Care Model (ECCM) from [13], which is based on [10], we establish a connection between this health informatics framework and medical evidence. Our major focus is on using the increasing quantity of patient-centric Big Data that is available to care providers within a contemporary, integrated primary healthcare net]work [70-85. We achieve this through innovative collaborative IT solutions. The patient's service journey can be automatically guided by intelligent systems. The five AIA technologies that were assessed are integrated into this three-step cycle, as shown in Figure 1:

- 1. Developing care pathway guidelines, integrating with administrative and clinical decision support systems, and extracting optimal rules and trajectories (AIA 1-4-5).
- 2. Ensuring patient autonomy in telehealth, automatically guiding treatment routes, and reusing rules from the knowledge base (AIA 1-2-3).
- 3. AIA 2-3-4 outlines the following: real-time patient guidance, high-frequency analysis of health needs, and evidence- and rule-based policy making.

Care pathway rules are validated and reused through the use of prequalified, evidence-based knowledge repertoires in our model, which is patient-centric and uses modern IT. To further increase continuity of front-line interprofessional care through knowledge exchange, we are also looking to include AI solutions that can connect to current administrative and clinical information systems, enhance rules and procedures within care trajectories, and so on.

Using this structure, an empirical study program will look for proof of this intelligent architecture's potential. In this study, we want to show how rules-based information sharing platforms have improved primary care collaboration between different specialities. We will

evaluate the efficacy, safety, and quality of treatment for long-term patients in collaboration with a major hospital network [86-90].

CONCLUSION

To aid with their integration into the intricate treatment pathways of patients undergoing chronic care, we surveyed the most important areas of AIA applied to healthcare research now underway and put forward a framework for doing so. Our goal was to highlight the most important developments in artificial intelligence (AI) in healthcare during the last five years, covering a wide range of medical specialities and procedures, and to talk about the problems and obstacles that are still plaguing this groundbreaking technology. Data mining, ontologies, semantic reasoning, clinical decision support systems, smart homes, and medical big data are just a few more healthcare technologies and application opportunities. The five technologies reviewed were chosen for their higher extent of application. While AI has the potential to revolutionise healthcare, there are still several technological hurdles to overcome before it can be put into practice in the real world. A key factor in the success or failure of these scientific endeavours is the absence of cooperation with the medical personnel. To fully incorporate AIA to the reality of healthcare services, more studies and analyses are required because to the social, economic, and legal obstacles. A lot of research has gone into AI for healthcare, but not enough has been done to evaluate it with actual clinical data and by actual professionals. This is because, among other things, these clinical data are not easily accessible. Furthermore, data mining algorithms' predictions are significantly affected by both the scarcity of training data and the rapid updates to that data. One more thing: if you train an algorithm on data that contains unreported incorrect situations, incorrect treatments, or misdiagnoses, the system will not be able to make accurate predictions. The scope of this conceptual study is too small to do justice to all of these issues. In order to guarantee dataset comparability and investigate relative bias and other factors impacting AIA efficacy, we want to do a comprehensive meta-analysis on a specific selection of papers in future work.

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