**Security Vulnerabilities in AI-Powered Health Care Decision Support Systems: Attack Vectors and Defensive Strategies**

**Abstract**

Artificial intelligence (AI) is often heralded as a potential disruptor that will transform the practice of medicine. The amount of data collected and available in health care, coupled with advances in computational power, has contributed to advances in AI-powered healthcare decision support system, and an exponential growth of publications. However, the development of AI-powered healthcare applications does not guarantee their adoption into routine practice. There is a risk that despite the resources invested in achieving these feet, patientsbenefit, staff benefits, and society development will not be achieved if artificial intelligence (AI) implementation is not better understood.This review on Security Vulnerabilities in AI-Powered Health Care Decision Support Systems: Attack Vectors and Defensive Strategies is ainnovative topic and needs further research analysis and funding. Also, to achieve this initiate, researchers need to work alongside programmers and medical consultants for adequate information and data needed for excellent regulations and implementations.

**Keywords:**  
Artificial Intelligence (AI), Health Care Decision Support Systems (CDSS), Cybersecurity, Attack Vectors, Data Privacy, Defensive Strategies, Machine Learning Security, Adversarial Attacks, Medical Informatics, Regulatory Compliance, Healthcare Technology, Secure AI Deployment.

**Introduction**

Artificial Intelligence (AI) encompasses a suite of computational technologies designed to emulate human intelligence in machines and systems. In healthcare, AI-powered technologies are increasingly applied to analyze complex and diverse health data, including clinical records, behavioral patterns, environmental influences, pharmaceutical profiles, and biomedical literature (Caroll, 2022). The automation of various healthcare functions traditionally dependent on human expertise has spurred significant interest across disciplines in AI-powered healthcare decision systems (Iluno and Nwaogwugwu, 2025). These systems leverage advanced AI methodologies, including computer vision, natural language processing, and speech recognition, to support medical decision-making processes (Lin *et al*., 2022).

The rapid evolution of computer hardware and software has enabled the digitization of medical information, paving the way for sophisticated computational models that harness AI to derive actionable insights from data (Tabriz *et al*., 2017; Iluno and Nwaogwugwu, 2025). Among these technologies, Machine Learning (ML) and Deep Learning (DL) subsets of AI have become central. While ML involves learning from structured data inputs, DL employs multi-layered neural networks for modeling complex patterns in raw data (Williams, 2020). Traditional ML models, such as logistic regression and support vector machines, often require manual feature engineering a process that deep learning overcomes by using end-to-end architectures capable of automatic feature extraction and prediction (He *et al*., 2023; Xu *et al*., 2021). Nevertheless, designing effective DL architectures and tuning model parameters still necessitates significant human oversight (Siriwardhana *et al*., 2020).

As the global burden of chronic illnesses rises, with conditions that persist over a lifetime and demand continual management, AI is increasingly viewed as a solution to improve patient outcomes and reduce healthcare costs (Lee and Lee, 2021; Mistry *et al*., 2021; Iluno and Nwaogwugwu, 2025). The World Health Organization has acknowledged the transformative potential of digital health interventions, shifting focus toward emerging domains such as big data analytics, genomics, and AI (Shakeel *et al*., 2022). AI applications now support early disease detection, treatment optimization, and novel intervention strategies, thereby playing a critical role in modern healthcare (Tran *et al*., 2019).

AI-powered chatbots, in particular, have emerged as a transformative tool in healthcare communication and support, driven by advancements in natural language processing and speech recognition (Sadiku *et al.,* 2018). These virtual agents simulate human conversation both written and verba allowing users to engage with digital systems as if interacting with human providers (Jiang *et al*., 2017; Javaid *et al*., 2022). As a result, chatbots are now widely deployed across industries, including e-commerce, tourism, and especially healthcare, to provide scalable, cost-effective, and continuous patient support (Hashimy *et al*., 2021; Alnuvaili, 2020).

In healthcare, chatbots have demonstrated effectiveness in alleviating patient anxiety, guiding behavioral change, supporting chronic disease management, and enhancing senior care (Iroju and Oluleke, 2015; Park and Kim, 2022; Trunfio and Rossi, 2022). Moreover, they aid in lifestyle coaching, cancer support, and patient history collection, thereby complementing conventional care models (Thomason, 2021). The ability of AI to identify complex data patterns beyond human capability has amplified its perceived value in medicine, though it also raises ethical, legal, and liability concerns about the autonomy of AI systems (Petrigna and Musumeci, 2022; Sallam, 2023; Iluno and Nwaogwugwu, 2025).Despite the clear benefits, integrating AI into routine healthcare remains challenging. Adoption is influenced by a multifaceted set of factors: economic, legal, sociocultural, organizational, technological, and individual attitudes (Sadiku *et al*., 2018). Furthermore, successful implementation requires collaboration between AI developers and healthcare providers. This synergy fosters innovation in diagnostic accuracy, treatment personalization, decision support, process optimization, and patient engagement (Park and Kim, 2022; Yang *et al*., 2022; Li *et al*., 2023).Ethical and regulatory considerations such as patient data protection, system transparency, and model accountability are paramount in these collaborations (Lin *et al*., 2022; Hassani and Silva, 2023). The convergence of AI's analytical capabilities with clinical expertise is thus crucial to realizing the full potential of AI in healthcare (Dong *et al.,* 2021; Kumar *et al*., 2022).

Nonetheless, existing research has predominantly focused on the technical development of AI-powered chatbots, often based on limited sample sizes or pilot study frameworks (Orth *et al*., 2017). Systematic reviews to date have examined diverse conversational interventions, yet they frequently rely on varied methodologies such as case studies, uncontrolled trials, or single-group designs, limiting the generalizability of findings (Briganti and Lemoine, 2020; Dash *et al*., 2019). Few have specifically assessed the efficacy, safety, or informational integrity of AI-chatbots in randomized controlled trials (RCTs), revealing a significant gap in the literature (Bendig *et al*., 2022; Hu *et al*., 2016). Therefore, this review aims to address this gap by evaluating the security vulnerabilities of AI-powered healthcare decision support systems focusing on both their susceptibility to adversarial attacks and the defense strategies employed to safeguard them. By scrutinizing the latest research evidence, this review will explore the intersection of AI implementation, system robustness, and clinical safety.

**2. Methodology**

The methodology of this review involved a meticulous literature search across Scopus, Web of Science, and Google scholar to evaluatethe security vulnerabilities of AI-powered health care decision support systems, focusing on known attack vectors and available defensive strategies. A Comprehensive Review of Techniques, Challenges and Future Directions.The methodology employed a structured yet flexible approach to ensure broad coverage of relevant interdisciplinary sources spanning artificial intelligence, cybersecurity, and digital health (Echeazarra *et al*., 2021). And it is reported in accordance with the preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement. Ethical approval and informed consent were not requiredfor the present study.

**2.1 Literature Search Strategy**

In conducting a comprehensive literature search for this systematic review, the selection of databases was crucial to ensure a broad and relevant collection of studies. The foundational databases employed are: PubMed, Scopus, IEEE Xplore, SpringerLink, Web of Science and Google scholar. The keywords used in different combinations were: "AI in healthcare", "decision support systems", "cybersecurity in medical AI", "adversarial attacks", "data poisoning", "model vulnerability", "privacy attacks", "defensive strategies in AI", and "healthcare cybersecurity threats". Boolean operators such as AND, OR, and NOT were used to refine searches. Cross references and software corroborations of important articles were also searched. The search encompassed original articles published within 2015 to 2025.

**2.2 Inclusion and Exclusion Criteria**

2.2.1: Inclusion Criteria:This focused on mapping of existing literature and articles on, "AI in healthcare", "decision support systems", "cybersecurity in medical AI", "adversarial attacks", "data poisoning", "model vulnerability", "privacy attacks", "defensive strategies in AI", and "healthcare cybersecurity threats". The research was further narrowed down to include the following; (a) Assessing the effectiveness of AI-Powered health care decision support system. (b) Evaluating the accuracy, scalability, and practical implementation of different AI-Powered health care decision support systems. (c) Identifying the defensive mechanism of most health care decision support systems. Data or selected journals reported at least 1 indicator of AI-Powered healthcare decision support system.

**2.2.2: Exclusion Criteria**

These includes all article before 2015, studies without experimental validation and Non-English Language papers (unless translated). The following were also excluded: (a) Articles or journals unrelated to AI-Powered health care decision support system. (b) Articles or journals related to AI-Powered health care decision support system but not on attack vectors and defense mechanisms.

**2.3 Data Extraction and Synthesis**

Data extraction was carried out by two (2) reviewers independently by adapting a standardized procedure. Data pertaining toAI-Powered health care decision support system: attack vectors and defense mechanisms over the years, were extracted from various selected research articles and journals. From this study which deals with Security Vulnerabilities in AI-Powered Health Care Decision Support Systems: Attack Vectors and Defensive Strategies. Changes from baseline in the endpoints were either extracted raw from the respective research articles or journals if provided, or calculated from both supervised and unsupervised algorithmic baseline values of successful AI-powered healthcare decision support operations, attack vulnerabilities and defensive measures.

**2.4 Analysis:**

The PRISMA framework diagram was used to sort the articles needed for this review and the data gathered were analyzed based on their year of publication using Excel graph sheets.

**2.5 Expected Outcomes:**

Technological intervention in healthcare using AI-powered chatbots has become increasingly dynamicbecause of improvements in artificial intelligence (AI), natural language processing and voice recognition (Higgins *et al*., 2016). These sophisticated computer programs are meticulously crafted to emulate and effectivehuman dialogues, activities and processes, whether they are in written or spoken form (Alder *et al*., 2020). The most recent developments in artificial intelligence is to enable interactions that are more and more like those between people and their computer agent counterparts (Knitza *et al*., 2021). The simulation of communication between humans and machines has become increasingly intricate and sophisticated (Morshid *et al*., 2019). The future of AI-Powered healthcare decision support system is basically independent unsupervised AI powered systems, where by the machine can carry out healthcare decision based on patient’s health changes without human intervention or assistance throughout the treatment processes (Al-Hilli *et al*., 2023; Iluno and Nwaogwugwu, 2025). Also, the use of advanced automated delivery systems and connectivity such as; 5G network. The future is possible through machine learning as artificial intelligence (Dierckx *et al*., 2020). This review is based on research articles, review papers and journals. Duplicate papers were thoroughly checked and removed to maintain the quality of this review. Abstracts of the articles used for this review were properly examined through analysis to ensure purification, quality and relevance of this academic literature. This review is limited to papers published in English language. Also, 1255 article and journals were extracted from the search after the filtration of exclusion criteria and duplicate records, 1055more articles and journals were removed from the review and a total of 200

**3.0 Results**

## Identification

## Eligibility

## Included

## Screening

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| Additional records identified through other sources (n = 5)  Records identified through database searching (n = 1255)  Total Records Extracted (n = 1260)  Records screened (n = 350)  Records excluded based on Exclusion Criteria  (n = 910)  Full-text articles assessed for eligibility (n = 350)  Full-text articles excluded Based on duplicate (n = 10)  Studies included in qualitative synthesis (n = 4)  Journal or Articles excluded based on irrelevance to the review (n = 498)  Studies included in systematic review (meta-analysis) (n = 4) |

Fig. 1: Prisma Frame Work Diagram of procedures involved in the selection of preferred journal for this review.

* 1. **Publication Chart**

Fig 2: Bar chart representation of total number of article and journal publication for the last tenyears.

Considering the chart above, 2024 has the highest number of journal publication Security Vulnerabilities in AI-Powered Health Care Decision Support Systems: Attack Vectors and Defensive Strategies. With a total publication of over 500000 journals.

**Discussion**

This systematic literature review on Security Vulnerabilities in AI-Powered Health Care Decision Support Systems: Attack Vectors and Defensive Strategies requires the use of AI-powered technologies in healthcare decision support systems based on the information acquired through machine learning and deep learning of patient data and professional procedures (Robinson *et al*., 2019). AI-powered healthcare technologies are being used for a range of healthcare applications. These technologies have been developed to support medical imaging and diagnostic services, fight the pandemic, provide virtual patient care, increase patient engagement and adherence to treatment plans, reduce the administrative burden on healthcare professionals, drive drug and vaccine innovation, monitor the compliance of patients with exercises, and carry out gait analyses used in technology-assisted rehabilitation (Knitza *et al*., 2021; Iluno and Nwaogwugwu, 2025). However, AI also faces various technical, ethical, and governance challenges as it moves forward in healthcare. It raises data security- and privacy-related issues because it utilizes sensitive and confidential data bound by legal panels (Venerito *et al*., 2022). The use of AI in addressing challenges could be limited by the quality of existing health data and AI’s failure to reflect certain human characteristics, such as compassion. AI is more beneficial while functioning efficiently; however, it cannot replace the human connections that form teams. Human functions such as teamwork and team management are not possible-to-achieve goals, since machines cannot form a bond with humans (Komiya *et al*., 2019). A key challenge to be solved for the future governance of AI-powered technologies will be to confirm that artificial intelligence (AI) can be developed and implemented in a way that aligns with people’s interests and considers technical, ethical, and social aspects (Shamseer *et al*., 2015). Also, modern healthcare ecosystem involves, emerging technologies, Internet of Things(IoT) medical devices playing major role for providing seamless and remote clinical care, disease diagnosis, patient monitoring and many more healthcare services. Wireless, seamless sensor devices and underlying infrastructure creates the IoT ecosystem (Dong *et al*., 2021). An IoT device identification and vital healthcare data collection is the most important where vulnerability management and security is a critical aspect of IoT security Against several vulnerabilities, attacks and cyber threats, a proactive approach needs to be built for Internet of Things medical devices security resilience (Gong *et al*., 2020). In the current fast moving digital transformation, integrating Artificial Intelligence (AI)-driven safety measures into IoT enabled healthcare applications represents a significant advance in building a secure and trustworthy healthcare system (Yang *et al*., 2022). The AI system can identify ordinary patterns of behavior and swiftly recognize any deviations suggestive of a possible security risk or unauthorized access through the continuous analysis of data flows from networked sensor devices (Messelink *et al*., 2022). To enhance the security of IoT medical devices, we explore security vulnerabilities in IoT enabled healthcare applications and propose an AI-powered healthcare approach for IoT Device level vulnerabilities management life cycle for known and unknown vulnerability detection and protection based on zero tolerance and zero-trust model.

**Conclusion**

AI-powered diagnostic decision support systems represent a transformative advancement in modern healthcare, with the potential to significantly enhance diagnostic accuracy, efficiency, and patient outcomes. These systems enable clinicians to access and analyze vast amounts of medical data rapidly, offering informed, data-driven recommendations that support precise diagnosis and effective treatment planning (Kumar *et al.,* 2022). By uncovering hidden patterns and correlations in complex datasets often beyond human capability AI technologies provide critical insights into conditions that may otherwise go undetected (Venerito *et al.,* 2022; Sallam, 2023).One of the most compelling advantages of AI in healthcare is its ability to reduce routine workload, allowing healthcare professionals to devote more time to patient-centered care (Park & Kim, 2022; Iluno and Nwaogwugwu, 2025). Additionally, AI can alleviate clinical burden, reduce the risk of human error, and contribute to more consistent healthcare delivery (Alder *et al*., 2020). By streamlining diagnostic processes and minimizing resource wastage, AI tools can also help lower healthcare costs (Xu *et al*., 2021; Li *et al*., 2023), while improving the precision of diagnoses and the effectiveness of treatments.

Moreover, AI-driven decision support systems can enhance early detection of potential health issues, optimize the use of healthcare resources, and promote timely interventions thereby improving overall clinical outcomes (Thomason, 2021; Dong *et al.,* 2021). These tools can provide customized treatment recommendations, monitor patient progress, and assist in identifying high-risk cases with impressive accuracy (Lin *et al*., 2022; Al-Hilli *et al*., 2023). As a result, healthcare providers can deliver personalized, timely, and effective care while also addressing systemic inefficiencies.

Despite the immense potential of these systems, their integration into healthcare requires further research, strategic funding, and collaborative efforts among medical professionals, AI developers, and policymakers. A focus on addressing security vulnerabilities, data privacy, and ethical use is also essential. Ultimately, AI-powered diagnostic decision support systems hold the promise of revolutionizing healthcare by making it smarter, faster, and more efficient. Their implementation will empower healthcare professionals to prioritize critical clinical decisions and improve patient care leading to better health outcomes and saving more lives.

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