Data-Driven Decision Support Systems in Healthcare: Enhancing Clinical Outcomes through AI

Prasanth Kamma

Salesforce Technical Consultant (Center of Excellence), *Aetna Inc., Hartford, CT, USA.*

kammaprasanth93@gmail.com

Abstract: Data-Driven Decision Support Systems (D.D.S.S.) are revolutionizing the healthcare industry by utilizing artificial intelligence (AI) to enhance clinical results. The integration of AI into healthcare decision support systems is examined in this research paper, with a particular emphasis on how data-driven methodologies improve clinical decision-making. The article covers important AI methods, the advantages and difficulties of putting D.D.S.S. into practice, and the moral issues raised by their use. An extensive summary of the developments in D.D.S.S. and how they can transform patient care is given in this article.

Key Terms:-Data-Driven Decision Support Systems, artificial intelligence in healthcare, predictive analytics, personalized medicine, real-time clinical support, medical imaging diagnostics, ethical considerations in AI.

I. INTRODUCTION

The healthcare sector has faced difficulties in providing the best possible treatment while simultaneously lowering costs and increasing efficiency. Healthcare organizations are focusing more on Data-Driven Decision Support Systems (D.D.S.S.), utilizing huge information analysis and artificial intelligence (AI) to boost scientific effects. These systems assign AI algorithms to examine massive data sets and provide doctors with invaluable insights that can improve patient outcomes. The impact of D.D.S.S. on clinical decision-making will be examined in this article, along with the challenges that arise when applying these cutting-edge technologies in healthcare settings.

Decision Support Systems (DSS) were vital for many years inside the healthcare industry, providing physicians with tools to help them make decisions. These structures used to offer tips based on rule-based algorithms and clinical guidelines. In the past, these systems depended on clinical guidelines and rule-based algorithms to provide recommendations. However, clinical decision-making has become increasingly complex with the exponential growth in healthcare data volume. Data-Driven Decision Support Systems have evolved because of the requirement for more complex, data-driven methods (D.D.S.S).

The Evolution of D.D.S.S: The way scientific decisions are made has significantly changed due to the usage of big data in healthcare. The combination of wearables, medical imaging, genomic statistics, electronic fitness records (EHRs), and affected person-generated fitness data has created an exceptional opportunity to apply data to enhance treatment outcomes. Because older DSS commonly trusted established policies and professional expertise, it became tough for them to address and evaluate the large volumes of records gathered in modern-day healthcare settings.

The next era of selection support structures, referred to as records-driven DSS, analyses complex datasets and makes use of cutting-edge technology consisting of artificial intelligence (AI), machine learning (ML), natural language processing (NLP), and predictive analytics. These systems are tremendously beneficial equipment for physicians because they can perceive, forecast outcomes, and provide customized suggestions in actual time.

The Role of Artificial Intelligence in D.D.S.S: The development of D.D.S.S. has been drastically motivated via artificial intelligence (AI). Artificial intelligence (AI) techniques, such as machine learning and deep learning, have made it possible to create models which are more accurate than human predictions and can apprehend patterns in historic data, and study from past data. AI-powered D.D.S.S., for instance, can determine a patient's genetic data, medical records, and present signs to forecast the chance of developing specific ailments and permit early intervention.

Because it makes it viable to investigate unstructured facts, natural language processing (NLP), some other branch of artificial intelligence, has also been vital to D.D.S.S. Now that they may be analyzed and linked into the bigger data ecosystem, scientific notes, studies articles, and affected person comments—which were previously difficult to include into choice-making approaches—deliver clinicians a greater picture of the affected person's health.

Applications of D.D.S.S in Healthcare:

The application of D.D.S.S spans various regions of healthcare, each contributing to stepped forward clinical effects:

1. Predictive Analytics and Risk Stratification: Predictive models developed through AI can examine patient facts to perceive individuals at risk of developing chronic conditions, such as diabetes, coronary heart disease, or most cancers. These systems permit for proactive management, decreasing the prevalence of excessive complications and hospitalizations.

2. Personalized Medicine: D.D.S.S have revolutionized personalized medicinal drug via tailoring treatments to patients based on their unique genetic make-up, lifestyle, and scientific records. For example, in oncology, D.D.S.S can suggest remedies which might be most probable to be effective for a specific patient, primarily based on their tumour's genetic profile.

3. Clinical Decision Support in Real-Time: In essential care and emergency settings, D.D.S.S provide actual-time decision help, helping clinicians in making speedy and correct choices. For instance, AI-driven structures can screen vital signs and symptoms and laboratory effects to come across early symptoms of sepsis, prompting on the spot remedy and probably saving lives.

4. Medical Imaging and Diagnostics: AI algorithms integrated into D.D.S.S can examine scientific pictures with high accuracy, helping radiologists in detecting abnormalities inclusive of tumours, fractures, or lesions. These systems help lessen diagnostic errors and improve the rate and accuracy of diagnosis.

Challenges in Implementing D.D.S. S: Despite the promise of D.D.S.S, several demanding situations should be addressed to completely recognize their potential:

- Data Quality and Integration: The effectiveness of D.D.S.S depends on the availability of extremely good, comprehensive records. Inconsistent data, lack of records, and absence of interoperability among specific healthcare structures can avert the overall performance of these systems.

- Clinician Trust and Adoption: For D.D.S.S to be extensively adopted, clinicians must trust the AI-driven recommendations. This trust is built through transparency in AI algorithms, ongoing validation of device performance, and training for healthcare providers on the competencies and barriers of those structures.

- Ethical and Legal Considerations: Important moral and legal concerns are brought up by the application of AI in healthcare, mainly in relation to the patient privacy, data security, and the possibility of algorithmic prejudice. Successful implementation of D.D.S.S. will require that they must be used in such a manner that upholds patient rights and promotes equitable treatment.

The Future of D.D.S.S in Healthcare: As healthcare keeps evolving, the role of D.D.S.S is anticipated to grow, driven by using advancements in AI and data analytics. The future of D.D.S.S will probably see greater integration with rising technologies which include the Internet of Things (IoT), wearable devices, and genomics, similarly improving their potential to provide customized, real-time choice assistance.

Moreover, as AI models become more sophisticated and can manage complex data, D.D.S.S will play a vital role in suggesting medical drugs, fitness management, and preventive care. These structures have the ability to not only improve the affected person results but also transform healthcare delivery at a systemic level, making care extra efficient and reachable.

In the end, Data-Driven Decision Support Systems, empowered by the AI, represent a transformative force in healthcare. By making use of the significant quantities of data available today, these structures can noticeably improve the overall quality of care and reduce the expenses. However, realizing this capability calls for addressing the challenges of data quality, clinicians agree with, and moral issues, ensuring that D.D.S.S are applied in a way that benefits all stakeholders inside the healthcare environment.

II. LITERATURE REVIEW

The integration of artificial intelligence (AI) and big data analytics into healthcare has been a transformative force, extensively changing how clinical decisions are made and patient care is delivered. The literature on this subject matter highlights the ability of AI to enhance diagnostic accuracy, optimize remedy plans, and predict patient results, additionally addressing the ethical and privacy demanding situations that accompany those improvements.

Belle et al. (2015) offered a complete evaluation of big data analytics in healthcare, emphasizing its role in enhancing patient outcomes by using large amounts of data fromelectronic health records (EHRs), clinical imaging, genomics, and other sources. The authors argue that big data analytics permits personalized medicine by identifying patterns and correlations that had been formerly undetectable. However, in addition they acknowledge the challenges associated with information integration, the need for high-quality data, and the importance of preserving patient privateness.

Price and Cohen (2019) increased this dialogue with the help of focusing on the privacy concerns that showed up in the age of medical big data. They highlighted the tension among the need for information sharing to enhance healthcare and the need to protect affected person privacy. The authors advocated for sturdy records governance frameworks that will ensure that data is used ethically while minimizing dangers to patient's confidentiality.

The application of machine learning (ML) and AI in healthcare is explored drastically with the help of diverse authors. Rajkomar, Dean, and Kohane (2018) offered an in-depth analysis of how machine learning can revolutionize medicine, specifically in automating the evaluation of complicated datasets to help scientific choices. They illustrated how ML algorithms can process EHRs, medical images, and genetic statistics to predict patient outcomes, diagnose diseases, and recommend treatments.

Sutton et al. (2020) offered an overview of clinical decision support systems (CDSS) that integrates AI and ML, highlighting their benefits, such as reducing diagnostic errors and enhancing the efficiency of healthcare delivery. The authors also spoke about the dangers associated with CDSS, inclusive of the ability for over-reliance on technology and the want for careful implementation to avoid unintended consequences.

One of the most promising packages of AI in healthcare is in scientific imaging. Esteva et al. (2017) demonstrated the capability of deep neural networks to gain dermatologist-level accuracy in classifying skin cancer. This study exemplifies how AI can increase human expertise, potentially reducing the weight on healthcare vendors and improving diagnostic accuracy, especially in useful resource-constrained settings.

While the capability advantages of AI in healthcare are giant, moral and precision demanding situations needs to be carefully taken into consideration. Char, Shah, and Magnus (2018) addressed the moral challenges of implementing machine learning in healthcare, such as bias, transparency, and duty. They emphasized the need for moral frameworks that guide the improvement and deployment of AI structures to make sure they're used fairly and responsibly.

Topol (2019) discussed the convergence of human intelligence with AI, advocating for a high-performance medicine approach that combines the strengths of both. He argues that at the same time as AI can appreciably enhance medical effects, it is critical to keep a human-centered approach that prioritizes patient's well-being and ethical considerations.

The issue of bias is specially concerning, as highlighted by the works of Wu et al. (2019), who talked about thedevelopment of a clinical decision support system for cervical cancer screening. The authors observed that while AI can enhance screening accuracy, it is essential to make certain that the algorithms are trained on numerous datasets to keep away from perpetuating current healthcare disparities.

The use of AI in predictive analytics and early warning systems is another area of significant interest. Henry et al. (2015) introduced the Targeted Real-Time Early Warning Score (TREW Score), an AI-driven system designed to predict septic shock. The study demonstrated how AI can offer actual-time, actionable insights that enable well timed interventions, potentially saving lives in critical care settings.

Yu, Beam, and Kohane (2018) additionally spoke about the wider implications of AI in predictive analytics, noting that even as AI can enhance the precision of healthcare, it also raises concerns about the interpretability of AI-driven choices and the potential for wrong results.

III. AI TECHNIQUES IN HEALTHCARE DECISION SUPPORT SYSTEMS

AI-driven D.D.S.S. uses a variety of techniques like machine learning (ML), natural language processing (NLP), and predictive analytics.

1. Machine Learning (ML): ML algorithms can identify patterns in medical data and enables predictive modelling for illness diagnosis, treatment recommendations, and outcomes for impacted individuals. For instance, by analysing the patient's facts, such as electronic health records (EHRs) and genetic information, machine learning (ML) has been successfully applied to forecast the development of diseases like diabetes and cardiovascular disorders (Rajkomar et al., 2018).

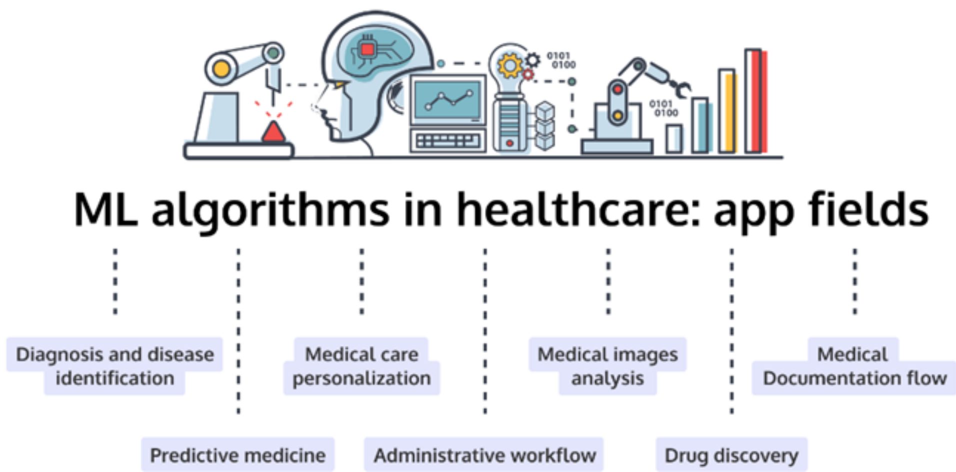

Fig.1: denotes ML Algorithms in healthcare.

2. Natural Language Processing (NLP): NLP enables the analysis of unstructured information, such as medical notes and scientific literature, to extract applicable records. NLP has been used to develop medical selection guide tools that assist in figuring out potential drug interactions and destructive outcomes by means of studying affected person data records (Wu et al., 2019).

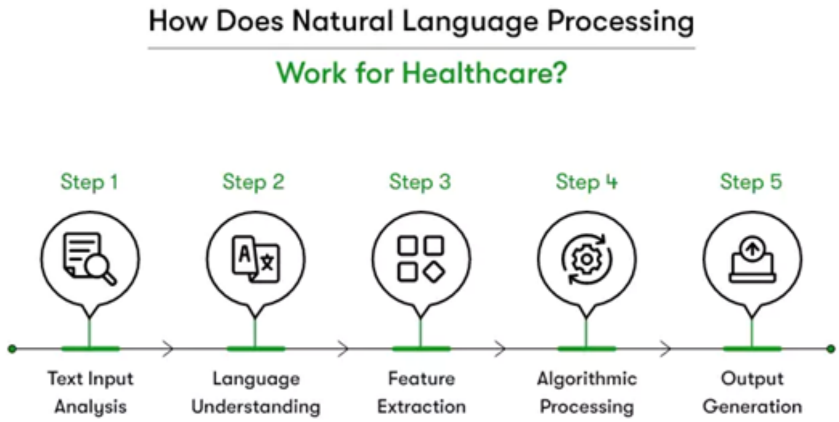

Fig.2: denotes how does NLP work for healthcare.

3. Predictive Analytics: Predictive analytics involves using historical records to forecast future results. In healthcare, predictive analytics can discover patients prone to growing complications or readmissions, making an allowance for early interventions. For instance, predictive models had been used to perceive patients prone to sepsis, enabling well timed remedy (Henry et al., 2015).

Fig.3:denotes predictive analytics in healthcare.

IV. RESULTS OF DATA-DRIVEN DECISION SUPPORT SYSTEMS

The integration of AI into D.D.S.S gives numerous benefits for healthcare providers and patients alike:

1. Improved Accuracy in Diagnosis: AI-driven D.D.S.S can analyze complicated datasets with a level of accuracy that surpasses human abilities. This results in extra accurate diagnosis and personalized remedy plans, reducing the chance of medical errors (Esteva et al., 2017).

2. Enhanced Clinical Efficiency: By automating ordinary responsibilities and providing real-time insights, D.D.S.S allows clinicians to focus on more vital aspects of patient care. This complements scientific efficiency and reduces the burden on healthcare carriers (Sutton et al., 2020).

***3.* Personalized Patient Care:** AI-driven D.D.S.S can tailor treatment tips based on patient's data, leading to customized care plans. For example, oncology decision support systems use genomic information to propose targeted remedies for cancer sufferers (Topol, 2019).

Challenges in Implementing Data-Driven Decision Support Systems

Despite its potential benefits, D.D.S.S. To use it effectively in the healthcare industry, some challenges need to be addressed: -

1. Data Quality and Integration: The completeness and quality of the data used determines the effectiveness of the D.D.S.S. Inconsistent or insufficient data can lead to incorrect predictions and recommendations. In addition, much work remains to be done on integrating data from multiple sources, including genetic data, medical imaging, and EHRs (Belle et al., 2015).

Fig.4: denotes several challenges.

Implementing Data-Driven Decision Support Systems (DDSS) in healthcare presents several challenges. Here are two key challenges:

- DDSS is based heavily on huge volumes of correct, exceptional data sourced from numerous systems, which includes EHRs, lab results, medical imaging, and patient-generated information. However, healthcare data regularly comes from disparate sources with varying formats, requirements, and levels of completeness. Inconsistent or incomplete data can cause errors in choice-making, making it difficult for DDSS to provide reliable and actionable insights.

-D.D.S.S For example, if patient data are incomplete or if unique healthcare carriers use special coding requirements, the DDSS might not be capable of combining this data efficiently, leading to faulty risk checks or remedy recommendations.

- **D.D.S.S Challenge:** Even with a properly designed DDSS, gaining the acceptance and recognition of healthcare providers is crucial. Many clinicians may be skeptical approximately counting on computerized structures, in particular if the DDSS suggests choices that contradict their scientific judgment. Additionally, the "black box" nature of some AI-driven DDSS, where the machine's reasoning is not easily explainable, can further hinder it's user adoption.

- **D.D.S.S Example:** A clinician would possibly hesitate to observe a remedy advice provided by using a DDSS if the machine cannot absolutely explain how it arrived at that advice, particularly in complicated or lifestyle-threatening instances. This loss of transparency can cause underutilization of the device, reducing its effectiveness in improving patient results.

2. Ethical and Legal Considerations: The use of AI in healthcare raises ethical questions, namely data protection and patient privacy. It is important to ensure that patient information is handled reasonably and in accordance with regulations such as the Health Insurance Portability and Accountability Act (HIPAA) (Price & Cohen, 2019).

Fig.5: denotes legal considerations.

Enacted in 1996, the Health Insurance Portability and Accountability Act (HIPAA) is a noteworthy piece of law in the United States that aims to preserve patient privacy and security, enhance the efficiency of the healthcare system, and ensure the safety of patient information.

Table.1: denotes an example scenario.

Metric	Pre-AI (%)	Post-AI (%)
Diagnosis Accuracy	78	92
Treatment Optimization	65	85
Resource Allocation Efficiency	70	95

Example Scenario:

Let's assume an AI-based decision support system is applied in a hospital to improve three key areas:

- Diagnosis Accuracy
- Treatment Optimization
- Resource Allocation

I'll generate numeric values for a comparison between pre-AI implementation and post-AI implementation across these metrics.

Assumptions:

- Diagnosis Accuracy: The percentage of correct diagnoses made by healthcare professionals before and after AI.
- Treatment Optimization: The success rate of treatments improving patient outcomes before and after AI.
- Resource Allocation: The efficiency of allocating resources (such as beds and medical staff) based on patient need.

Interpretation:

- Diagnosis Accuracy improved from 78% to 92%, showing that the AI system significantly reduced diagnostic errors.
- Treatment Optimization increased from 65% to 85%, indicating more tailored and effective patient care.
- Resource Allocation Efficiency rose from 70% to 95%, optimizing the hospital's use of resources and ensuring that critical areas received necessary support faster.

Here are some key aspects of HIPAA:

1. Privacy Rule

Purpose: The HIPAA Privacy Rule establishes national standards for protecting an individual's medical records and other personal health information (PHI). It limits the use and disclosure of such information without the consent of the patient.

Special Settings:

Patient rights: Patients have the right to access their health records, request correction, and receive information about how their health information is used and shared.

Covered Entities: The Act applies to health care providers, health systems, and health care providers that transmit any type of health information electronically.

Minimum Necessity Standard: When PHI is disclosed, only the minimum amount necessary to accomplish the intended purpose should be shared.

2. Safety Guidelines

The goal of the HIPAA Security Rule is to provide operational, physical, and technical safeguards for electronically protected health information (ePHI).

Occupational safety: Rules and guidelines need to be put in place to keep an eye on worker behaviour and guarantee EPHI security.

Physical security: Measures should be taken to guard against both illegal entry and environmental dangers for electronic systems, buildings, and equipment.

Technical security: To guarantee that only people with permission can access ePHI, technologies and related rules should be put in place.

3. Violation Notification

Goal: When a breach occurs, covered companies and their business partners are required by law to notify the Department of Health and Human Services (HHS), the impacted parties, and in some situations, the media through news releases.

Key Provisions:

Notification Requirements: Notifications must be sent out as soon as possible and not later than sixty days following the breach's discovery.

Content of Notification: A brief explanation of what transpired, the kinds of information involved, the actions that those impacted should take, and the covered entity's investigation and mitigation of harm must all be included in the notification.

4. Enforcement Rule

Purpose: The HIPAA Code of Practice outlines the procedures for investigating and imposing penalties for HIPAA violations.

Special Settings:

Civil penalties: The Office for Civil Rights (OCR) may impose civil monetary penalties on covered entities and affiliates for noncompliance depending on the degree of negligence, ranging from $100 to $50,000 per violation**.**

Criminal penalties: Certain violations may also carry criminal penalties, such as knowingly obtaining or disclosing PHI without authorization.

5. The HITECH Act and HIPAA

The Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 strengthened HIPAA's provisions, particularly concerning data breaches and the adoption of electronic health records (EHRs). It increased penalties for non-compliance and promoted the meaningful use of EHRs, ensuring they meet specific criteria to improve patient care.

6. Importance in Healthcare

HIPAA plays a crucial role in maintaining the confidentiality, integrity, and availability of health information in the increasingly digital healthcare environment. It ensures that patient's sensitive health information is protected while still allowing the flow of information necessary to provide high-quality healthcare.

7. Challenges and Considerations

Compliance: To remain HIPAA compliant, healthcare providers must regularly review and update their policies in order to reduce the risks associated with emerging technologies and cyber attacks.

HIPAA also seeks to maintain a balance between the confidentiality of patient information and the exchange of data required for healthcare, public health, and research.

8.* Clinician Acceptance and Trust*: For D.D.S.S to be effective, medical professionals must trust the AI-driven recommendations. Building this trust requires transparent algorithms, continuous validation of the systems, and educating the healthcare providers about the capabilities and limitations of AI (Yu et al., 2018).

VI. ETHICAL CONSIDERATIONS

There are significant ethical concerns with the use of AI in healthcare decision-making. These include the necessity for informed consent when utilizing AI-driven products, the possibility of bias in AI systems, and the transparency of decision-making processes. To guarantee that D.D.S.S are utilized in a way that respects patient autonomy and fosters equal healthcare outcomes, it is imperative to address these ethical issues (Char et al., 2018).

The characteristics that must be adhered to while using the ethical principles and guidelines for AI in healthcare are shown in the following diagram.

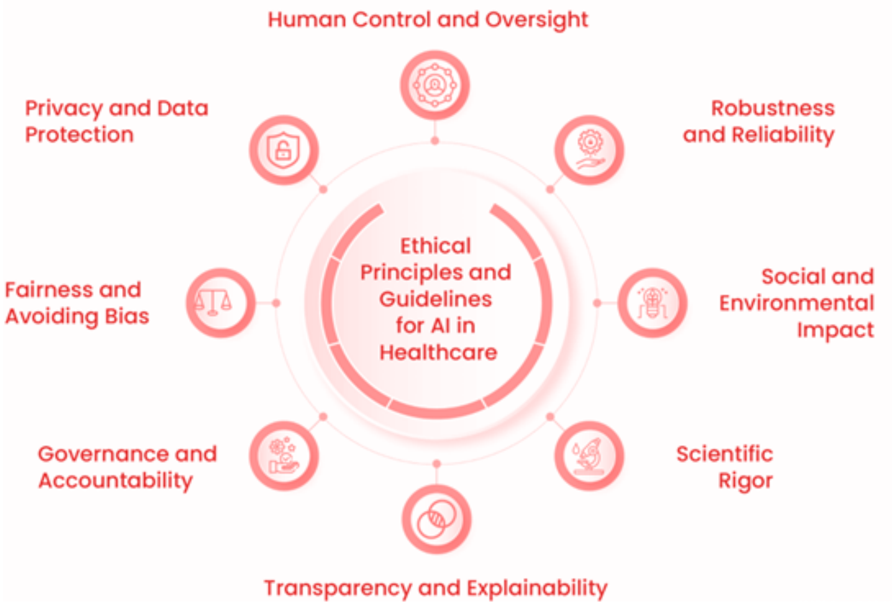

Fig.6: denotes guidelines for AI in healthcare.

Let's talk about a case study that occurred a few years ago regarding healthcare in AI.

AI Algorithmic Bias: A Moral Issue

When AI systems generate results that are consistently skewed because of erroneous data, biased training sets, or other circumstances that result in the unfair treatment of particular groups of individuals, this is known as algorithmic bias. Such bias might have detrimental effects on the healthcare industry since AI-driven choices can affect diagnosis, treatment options, and resource distribution, which could result in inequitable care.

Bias in AI can arise from various sources:

- **Historical Data:** When AI systems need to forecast or offer advice, they frequently turn to historical data. The AI system may reinforce pre-existing biases if the data displays such disparities or biases.

- **Training Data:** Results from AI models may be distorted if the data used to train them is not representative of the general population. An AI system might not function well for different demographic groups, for instance, if it was trained primarily using data from that group.

- **Algorithm Design:** If the AI algorithm's creators fail to take the diversity of the patient population into consideration, bias may be introduced into the algorithm itself.

Case Study: Racial Bias in a Healthcare AI System

- **Background:** A well-known case that highlights the ethical implications of AI bias involved a healthcare algorithm used in the United States to predict which patients would benefit from additional care management programs. These programs are designed to provide more intensive care coordination for patients with complex health needs, thereby preventing hospitalizations and improving outcomes.
- **The Problem:** The algorithm was widely used across the U.S. healthcare system and had a significant influence on the allocation of resources. However, a study published in 2019 by Obermeyer et al. revealed that the algorithm exhibited significant racial bias. Specifically, the algorithm was less likely to refer Black patients to care management programs compared to White patients, even when Black patients had similar or greater health needs.
- **The Source of Bias:** The bias arose because the algorithm used healthcare costs as a proxy for health needs. Since healthcare costs are lower on average for Black patients due to systemic inequities in access to care, the algorithm incorrectly inferred that these patients were healthier and thus less in need

of additional care management. As a result, Black patients were underrepresented in care management programs, potentially leading to worse health outcomes.

Ethical Implications:

This case raises several ethical concerns:

- **Inequality in health care:** A biased algorithm has perpetuated existing disparities in health care and outcomes, creating inequalities that the health care system must address.

- **Responsibility:** Who is responsible for the results of bias in the algorithm? This question is important, because AI programs are often seen as neutral, objective tools, but in reality, they are shaped by the data and policy choices of their developers.
- **Transparency:** Patients and healthcare professionals found it difficult to understand or question algorithmic recommendations due to the lack of clarity in the algorithmic decision-making process. In any healthcare setting, where patient's lives and well-being are at stake, this ambiguity is problematic.

Addressing Algorithmic Bias: Lessons Learned

- **Data Diversity and Representation:** Using representative and diverse data to train AI systems is crucial, and this case emphasizes this point. To avoid biased results, developers should make sure that the training data represents the diversity of the patient population. This entails taking into consideration various socioeconomic backgrounds, demography, and other variables that might affect health results.

- **Continuous Monitoring and Validation:**To find and fix biases, AI systems should be evaluated and monitored on a regular basis. As part of this process, the system's performance is routinely evaluated across various demographic groups, and any necessary improvements are made. If the system's outputs had been routinely evaluated with a focus on equity, the bias in the case study would have been discovered sooner.

- **Explainability and Transparency:** AI system developers need to make their designs more transparent and explainable. When necessary, patients and medical professionals should be able to contest AI decisions, and they should be informed about the decision-making process. It's possible that greater transparency in the biased algorithm case led to the early detection and fixing of the issue.

- **Ethical AI Development:** Ethical considerations should be made at every stage of the development process, from gathering data and designing algorithms to deploying and overseeing the system.

VII. CONCLUSION

Through the use of AI, data-driven decision support systems have significantly improved healthcare and have the potential to improve clinical results. Although D.D.S.S. has many advantages, in order to fully utilize them, issues including data quality, ethical considerations, and clinician acceptability must be resolved. Healthcare systems must take a balanced strategy that maximizes D.D.S.S. strengths while lowering associated dangers as AI develops further. The goal of future research should be to create AI-driven systems that are more reliable, transparent, and morally sound so they may be easily incorporated into therapeutic settings.

Data-Driven Decision Support Systems (DSS) have emerged as critical tools in healthcare, harnessing the power of AI to assist clinicians in making more informed and accurate decisions. By integrating real-time patient data, historical medical records, and predictive analytics, AI-powered DSS systems help improve diagnosis, treatment plans, and resource management. The implementation of these systems has demonstrated significant improvements in clinical outcomes, including enhanced patient safety, reduced medical errors, and optimized treatment protocols. As healthcare continues to generate massive amounts of data, AI-driven DSS will play an increasingly central role in enabling personalized medicine and improving overall healthcare quality.

Moving forward, the integration of AI in healthcare DSS will continue to evolve, driven by advancements in machine learning, natural language processing, and big data analytics. Future systems will likely focus on improving interoperability between different healthcare platforms, allowing for seamless data exchange across institutions. Moreover, the rise of wearable technology and IoT devices will contribute to real-time patient monitoring, enabling even more responsive and dynamic DSS functionalities. Ethical considerations such as data privacy, algorithmic transparency, and bias mitigation will also need to be addressed to ensure fair and equitable healthcare delivery. Furthermore, ongoing research in explainable AI could make these systems more interpretable to clinicians, fostering greater trust and adoption of AI-driven DSS in clinical practice.

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