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Chapter 2: Enhancing clinical decision-making using artificial intelligence applications

2.1. Introduction to Clinical Decision-Making

Making appropriate clinical decisions is one of the most important responsibilities of healthcare professionals. In fact, the quality of clinical decisions determine the success of the diagnostic journey as well as treatment and management of medical conditions, and thus ultimately affect the outcomes of patients. Throughout the long history of clinical practice, healthcare professionals have carried out clinical decisions with the integration of the knowledge which they gained during their courses of medical education and training, and the experience they acquired through years of working practice as well as scientific evidence. Initial attempts to make clinical decisions more objective and less dependent on the varying levels of skills and experience of medical practitioners focused on the establishment of diagnostic and management guidelines, and standardized treatment protocols. Medical Holistic Methodology, which advocates the joint consideration of clinical findings and patients' responses, enabling the identification of management strategies with the best risk/benefit ratio based on overall assessments, was proposed as a more objective and systematic method for decision-making of treatment and management of patients suffering from complex and progressive chronic diseases (Miotto et al., 2017; Mollah et al., 2017; Grust et al., 2020).

Consequently, Clinical Decision Support Systems have been developed employing artificial intelligence and other technologies, providing evidence-based assistance to practitioners to enhance objectivity, accuracy, and efficiency of their decision-making. Evolving from early rule-based systems into contemporary hybrid and machine learning-based systems, Clinical Decision Support Systems have been shown to enhance decision making for disease diagnoses, treatment, and management not only in medicine but also in other areas including psychology, pharmacy, and radiology. As the service delivery in healthcare is increasingly transitioning from resource-driven to value-based, with an emphasis on high-quality, accurate, timely, and cost-effective services; and with the advent of technology-enabled health services and telemedicine, it is envisaged that the development of Clinical Decision Support Systems will further evolve in the near future.One’s level of medical knowledge and experience, together with the complexity of the presented clinical vignette, lead to a variable degree of automaticity in executing and completing this decision-making process. Thus, there exists a great degree of variability in clinical decision-making. Research into how different clinicians approach diagnostic and therapeutic decision-making has highlighted that important differences in managing risk exist across specialists, with some specialists focusing on immediate health outcomes while others address the need for longer-term outcomes or patient satisfaction (Rolim et al., 2010; Obermeyer & Emanuel, 2016).

Fig 2.1: Clinical Decision-Making Using Artificial Intelligence

2.1.1. Background and Significance

Decision-making is one of the most crucial elements of a physician’s work. In today’s fast-paced and highly technological world of medicine, the quality of medical decisions has become increasingly important, in order to ensure that patients receive the most efficient and effective treatment. Accordingly, any resources that can assist in improving medical decision-making must be utilized. Although conflict-of-interest-related errors in judgment have always occurred, the prevalence of such errors has significantly increased over the past decade. Developing an understanding of the factors that lead to poor medical decision-making is paramount in order to minimize such errors, since inadequate choices on the part of a physician can significantly hinder the quality of care that he or she provides to a patient.

A multifactorial phenomenon, medical decision-making consists of procedure and processing components. The procedural component is characterized by a series of rules regarding how to arrive at a decision, while the processing component reflects how these rules should be executed during a given patient encounter.

2.2. Overview of Artificial Intelligence in Healthcare

Artificial intelligence (AI) applications have become part of our ubiquitous lives, impacting a broad range of areas, including various fields of science and technology, economics, business, banking, social science, aviation, and healthcare. Rapid developments in AI technologies have resulted in the acceleration of data-driven AI developments and enhanced AI applications. Health data are complex and multifactorial. Healthcare AI technologies, models, algorithms, and applications need to be highly advanced and sophisticated. Research and investments in the integration of AI–healthcare have exploded in recent years, with companies and industries willing to invest billions in university and institutional research in various fields of medicine and health. In healthcare, AI applications have demonstrated great advancements in terms of disease prevention and health promotion, risk prediction, screening, diagnosis, clinical decision-making, treatment options, prognosis and outcomes, and healthcare systems. AI-driven computerized decision support systems will help healthcare professionals transition from and improve the traditional methods of decision-making and establish treatment guidelines for better patient care.

AI in healthcare has the potential to facilitate or substitute humans' ability to make decisions. However, there is also criticism regarding the adverse effect of AI on human decision-making and a growing concern about AI's accountability. Reticence toward the operationalization of AI technologies is also observed in the field of healthcare. Many of the concerns can be resolved when expert humans with the capacity to understand and interpret AI-generated decision-making work together with AI application technologies. The aim of this paper is to provide an overview of the use of AI applications in healthcare to enhance clinical decision-making. In particular, the paper places a focus on AI applications of concern to clinical medicine, with a discussion of the function, purpose, and demand for integrating AI–healthcare–decision-making.Building on previous research protocol principles, the publication types targeted in this map update include published descriptive and randomized controlled trials, but exclude opinion papers, editorials, case studies, letters to the editor, grey literature, and articles not written in English. The country of the first author was the only inclusion criteria, while exclusion criteria related to the type of AI application assessed. The systematic map process flowchart is shown. Ethical Approval is not needed for this literature review since humans are not affected by any of its stages or findings. This systematic map will be regularly updated as more studies emerge, sharing it and its update procedures on institutional repositories. The requests for the database dataset will be addressed upon request.

2.2.1. Research design

This section is part of a larger project to update a systematic map of the impact of AI applications on healthcare outcomes. Updates to an existing systematic map have to follow a methodologically robust approach. The map update strategy followed in this case was guided by five steps and is briefly summarized next. Keywords identified from the original map were used to formulate a new literature search in the original database. The results were extracted with a reference management tool. All the results were screened by the research team to select relevant articles. Relevant articles were subjected to a thorough data extraction using a standardized data extraction tool used in Step 5 to keep the findings consistent with the previous map, performed by two independent reviewers. Data items abstracted included the authors, date/year, journals, country, study purpose, setting (general or type of hospital), AI application (general or type), study design, sample size, outcome measures, type of patients, controls, and effect. Based on the findings of this updated map, commentary and recommendations will be provided about the existing evidence supporting the use of AI applications in the targeted map areas, including how the evidence compares with previous findings, as well as the current knowledge gap and future research directions.

2.3. Types of AI Applications in Clinical Settings

Advancements in machine learning and natural language processing (NLP) technologies have created several artificial intelligence (AI) applications in clinical and operational workflows. AI applications can be broadly categorized into three groups: machine learning algorithms that provide clinicians with a second opinion, NLP applications that allow unstructured free text to be searched for relevant clinical information, and predictive analytic tools that provide projections of patient risk for specific clinical conditions and logistical predictions of hospital needs and surges. A reviewer pointed out that the most useful AI tools would be those that are well integrated into the clinical workflow without placing an undue burden or resistance from clinician teams.

The combination of advanced machine learning algorithms with a rapid increase in computational power, massive increase in the quantity and variety of health data across diverse clinical specialties and application areas, availability of curated health data sets, and a growth in quality peer-reviewed publications have led to successful and advanced AI-based healthcare tools. Clinical AI tools can provide clinicians with a validated, precise, and timely second opinion that augments the capabilities and expertise of clinical teams, leading to better decisions, improved efficiency, minimized workload, and reduced clinical burnout. There are numerous examples of machine learning-based tools that have been developed for image-based evaluations in radiology, ophthalmology, dermatology, pathology, and cardiology that have improved.

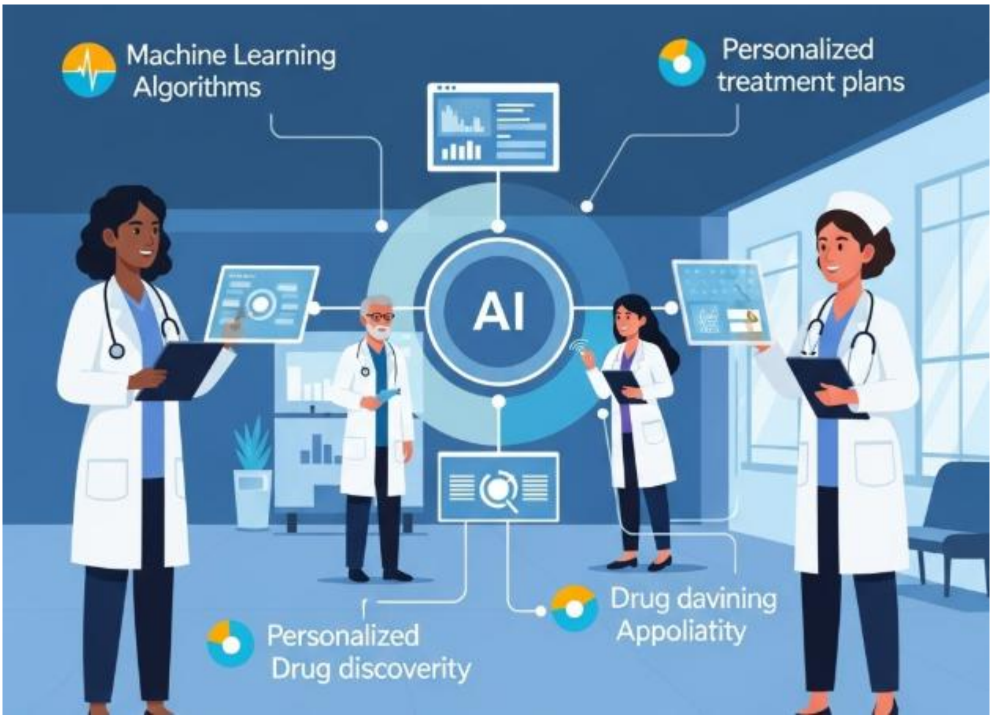

Fig 2.2: Enhancing Clinical Decision-Making

The application of NLP tools can distill meaningful information embedded in large amounts of clinical data locked in unstructured text to help inform clinical decision-making. With the electronic health record (EHR) systems transitioning patient data into a digital body, NLP allows clinicians to quickly retrieve clinical data and other patient-specific information needed for clinical decision-making rather than having to sift through long clinical notes.

2.3.1. Machine Learning Algorithms

Machine Learning (ML) is a computer science discipline that makes it possible to extract useful information from large data collections. With the widespread adoption of electronic health records and other large health data sources, healthcare organizations are increasingly using ML techniques to inform clinical decision-making, often with the expectation that the solutions offered will produce better and cheaper patient care. In this chapter, we describe ML methods in more detail, focusing on applications that do not make complex, real-time decisions for clinicians, but simply use large amounts of clinical data to obtain predictive information. Thus, the focus of this chapter is narrow, as ML methods are potentially useful for a wide variety of healthcare-related tasks and decisions.

The increasing use of ML for health data raises important questions. First, should ML methods be used instead of classical statistics? In principle, the answer should be "no," both the ability to search large sets of predictors and the ability of sophisticated algorithms to summarize complex combinations of predictors make ML methods more attractive. However, classical statistical modeling, with its focus on testing specific scientific hypotheses, model evaluation, offers a simpler logic. Does the power and flexibility offered by ML warrant the greater complexity and risk of model mis-specification inherent in such methods? How should we validate and evaluate ML-derived prediction models on new, unseen data? In this chapter, we provide guidance on these and other questions to those who seek to use ML methods to generate new predictive information from clinical data.

2.3.2. Natural Language Processing

Automation of clinical decision support systems using human language is difficult when compared to numerical or structured data. Clinical language is more variable, ambiguous and efficient than other domains, reflecting the particularities of every field. Clinical NLP leverages the regularities of clinical language and domain knowledge to solve tasks, such as word sense disambiguation, term normalization, named entity recognition or relation extraction. Improvements in speed, accuracy and availability of machine learning techniques, and the advent of deep learning methods have allowed progress in NLP for clinical language. However, the need for labeled training data is still a serious restriction. This chapter on clinical NLP shows tasks study and product research, focusing on clinical applications and resources. Although it is possible to develop NLP tools without domain-specific training data and to use standard techniques on clinical language without special adjustments, we propose to always include domain- and task-specific knowledge. Tools and techniques have been built for clinical coding, admission note generation, clinical note de-identification, mortality prediction, genomics interpretation, clinical concept normalization, clinical synthetic data generation, anaphora resolution, deep clinical NLP with Transformers, disease detection, clinical concept extraction, clinical timeline generation, clinical information extraction, clinical language annotation, triage of emergency department visit notes, and health care cost book of business analysis, among others. The steps of developing a system are similar to NLP in other domains, but we advise considering the general principles of NLP in the clinical domain, specifically domain data, the high interest in privacy, ethical needs, and resource constraints.

2.3.3. Predictive Analytics

Predictive algorithms analyze specific features to categorize an individual or event. It is very common that the results of a predictive algorithm will be published back to the clinical UIs via alerts. Predictive analytics can be done via probabilistic models that use Bayes' rule, in a simpler version called Naïve Bayes, or graphical models that show conditional probabilities. Both models can be unsupervised or fully supervised. An example of a Naïve Bayes approach was a classifier trained on facial images linked to the labels of a major personality trait that had a very good accuracy at the personality classification task. AI systems have also been used to augment users in prediction. Sometimes it works better than just outputting a binary outcome. An interesting application of embeddings is in the generation of prior probabilities based on a large amount of data, but implemented in a way that relates the output to the individual about to be queried.

Neural networks have been used to improve predictive analytics in medicine for decades now. In cardiology, it has been possible to achieve predictions of Sudden Cardiac Death and Coronary Visitation. In the last few years, deep neural networks that allow automatic feature learning of abstract representations from raw data have been trained with great success for predictive analytics at an increasing variety of medical applications, among which: medical image classification and detection tasks, predicting clinical outcomes, and diagnosis or detection via EEG signals. Recently, an innovative application of computer vision has shown that large pre-trained models, trained on large scale datasets of images, can be effectively used for tasks requiring transfer learning within the specialty of pathology.

2.4. Benefits of AI in Clinical Decision-Making

In clinical diagnostics, accuracy is most significant, as delays or errors can severely compromise patients' health status. Despite inevitable efforts to consider all relevant factors and use established reference procedures, diagnostic errors design clinical practice. In the US alone, about 400,000 patients die each year due to diagnostic errors; these numbers make diagnostic errors the most common expression of medical malpractice. What is particularly disturbing is that diagnostic errors at the beginning of a patient's clinical development can lead to a cascade of errors during all phases of the patient's clinical journey, leading to suboptimal treatment. Artificial intelligence can help enhance clinical decision-making and consequently cut down on diagnostic errors, improving clinical outcomes for individual patients and decreasing costs incurred by healthcare systems. It is created to emulate or support human decision-making capabilities and empower the healthcare workforce throughout the patient's clinical journey.

It is commonly accepted that the performance of AI applications in structured domains, such as medical imaging, radiological diagnostics, dermatology, and pathology surpasses human-level accuracy. Moreover, research has demonstrated that AI-enabled clinicians are better than both human and AI-only teams, resulting in lesser errors and better patient outcomes. However, the creation of clinical AI applications is extremely costly and time-consuming. AI still poses some limitations and relevant hurdles in clinical settings, such as the number of false-positive errors made, the performance on unseen distributions, median performance or error rates that can be worse than those of humans, a focus on aspect-specific performance, incomplete automation, lack of up-to-dateness, bias, additional burden on the healthcare workforce, problems with clinical ethics, consent, and liability, and difficulties integrating AI-enabled decision support into clinical workflows.

2.4.1. Improved Diagnostic Accuracy

The healthcare community has long turned to advanced technology to help physicians improve patient diagnosis and treatment. Ever since the dawn of medicine, from Galen to William Harvey, the study of physiology and pathology gained a theoretical foundation. The later discoveries of X-rays, electrocardiograms, and magnetic resonance imaging have expanded the diagnostic toolbox for medical practitioners. The advent of AI in conjunction with deep learning has brought new excitement, fueled partly by machine goal progress in pattern recognition with trained algorithms that match or exceed human abilities in tasks such as detecting congenital anomalies in chest X-rays, predicting diabetic retinopathy from retinal fundus images, and interpreting digital pathology slides. In principle, AI should amplify the diagnostic and treatment abilities of medical practitioners. In practice, however, AI is an inert force and requires the initiative and engagement of clinicians to discover and exploit the potential uses within clinical decision-making.

Diagnostic accuracy is traditionally assessed by the area under the curve of the receiver operating characteristic for the study of patients with and without disease. Recent reports from AI's early breakout success in clinical diagnostic medicine cite results that not only match but exceed those of expert human clinicians for diagnostic accuracy. The high-performance diagnostic abilities of AI for specific diseases with proven technical efficacy are specific to a narrow area and often employ state-of-the-art methods that might differ among disease-specific applications. For example, deep-learning convolutional neural networks translate the examination of fundus photographs into ratings in the diagnosis of diabetic retinopathy either comparable or superior to those of expert human graders. The model combined images of both eyes as well as provided uncertainties about predictions and used pre-training to win the subsequent challenge.

2.4.2. Enhanced Patient Outcomes

AI can help clinical decision-making improve communication and patient engagement. The most effective role for machine learning in decision support is not by replacing human judgment, but by augmenting it. Algorithms that automatically track clinical trends and alert staff when problems arise have a positive impact on clinical outcomes. Moreover, AI, particularly deep learning, may improve biomarker identification and increase the efficiency of early clinical trials, thus accelerating the development of next-generation therapies. Overall, there is an expanding role for AI to support clinical decision-making processes across various oncology services.

AI can enable more accurate stratification of patients according to their risk profiles, perhaps identifying patients at higher risk for complications and readmissions, and thus targeting them for more intensive supervision and management. Predictive algorithms could assist with earlier identification of disease exacerbations. AI can help personalize treatment selection and thus lead to improved patient outcomes. Several applications presently use AI to analyze large data sets and propose possible treatment options or investigate the optimal treatment for an individual patient. These applications evaluate large patient data repositories of prior treatment efficacy and are currently in use for cancer therapy management, cardiac surgery planning, and skin and soft tissue infection guidance. Finally, using data analytics to optimize logistic processes could streamline medical activities, increasing productivity and enhancing the quality of the care delivered. AI systems can supply clinical practitioners with recommendations at the bedside while considering the overall clinical workflow, thus improving overall guideline adherence and patient outcomes. Improving clinical practice can lead to optimized patient outcomes through the equilibrium of algorithms and critical thinking in clinical decision-making.

2.5. Challenges and Limitations of AI in Healthcare

Over the past years, artificial intelligence (AI) has become a widely used research tool in many healthcare applications. Specifically, there have been thousands of published manuscripts covering AI applications for computer-assisted diagnostic imaging, decision support systems, and natural language processing for health records. However, despite its success in some situations, AI use in healthcare is still limited in practice, and only a few AI algorithms are actively being used in clinical decision-making on a regular basis. Thus, we can recommend several possible challenges and limitations for applying AI in healthcare.

Many health and clinical data contain sensitive personal information that should be protected from improper usage and disclosure, especially with recent advances in various data search techniques, data matching, data linkage, record linkage, and re-identification based on publicly available datasets. Moreover, most AI algorithms require a vast amount of healthcare data to learn and extract useful information. As a result, with increased data size, the exposure of the sensitive information poses an increasing risk of causing adverse effects. In addition, the data employed to develop and evaluate the AI model should contain sufficient representativeness. If the disease-related information is ill-represented or not available, the safety of using the AI models can be compromised. Moreover, if the datasets used to train and validate the AI models are not representative of the population, it may lead to disparate performance of the algorithms among different populations.

In addition, the nature of a learning algorithm can also cause inherent biases. For instance, deep learning methods may not be able to properly generalize their prediction performance if the test data differ from the training data. Furthermore, the results may depend on data feature noise, the initialization of the AI model, and the tuning of different hyperparameters and learning parameters, where hyperparameters are configuration settings that can be adjusted to optimize model performance, and learning parameters are optimization settings that govern how a machine learning model learns during training, and can also be adjusted to optimize model performance.

2.5.1. Data Privacy Concerns

With health-related data being stored in digital formats at an increasing pace, data privacy has gained particular attention. The term 'data privacy' is often used in place of 'data protection' but is, actually, more specific. Data privacy refers to the question of who gets to access sensitive data, with data protection aiming to create and enforce strict measures that can protect sensitive data. Generally speaking, personal data breach notifications are required by law. Organizations generally must notify affected individuals as soon as possible after becoming aware of a breach involving an individual's personal data, and no later than 72 hours after the breach occurred, if feasible. Failure to comply carries severe penalties.

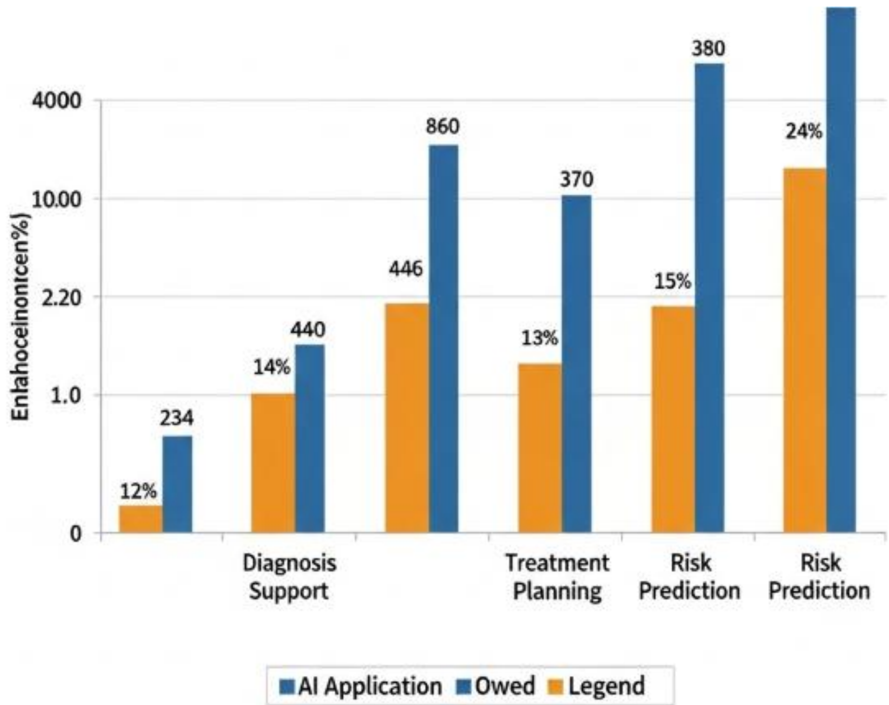

Fig : Decision-Making Using Artificial Intelligence Applications

Some of the health-related data trends that are causing growing concern in regard to data privacy include: the increased sharing of health-related data via health apps and online services and websites; the increased push toward electronic records and concerns about their privacy and security; the use of health-related data in legal cases; the use of health-related data by life insurers; and the growing presence of cybercriminals and security threats to health-related data. Cybercriminal attacks are increasing in frequency and growing in sophistication, driving up the cost of data breach recovery. Health organizations must invest in top-notch tools, techniques, systems, and policies to ensure data confidentiality and keep patient records secure and accessible in order to avoid the dreadful penalties for being careless about data protection. But it's not just hackers; employees inside a healthcare organization are dangerous too. Employees might try to access or tamper information they have no authority to view, or they could accidentally leak confidential information.

Healthcare leaders must enforce strict measures to protect all patient records, sensitive clinical data, and related information against data breaches. These measures must include Data Management, Security, and Breach Planning Policies; Employee

Agreements; Access Control Lists; System Learning; Contingency Plans; and Security Awareness Training.

2.5.2. Bias in AI Algorithms

Artificial intelligence (AI) algorithms are statistical models designed to find patterns of correlations in data. For AI algorithms to be accurate, they must be trained with adequate data that represent the real-world problem for which the algorithms are designed. The subsequent model decision quality relies on the representativeness of training data, including the sample size, diversity of data sources, and data inclusion and exclusion rules. Without representative training data, AI algorithms can be biased and perform poorly for underrepresented groups. Patterns in data could reflect historic inequities; for example, using data from retrospective studies of patients who are predominantly white, male, and upper class to train AI algorithms could reflect biased patterns.

For these reasons, the sudden use of predictive algorithms in the clinical practice environment must be approached with caution. AI algorithms could be used to further dehumanize individuals or incorrect assumptions about groups with established health disparities. Despite the proven value of AI algorithms in clinical practice, investigators should be cautious about the potential harm they may cause. AI requires a grounding in current knowledge and trends; this must accompany its use in fields with specific but yet varying issues, such as health care.

2.5.3. Integration with Existing Systems

Integrating artificial intelligence applications into existing clinical workflows poses its own set of unique challenges. AI applications need to be useful but also very easy to navigate, in order to prompt physicians to utilize the application during hospice treatment decisions. Careful consideration of the design and integration into the physician’s environment will allow the maximum benefit, but often these factors are not prioritized and instead are left to the individual developer for consideration. AI applications can appear in many forms, including autonomous or semi-autonomous decision support systems, wearable monitoring devices, robotics, genetic/pathological analysis and clinical imaging classifications. Each of these various methods requires different types of integration and thus, standardization of interfaces as well as health information technology infrastructure will be integral to their successful implementation in clinical practice.

Integration into already-existing workflows for care providers have already seen many challenges specifically in the realms of EHR, quality reporting systems, telemedicine and remote patient monitoring systems. For these systems, integration is key, as failing to have the system connected to others presents issues of duplicate entry and retrieval for the care provider as well as confusing information for the patients themselves.

2.6. Conclusion

Sony has developed a unique system of secure and comfortable telecompression environments and devices, which minimizes side effects for the disabled and the medical staff, while helping patients to recover function related to movement and the senses. Such systems of virtual telemedical environments can help disabled patients interact with their relatives and friends. This not only facilitates the mental wellbeing of the patients, but also supports important family relationships and mutual emotional assistance, which is key for the patient recovery process. The telecompression systems can not only be used externally, but can also be built into embedded systems that can be employed for other medical conditions, such as pain relief or long distance anaesthesia. Thus, such systems of sensory telecompletion support not only the patient's wellbeing, but can also facilitate a more complex telemedical cooperation between specialists and the medical staff. In the future, more systems for Health and Telemedicine will be developed that will help to minimize a shortage of specialists in hospitals around the globe, as well as cope with pandemics and the need for new areas of treatment and therapy. It seems likely that more processes will be automated in telemedicine and e-health by introducing the capabilities of robotic services and artificial intelligence, which will help both the patients and the specialists to deal with everyday mundane problems and tasks. It is expected that the expansion of telehealth services will provide a more timely and consistent virtual accessibility to specialized answers and recommendations from specialists, thus effective disease prevention, treatment and recovery will be implemented.

2.6.1. Future Trends

A significant shift in the field of artificial intelligence has been the rapid advancement of models focused on mimicry and understanding of human languages. It enables intuitive communications which were not available in prior generations of language models. Importantly, the security and risk management issues associated with such democratization of access to sophisticated AI tools must be addressed even as we explore the potential applications within medicine. AI applications provide different functionalities in clinical practice from electronic health record mining, disease progression modeling, clinical trial design or optimization and automated patient interactions through chatbots. Increasingly, these tasks can be accomplished with proven robustness and clinical fidelity.

Radical new avenues using AI include predicting response or lack of response to treatment down to the level of the individual patient, helping physicians establish a differential diagnosis and then predict disease prognosis, streamlining analysis of clinical trial data, and acting as a support for physicians in charge of patients' treatment decisions.

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