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SoK: Security and Privacy Risks of Healthcare AI

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Abstract

The integration of artificial intelligence (AI) and machine learning (ML) into healthcare systems holds great promise for enhancing patient care and care delivery efficiency; however, it also exposes sensitive data and system integrity to potential cyberattacks. Current security and privacy (S&P) research on healthcare AI is highly unbalanced in terms of healthcare deployment scenarios and threat models, and has a disconnected focus with the biomedical research community. This hinders a comprehensive understanding of the risks that healthcare AI entails. To address this gap, this paper takes a thorough examination of existing healthcare AI S&P research, providing a unified framework that allows the identification of under-explored areas. Our survey presents a systematic overview of healthcare AI attacks and defenses, and points out challenges and research opportunities for each AI-driven healthcare application domain. Through our experimental analysis of different threat models and feasibility studies on under-explored adversarial attacks, we provide compelling insights into the pressing need for cybersecurity research in the rapidly evolving field of healthcare AI.

1 Introduction

Growing Market of Healthcare AI. As technology advances, software systems play an increasingly vital role in commercial products and are becoming integral in the medical field [135]. The development of AI/ML has transformed modern healthcare systems, providing valuable new insights obtained from the vast amount of data collected through patient diagnostics, monitoring, and healthcare research [138]. It was predicted that the global healthcare AI market would reach 188 billion U.S. dollars by 2030 [166]. Approximately 22% of healthcare organizations worldwide stated that they were in the early stage of AI model adoption, while 24% reported being in the pilot stage [165]. A recent survey indicated that 44% of people globally are open to using AI in healthcare for diagnostic and therapeutic purposes [167]. These highlight the significant benefits of improved diagnostic accuracy and treatment precision for patients, as well as the potential to allow healthcare practitioners to devote more time to patient care instead of routine administrative tasks.

Gaps in Healthcare AI S&P Research. While healthcare AI research has received unprecedented attention among biomedical communities, there is a limited amount of understanding of the adversarial robustness of this technology in the context of medical applications. Among all the papers we surveyed from both computer science venues (including security and AI/ML venues) and biomedical venues, there is a limited amount of research work focusing on these systems, with roughly 10-20 publications each year (Figure 1). Besides the difference in research volume, there is also a disconnect between the security and the biomedical community in the assumed threat models and technologies under study. Given the increasing role AI plays in delivering healthcare solutions, we aim to identify this gap and contextualize the risks of AI applications in different healthcare sub-domains.

Our Methodology. To understand the most pressing research need for healthcare AI, we surveyed 3,162 articles in the past 5 years in major medical journals (including but not limited to Nature, Science, Cell, Lancet, and New England Journal of Medicine). Drawing from this exercise, we developed the systematization of healthcare application of AIs, based on which, it then becomes possible to contextualize the threat model for the analysis of the security works. To understand the current state-of-the-art of security and privacy for healthcare AI, we collected 101 articles from both the security venues (IEEE S&P, USENIX Security, ACM CCS, etc.) as well as the AI venues (NeurIPS, AAAI, CVPR, etc.) in the past 10 years (See Appendix A). Building on these articles, we not only systematize the common threat models, but also create a taxonomy of existing attacks and defenses based on the healthcare application domains (Table 1 and Table 2). Through this exercise, we highlight areas where there is limited understanding, and discuss future directions to safeguard these lifesaving technology. To test our findings

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regarding research opportunities in under-explored domains, we conducted proof-of-concept validations with attack experiments considering realistic threat models in healthcare.

Our Findings. Our systematization reveals several interesting insights into the current state of S&P research in healthcare AI. First, the current research is skewed toward certain threat types. For example, 43.8% of surveyed studies focused on adversarial examples for evasion attacks, while only 8.2% addressed issues related to AI model availability. Furthermore, the healthcare domain being studied is highly unbalanced. 41.1% of healthcare AI S&P research focused on image-related diagnostic tasks, while other application domains, such as disease risk prediction, are largely overlooked (2%). Another emerging trend is the rapid rise of generative AI in healthcare research, which has gained increasing attention in the biomedical community since 2020. Although generative models raise new security risks for healthcare providers, the security community has largely overlooked these concerns (Appendix B). These gaps point to numerous opportunities for future research, underscoring the need to extend security and privacy investigations into a broader range of healthcare AI application domains.

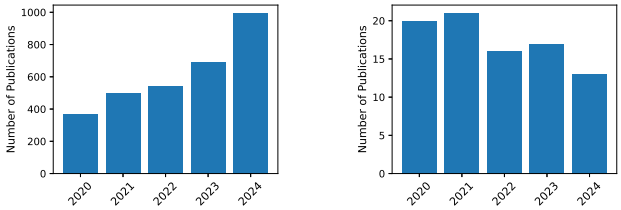
Contributions. While there have been works systematizing AI/ML research in network intrusion detection [116], security applications [6], explainability [119], accountability [17], and privacy [145], a unified view on the topic in healthcare settings is not yet available. To bridge the gaps, we aim to present a systematic survey unifying existing works and propose a comprehensive framework that helps shed light on challenges and opportunities for future research. Our SoK makes the following contributions:

- We contextualize traditional AI attack threat models with the healthcare setting, providing a taxonomy of threats in healthcare, including common adversarial identities, knowledge, capabilities, and goals. (§2)
- We provide a comprehensive systematization of current S&P research on healthcare AI in various application domains, pointing out challenges and opportunities for future research. (§3 - §7)
- We conducted proof-of-concept validation of research opportunities with tailored attack experiments in diverse under-explored healthcare domains. We specifically sought to explore the S&P risks of generative AI in healthcare, along with traditional ML methods and deep neural networks (DNN), through experiments to validate the reasoning of our insights. (§8)

2 Taxonomy of Threats in Healthcare

2.1 Adversarial Identity

We identify the adversary's potential identity in the healthcare domain and their respective motivations. However, it should be noted that in the real world, multiple adversaries can work together to achieve malicious intent. Their adversarial capability and knowledge may, therefore, be expanded and need to be discussed case-by-case.



(a) Biomedical (b) Security

Figure 1: Number of healthcare AI publications from the biomedical and security community in the past five years.

Patient. Patients generally would not have access to healthcare systems that employ ML algorithms. However, except for data that come directly from hospital measurements, there are cases where they are provided by the patients themselves, especially with the rise of telemedicine. Such patient-provided healthcare data is vulnerable to manipulation [62]. Malicious patients can be motivated to generate false-negative diagnostic results to avoid social stigma associated with certain medical conditions or generate false-positive results to receive higher priority on surgery waitlists.

Healthcare Practitioner. Healthcare practitioners include clinicians, nurses, or any other person working at or near the point of care. Healthcare practitioners usually have only black-box access to the healthcare AI systems. Since their main task is to obtain prediction results from the models, compared to the patients, they have the added capabilities of query access and testing data control. Malicious healthcare practitioners can be motivated to manipulate model outputs to incur additional expenses for unnecessary treatments. They may also conduct healthcare insurance fraud, such as phantom billing, which bills services or supplies that the patients never actually received [80]. For example, the U.S. Department of Justice recently charged 193 defendants, including 76 doctors, nurse practitioners, and other medical professionals across 32 federal districts in a healthcare fraud scheme that resulted in $1.6 billion in actual losses [122].

ML Service Provider. Hospitals may opt for cloud-based ML service instead of on-site deployment to minimize investments in hardware and related IT infrastructures [53]. Adversarial service providers are typically considered honest-but-curious [10, 12] by the community, and may have capabilities that range from training data control to model control. This implies that while model integrity is presumed intact, confidentiality may be at risk.

Third-party Healthcare Organization. The profit and service of organizations such as healthcare insurance companies may depend directly on the outcome of healthcare AI predictions. These organizations may have the highest monetary

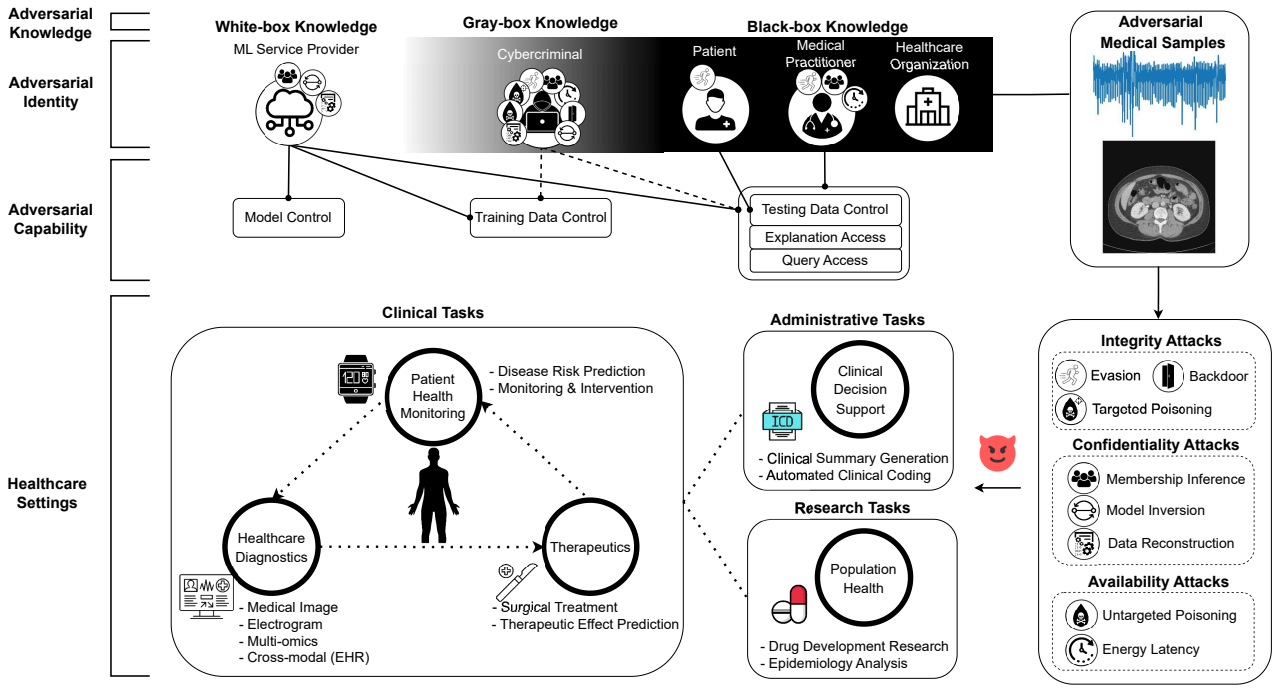


Figure 2: Adversarial knowledge, capability, and goals based on adversary's identity in the healthcare setting.

incentives to manipulate healthcare AI [80, 176]. They typically have limited capability, knowledge, and access to the models, and are more likely to work with other adversaries.

Cybercriminal. Cybercriminals' roles in healthcare AI attacks largely mirror those seen in traditional threat models. Although they typically lack direct model or training data control, they often exploit known vulnerabilities in common healthcare systems, such as Picture Archiving and Communication Systems (PACS) [31] and legacy OSes (e.g., Windows XP or unpatched Windows Server) that are still in use by many hospitals [44] to deploy ransomware [110]. In addition, cybercriminals could use social engineering and spear-phishing to install malware, which is what prevents Illinois hospitals from submitting insurance claims to Medicaid, complicating their finances [35]. Through these methods, they can hamper or shut down AI diagnostic systems, poison training data, or steal patient information.

2.2 Adversarial Capability

Training Data Control. Adversaries may gain partial control over the training data, enabling them to insert or modify training samples. This is a foundational strategy in data poisoning attacks. Particular to clean-label attacks is the constraint on label manipulation, where adversaries can not assign labels to the poisoned samples, unlike regular poisoning attacks that assume label control over poisoned samples.

Model Control. Adversaries may take control of the model parameters through various means, such as embedding a Trojan trigger within the model parameters or executing malicious updates in federated learning scenarios.

Testing Data Control. At the model deployment stage, attackers can introduce perturbations to testing samples. This is required for evasion and backdoor poisoning attacks.

Query Access. Adversaries can query the model for predictions, which can include both labels and confidence scores. This capability is required for black-box evasion attacks, energy latency attacks, and various privacy attacks.

Explanation Access. This capability is especially related to healthcare systems that employ explainable ML. Adversaries who obtain access to the explanations generated by these tools can exploit this information not only to undermine the integrity of the explanations themselves but also to enhance the effectiveness of other attacks.

2.3 Analysis of Adversarial Goals

Integrity Attacks. Patients, healthcare practitioners, and cybercriminals may have motivations to engage in evasion attacks. These usually execute attacks in black-box scenarios (*i.e.*, score-based and decision-based attacks) or gray-box scenarios (*i.e.*, using auxiliary datasets and models) [18]. Model poisoning, where malicious functionality is embedded directly into the model, is typically executed by ML service providers to facilitate further privacy breaches. Targeted poisoning, backdoor poisoning, and clean-label attacks assume control over a portion of the training data, achievable by cybercriminals who have gray-box or black-box knowl-

edge to maliciously impact service operations [148].

Confidentiality Attacks. Typically in confidentiality attacks, the adversary's knowledge consists of aspects such as the training algorithm, model architecture, model parameters, training data, training data distribution, and the number of training samples. A prevalent assumption in privacy inference attacks is the adversary's familiarity with the target model architecture and possesses an auxiliary dataset derived from a distribution identical to that of the target model's training dataset. Within this threat model, both the ML service provider (white-box knowledge) and cybercriminals (gray-box knowledge) can compromise sensitive information associated with the target model (*i.e.*, model privacy attacks [49]) and its training data (*i.e.*, data privacy attacks [14] with personal health information).

Availability Attacks. The primary category of availability attacks employs poisoning strategies to *indiscriminately compromise the performance of entire machine learning models*. These attacks assume control over the training data and are predominantly executed by cybercriminals aiming to disrupt services. Consequently, these attacks typically operate with gray-box or black-box knowledge. A notable technique in gray-box settings involves the concept of transferability, where an auxiliary model is used to generate poisoning samples that aim to degrade the target model's overall performance [42, 171]. Since model poisoning assumes control over the model, it is generally not feasible for cybercriminals. The second category is *energy-latency attacks* [94], which requires either white-box or black-box access to the target model. Instead of output accuracy, cybercriminals can induce excessive energy consumption and/or increase inference latency, disrupting normal operation.

2.4 Framework for Under-explored Attacks

Under-explored attacks in healthcare can serve as potential future research directions. We aim to develop a framework that identifies areas where future research is feasible. We categorized attack feasibility across two dimensions: the technical barrier and the threat model. The technical barrier determines whether an attack can succeed in a specific scenario, while the threat model determines the effectiveness of the attacks. Due to notable differences in data and models, we analyze each healthcare sub-domain separately.

To determine whether an attack can succeed in under-explored scenarios, we drew on existing research in analogous domains where data and models exhibit similar characteristics (Table 1). For instance, if an attack has been done in medical image classification, it is likely to succeed in medical image detection due to task/modality similarities. If an attack assuming stronger adversarial capabilities within the same domain is present, it also suggests the feasibility of easier attacks. For example, if data reconstruction attacks are successful, we can predict that membership inference attacks will achieve a similar level of success in the same domain. However, this is merely a hypothesis that should be validated through experiments (§8).

3 Healthcare Diagnostics Systems

Healthcare AI in patient diagnostics is rapidly revolutionizing the medical field, with AI-driven tools capable of detecting subtle patterns in medical images, genetic data, and patient records at or above the level of experienced clinicians. However, with the involvement of various forms of patient data also comes security and privacy concerns. In this section, we discussed diagnostics AI that takes different data modalities as inputs, including images (§3.1), electrograms (§3.2), multi-omics data (§3.3), and cross-modal data (§3.4).

3.1 Image Diagnostics

State-of-the-art AI Applications. Healthcare AI for image diagnostics often performs tasks in various fields of medicine. These tasks are often categorized into *classification*, *detection*, and *segmentation* in the biomedical literature. In healthcare, classification tasks separate medical images into categories according to the type of image or the presence of different conditions for a specific disease [55]. Detection tasks involve establishing spatial localization of regions of interest in medical images [87, 149, 197]. Finally, segmentation tasks focus on grouping at a pixel or voxel level for a given image type [65, 179].

Attacks on Medical Image *Classification*. Many prior works have explored adversarial examples targeting medical image classification systems in both white-box and black-box settings [48,99,127]. For instance, Ma et al. [99] demonstrated 4 different untargeted white-box classification evasion attacks on 5 distinct medical datasets. Data poisoning [76, 103, 115, 161] and backdoor attacks [47, 71, 120] are also widely explored. Nwadike et al. [120] attacked a multi-label disease classification system using chest radiography, assuming attackers have training data control. They showed that ML explainability can be leveraged to identify such backdoor attacks during testing time. In AI confidentiality, Gupta et al. [56] demonstrated membership inference attacks with centralized and federated training schemes for brain age prediction from MRIs. Moreover, Jin et al. [71] attacked MedCLIP, a contrastive learning-based medical foundation model designed using unpaired image-text training. They showed that backdoor adversaries can diminish model performance with both targeted and untargeted attacks.

Attacks on Medical Image *Detection*. Mangaokar et al. [101] proposed Jekyll, which was able to transfer chest X-ray or retinal images into one that can be misdiagnosed as having an attacker-chosen disease. Meanwhile, Yao et al. [193] performed evasion attack on cephalometric landmark detection. Sun et al. [172] proposed data poison-

Table 1: Systematization of existing integrity, confidentiality, and availability attacks in the healthcare setting.

			Integrity			Confidentiality			Availability
			Evasion	Poison	Backdoor	Membership Inference	Model Inversion	Data Reconstruction	
Healthcare Diagnostics	Image Diagnostic	Classification	□ [99] ■ [18, 209] ■ [127] □■ [43, 48] □ [143]	[103] ■ [115, 161] [76]	■ [47, 120] □ [71]	□■◧ [56]	■ [184]	◐	■ [174] □ [71]
		Detection	■ [101] ■ [193]	■ [172]	■ [47] □ [104]	○	○	◐	○
		Segmentation	■ [125, 155] □■ [43, 182]	○	■ [47]	◧ [30]	◧ [170]	◐	■ [92]
	Electrogram Diagnostics		□ [59, 124] ■ [4] ■ [25, 85]	□ [66]	◐	○	○	◧ [1]	□ [66]
	Multi-omics Diagnostic		■ [113, 162] □■ [52]	○	□ [148]	□ [27] ◧ [57]	○	◧ [14, 126]	○
	Cross-modal Diagnostic		[173] □◧ [5]	○	[73]	■ [206]	○	◧ [184]	○
Clinical Decision Support	Clinical Summary Generation		■ [7] □■ [46, 180]	■ [39]	□ [39]	■ [109] □■ [67] ◧■ [64]	◧ [117]	◧ [88]	○
	Automated Clinical Coding		□ [132]	?	?	◧ [147]	◐	◐	?
Therapeutics	Surgical Treatment		?	?	?	●	●	●	◐
	Therapeutic Effect Prediction		■ [111] ■ [24]	□■ [68]	◐	○	■ [49]	?	□■ [68]
Population Health	Drug Development Research		◐	◐	?	●	●	●	[144]
	Epidemiology Analysis		□ [107]	◐	?	◐	?	?	◐
Patient Health Monitoring	Disease Risk Prediction		■ [77, 195]	?	?	?	?	?	?
	Monitoring & Intervention		□■ [118]	□ [153] □■ [118] ■ [172]	◐	?	?	?	○

□ white-box knowledge, ◧ gray-box knowledge, ■ black-box knowledge, training data control, testing data control, model control, query access, explanation access, ○ attack feasible but not done in prior work, ◐ attack possible but not done in prior work, ● attack with impractical or unrealistic threat model, ? not enough information to conclude

ing attack against federated learning models and demonstrated their attack feasibility using the Endoscopic Image Abnormality Detection (EndAD) dataset. Finally, Matsuo et al. [104] and Feng et al. [47] demonstrated backdoor attacks against COVID-19 detection and across a wide application domain of medical image diagnostic systems, respectively.

Attacks on Medical Image *Segmentation*. Unlike adversarial examples in classification tasks that target a single class, adversarial targets in medical image segmentation are masks and involve optimizing many individual pixels in the generation process [125]. Feng et al. [47] considered the adversarial robustness of medical image segmentation against backdoor attacks on KiTS-19, a tumor segmentation dataset of kidney organ and tumor CT images. Chobola et al. [30] bridged the gap in existing studies on membership inference attacks against semantic image segmentation. Meanwhile, Subbanna et al. [170] analyzed the susceptibility of U-Net and SegNet against model inversion attacks on 3D brain MRI scans. Finally, Lin et al. [92] proposed unlearnable medical image generation (UMed). They aim to inject contour- and texture-aware perturbations into medical image segmentation datasets to prevent unauthorized training, effectively using AI availability attacks as a privacy defense.

Challenges & Research Opportunities. Though no work that compromised the confidentiality or availability of medical image detection systems was found, we conjecture that these are feasible given existing attacks in classification and segmentation tasks. One challenge with defending image diagnostic AI is the involvement of multiple image modalities, digitization protocols, and population samples during the diagnostic procedures [181, 198]. While medical image diagnostics AI has been extensively studied by prior attack and defense research [43, 72, 185, 208], they are often highly specialized and have limited generalizability even within the same data modality. Furthermore, dataset biases have been demonstrated across multiple image diagnostic domains [178], and research on certain data modalities (such as X-ray images) are much higher than the others. One key implication for future research observed from this challenge is the development of suitable foundation models that can generalize with and across modality and datasets, which has been started in recent years [141, 181].

3.2 Electrogram Diagnostics

State-of-the-art AI Applications. Electrograms are used to record and visualize electrical activity within the body. ML methods have been involved in diagnosing arrhyth-

Table 2: Defense research on healthcare AI.

ID	Defense Type: Int.	Conf.	Avail.	Exp.	Data Modality	Healthcare Domain	Ref.
D1	•	-	-	-	Genomic Data	Multi-omics Diagnostics	[68]
D2	•	-	-	-	Lung CT	Medical Image Detection	[185]
D3	•	-	-	-	Brain MRI	Medical Image Segmentation	[199]
D4	•	-	-	-	Electrogram	Electrogram Diagnostics	[154]
D5	•	-	-	•	Chest X-Ray, EHR	Cross-modal Diagnostics	[183]
D6	•	-	•	-	Fundus Image	Medical Image Segmentation	[205]
D7	•	•	-	•	Network Traffics	Monitoring & Intervention	[159]
D8	•	-	•	-	Chest X-Ray, Dermoscopic Image	Medical Image Classification	[188]
D9	•	-	-	-	Brain MRI, Chest X-Ray, Histological Image	Medical Image Classification	[192]
D10	•	-	-	-	Fundus Image	Medical Image Classification	[84]
D11	•	-	-	-	Chest X-Ray, Dermoscopic Image	Image Diagnostics	[72]
D12	•	-	-	-	Lung CT, Brain MRI, Mammogram	Image Diagnostics	[74]
D13	-	•	-	-	Genomic Data	Multi-omics Diagnostics	[12]
D15	-	•	-	-	Electrogram	Electrogram Diagnostics	[1]
D14	-	•	-	-	Motion Sensor	Monitoring & Intervention	[19]
D16	-	•	-	-	Body Measurements	Therapeutic Effect Prediction	[189]
D17	-	•	-	-	Contact Patterns	Epidemiology Analysis	[140]
D18	-	•	-	-	Text Data, EHR	Cross-modal Diagnostics	[187]
D19	-	•	-	-	Image Data	Medical Image Classification	[175]
D20	-	•	-	-	EHR	Theorapeutic Effect Prediction	[40]
D21	-	•	-	-	Chest X-Ray, Histological Image	Medical Image Classification	[208]
D22	-	•	-	-	Fundus Image	Medical Image Classification	[129]
D23	-	•	-	-	Chest X-Ray	Image Diagnostics	[190]
D24	-	•	-	-	EHR	Cross-modal Diagnostics	[32]
D25	-	•	-	-	EHR	Cross-modal Diagnostics	[139]
D26	-	•	-	-	Image Data	Image Diagnostics	[174]
D27	-	•	-	-	Genomic Data	Multi-omics Diagnostics	[27]
D28	-	-	•	-	Genomic Data	Multi-omics Diagnostics	[207]
D29	-	-	-	•	Brain MRI	Medical Image Classification	[160]
D30	-	-	-	•	Electrogram	Electrogram Diagnostics	[105]
D31	-	-	-	•	Lung CT, Chest X-Ray, Knee MRI	Medical Image Classification	[58]
D32	-	-	-	•	Image Data	Medical Image Segmentation	[37]

Genomic Data, Lung CT, Brain MRI, Knee MRI, Electrogram, Chest X-Ray, EHR, Fundus Image, Dermoscopic Image, Histological Image, Mammogram, Text Data, Image Data, Int. = Integrity, Conf. = Confidentiality, Avail. = Availability, Exp. = Explainability

mias [34, 60] with electrocardiograms (ECG), schizophrenia with electroencephalograms (EEG) [157], neuromuscular disorder diagnostics [169] with electromyograms (EMG), and sleep stage classification [131] with electrooculograms (EOG). Notably, Kiranyaz et al. [79] was the first to use DNN over 1D signals, particularly for ECG classification tasks.

Existing Attacks. Prior work mostly focused on adversarial attacks with ECG [1,25,59,66,85,124]. For instance, Chen et al. [25] added imperceptible perturbations to patient's ECG such that the arrhythmia classification system outputs incorrect diagnostics. Ismail et al. [66] applied both targeted and untargeted data poisoning attacks against SplitFed Learning (SFL) models, which is a combination of split learning and federated learning. Their attack on ECG classification tasks showed a significant performance impact on classification accuracy. Abuadbba et al. [1] explored whether split learning retains its privacy-preserving capability on 1D CNN models for ECG classification. They concluded that such adaptation would result in a high probability of privacy leakage and even the reconstruction of raw time-series/sequential data.

3.3 Multi-omics Diagnostics

State-of-the-art AI Applications. Multi-omics diagnostics analyzes data from various -omics sources, including genomics, metabolomics, proteomics, etc. ML can be applied to multi-omics diagnostic to improve the detection and classification of various diseases [63]. When considering early cancer detection, multi-omics data can include information about mutations, gene expression, and copy number variation [150]. Meanwhile, multi-omics approaches can also be used to more accurately classify chronic kidney disease. By operating ML on molecular data composed of kidney biopsy, blood, and urine samples, Eddy et al. [45] classified patients into molecularly defined subgroups that better reflect the underlying mechanisms associated with the disease.

Existing Attacks. Recent work has explored the vulnerability of genomics-related diagnostic pipelines against evasion attacks [113, 162]. Ghaffari et al. [52] also evaluated the susceptibility of CNN models in computational pathology, and proved that vision transformers (ViTs) are inherently more robust against input perturbations. On the other hand, Sarkar et al. [148] repurposed backdoor attack to detect bias in genomic datasets. Their threat model involves a benevolent cloud collaborator, whose goal is to identify biased information in the dataset without hampering the predictive model's performance. Notably, the emerging genomic datasets have also shown vulnerability against membership inference attacks [12, 57] and genome reconstruction attacks [14, 126], particularly with the rise of genomic beacons [11].

3.4 Cross-modal Diagnostics

State-of-the-art AI Applications. Electronic health records (EHRs) store patient records digitally and contain various data modalities to support efficient retrieval of patient information. Traditional medical expert systems often employ feature-level fusion or rule-based reasoning, with performance significantly affected by subjective expert-defined rules that cannot be dynamically updated. Especially for multi-source, multi-modal healthcare data, these fall short of offering integration, reasoning, and interactive decision support. Meanwhile, cross-modal AI employs a multi-network link or network reconstruction based on DNN with feature coupling [98], extracting high-level features from the original data's bottom-up representation. This helps achieve intellectual auxiliary support in complex in-hospital scenes. Often, entity mining is used to realize semantic perception and correlation mining to support data fusion [78].

Existing Attacks. Prior work has shown that EHR diagnostic systems can be susceptible to adversarial attacks [5, 173]. For instance, Sun et al. [173] attacked LSTM models that take EHR as input to identify susceptible fields in a patient's EHR. Joe et al. [73] injected a backdoor into ML models that decide whether a patient should be admitted to the Intensive Care Unit (ICU). They pointed out that the backdoor triggers needed to reflect the heterogeneity and multimodality of EHR to be imperceptible. Zhang et al. [206] performed membership inference attack against synthetic EHR data, a promising solution that balance patient privacy and health data sharing. They showed that partially synthetic EHRs are still susceptible to privacy leakage, while fully synthetic ones may be sufficient to defend against membership inference.

Challenges & Research Opportunities. Healthcare AI using electrograms as inputs faces challenges in handling multivariate time-series data, needing to consider the integrity, confidentiality, and explainability of spatial and temporal features [1, 105, 154]. Meanwhile, multi-omic data are usually more structured, albeit coming from various sources and data acquisition technologies [207]. While healthcare AI may benefit patients and physicians, it inevitably introduces complexity and new attack vectors to infrastructure that is already difficult to secure. Emerging cross-modal healthcare AI has prompted notable research directions focusing on data privacy [32, 139, 187], leveraging the power of generative models to produce synthetic data [72, 129] and expandability for adversarial detection [183]. Policies must be updated alongside technological advancement, as current initiatives for high-quality reporting of healthcare AI (e.g. TRIPOD or CONSORT-AI) do not require any model security analysis [36, 96].

4 Clinical Decision Support

The emergence of language models has enabled administrative tasks that support clinical decisions, such as *creating discharge summaries* [8] from or *assigning ICD-10 structured codes* [69] to hand-written healthcare records, which require named-entity recognition [202] or relation extraction [204] but with minimal need for problem-solving skills. However, similar to images, the integrity and confidentiality of textual data may be compromised by adversaries as well.

Attacks on *Clinical Summary Generation*. Prior work has considered edit adversaries in clinical settings, where existing semantic and syntactic adversarial attacks on text data show vulnerability in state-of-the-art text-based healthcare AI, with the attacker having both black-box and white-box knowledge [7, 46, 180]. For data poisoning and backdoor attacks, Das et al. [39] performed both black-box and white-box clean-label attacks in the breast cancer clinical domain. There are also existing attacks targeting the confidentiality aspect of medical language models. Jagannatha et al. [67] and Mireshghallah et al. [109] both showed that pre-trained medical models such as ClinicalBERT can be susceptible to membership inference attacks. Meanwhile, Nakuma et al. demonstrated the feasibility of inverting these pre-trained models to extract name-disease pairs from clinical documents [117], and Lehman et al. [88] were able to reconstruct certain sensitive personal health information from them.

Attacks on *Automated Clinical Coding*. Raja et al. [132] leveraged imperceptible typo-based adversarial attack to downgrade the performance of clinical ICD-code prediction systems. The intuition is that clinical documents are often generated hastily and may contain more typos than regular documents. Sarkar et al. [147] explored the possibility of membership inference attack against ICD-coding classification. They demonstrated that simply de-identifying clinical notes for training may not be sufficient to guarantee patient privacy, yet it is possible to generate synthetic notes from the original data that maintains the performance of the classifier.

Challenges & Research Opportunities. Clinical texts often contain naturally occurring typos, misspellings, and abbreviations of medical terms [83, 128]. Research should consider the impact of various denoising strategies on adversarial manipulations when targeting healthcare AI that takes texts as input. As there exist clear definitions for ICD codes, the explainability of automated clinical coding systems is crucial. However, this may expose additional attack surfaces, which must also be taken into account.

5 Therapeutics

Besides diagnostics and administrative tasks, AI in intraoperative guidance [152, 210] and surgical robots [82, 93, 102] provide enhanced visualization and localization. Moreover, the emerging use of generative AI in healthcare has enabled the localization of bronchoscope in the lung even in less conserved regions [152]. For therapeutic prognosis, AI can assist in the estimation of treatment effects, which helps both patients and clinicians evaluate the effectiveness of current treatment plans [168, 211]. The following discusses the current threat landscapes on surgical AI and prognosis models.

Attacks on *Surgical Treatment*. Currently, no prior work has attacked AI for intraoperative guidance or surgical robots. While performing attacks is possible, surgical treatment AI may not be easily accessible by attackers or researchers. Even if access is granted or assuming black-box attacks, attackers need to consider the real-world realizability of adversarial input, especially for surgical robots that take in real-time inputs. Profit may also be minimal compared to the attacker's cost of sabotaging the system.

Attacks on *Therapeutic Effect Prediction*. Mondal et al. [111] proposed BERT-based adversarial example generation using domain-specific synonym replacement for biomedical named entities. Meanwhile, Hai et al. [24] leveraged model explainability and query access to craft adversarial examples from drug review datasets. For confidentiality attacks, Fredrikson et al. [49] performed model inversion to infer patient genotype by repurposing warfarin dosing pharmacogenetic model, assuming the adversary has partial knowledge of the training dataset and the target individual.

Challenges & Research Opportunities. Few prior work have explored AI's application in surgical treatments. Recently, digital twin technology has emerged as a promising solution for computer-assisted surgery for its ability to provide real-time feedback [9, 40]. While surgical AI may be similar in input as image diagnostics in addition to positional data, defending such applications with real-time constraints requires solutions to be lightweight and

should not affect the system's responsiveness. Meanwhile, prognostic models may be rejected by physicians due to a lack of trust in outputs [177]; this has led to an increase in model explainability through methods like feature importance (SHAP scores) and textual explainability (captioning), as well as strategies that address privacy concerns of patients [40, 189].

6 Population Health

In addition to individual patient care, healthcare AI has contributed to population-level causes. This is evident in drug development research, including target identification [114], drug discovery [123, 151], and drug-drug interaction (DDI) [13], where the abundant availability of drug-related information from biomedical texts, EHRs, and public databases provides fertile ground for literature-based extractions [156, 186]. Meanwhile, predictive models based on chemical and biological knowledge are useful in treating DDI as a link prediction task [191], detecting the presence or absence of interactions between drug pairs. On the other hand, healthcare AI can help monitor epidemiological incidences [15, 20, 20]. AI used for pandemic early warning, such as HealthMap [50], can compile web texts for indications of infectious disease occurrences [20]. The data gathered can also be used for real-time outbreak analysis [15] or integrated into healthcare IoT devices for real-time infection identification [2]. For these systems, any compromise in input integrity can have immediate public implications, and we describe these attacks as follows.

Attacks on *Drug Development Research*. Predatory research [137] has become a problem for healthcare AI that explores drug discovery or extracts DDI information from published literature. Though the work of Saini et al. [144] did not involve training from the polluted data, they demonstrated that predatory science can indeed affect the performance of state-of-the-art DDI systems. We conjecture that it is very likely for poisoning attacks to target a specific drug or medical condition, which warrants future work. As data relevant to DDI are often public and seldom involve personal information, confidentiality is unlikely to be targeted.

Attacks on *Epidemiology Analysis*. Meiseles et al. [107] performed adversarial evasion attacks on an open-sourced viral lineage assignment model for SARS-CoV-2 lineage assignment. The attack perturbs the genomic sequences in the COVID-19 genome FASTA file, causing incorrect lineage assignment that hampers public health management. This is the only adversarial attack on epidemiological ML.

Challenges & Research Opportunities. One challenge for AI in population health management is the extremely imbalanced data due to the localization of infected individuals or sampled populations [33, 89]. A few maliciously modified samples can disproportionately affect the model's behavior toward the underrepresented classes. Overfitting to the training data can also potentially make inference attacks easier, and requires strategies such as differential privacy to guarantee confidentiality [140]. From the perspective of defenses, addressing dataset imbalance and achieving fair models should be a research priority to avoid attacks targeting underrepresented populations.

7 Patient Health Monitoring

Finally, prior research efforts have been dedicated to predicting disease—particularly cancer—susceptibility [108], survivability [38], occurrence [130], and reoccurrence [81], taking into account a person's genomic information, inheritance, lifestyle, and other relevant traits. Systems using AI to analyze personal lifestyles and provide appropriate interventions in non-hospital settings also offer a convenient and less intrusive way for individuals to manage their health [112]. While privacy and real-time responsiveness of these systems are significant, prior attacks in this domain primarily focused on compromising the integrity of system outcomes.

Attacks on *Disease Risk Prediction*. For evasion attacks, Ye et al. proposed MedAttacker [195], showing that the accuracy of clinical risk prediction systems can be influenced by maliciously replacing certain codes in EHR. Karim et al. [77] also conducted an untargeted black-box attack against a cancer susceptibility system that uses multi-omics data for prediction. To the best of our knowledge, there is currently no prior work exploring attacks targeting risk prediction systems in the confidentiality and availability domain.

Attacks on *Monitoring & Intervention* Systems. Existing attacks primarily fall into the AI integrity domain, where Newaz et al. [118] conducted white-box and black-box evasion and poisoning attacks against ML-based smart healthcare systems, and Shahid et al. [153] explored white-box label flipping attacks against wearable human activity monitoring devices. Both assumed that attackers have access to training data and can perform malicious manipulations. No work on confidentiality and availability attacks were found.

Challenges & Research Opportunities. AI in patient health monitoring generally deals with data collected over time and may also need to respond to patient conditions in real time [3]. Future research needs to account for the data's temporal dependencies, as well as attack transferability to and defense usability on different monitoring devices. For AI involved in critical life monitoring and intervention tasks, merely detecting malicious behavior is not enough. It is necessary to have strategies in place for prompt system recovery to ensure patient safety [159].

Table 3: The median, mean l_2 distortion and model accuracy for attacks under $\epsilon = 8/255$ (PGD) and $\epsilon = 3$ (C&W).

largely

Method	Median Distance	Mean Distance	Robust Accuracy
PGD Targeted	0.026	0.028	0.32
PGD Untargeted	0.012	0.014	0.05
C&W Targeted	2.731	2.899	0.37
C&W Untargeted	2.084	2.249	0.03

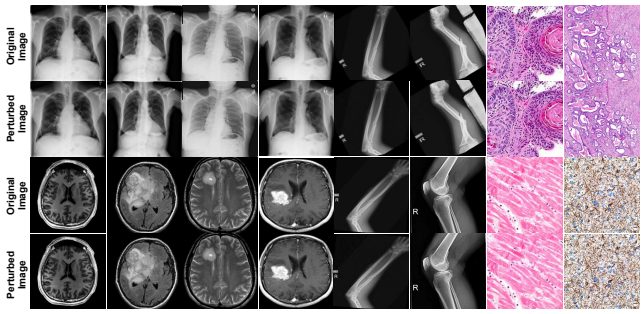


Figure 3: Visualization of original and adversarial images.

8 Under-Explored Attacks in Healthcare AI

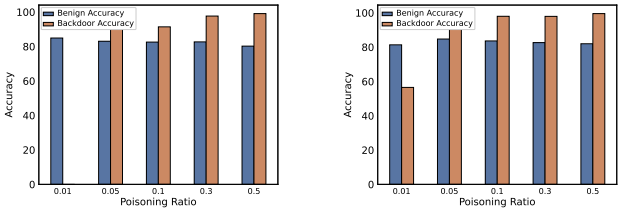
To validate the applicability of our framework to under-explored attacks, we conducted case studies examining four representative attack types across various healthcare subdomains and tasks. Aiming to shed light on newly arising vulnerabilities, we have investigated adversarial threats against emerging AI techniques applied in healthcare, including multi-modal biomedical foundation models (§8.1), federated learning (§8.2.2), and diffusion models (§8.4.1).

8.1 Evasion Attacks

Conjecture. The emergence of generative AI is revolutionizing healthcare, with one prominent example being the deployment of multi-modal foundation models. These models are increasingly being utilized to assist diagnostic processes by analyzing multi-modal healthcare data. While there is currently a lack of studies exploring the adversarial vulnerabilities of these models, we hypothesize that with a strong internal adversary, they remain susceptible to evasion attacks.

Threat Model. We assume the adversary to be a malicious ML service provider with white-box knowledge, having complete access to the target model's architecture, parameters, and gradients. Such an adversary may collaborate with healthcare practitioners to commit fraud, for instance, by manipulating diagnoses to misclassify healthy patients as ill to enable fraudulent insurance claims.

Datasets and Models. We targeted BiomedCLIP [203], a recent multi-modal biomedical foundation model trained on 15 million biomedical image-text pairs. Following the paper, we focused on biomedical image classification and selected images from the following categories: adenocarcinoma histopathology, brain MRI, squamous cell carcinoma histopathology, immunohistochemistry histopathology, bone X-ray, chest X-ray, and hematoxylin & eosin histopathology.



(a) Length Ratio 2% (b) Length Ratio 5%

Figure 4: Backdoor attack performance against ECG-based CNN with different trigger lengths and poisoning ratios.

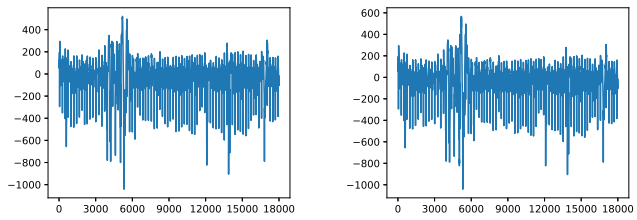
Experimental Setup. In line with existing studies on evasion attacks [26, 51], we selected 100 correctly classified test images for evaluation. We report the median and mean l_p distortion values across all adversarial examples, following [26, 29]. Additionally, we evaluated the model's robust accuracy under a given perturbation budget ϵ. Robust accuracy is determined as the proportion of adversarial examples whose minimum distortion magnitude exceeds ϵ. For the attacks, we selected PGD [100] (conducted in the l_∞ norm) and C&W attack [22] (performed in the l_2 norm). We fixed the text prompt and only added noises to the images.

Empirical Results. The results are shown in Table 3, which indicate that white-box adversarial attacks remain highly effective against multi-modal foundation models. For instance, under a perturbation budget of 8/255, the untargeted PGD attack reduces the model's accuracy to 0.05. Figure 3 provides examples of original and adversarial images, demonstrating the imperceptibility of the adversarial perturbations.

8.2 Backdoor Attacks

Conjecture. Backdoor attacks have been studied in time series data [70], which is similar to electrogram signals. Therefore, we hypothesize that backdoor attacks will also achieve decent performance against ECG diagnostics. Conversely, conducting attacks against disease risk prediction may be more challenging due to the input's heterogeneous nature.

Threat Model. We assume the adversary to be a cybercriminal who does not know the target model's architecture or weights, but has partial control over the training and testing data (for instance, by planting a computer virus in the data storage system). In a federated learning scenario, the adversary can only affect a subset of participating clients. We follow common settings in prior work [73, 104], where a trigger pattern is used to poison a subset of training data, then added to testing examples to exploit model operation.



(a) Normal Signal (b) Backdoored Signal

Figure 5: A backdoored signal that closely resembles a normal signal, demonstrating the stealthiness of the attack.

8.2.1 ECG Diagnostics

Attack Method. To pioneer the study of backdoor attacks on ECG data, we designed the trigger as a cosine waveform time series with a fixed amplitude and length. During the experiment, we fixed the amplitude to 25 and investigated the impact of the trigger's length on the performance.

Datasets and Models. We selected the widely used 2017 PhysioNet/CinC Challenge dataset [34]. The goal of the challenge was to classify single-lead ECG recordings into four types: normal sinus rhythm (Normal), atrial fibrillation (AF), alternative rhythm (Other rhythm), or noise (Noisy). The dataset contains single-lead ECG recordings collected using the AliveCor device, sampled at 300 Hz. In total, there are 8,528 recordings, with durations ranging from 9 seconds to over 60 seconds. We used a 13-layer CNN that won the 2017 PhysioNet/CinC Challenge [54] as our target model. This model has achieved a training accuracy of 98.57% and a testing accuracy of 85.08% on the target dataset.

Experimental Setup. We selected atrial fibrillation (AF) as the target label for targeted backdoor attacks, as transforming other labels into AF labels could potentially cause false alarms. For attack impact assessment, we varied two parameters: the fraction of poisoned data in the training set (0.01 - 0.5) and the trigger length (2% and 5% of the ECG recording length). We repeated the trial 5 times with the random generation of triggers and random subset selection and evaluated the accuracy of the benign and poisoned data.

Empirical Results. Figure 4 demonstrates that ECG diagnostic CNN is highly vulnerable to our proposed backdoor attacks. With a trigger length that is only 2% of the recording length and a poisoning ratio of 0.05, backdoor accuracy reached 97.67% without significantly affecting the benign accuracy. In the normal setting, the accuracy is 85.08%, while the benign accuracy drops only 2% (83.05%). Furthermore, backdoor performance improves with increased poisoning ratio and trigger length. When the trigger length ratio is 2% and the poisoning ratio is 0.01, backdoor accuracy is 0%. However, when the poisoning ratio is 0.1 and the length ratio is 5%, backdoor accuracy reaches nearly 100%.

Table 4: Performance of backdoored FL-based ECG diagnostics models with varying client and data poisoning ratios.

Client Poi. Ratio	Data Poi. Ratio	Benign Accuracy	Backdoor Accuracy
0.2	0.1	0.631	0.228
0.2	0.2	0.603	0.423
0.2	0.4	0.630	0.603
0.3	0.1	0.711	0.242
0.3	0.2	0.706	0.339
0.3	0.4	0.664	0.654
0.5	0.1	0.639	0.170
0.5	0.2	0.611	0.479
0.5	0.4	0.610	0.710

8.2.2 Federated Learning-based ECG Diagnostics

Federated learning (FL) has emerged as a promising approach for developing high-performance models using distributed medical datasets across multiple institutions while preserving patient privacy and data confidentiality. As FL systems become more widespread, it is important to investigate their potential vulnerabilities to backdoor attacks.

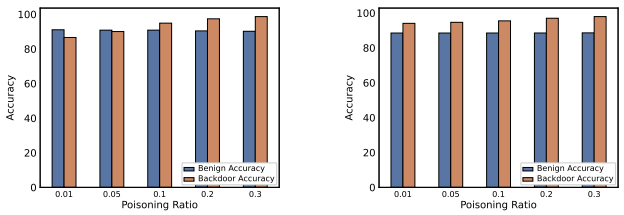
Experimental Setup. We followed §8.2.1, using the same datasets, models, and attack methods. For the FL implementation, we configured a system with 100 clients. During each communication round, 20% of the clients were randomly selected for training. Each selected client performed two local updates with a batch size of 32. The training process consists of 100 global rounds, and we adopted FedAvg [106] as the aggregation protocol. We varied the local data poisoning ratio in each client and the client poisoning ratio, and analyzed the accuracy on normal and backdoor tasks.

Empirical Results. The empirical results are shown in Table 4. As observed, varying the client poisoning ratio and data poisoning ratio results in only a modest drop in benign accuracy. For instance, the accuracy with clean data is 0.702. When the client poisoning ratio is 0.3 and the data poisoning ratio is 0.4, the benign accuracy decreases to 0.664, representing a drop of 0.038. Conversely, as the client poisoning ratio and data poisoning ratio increase, the backdoor accuracy consistently rises. Even under low poisoning ratios, the achieved backdoor accuracy is sufficient to cause severe impacts on FL-based ECG diagnostic models.

8.2.3 Disease Risk Prediction

Attack Method. Inputs for disease risk prediction are heterogeneous, containing both continuous and categorical variables, which require different handling. Relying on existing approaches in image domain attacks, such as Gaussian white noise, is impractical because such backdoored data could be easily detected due to unrealistic patterns. For example, a patient's sex and height should not change over time during the ICU stay, while blood pressure can vary. To address this, we design our trigger as additive Gaussian perturbations applied only to those changeable numerical features.

Datasets and Models. We utilized the widely used Medical Information Mart for Intensive Care III (MIMIC-III)



(a) Random Forest (b) Logistic Regression

Figure 6: Backdoor attack against mortality prediction.

dataset [75], which contains data associated with 53,423 distinct hospital admissions for adult patients (aged 16 years or above) admitted to critical care units between 2001 and 2012. The dataset covers 38,597 distinct adult patients and 49,785 hospital admissions, providing rich information about patients' demographic characteristics, various in-hospital measurements, and laboratory test results over time. We specifically focus on the task of mortality prediction [61], which aims to predict whether a patient admitted to the Intensive Care Unit (ICU) will survive or perish using the first 48 hours of EHRs. This task is crucial for hospitals to triage patients based on predicted mortality, enabling efficient resource management. We followed Harutyunyan et al. [61] to select 17 features from the MIMIC-III dataset and trained the Random Forest and Logistic Regression.

Experimental Setup & Results. We randomly generated a backdoor trigger matrix with a mean of 0.1, applying it only to the selected features. We repeated each trial 5 times with different poisoning ratios and reported the average benign accuracy and backdoor accuracy. Figure 6 shows that backdoor accuracy increases as the poisoning ratio increases. Notably, our attacks have minimal impact on benign accuracy and maintain high backdoor accuracy (94.05%) even at low poisoning ratios (0.01) for Logistic Regression.

8.3 Membership Inference Attacks

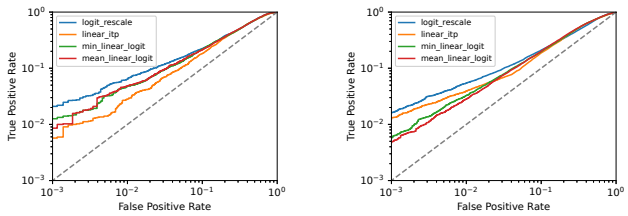
Conjecture. Membership Inference Attacks (MIAs) typically assume access to an auxiliary dataset originating from the same distribution as the training dataset of the target model and is aware of the target model's architecture [90, 146, 163, 164, 201]. State-of-the-art MIA typically relies on the adversary's ability to train a large number of shadow models [21, 194]. We begin by evaluating the performance of state-of-the-art MIA against ECG diagnostics to investigate whether the use of medical data or models introduces additional privacy risks. Subsequently, we assume more practical threat scenarios, where adversaries—often cybercriminals—lack such extensive adversarial power. These practical threat models present significant constraints, and we hypothesize that MIAs may not be as successful.

Threat Model. We consider two distinct threat models. In the first, the adversary has access to an auxiliary dataset from the same distribution as the target model's training data and is capable of training a large number of shadow models. In a more practical threat model, the adversary lacks access to an auxiliary dataset and detailed knowledge of the target model's parameters or architecture. Instead, we assume that the adversary has access to a small portion of the target model's training data, potentially obtained through data poisoning during the model's training process [97]. Beyond this, the adversary only has access to the output of the target model without knowledge of its parameters or architectures.

Attack Method. In the first threat model, we adopted the attack method proposed by Ye et al. [194]. In the second threat model, we selected four representative methods: Shokri et al. [158], Salem et al. [146], Yeom et al. [196], and Song et al. [163]. The adversary holds a portion of members from the target model (*e.g.*, injected through data poisoning) and non-members. This combined dataset was then used to train the attack model. Attack efficacy is assessed using the remaining member and non-member data of the target model.

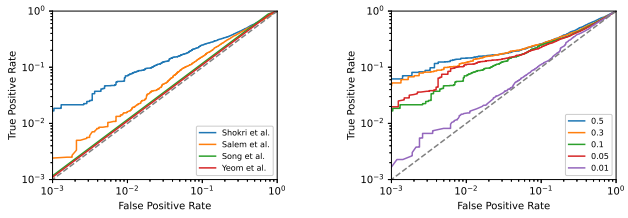
Experimental Setup. We used the same datasets and models as in § 8.2.1. In the first setting, we followed the official implementation of Ye et al. [194], training one target model and 16 shadow models using randomly partitioned, evenly split data. In the second setting, we split the dataset into two equal subsets: $\mathcal{D}_{target}^{train}$ and $\mathcal{D}_{target}^{test}$. The $\mathcal{D}_{target}^{train}$ subset is used to train the target model $\mathcal{M}$, and its samples are considered members of $\mathcal{M}$, whereas samples in $\mathcal{D}_{target}^{test}$ are treated as non-members. We further split out a certain ratio of the target member samples as the known member samples by the adversary. Similarly, we split out the same ratio of the target non-member samples to create a balanced dataset. We used these datasets to train the attack model following different attack strategies and evaluated them with the remaining datasets. In alignment with state-of-the-art studies [21, 95], we employed the following metrics: (1) Full Log-scale Receiver Operating Characteristic (ROC) Curve, a widely utilized ROC curve reported on a logarithmic scale to highlight low false positive rates; (2) True Positive Rate (TPR) at Low False Positive Rate (FPR), which measures attack performance at a specific FPR (*e.g.*, 0.1%), and (3) Balanced Accuracy and Area Under the ROC Curve (AUC).

Empirical Results. For the first threat model, we investigated the vulnerability of ECG-based models by comparing them to a benchmark image dataset and model. Specifically, we conducted MIA on a WideResNet trained on CIFAR-10, using 16 shadow models with randomly partitioned, evenly split data. Each shadow model achieves approximately 92% testing accuracy. The results are presented in Figure 7 and Table 7. For ECG diagnostics models, the leading loss-based processing method achieved a TPR at 0.1% FPR of 2.1%, balanced accuracy of 0.613, and AUC of 0.659. In comparison, the CIFAR-10 model achieved a TPR at 0.1% FPR of 1.6%, balanced accuracy of 0.598, and AUC of 0.636. Since there is a slight difference in the testing accuracy between



(a) ECG (b) CIFAR-10

Figure 7: Membership inference performance against models trained on ECG signals and models trained on CIFAR-10.



(a) Different Methods (b) Different Ratios

Figure 8: Performance of membership inference against ECG-based CNN models with different methods and ratios.

the two models (85% vs. 92%), the similarity in attack performance demonstrates that ECG diagnostics models remain vulnerable to MIA as standard image datasets and models when the adversary has the same level of knowledge. In the second threat model, we fixed the control ratio of target member samples at 0.1. The results are given in Figure 8(a) and Table 8, with different methods exhibiting varying performance. Though the approach by Shokri et al. achieved the best performance, this remains suboptimal compared to what state-of-the-art methods have achieved. Next, we examined the impact of the control ratio of target member samples on the attack performance, which reflects the extent of access to a portion of the target model's training data. This ratio directly measures the strength of the attack. Selecting Shokri et al. as the attack strategy, we varied the control ratio and presented the results in Figure 8(b) and Table 9. The results indicate that when the adversary controls a substantial number of training samples, the inference performance is satisfactory. However, as the attacker's control over training data decreases, the performance declines, eventually approaching random guessing when the ratio is low (*e.g.*, 0.01). It is important to note that in practical healthcare scenarios, it is challenging for an adversary to control a large number of training samples. This implies that current MIAs may not pose severe privacy risks to ECG diagnostics.

8.4 Availability Attacks

Conjecture. Availability attacks typically operate under gray-box settings, where the adversary uses an auxiliary model that performs similarly to the target model to generate poisoning samples. These samples are subsequently applied to the target model. In this study, we identify the adversary as a cybercriminal who lacks access to such an auxiliary model. We hypothesize that this type of attack may not be feasible in image segmentation and disease risk prediction.

Threat Model. We consider black-box poisoning attacks, wherein the adversary blindly injects poisoned samples into the training dataset. The adversary operates with limited knowledge and does not have access to the original training data, model architecture, or weights. The adversary's primary objective is to degrade the overall accuracy of the target model, severely undermining the model's normal functionality and its ability to make accurate predictions on data.

8.4.1 Image Segmentation

Attack Method. We attacked with a common data poisoning technique, label flipping [16]. The adversary randomly selects a subset of training samples and modifies their segmentation masks. This entails flipping a masked region (labeled 1) to background (labeled 0) or vice versa. For each poisoned sample, we randomly flipped 50% of its mask area to produce the final corrupted masks.

Datasets and Models. We used the Multi-Atlas Labeling Beyond the Cranial Vault (BTCV) Challenge dataset [86], a collection of 3D abdominal CT images introduced during MICCAI 2015. We adopted the latent diffusion segmentation model proposed by Lin et al. [91], which has demonstrated state-of-the-art performance on this benchmark.

Experimental Setup. We varied the proportion of poisoned samples in the training set from 0 to 0.5, mixing poisoned samples with the original benign data. We then trained the segmentation model on this combined dataset. Following [91], we evaluated performance using Dice Coefficient and Intersection over Union (IoU), both of which quantify the overlap between predicted segmentation masks and the ground-truth labels on the test set. We repeated each trial 5 times with a random subset to ensure the result's reliability.

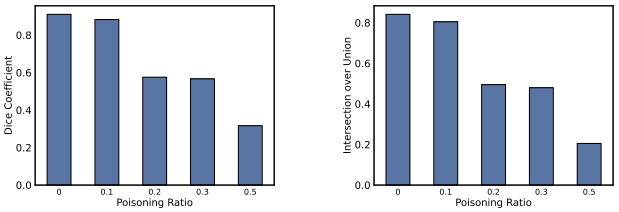
Empirical Results. Figure 9 shows that lower poisoning ratios lead to relatively robust models: when 10% of the training set is poisoned, the Dice Coefficient is 0.88, only 0.03 lower than the unpoisoned baseline. As the poisoning ratio increases, both the Dice Coefficient and IoU experience more pronounced declines, indicating a substantial degradation in segmentation performance. Nonetheless, achieving a high poisoning ratio is less practical in real-world scenarios.

8.4.2 Disease Risk Prediction

Datasets and Models. We used the same set of features from MIMIC-III [75] as in §8.2.3 and trained models including Support Vector Machine (SVM), Logistic Regression (LR), Decision Tree, and Multi-Layer Perceptron (MLP), follow-

Table 5: Untargeted poisoning attack performance with different poisoning ratios on four ML models.

Poison Ratio	SVM	LR	Decision Tree	MLP	Random Forest	G.B. Tree
0.5	0.115	0.191	0.482	0.423	0.420	0.203
0.3	0.872	0.837	0.628	0.809	0.812	0.863
0.1	0.885	0.884	0.776	0.875	0.906	0.902
0.05	0.885	0.885	0.823	0.890	0.911	0.902
0.01	0.885	0.885	0.857	0.896	0.912	0.904
0	0.885	0.885	0.865	0.898	0.912	0.904



(a) Flip Label (b) Flip Label & Add Noise

Figure 9: Untargeted poisoning attack performance against diffusion-based segmentation models.

ing [61]. We also incorporated two ensemble methods: Random Forest and Gradient Boosting Tree (G.B. Tree).

Experimental Setup and Results. We randomly flipped the labels [16] of a certain ratio (0.01 - 0.5) of the training data. We then trained the four models on the poisoned data, together with the benign data, and evaluated the accuracy of the models on the test data. To ensure result reliability, we repeated the trial 5 times with random subset selection. Table 5 show that most models are quite robust against this attack. For instance, with a poisoning ratio of 0.1, the accuracy of decision trees drops by nearly 10%, while the other five models are almost unaffected. As poisoning ratio increases, all models exhibit a notable decline in accuracy. Specifically, when the poisoning ratio reaches 0.5, the accuracy of the SVM model decreases by 77%. However, such a high poisoning ratio is generally impractical in real-world settings.

9 Discussion and Conclusion

Implications of S&P Risks in Healthcare AI. The risks of healthcare AI shown in this paper suggest significant ethical and practical challenges. Manipulated diagnoses or treatment recommendations due to integrity attacks could result in improper care, delayed treatment, or even physical harm. Meanwhile, privacy breaches can expose highly sensitive personal information, risking identity theft, discrimination, or psychological distress. These risks erode stakeholders'—especially patients'—trust and confidence in the reliability of healthcare AI, which may lead to decreased adoption of AI's assistance in healthcare. We urge future research to treat robust defenses not only as a technical priority but also as an ethical imperative to safeguard patient welfare. Additionally, it may be beneficial to adopt certain measures of security and privacy evaluations in existing reporting guidelines, such as the CONSORT-AI extension [96].

Research Opportunities in Under-explored Healthcare Domains. For each healthcare application domain, we highlighted opportunities for future research suggested by our systematization. Healthcare diagnostics systems have been explored and discussed extensively in prior work, particularly when the data modality involves images and texts. Comparatively, there are fewer discussions involving structural features from patient measurements and population-level health dynamics. In terms of the attacker's goal, Appendix B shows that many prior works focused on demonstrating integrity attacks, while AI confidentiality and availability are less explored. There have not been any data poisoning studies for clinical coding, therapeutic effect prediction, and epidemiology analysis, likely due to the inaccessibility of suitable training datasets. Healthcare AI in disease risk prediction also received minimal attention, albeit being a critical application in precision medicine [142].

Limitations in Healthcare Adversarial Research. Healthcare datasets are generally private, thus adversarial research in this domain is inevitably restricted to publicly available data. Furthermore, ethical concerns create additional barriers to evaluating adversarial research in real-world systems. As a result, current research is primarily conducted in controlled, experimental settings, which may not fully capture the risks in actual healthcare environments. While our experiments face similar limitations, this paper takes an important step forward by considering more realistic threat models, thereby building a solid foundation for understanding the practicality of healthcare AI threats in healthcare settings.

AI Fairness & Explainabiltiy in Healthcare. Given the already biased datasets used in the healthcare AI training process [23], there have been no specific attack studies targeting the fairness of healthcare AI. The issue of fairness is a prominent one in population health management [121], and while prior work has proposed some methods to mitigate the issue [28, 136], future research must provide a systematic overview of current strategies, as well as metrics to measure AI fairness lest an unfair model gets clinically deployed. On the other hand, while AI explainability can foster trust in model outputs, it is a tool adversaries can leverage. Though there have been few explainability attacks in prior literature, they cover a wide range of medical data modalities such as breast ultrasound [133], pneumonia chest X-ray and CT [41], EHR documents [134], and multivariate numerical data [200]. These focused on altering the importance maps without changing the classification results, or changing model interpretation while evading existing detectors.

Conclusion. We conducted extensive systematization across different healthcare domains to investigate the S&P risks each may face when AI is involved in the action, revealing significant knowledge gaps and unbalanced research focus within the security community. We systematically analyzed

the adversarial threat models in healthcare environments and identified under-explored application areas. Our demonstration of various attack threat models and validation of under-explored attacks emphasizes the urgent need for cybersecurity research in healthcare AI technology. Hopefully, this will pave the way for future research to focus on the security, privacy, and robustness of AI-powered healthcare systems.

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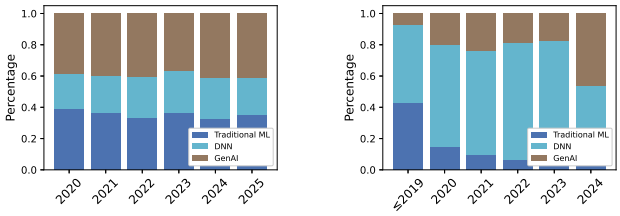
A Paper Inclusion Criteria

Table 6: Summary of healthcare AI S&P research in selected venues. *We manually reviewed the first 10 pages.

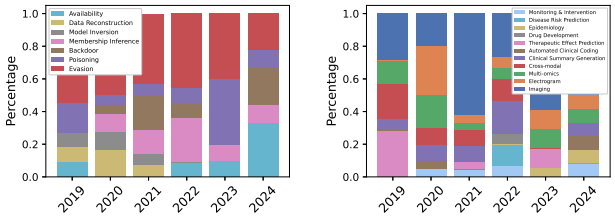
Domain	Venue	Database	Search String	# Included
Computer Security	S&P	IEEE Xplore	Abstract: [medical OR health OR healthcare] AND Body Text: [machine learning OR artificial intelligence OR neural network] AND [attack OR defense]	3/8
	Security	USENIX.org	[medical OR health OR healthcare]	1/34
	CCS	ACM DL	*same as S&P*	1/17
	AsiaCCS	ACM DL	*same as S&P*	4/7
	EuroS&P	IEEE Xplore	*same as S&P*	3/4
AI/ML	AAAI	ojs.aaai.org	[medical OR health OR healthcare] AND [attack OR defense]	8/17
	CVPR	IEEE Xplore	*same as S&P*	1/15
	NeurIPS	ACM DL	*same as AAAI*	3/29
	KDD	ACM DL	*same as AAAI*	4/28
Various	*Various*	Google Scholar	*same as S&P*	46/19K*
	Various	arXiv	*same as S&P*	27/108

B Healthcare AI Research Trends



(a) Biomedical (b) Security

Figure 10: Model types focused by biomedical and security community in the past years.



(a) Attack Types (b) Healthcare Domain

Figure 11: Attacks and healthcare domain focused by existing research in the past years.

C Membership Inference Attack Results

Table 7: Membership inference performance against models trained on ECG signals and models trained on CIFAR-10.

Data	Methods	TPR at 0.1% FPR	Balanced Accuracy	AUC
ECG	logit_rescale	2.1%	0.613	0.659
	linear_itp	0.6%	0.610	0.646
	min_linear_logit	1.3%	0.609	0.655
	mean_linear_logit	0.9%	0.612	0.657
CIFAR-10	logit_rescale	1.6%	0.598	0.636
	linear_itp	1.2%	0.613	0.641
	min_linear_logit	0.6%	0.613	0.646
	mean_linear_logit	0.5%	0.613	0.649

Table 8: Attack performance when applying different membership inference attacks on ECG-based CNN models.

Method	TPR at 0.1% FPR	Balanced Accuracy	AUC
Yeom et al. [196]	0.1%	0.599	0.562
Song et al. [163]	0.1%	0.599	0.563
Salem et al. [146]	0.2%	0.545	0.559
Shokri et al. [158]	1.7%	0.552	0.584

Table 9: Attack performance when applying Shokri et al. with different control ratios on ECG-based CNN models.

Control Ratio	TPR at 0.1% FPR	Balanced Accuracy	AUC
0.01	0.2%	0.535	0.539
0.05	2.0%	0.546	0.576
0.1	1.7%	0.552	0.584
0.3	4.7%	0.558	0.600
0.5	6.2%	0.582	0.621