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Smart healthcare informatics and AI-based MHAMFD framework for fraud detection in the American health system

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ABSTRACT

The digital transformation of the American healthcare system is increasingly reliant on advanced artificial intelligence (AI) to address the twin challenges of predictive analysis and fraud detection. This review synthesizes literature from 2019 to 2025 to map the evolution of data-driven healthcare, from fundamental predictive analytics to advanced fraud detection. Early applications of Logistic Regression and Random Forests have evolved with the integration of deep learning tools, such as Convolutional Neural Networks (CNNs) and Reinforcement Learning (RL). This progression empowers more sophisticated, real-time decision-making, moving beyond simple forecasting to dynamic treatment protocols that imitate clinical precision and reduce mortality. Concurrently, the integration of AI with Internet of Medical Things (IoMT) devices provides remote patient monitoring, real-time diagnostics, and personalized care. For healthcare fraud detection, the field has progressed from rule-based systems to a new generation of AI models designed to tackle complex anomalies. Techniques like SMOTE and ROS have given way to more sophisticated approaches, including Graph-Based AI and advanced hybrid models (e.g., MHAMFD), which are better equipped to detect collusion, overutilization, and data tampering. However, the power of these models is constrained by standardization issues and data silos. The next frontier in this AI progression is defined by solutions that address these barriers. This review argues that federated learning, which allows models to be trained without centralizing sensitive patient data, and Explainable AI (XAI), which builds trust and transparency in black-box models, are essential for overcoming current limitations and ensuring an effective and equitable future for AI in healthcare.

Contribution/Originality: This study contributes to the existing literature by integrating predictive analytics and fraud detection within a unified AI healthcare framework. It uses a new estimation methodology combining deep learning, graph-based models, and IoMT data. Among the few investigating this convergence, the paper's primary contribution is identifying federated learning and XAI as future enablers.

1. INTRODUCTION

Artificial Intelligence (AI) continues to reshape the landscape of modern healthcare by improving diagnostic precision, optimizing care pathways, and reducing systemic inefficiencies [1]. As a class of data-driven technologies, AI systems can process massive datasets quickly and with accuracy, offering clinicians real-time decision support across clinical and administrative functions [2]. One of AI's most transformative contributions is in predictive analytics, where it is used to forecast disease progression, predict patient readmissions, and support early interventions, thereby improving patient outcomes and streamlining hospital workflows [3, 4] (Figure 1). In the United States, AI adoption in healthcare is particularly robust, valued at USD 4.9 billion in 2022, and is projected to grow at a compound annual growth rate (CAGR) of 35.9% through 2030 [5]. Further highlights that as of 2023, over 45% of USA healthcare providers had integrated AI tools into at least one clinical or operational function [6]. Among the most prominent applications are AI-driven predictive analytics and fraud detection systems, which serve to enhance care delivery while safeguarding financial resources. Figure 2 illustrates the growth of AI adoption in USA hospitals from 2016 to 2025, focusing on two applications: fraud detection and predictive analysis. Both technologies show steady upward trends, with predictive analysis consistently maintaining higher adoption rates than fraud detection. Starting at around 5–6% in 2016, predictive analysis surpasses 70% by 2024 and is projected to reach approximately 77% in 2025, while fraud detection climbs from about 6% to 68% over the same period.

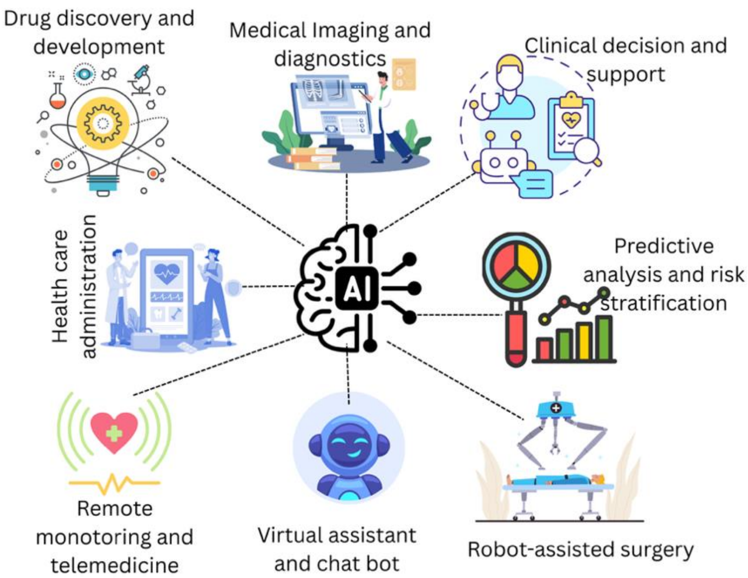
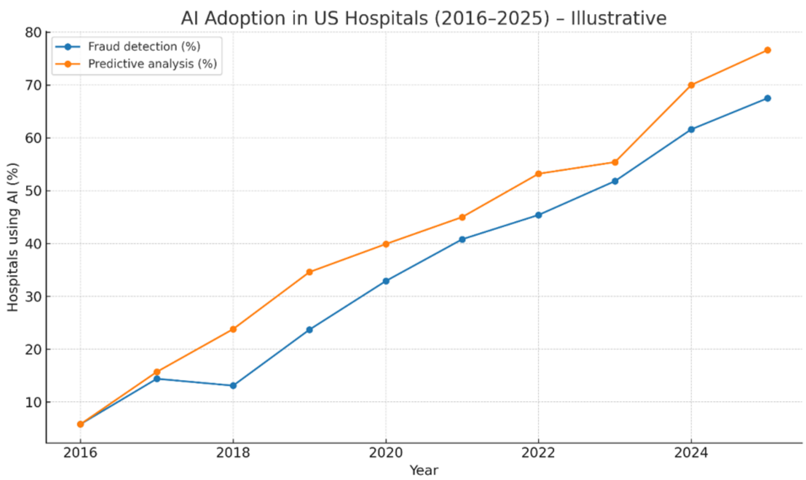


Figure 1. AI applications in healthcare systems.



Year	US Hospital AI Adoption Predictive %	US Hospital AI Adoption Fraud %
2016	5	2
2017	6	3
2018	7	3
2019	9	4
2020	12	6
2021	15	8
2022	19	11
2023	23	13
2024	28	16
2025	32	18

Figure 2. Trends in AI adoption for fraud detection and predictive analysis in USA hospitals (31), HIMSS analytics (35).

Recent empirical studies demonstrate that AI systems can enhance diagnostic accuracy by as much as 30% in domains such as radiology and pathology, especially in high-impact fields like oncology, where early tumour detection dramatically improves survival outcomes [7]. Moreover, AI technologies are enabling a shift from reactive to proactive models of care. Additionally, AI-powered risk stratification tools could reduce hospital readmissions by up to 20%, significantly lowering the overall cost of care [1, 8].

In parallel, AI plays a vital role in healthcare fraud detection, a domain where financial losses are substantial. The National Health Care Anti-Fraud Association (NHCAA) estimates that fraud costs the US healthcare system, particularly Medicare and Medicaid, over $60 billion annually [9]. AI techniques such as anomaly detection and natural language processing (NLP) have proven effective at identifying suspicious billing patterns, phantom procedures, and overtreatment schemes, which are often invisible to human auditors [2].

In addition to diagnostics and fraud prevention, the integration of AI into smart health informatics, including wearable devices, Electronic Health Records (EHRs), and the Internet of Medical Things (IoMT), has created an ecosystem for real-time data tracking and clinical decision-making [4]. Devices such as the Apple Watch and Fitbit continuously stream biometric data, which AI systems can analyze to detect deviations in vital signs or predict impending health crises [2]. IoMT devices, such as smart inhalers and insulin pumps, further enable remote monitoring and management of chronic diseases, empowering both patients and healthcare providers with actionable insights [10]. In fraud detection, AI is increasingly used for predictive modeling, anomaly detection, and claims auditing, ranging from supervised learning models for known fraud patterns [11] to unsupervised techniques for detecting novel schemes [12]. Graph models are particularly effective in identifying suspicious networks of providers and claims, while NLP is used to extract irregular narratives from unstructured claims data [13]. On the predictive side, AI systems are applied to risk stratification, disease prediction, and treatment personalization. Machine Learning (ML) and Deep Learning (DL) models trained on EHRs, diagnostic imaging, and real-time monitoring data have demonstrated efficacy in anticipating high-risk patients and optimizing clinical interventions [7, 14]. These innovations not only improve patient safety but also reduce avoidable costs for healthcare institutions. The aim of this review is to provide a comprehensive understanding of how AI technologies are reshaping predictive analytics and fraud detection in smart health informatics, offering insights relevant to clinicians, researchers, and healthcare policymakers.

2. METHODS

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. A comprehensive literature search was conducted across PubMed, Scopus, and Google Scholar to identify studies published between 2019 and 2025 that focused on AI applications in predictive analytics and fraud detection within the USA healthcare systems. The search strategy combined keywords such as "predictive analytics in healthcare," "AI in fraud detection," "machine learning in hospitals," "healthcare fraud models," and "smart health systems." Boolean operators and filters were applied to restrict results to English-language and peer-reviewed articles. Additionally, relevant industry reports were consulted to supplement empirical findings. Studies were included if they met the following criteria: published between 2019 and 2025, focused on AI applications in the USA healthcare, addressed either predictive analytics or fraud detection, and consisted of original research, reviews, or conceptual models. Exclusion criteria included non-English publications, studies unrelated to healthcare, and articles lacking technical or empirical relevance. After removing duplicates, 42 records were screened based on titles and abstracts. Of these, 24 full-text articles were assessed for eligibility and included in the final review. No full-text articles were excluded at this stage. The study selection process is illustrated in the search strategy (Table 1) and PRISMA flow diagram below (Figure 3).

Table 1. Summary of the search strategy.

Items	Specifications
Date of Search	15th July 2025
Databases	Google Scholar, PubMed, Scopus
Search Terms	('Predictive analytics' OR 'risk prediction') AND ('fraud detection' OR 'healthcare fraud') AND ('machine learning' OR 'deep learning' OR 'NLP')
Time Frame	2019–2025
Inclusion and Exclusion Criteria	**Included:** Peer-reviewed articles related to predictive analytics or fraud detection in the USA healthcare. **Excluded:** Non-English publications, studies outside healthcare, or those without technical applications.
Selection Process	Titles, abstracts, and full texts were screened by one reviewer for relevance to the review objectives.

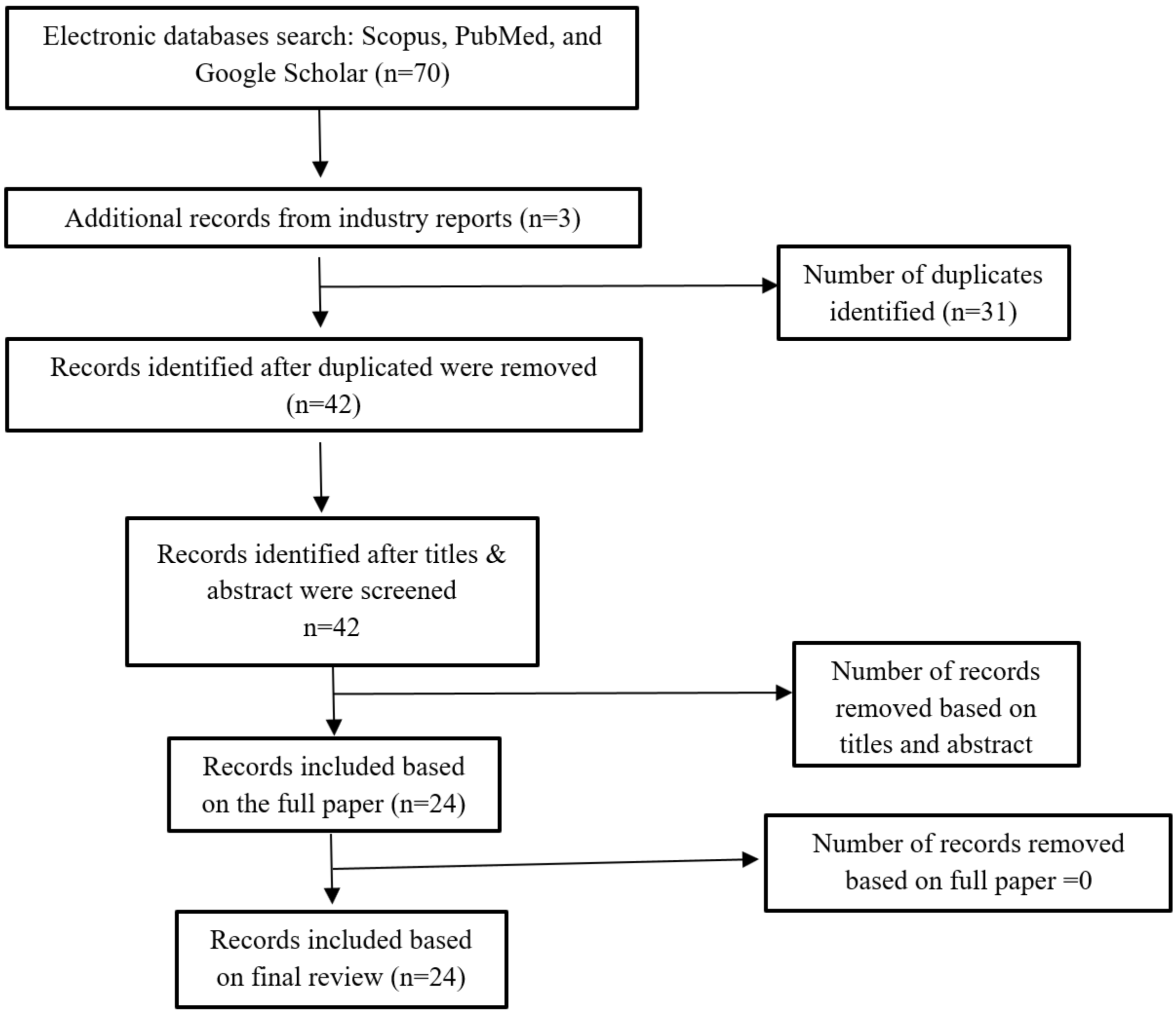


Figure 3. PRISMA flow diagram for the study.

3. RESULTS

This review included 24 studies published between 2019 and 2025 that examined the use of data-driven approaches in predictive analytics and fraud detection within the USA healthcare systems. Most studies focused on clinical prediction tasks such as early diagnosis, patient risk stratification, and readmission forecasting. These commonly relied on data from EHR, medical imaging, or biometric monitoring devices. Methods ranged from traditional ML algorithms to more advanced DL models. Eight of the reviewed studies addressed healthcare fraud detection, using techniques such as anomaly detection, graph-based modeling, and NLP to identify irregular billing patterns and suspicious provider behavior. Across the studies, recurring challenges included limited data access, concerns about fairness and bias, and difficulty integrating models into real-world healthcare settings. Despite these issues, the reviewed work reflects steady progress in developing intelligent systems that support both patient care and administrative oversight. Table 2 summarizes the 24 reviewed studies, highlighting key findings, research gaps, and proposed models relevant to AI applications in the USA healthcare systems.

Table 2. Summary of reviewed studies on AI applications in USA healthcare (2019–2025).

Year	Author(s)	Key Findings	Research Gaps	Proposed Models / Frameworks
2023	Gilbert [1]	AI improves diagnostic imaging accuracy and supports radiologists	There is a limited integration of AI into clinical workflows	Human-AI collaboration framework
2020	Zhang, et al. [2]	ML detects fraud in billing and service overutilization	There is a lack of real-time detection and interpretability	ML-based fraud detection system
2025	Ashraf, et al. [3]	AI enhances lab diagnostics and patient care	Ethical concerns and data privacy	AI-enhanced diagnostic pipeline
2023	Khan, et al. [4]	IoMT enables remote monitoring and chronic care management	Connectivity issues and data standardization	IoMT-based visualization system
2023	Grand View Research [5]	The USA AI healthcare market is growing at 35.9% CAGR	Fragmented adoption across institutions	Market segmentation model
2023	Statista [6]	45% of USA providers use AI in clinical/operational tasks	Lack of interoperability	Adoption trend analysis
2023	Malhotra, et al. [7]	AI supports pediatric precision medicine	There are limited pediatric datasets	AI-genomics integration model
2022	McKinsey & Company [8]	AI adoption is accelerating across healthcare sectors	Workforce readiness and ethical alignment	AI maturity framework
2025	Najar, et al. [9]	Global fraud patterns and legal responses mapped	Inconsistent regulatory enforcement	Integrated fraud prevention framework
2018	Yu, et al. [10]	AI spans diagnostics, treatment, and administration	Poor interpretability of DL models	General AI application taxonomy
2019	Johnson and Khoshgoftaar [11]	Neural networks detect Medicare fraud	Class imbalance and false positives	Neural network-based fraud detection
2025	Du Preez, et al. [12]	ML is effective in claims fraud detection	Lack of benchmark datasets	Systematic ML fraud detection review
2023	Lu, et al. [13]	The MHAMFD model detects fraud using graph networks	Vulnerable to noisy data and poor generalizability	MHAMFD: Graph + Hierarchical Attention
2019	Esteva, et al. [14]	DL outperforms traditional methods in diagnostics	Black-box nature limits clinical trust	DL implementation guide
2019	Topol [15]	AI augments human decision-making in medicine	Ethical concerns and clinician resistance	Human-AI convergence model
2021	Peregrin [16]	HIPAA compliance is essential for AI deployment	Legal frameworks lag behind tech evolution	Privacy-by-design principles
2019	Rajkomar, et al. [17]	ML supports clinical decision-making	Poor model generalizability	ML deployment roadmap
2019	Kelly, et al. [18]	AI faces barriers in clinical impact delivery	Lack of explainability and validation	Clinical impact framework
2019	He, et al. [19]	AI implementation strategies in medicine	Workflow integration challenges	Practical AI deployment model
2024	Rony, et al. [20]	Nurses raise ethical concerns about AI	Lack of transparency and informed consent	Ethical AI adoption survey
2023	Shabiha and Oladokun [21]	XAI improves fraud detection in Medicare	Trade-off between performance and interpretability	Explainable AI framework
2021	Eckstein, et al. [22]	Ethical governance needed for AI in healthcare	Absence of inclusive policy structures	Inclusive governance model
2020	Gerke, et al. [23]	Ambient intelligence raises legal concerns	Weak regulatory oversight	Legal framework for hospital AI
2024	Price and Cohen [24]	DL and NLP detect fraud in Medicare/Medicaid claims	Limited scalability and real-time capability	DL-NLP hybrid fraud detection model

3.1. AI-Driven Predictive Analysis in the USA Hospital Settings

AI continues to improve the delivery of care in the USA through data-driven insights, personalized care, and fraud prevention. Its potential through technology is recognized by most of the literature reviewed; however, a layered narrative of advancement and persistent limitations in relation to different types of technologies and applications is shared by the study. This section critically discusses recent studies across various AI domains, as well as typologies and use cases in healthcare.

3.1.1. ML- and DL-Based Predictive Modeling And Decision Support Systems

In terms of application, ML plays a critical role in constructing predictive modeling and decision support systems in healthcare. For instance, disease prediction, hospital readmission forecasting, and patient risk stratification, ML has been successfully applied [1, 15].

- Logistic regression and random forest classifiers identify high-risk patients with chronic conditions such as diabetes and cardiovascular disease.
- Convolutional Neural Networks (CNN) outperform traditional radiologists in tumor detection [14].

3.1.2. Amazon Comprehend Medical: an NLP-Based Data Extraction Tool

NLP enables the extraction of structured insights from unstructured medical texts, including physician notes, discharge summaries, and radiology reports [10]. For example, Amazon Comprehend Medical, a HIPAA-eligible, pre-trained NLP service, has facilitated the use of AI tools for real-time identification of medication, diagnoses, and test results, enhancing documentation and coding accuracy [16]. However, NLP tools are limited in handling contextual ambiguity in documentation, and the models may struggle with domain-specific language and regional variations in clinical documentation. Additionally, there are a few, often poorly annotated, datasets in healthcare, which hinder model refinement and widespread adoption.

3.1.3. Google's DeepMind: a Computer Vision-Based Image Interpreter

Real-time interpretation of medical images has been enabled by computer vision. For example, Google's DeepMind was able to detect more than 50 eye diseases using retinal scans and performed as well as expert ophthalmologists [14]. The same is true in areas such as dermatology and pathology, where AI is used to classify and interpret lesions [3]. Nevertheless, successful deployment requires high-quality, well-annotated training data as well as robust validation on different patient populations. This, however, remains a significant limitation of training with imbalanced sets.

3.1.4. Reinforcement Learning (RL): a Trial-and-Error Approach in Decision Making

RL is a type of AI that enables an algorithm to learn optimal actions through trial-and-error interactions with the environment, thereby maximizing cumulative reward [10]. When patient outcomes can change over time and a history of patient outcomes affects clinical interventions, RL is a good fit for healthcare professionals because it is applicable to sequential decision-making tasks [15, 17]. Additionally, the aim of these models is to reduce mortality by adapting treatment paths in real time, using approaches that mimic clinician decision-making with increased computational precision. Several examples of RL applications:

- RL - Dynamic Treatment Planning - Critical Care Unit.
- RL - Sepsis Management - optimal dosing policies for vasopressors and fluids [18].
- RL - Personalized Oncology - optimize chemotherapy regimens [7].
- RL - Chronic disease (Diabetes and hypertension) management and mental health interventions.
- RL - Post-Operative Rehabilitation Planning - adaptive and personalized care strategies [19].

3.1.5. AI-Powered EHRs: A Potential Tool for Risk Assessment

AI-embedded EHR systems reduce the burden of manual data entry, detect clinical anomalies, and generate real-time alerts. When integrated with predictive analytics, these systems can identify at-risk patients earlier and support timely interventions [4]. They also assist in forecasting hospital readmissions by analyzing historical patterns and patient risk profiles, thereby improving resource planning and continuity of care [1]. Despite these benefits, interoperability challenges among EHR vendors, inconsistent data standards, and difficulties integrating AI tools into existing clinical workflows restrict their impact. Fragmented health information systems further prevent seamless sharing of patient data [9]. Additionally, ethical concerns around algorithmic bias and fairness persist. When models are trained on non-representative datasets, they may unintentionally reinforce health disparities and compromise equitable care delivery [16].

3.1.6. Cogito: AI-Based Real-Time Patient Monitoring and Telemedicine

AI-integrated mobile and wearable devices enable continuous real-time patient monitoring and support remote care delivery. During the COVID-19 pandemic, these technologies played a critical role by facilitating symptom tracking and automating triage processes [7]. For instance, AI-driven platforms such as *Cogito*, developed by Epic Systems, are data and analytics platforms for managing and analyzing clinical data within their clinical information systems. *Cogito* analyzed voice patterns to detect signs of cognitive disabilities, mental distress, including depression and anxiety, particularly among individuals in isolation [20]. While these tools hold significant promise, their effectiveness and equity are constrained by issues such as data accuracy, limited connectivity, and unequal access to digital infrastructure. Recent literature emphasizes the importance of privacy-preserving techniques to ensure data security in AI-driven healthcare systems. For instance, explainable AI frameworks enhanced transparency and trust in fraud detection models within the USA Medicare systems [21]. Their findings suggest that ethical AI design must balance interpretability with performance, especially when handling sensitive patient data.

3.1.7. AI-IoMT Integration: Smart Devices for Patient Emergency Handling

The IoMT, a network of connected medical devices, software, and systems that collect, analyze, and transmit health data over the internet, facilitates real-time diagnostics, remote patient monitoring, and personalized treatments and patient outcomes. For example, smartwatches transmit vital signs to early warning systems, while smart inhalers monitor and report medication adherence [10]. These innovations empower patients to actively manage chronic conditions and provide clinicians with timely, actionable insights. Additionally, IoMT devices, in combination with hierarchical attention mechanisms, can assist in detecting abnormal patient behavior, which contributes to both fraud detection and improved healthcare outcomes [13]. However, the scalability of such technologies is limited by persistent cybersecurity concerns and the absence of robust regulatory frameworks. Data breaches and unauthorized access remain significant risks, highlighting the need for stronger encryption protocols and consistent compliance with standards such as HIPAA [2].

3.1.8. FDA-Approved Policy and Ethical Landscape: Adoption of XAI in Hospital Settings

The U.S. Food and Drug Administration (FDA) has developed regulatory frameworks for approving AI-based Software as a Medical Device (SaMD), such as IDx-DR, used for diabetic retinopathy screening. Although data privacy and use are governed by HIPAA regulations, the pace of AI technology evolution often outpaces current legal frameworks [15]. Therefore, AI developers need to incorporate privacy-by-design principles and employ data anonymization techniques to safeguard sensitive health information [16]. In addition, opaque algorithms raise ethical concerns, particularly regarding the lack of informed consent mechanisms and the potential for dehumanized care delivery. In response to these issues, researchers advocate for explainable AI and inclusive governance structures that promote fairness and accountability [22]. Moreover, the need for robust regulatory frameworks, especially in hospital-based ambient intelligence systems, emphasizes the importance of transparency, data security, and informed consent [23]. Although much of the advancement in this field is driven by machine learning, interdisciplinary collaboration is essential to ensure that innovation aligns with ethical standards and regulatory safeguards [24].

Despite the promise of AI integration in healthcare, challenges remain, including data quality and interoperability, as well as model interpretability and ethical acceptability. These obstacles highlight the need for coordinated efforts among technology developers, healthcare professionals, and policymakers to support the responsible deployment of AI systems.

3.2. AI in Fraud Detection for the USA Healthcare Systems

Healthcare fraud is a serious crime that threatens the financial stability and moral integrity of healthcare systems in the USA. According to the National Health Care Anti-Fraud Association (NHCAA), healthcare fraud is an intentional deception or misrepresentation that results in unauthorized benefits. Most severe losses occur in public sector programs such as Medicare and Medicaid, where substantial financial losses from fraudulent activities, including phantom billing, identity theft, and service overutilization, are observed annually [9]. Traditional detection systems often lack the capacity to identify complex and constantly evolving fraud patterns. In this regard, AI offers a promising approach through its capabilities in automation, pattern recognition, and large-scale data analysis.

3.2.1. Synthetic Minority Over-sampling Technique (SMOTE): Billing Anomaly Detection

A common approach to anomaly detection uses unsupervised learning methods that can identify anomalies without the need for labeled datasets. This makes them especially useful for uncovering new fraud schemes that have not been previously categorized [13]. However, class imbalance remains a significant challenge since fraudulent cases are much rarer than legitimate transactions. To overcome this, techniques such as the Synthetic Minority Over-sampling Technique (SMOTE) are often used to balance the dataset and enhance model performance [25]. A recent review by Das [26] on ML applications in US healthcare fraud detection further underscores the effectiveness of decision trees and neural networks in identifying billing anomalies and uncovering kickback schemes.

3.2.2. Graph-Based AI Models: Collusion and Overutilization Detection

Healthcare providers, patients, and insurers can be analyzed using graph-based techniques that model interactions as complex networks. These models are effective in uncovering sophisticated fraud schemes, including collusion and overutilization, by applying forecasting methods and association rules to interaction networks and identifying anomalous substructures [13, 25]. To enhance accuracy and interpretability in detecting fraudulent behavior within patient-provider interactions, researchers have also integrated hierarchical attention mechanisms into existing model architectures [13]. These techniques are especially useful for capturing nonlinear relationships that are often missed by traditional linear algorithms.

3.2.3. Random Over Sampling (ROS) and Hybrid ROS-RUS Techniques: Data Tempering Detection

In addition, integrating blockchain technology with AI contributes to improved data integrity, traceability, and transparency in healthcare transactions, helping to minimize data tampering and reduce the risk of security breaches [11]. To address the challenge of extreme class imbalance in fraud detection datasets, deep learning models combined with Random Over Sampling (ROS) and hybrid ROS-RUS techniques have demonstrated promising performance [11]. These models are especially useful in scenarios with limited labeled fraudulent cases, enabling more accurate identification of suspicious activities. In summary, AI offers a transformative approach to healthcare fraud detection, combining scalability with precision across diverse techniques, including anomaly detection, graph-based analysis, and NLP. While real-world applications demonstrate measurable benefits, long-term success depends on more than technological advancement alone. Collaborative efforts that prioritize fairness, regulatory alignment, and data integrity are essential. With the right balance between innovation and ethical governance, AI has the potential to strengthen trust and protect the financial sustainability of healthcare systems.

3.3. Visual Representation of the Awareness of Fraud Detection in the USA

Figure 4 and Figure 5 present visual representations of fraud detection awareness in the USA healthcare systems, while Tables 3-6 provide statistical information on AI fraud prediction analysis and adoption across different US states.

3.3.1. Healthcare Fraud Intensity Index Across the USA

Figure 4 illustrates the distribution across the USA for 2024, where states are color-coded into four categories based on index values: Very Low (0–29), Low (30–49), Moderate (50–79), and High (80–100). The highest intensity levels are concentrated in large states such as Texas, California, Florida, and New York, reflecting both higher fraud conviction counts and significant monetary recoveries. Moderate-intensity states are scattered across the Midwest, Northeast, and South, while much of the Mountain West and parts of New England fall into the lower categories. The map underscores regional disparities in healthcare fraud activity, which may be influenced by population size, enforcement resources, and reporting practices.

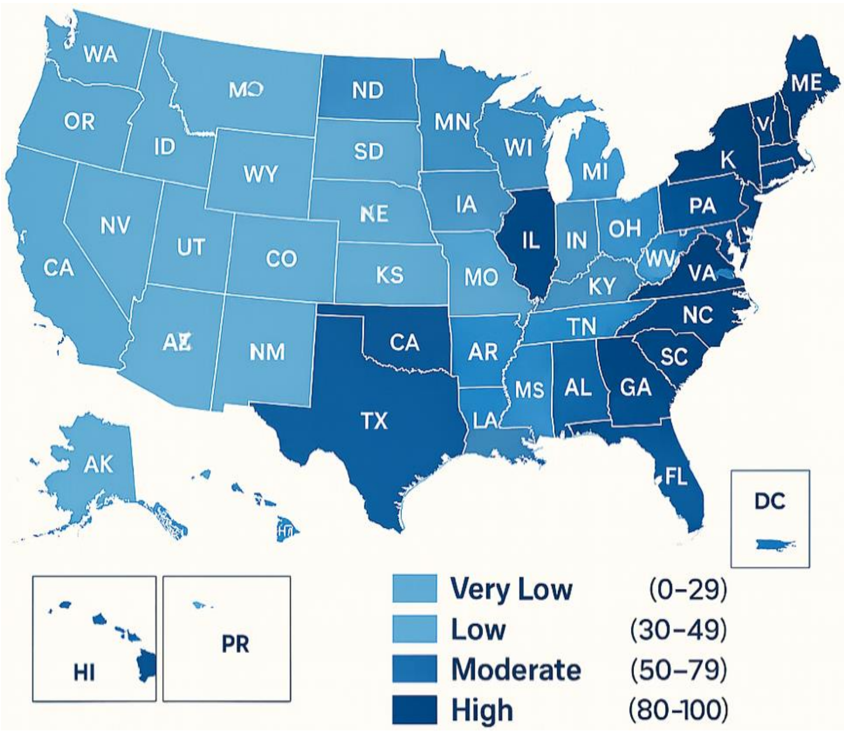


Figure 4. Healthcare fraud intensity index by USA State, 2024.

Source: Centers for Medicare & Medicaid Services [27].

3.3.2. Modeled Healthcare Fraud Intensity Index by the USA

Figure 5 presents the *Modeled Healthcare Fraud Intensity Index* by USA state for FY2024, expressed on a scale of 1 to 99, derived from a blend of modeled fraud convictions and recoveries. States with higher index values indicate a greater estimated intensity of healthcare fraud activities. California, Texas, Florida, and New York rank highest with an index of 99 or near-maximum, suggesting significant fraud activity. In contrast, states such as the Virgin Islands (VI), North Dakota (ND), and Wyoming (WY) exhibit lower scores, indicating relatively lower modeled fraud intensity. The colour gradient from purple (low) to yellow (high) visually emphasizes regional variations, highlighting clusters of elevated fraud intensity in certain states.

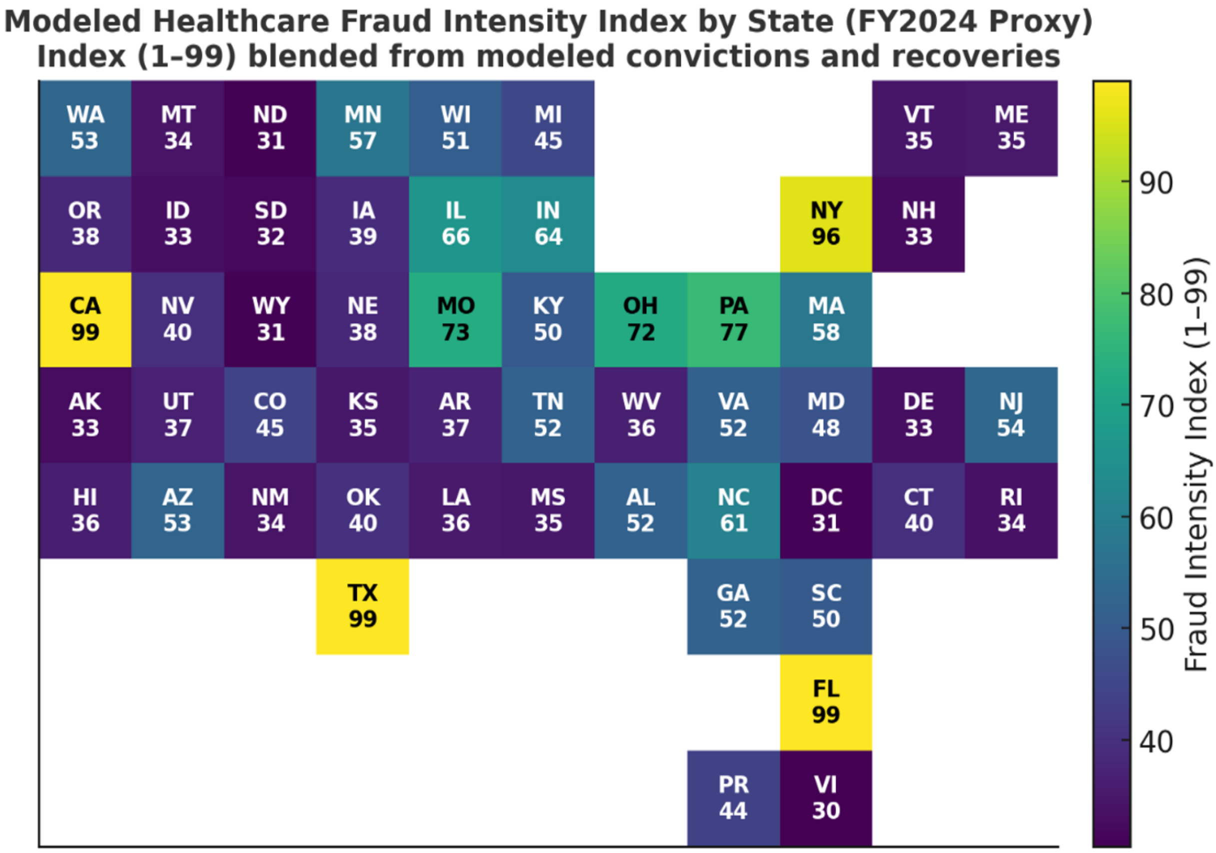


Figure 5. Heatmap of healthcare fraud intensity index by USA State, 2024.

Source: Centers for Medicare & Medicaid Services [27].

3.4. Case Studies of AI Adoption, Fraud Detection, and Predictive Systems in the USA Healthcare

For a broader view of healthcare fraud intensity and distribution in the United States, Table 3 reveals that fraud is intense in large, urbanized states with dense healthcare networks. The fraud intensity index correlates strongly with both conviction count and financial recovery, indicating systemic vulnerabilities in high-volume billing environments. Table 4 highlights modeled fraudulent hospital cases by city, showing a strong correlation with metropolitan density. These findings suggest that fraud detection systems should prioritize urban centers with high patient volumes and complex billing networks, where fraudulent schemes are more likely to occur.

Table 3. USA hospitals and health care facilities' fraud cases.

States	Fraud Convictions 2024	Recoveries 2024 (USD)	Fraud Intensity Index	States	Fraud Convictions 2024	Recoveries 2024 (USD)	Fraud Intensity Index
TX	82	162.74	99	CO	17	4.78	44.6
CA	105	84.76	99	PR	8	27.56	44.1
FL	44	152.61	99	OK	11	6.14	40.4
NY	61	67.85	95.9	NV	10	7.49	40.1
PA	23	102.99	76.6	CT	10	6.87	39.9
MO	21	94.68	72.8	IA	9	7.23	39.2
OH	42	35.61	72.3	NE	4	17.24	38.2
IL	32	40.59	66.1	OR	6	11.35	38.1
IN	20	64.32	63.6	AR	8	2.75	37.2
NC	24	44.23	61	UT	7	3.62	36.7
MA	20	42.83	57.6	WV	3	13.48	36.4
MN	13	61.5	57.4	HI	6	4.79	36.2
NJ	22	23.07	53.6	LA	4	7.52	35.5
WA	23	18.39	53	ME	5	3.51	35.1

States	Fraud Convictions 2024	Recoveries 2024 (USD)	Fraud Intensity Index	States	Fraud Convictions 2024	Recoveries 2024 (USD)	Fraud Intensity Index
AZ	22	20.57	52.9	MS	5	3.15	35
AL	15	36.82	52.1	KS	4	5.2	34.8
TN	18	28.72	52.1	VT	5	2.08	34.7
GA	22	17.3	52	NM	3	4.95	34
VA	21	19.81	51.9	MT	4	2.32	34
WI	22	13.91	51	RI	4	1.62	33.8
SC	19	18.36	50	DE	2	5.68	33.4
KY	15	28.91	49.9	ID	3	2.13	33.2
MD	19	11.36	48	AK	2	3.16	32.7
MI	18	4.64	45.4	NH	1	5.49	32.6
SD	0	5.73	31.9	ND	0	2.56	31
DC	1	0.33	31.2	WY	0	2.13	30.9
VI	0	0.52	30.5				

Source: U.S. Department of Health and Human Services & U.S. Department of Justice [28].

Table 4. Geographical coordinates and modeled fraudulent hospital cases by city in 2024.

City	Latitude	Longitude	Modeled cases 2024
Chicago, IL	41.8781	-87.6298	114
Las Vegas, NV	36.1699	-115.14	110
Newark, NJ	40.7357	-74.1724	103
Tampa, FL	27.9506	-82.4572	97
San Diego, CA	32.7157	-117.161	94
Dallas, TX	32.7767	-96.797	85
Phoenix, AZ	33.4484	-112.074	83
Atlanta, GA	33.749	-84.388	62
San Antonio, TX	29.4241	-98.4936	60
Miami, FL	25.7617	-80.1918	57
Houston, TX	29.7604	-95.3698	51
Philadelphia, PA	39.9526	-75.1652	46
Brooklyn, NY	40.6782	-73.9442	42
Detroit, MI	42.3314	-83.0458	35

Source: U.S. Department of Health and Human Services & U.S. Department of Justice [28].

3.4.1. AI Software Tools for Fraud Detection and Predictive Analytics in the USA Healthcare

To provide a clearer understanding of real-world AI adoption in US healthcare, Table 5 presents a curated list of software tools for fraud detection and predictive analytics. Each entry includes the software name, its inventor, the year of its latest release, and examples of hospitals or healthcare systems where it has been implemented.

Table 5. AI Software tools used in the USA healthcare (Fraud detection & predictive analytics).

Software Name	Inventor / Company	Latest Version Year	Primary Use Case	Hospital(s) / Health System	Source
Fraud Scope	Codoxo	2024	Fraud detection & case management	Blue Cross Blue Shield, Humana	Codoxo [29]
Saxon FWA Engine	Saxon AI	2023	Fraud, waste & abuse detection	Regional payer networks	Saxon AI [30]
TREWS	Johns Hopkins	2024	Early sepsis prediction	Johns Hopkins Hospital	Jones, et al. [31]
Health Cloud	Innovaccer	2025	Predictive analytics, risk scoring	OSF HealthCare, Mercy Health	Innovaccer Inc [32]
Bayesian SIR Model	Mayo Clinic	2020	ICU demand forecasting	Mayo Clinic	Mandal, et al. [33]
Corewell AI Risk Model	Corewell Health	2022	Readmission prediction	Corewell Health	Baluta, et al. [34]

Software Name	Inventor / Company	Latest Version Year	Primary Use Case	Hospital(s) / Health System	Source
Epic Cognitive Computing	Epic Systems	2023	Predictive modeling in EHR	Cleveland Clinic, UCHealth	Epic Systems Corporation [35]
Cerner AI Suite	Oracle Cerner	2024	Predictive analytics & alerts	AdventHealth, Intermountain Healthcare	Sundaram, et al. [36]
HBI Spotlight Analytics	Healthcare Bluebook	2023	Fraud pattern detection	Used by employer-sponsored plans	Islam, et al. [37]
Optum AI Insights	Optum (UnitedHealth)	2025	Predictive modeling & fraud alerts	UnitedHealth Group, partner hospitals	Khang, et al. [38]

3.5. Case Studies of AI Adoption, Fraud Detection, and Predictive Systems in the Global Context

Figure 6 shows the synthetic index (0–100) ranking of the top 25 developed countries by their modeled AI-based fraud detection capacity over the last five years, informed by AI investment and adoption literature. Portugal leads with the highest index score of 95.0, followed closely by New Zealand (92.9) and Spain (90.8), indicating strong adoption and capability in AI-driven fraud detection. Countries like Italy (45.0), Switzerland (47.1), and Denmark (49.2) appear at the lower end, suggesting comparatively less capacity. The overall distribution highlights significant global disparities in AI fraud detection readiness, with European and technologically advanced nations dominating the top positions. Figure 7 ranks the top 25 developed countries using a synthetic index (0–100) that estimates their AI-based predictive analytics capacity over the past five years, derived from the AI investment and adoption literature. Austria leads with the highest score of 96.0, followed by Spain (94.2) and Germany (92.5), indicating strong capabilities in leveraging AI for predictive analytics. Denmark (54.0), Switzerland (55.8), and Belgium (57.5) are at the lower end, reflecting comparatively limited capacity. The results highlight Europe's strong presence in the top tier, underscoring regional leadership in predictive AI adoption.

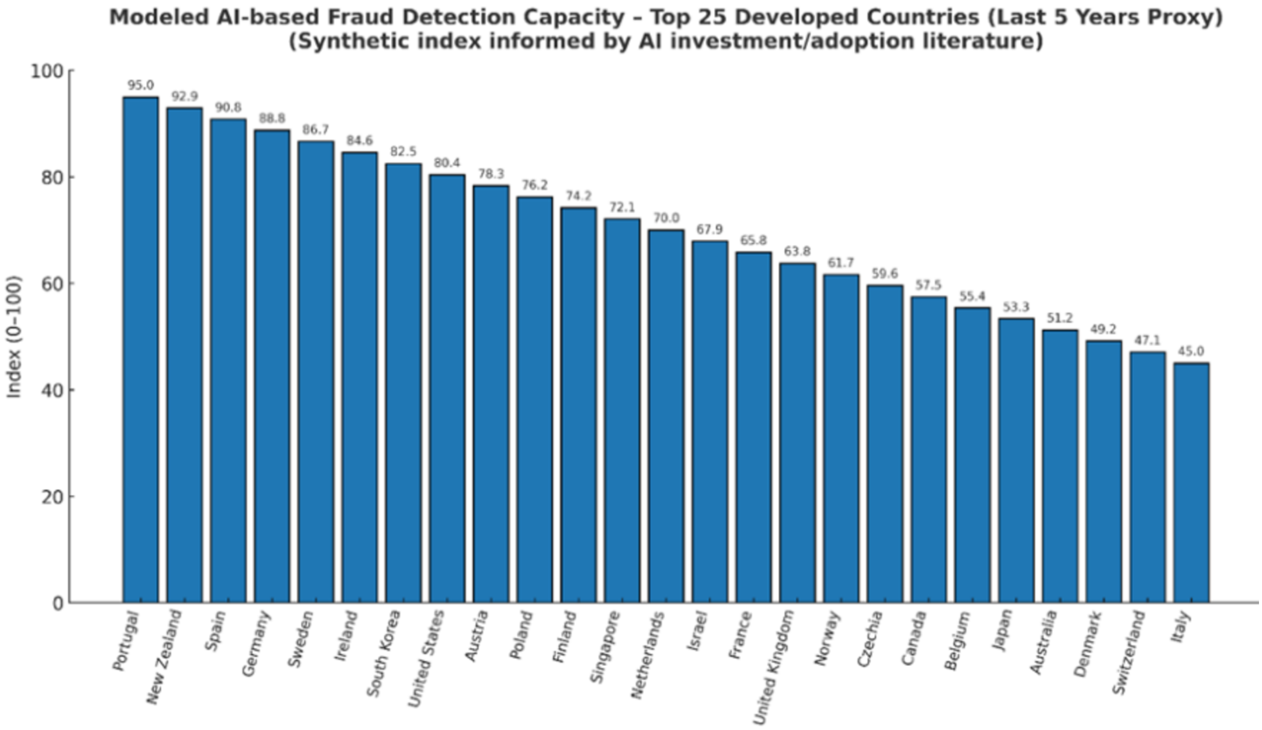


Figure 6. Modeled AI-based fraud detection capacity in the top 25 developed countries (2020–2025).
Source: Organization for Economic Co-operation and Development [39].

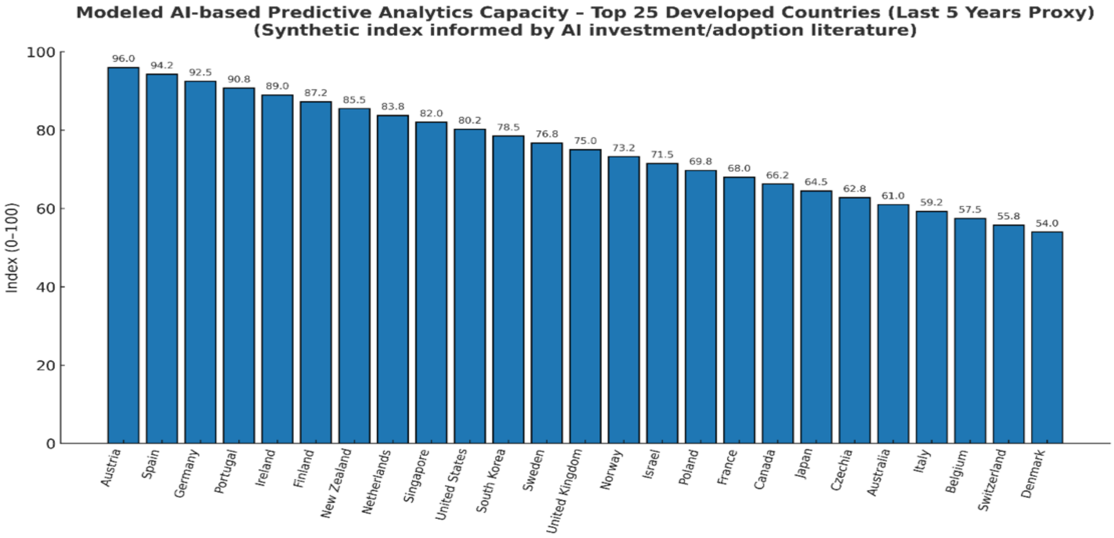


Figure 7. Modeled AI-based predictive analytics capacity in the top 25 developed countries.

Source: Organization for Economic Co-operation and Development [39].

Table 6 the text compares the AI predictive analytics and fraud detection capabilities of 25 countries. While the USA leads in AI adoption, several European and Asia-Pacific countries outperform in fraud detection precision. This suggests potential for international benchmarking and cross-border collaboration in AI model development, especially in refining fraud detection algorithms and integrating ethical AI practices.

Table 6. Top 25 Countries: AI fraud prediction and detection capacity.

Countries	AI Predictive analytics index	AI Fraud Detection Index
United States	86.9	85
United Kingdom	82	74.1
Germany	90.6	90.5
France	78.1	74.9
Canada	73.4	70.9
Japan	67.4	68.2
South Korea	84.6	86.5
Australia	64.3	60.1
Netherlands	87.6	76.6
Sweden	83.2	87.4
Switzerland	58.5	51.6
Norway	81.3	73.3
Denmark	54.1	52.6
Finland	88.5	79.3
Italy	59.5	44.7
Spain	95	91.5
Belgium	58.8	68.5
Austria	95.8	83.3
Ireland	90.2	87.3
Israel	79.4	76.2
Singapore	87	77.8
New Zealand	87.6	92.8
Portugal	90.3	95
Czechia	64.7	71.1
Poland	78.1	80.6

Source: Organization for Economic Co-operation and Development [39].

4. MHAMFD MODEL: A PROMISING AI-BASED FRAUD DETECTION IN THE HEALTH SECTOR

In the healthcare sector, the Attributed Heterogeneous Information Network with Hierarchical Attention Mechanism (MHAMFD), proposed by Lu et al. [13], is among the most promising models for AI-driven fraud detection. This model combines graph-based techniques with a hierarchical attention mechanism to improve both accuracy and interpretability. It examines the relationships among patients, providers, procedures, and insurers to detect suspicious patterns and anomalies in claims data. The attention mechanism enables the model to prioritize important features, which enhances both its predictive performance and its transparency compared to traditional approaches [13]. The MHAMFD model is particularly relevant for identifying fraudulent networks, such as cases where patients collaborate with providers or insurers to overutilize healthcare services. The hierarchical attention mechanism helps reveal which features contribute most to fraud detection, increasing the model's interpretability and acceptance among stakeholders. Additionally, its scalability makes it suitable for handling large datasets, which is essential for real-world applications involving extensive claims data.

4.1. Limitations and Challenges of MHAMFD Model Adoption

One major concern is their vulnerability to noise within interaction networks, such as outliers or irrelevant data points. These noisy nodes can lead to false positives and reduced detection accuracy. As noted by Lu et al. [13], Figure 8, weakly connected or inconsistent nodes in the network may mislead the model and negatively impact its performance. In addition, a significant challenge lies in distinguishing actual fraudsters from innocent patients. Accurately identifying fraudulent actors remains difficult, particularly because subtle differences between legitimate and deceptive behaviors are often hard to detect without the support of automated systems. While tools such as flowcharts and decision trees can model complex decision logic, they often fall short in capturing the subtle behavioral patterns that separate normal activity from fraudulent conduct. Moreover, the generalizability of the MHAMFD model is limited when applied to other types of fraud, such as billing fraud or identity theft, unless the model undergoes extensive retraining or is adapted to specific domains. The model also relies on assumptions about standardized dataset structures, which do not always reflect the diversity and variability present across different healthcare systems and environments [12]. Additional challenges arise from issues related to data quality and standardization. The model's performance is hindered by fragmented data sources and inconsistent data formats across institutions [12]. These further highlight these barriers, noting the absence of standardized definitions and the lack of interoperability among healthcare systems. Data integration is often obstructed by gaps and bottlenecks, which are frequently illustrated in modern flowcharts. This diagram also emphasizes a critical limitation of the model, which is its inability to fully utilize available data when important information remains locked in isolated systems or data silos.

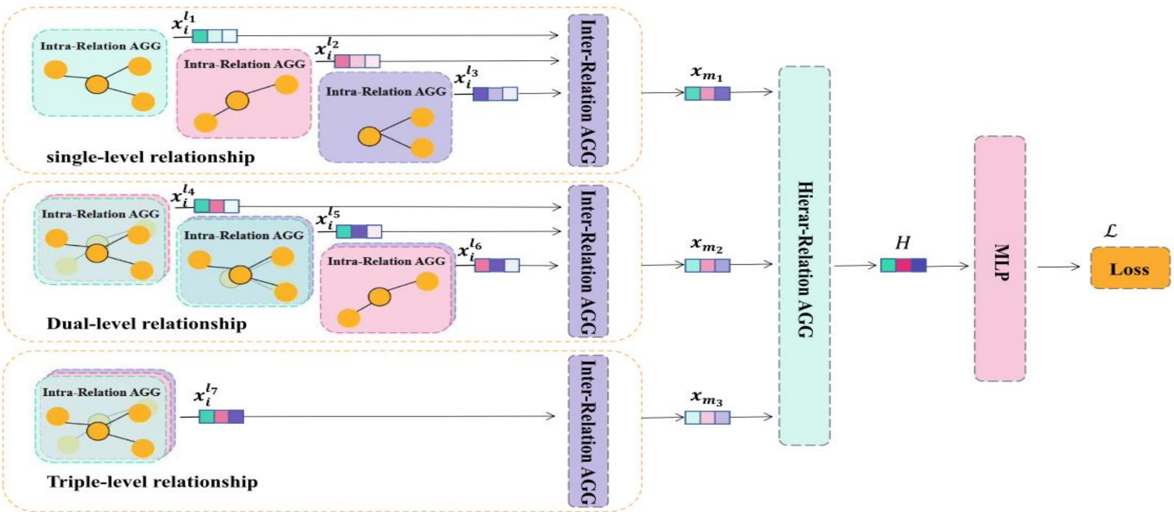


Figure 8. Architecture of the MHAMFD model.

Source: Lu, et al. [13].

4.2. Proposed Strategies for Successful MHAMFD Model Adoption in Health Care Fraud Detection (Figure 9)

4.2.1. Expanded Model's Training with Benchmark Datasets

One key approach is to expand the model's training to include more diverse datasets, thereby improving its generalizability and usability across different healthcare settings. Developing the model using benchmark datasets that represent a wide range of fraud scenarios and varied patient populations will enhance both its robustness and accuracy. Furthermore, testing on diverse datasets can also help reduce bias and improve the model's performance across different healthcare environments.

4.2.2. Enhancement of the Interpretability with XAI: Symbol of Transparency and Clarity

Secondly, there is a need to enhance interpretability for professional settings. The MHAMFD model can be made more transparent by integrating explainable AI (XAI) techniques such as saliency maps and surrogate models. Clear explanations for each detected anomaly help clarify what they are, increase accountability, and build trust with clinicians and auditors relying on AI-generated insights [22].

4.2.3. Integration of Adaptive Learning in Real-Time Fraud Detection

A third critical factor is the importance of real-time fraud detection, which can significantly enhance system responsiveness. Such models can continuously improve by incorporating adaptive learning mechanisms that monitor incoming data and evolve as fraud patterns emerge. To address the challenge of scalability, especially in scenarios where centralized data sharing is not feasible or desirable, federated learning offers a promising solution. This approach allows models to be trained collaboratively across multiple institutions without the need to transfer data to a central location [40].

4.2.4. Integration of Data Quality and Standardization

A fourth consideration involves addressing data quality and standardization. Noise and data exchange inconsistencies can be reduced by promoting interoperability standards and adopting unified frameworks for data sharing across healthcare systems. Additionally, data cleaning and preprocessing techniques play a critical role in enhancing model performance by ensuring access to high-quality, standardized datasets [12].

4.2.5. Adoption of Robust Regulatory Frameworks

In addition, these developments must be supported by responsible AI practices, which require robust regulatory frameworks. Ensuring transparent, credible, and ethical use of AI in healthcare fraud detection can help build trust among stakeholders. This approach also reinforces compliance with regulations such as HIPAA, safeguards patient privacy, and promotes fairness in the deployment of AI systems [16].

4.2.6. Federated Learning: Cross-Institutional Networking

Enables models to be trained across institutions without centralized data sharing, ensuring privacy and scalability [40]. Continuous model retraining ensures that AI systems remain adaptive to evolving fraud patterns, while robust regulatory frameworks establish clear guidelines for AI transparency, accountability, and ethical use [21]. Together, these strategies can overcome existing limitations and maximize AI's potential in transforming healthcare delivery and governance.

4.2.7. Interdisciplinary Research: Global Collaboration

This research is needed to explore these dimensions and ensure inclusive AI-driven healthcare innovation in the global context and in real-time case scenarios across institutions and healthcare sectors. By aligning innovation with ethical and regulatory guardrails, AI can sustainably transform healthcare delivery, improve patient outcomes, and reduce systemic inefficiencies.

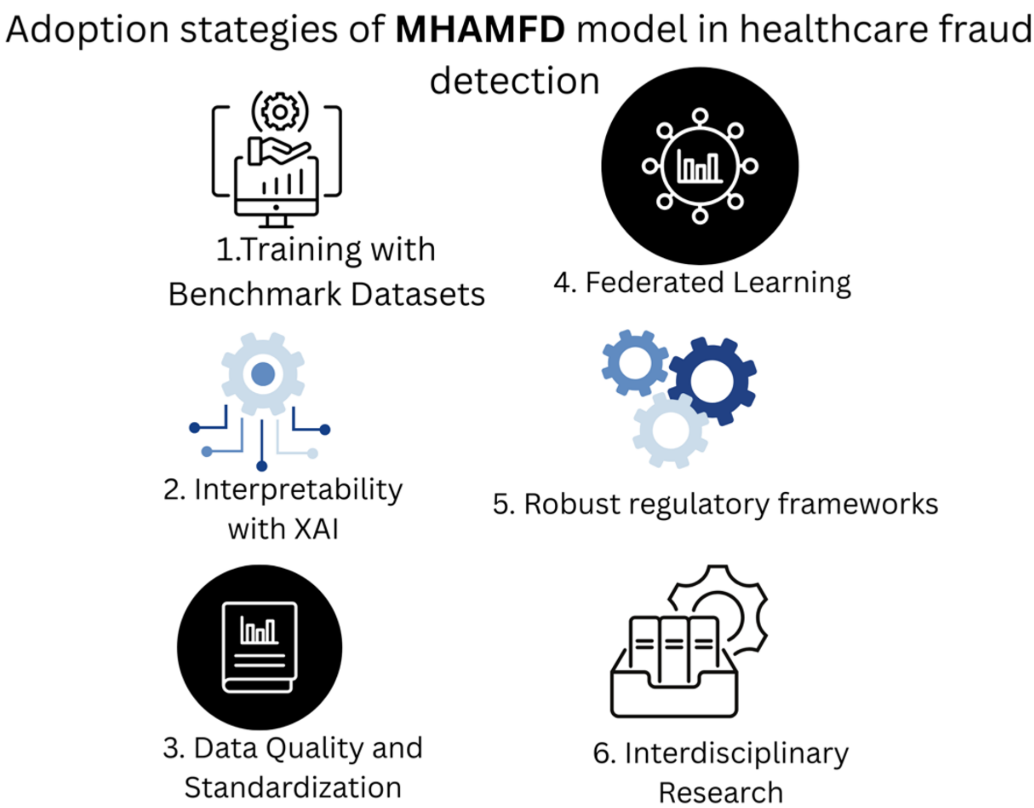


Figure 9. Strategies for MHAMFD adoption in health care fraud detection in real-time.

5. CONCLUSION

AI adoption in the USA healthcare sector is particularly robust and is projected to grow by 35.9% through 2030. Forty-five percent of US healthcare providers have integrated AI tools, with the most prominent applications being predictive analytics and fraud detection systems. For instance, machine learning, including logistic regression, random forest, and CNN, has been successfully applied to disease prediction, forecasting, and patient risk stratification. NLP tools like Amazon Comprehend Medical, Google's DeepMind, and reinforcement learning have enabled AI tools for real-time medication management, diagnosis, test result identification, improved documentation, sequential decision-making tasks, and coding accuracy. The goal of these models is to reduce mortality by adapting treatment paths in real time, mimicking clinician decision-making with increased computational precision. AI-embedded EHR systems further reduce manual data entry, detect clinical anomalies, and generate real-time alerts. When integrated with predictive analytics, these systems can identify at-risk patients earlier, forecast hospital readmissions, and support timely interventions. AI-integrated mobile and wearable devices, including smartwatches and smart inhalers, along with tools like Cogito, analyze voice patterns to detect signs of cognitive disabilities and mental distress, enabling real-time patient monitoring and remote care delivery. AI-IoMT integration facilitates the collection, analysis, and transmission of health data over the internet, supporting real-time diagnostics, remote patient monitoring, personalized treatments, improved patient outcomes, and healthcare fraud detection.

Healthcare fraud is a serious crime that threatens the financial stability and moral integrity of healthcare systems in the USA. The highest intensity levels are concentrated in large states such as Texas, California, Florida, and New York, reflecting both higher fraud conviction counts and significant monetary recoveries. Moderate-intensity states are scattered across the Midwest, Northeast, and South. In this regard, AI offers several promising approaches, such as SMOTE for hospital billing anomaly detection, Graph-Based AI models for collusion and overutilization detection, and ROS and hybrid ROS-RUS techniques for data tampering detection. Besides, the MHAMFD model is regarded as one of the most promising models for AI-driven fraud detection in healthcare, by examining relationships among patients, providers, procedures, and insurers to detect suspicious patterns and anomalies in claims data. Nevertheless, several major concerns about its vulnerability to noise within interaction networks lead to false positives and reduced detection accuracy. Moreover, the generalizability of the MHAMFD model is limited when applied to other types of fraud, such as billing fraud or identity theft, unless the model undergoes extensive retraining or is adapted to specific domains. Additional challenges arise from issues related to data quality and standardization. The model's performance is hindered by fragmented data sources and inconsistent data formats across institutions. Together with XAI, Federated Learning, and interdisciplinary research, these approaches can overcome existing limitations and maximize AI's potential to transform healthcare delivery and governance.

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Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

REFERENCES

[1] F. Gilbert, "Balancing human and AI roles in clinical imaging," *Nature Medicine*, vol. 29, no. 7, pp. 1609-1610, 2023. https://doi.org/10.1038/s41591-023-02441-1

[2] C. Zhang, X. Xiao, and C. Wu, "Medical fraud and abuse detection system based on machine learning," *International Journal of Environmental Research and Public Health*, vol. 17, no. 19, p. 7265, 2020. https://doi.org/10.3390/ijerph17197265

[3] A. A. Ashraf, S. Rai, S. Alva, P. D. Alva, and S. Naresh, "Revolutionizing clinical laboratories: The impact of artificial intelligence in diagnostics and patient care," *Diagnostic Microbiology and Infectious Disease*, vol. 111, no. 4, p. 116728, 2025. https://doi.org/10.1016/j.diagmicrobio.2025.116728

[4] M. A. Khan, I. U. Din, B.-S. Kim, and A. Almogren, "Visualization of remote patient monitoring system based on internet of medical things," *Sustainability*, vol. 15, no. 10, p. 8120, 2023. https://doi.org/10.3390/su15108120

[5] Grand View Research, *Artificial intelligence in healthcare market size, share & trends analysis report by component, by application, by end-use, by region, and segment forecasts*. California: Grand View Research, 2023.

[6] Statista, "Healthcare AI market revenue worldwide from 2020 to 2030," Retrieved: https://www.statista.com/statistics/1107578/ai-in-healthcare-market-size-worldwide/. 2023.

[7] A. Malhotra, E. J. Molloy, C. F. Bearer, and S. B. Mulkey, "Emerging role of artificial intelligence, big data analysis and precision medicine in pediatrics," *Pediatric Research*, vol. 93, no. 2, pp. 281-283, 2023. https://doi.org/10.1038/s41390-022-02422-z

[8] McKinsey & Company, *The state of AI in 2022—and a half-decade in review*. USA: McKinsey & Company, 2022.

[9] A. V. Najar, L. Alizamani, M. Zarqi, and E. Hooshmand, "A global scoping review on the patterns of medical fraud and abuse: Integrating data-driven detection, prevention, and legal responses," *Archives of Public Health*, vol. 83, no. 1, p. 43, 2025. https://doi.org/10.1186/s13690-025-01512-8

[10] K.-H. Yu, A. L. Beam, and I. S. Kohane, "Artificial intelligence in healthcare," *Nature Biomedical Engineering*, vol. 2, no. 10, pp. 719-731, 2018. https://doi.org/10.1038/s41551-018-0305-z

[11] J. M. Johnson and T. M. Khoshgoftaar, "Medicare fraud detection using neural networks," *Journal of Big Data*, vol. 6, no. 1, p. 63, 2019. https://doi.org/10.1186/s40537-019-0225-0

[12] A. Du Preez, S. Bhattacharya, P. A. Beling, and E. Bowen, "Fraud detection in healthcare claims using machine learning: A systematic review," *Artificial Intelligence in Medicine*, vol. 160, p. 103061, 2025. https://doi.org/10.1016/j.artmed.2024.103061

[13] Y. Lu, J. Huang, G. Yang, and H. Zhang, "Health insurance fraud detection by using an attributed heterogeneous information network with a hierarchical attention mechanism," *BMC Medical Informatics and Decision Making*, vol. 23, no. 1, pp. 1-24, 2023.

[14] A. Esteva *et al.*, "A guide to deep learning in healthcare," *Nature Medicine*, vol. 25, no. 1, pp. 24-29, 2019. https://doi.org/10.1038/s41591-018-0316-z

[15] E. J. Topol, "High-performance medicine: The convergence of human and artificial intelligence," *Nature Medicine*, vol. 25, no. 1, pp. 44-56, 2019. https://doi.org/10.1038/s41591-018-0300-7

[16] T. Peregrin, "Managing HIPAA compliance includes legal and ethical considerations," *Journal of the Academy of Nutrition and Dietetics*, vol. 121, no. 2, pp. 327-329, 2021. https://doi.org/10.1016/j.jand.2020.11.012

[17] A. Rajkomar, J. Dean, and I. Kohane, "Machine learning in medicine," *New England Journal of Medicine*, vol. 380, no. 14, pp. 1347-1358, 2019. https://doi.org/10.1056/NEJMra1814259

[18] C. J. Kelly, A. Karthikesalingam, M. Suleyman, G. Corrado, and D. King, "Key challenges for delivering clinical impact with artificial intelligence," *BMC Medicine*, vol. 17, no. 1, p. 195, 2019. https://doi.org/10.1186/s12916-019-1426-2

[19] J. He, S. L. Baxter, J. Xu, J. Xu, X. Zhou, and K. Zhang, "The practical implementation of artificial intelligence technologies in medicine," *Nature Medicine*, vol. 25, no. 1, pp. 30-36, 2019. https://doi.org/10.1038/s41591-018-0307-0

[20] M. K. K. Rony *et al.*, "Nurses' perspectives on privacy and ethical concerns regarding artificial intelligence adoption in healthcare," *Heliyon*, vol. 10, no. 17, p. e36702, 2024. https://doi.org/10.1016/j.heliyon.2024.e36702

[21] G. A. Shabiha and P. Oladokun, "Enhancing financial fraud detection in the United States healthcare systems using explainable AI models," *International Journal of Engineering Technology Research & Management*, vol. 7, no. 12, pp. 276-284, 2023. https://doi.org/10.5281/zenodo.14871264

[22] L. Eckstein, Y. Tan, and B. D. Earp, "Ethical and policy challenges in AI-driven healthcare," *Journal of Medical Ethics*, vol. 47, no. 3, pp. 153–158, 2021.

[23] S. Gerke, S. Yeung, and I. G. Cohen, "Ethical and legal aspects of ambient intelligence in hospitals," *JAMA*, vol. 323, no. 7, pp. 601-602, 2020. https://doi.org/10.1001/jama.2019.21699

[24] W. N. Price and I. G. Cohen, "Privacy in the age of medical big data," *Nature Medicine*, vol. 25, no. 1, pp. 37-43, 2019. https://doi.org/10.1038/s41591-018-0272-7

[25] E. Nabrawi and A. Alanazi, "Fraud detection in healthcare insurance claims using machine learning," *Risks*, vol. 11, no. 9, p. 160, 2023. https://doi.org/10.3390/risks11090160

[26] A. Das, "Healthcare fraud detection using machine learning," *International Journal of Creative Research Thoughts*, vol. 12, no. 4, p. 517, 2024.

[27] Centers for Medicare & Medicaid Services, *Medicare fraud strike force and healthcare fraud prevention partnership annual report 2024*. USA: U.S. Department of Health & Human Services, 2024.

[28] U.S. Department of Health and Human Services & U.S. Department of Justice, "Health care fraud and abuse control program annual report for fiscal year 2023," Retrieved: https://oig.hhs.gov/reports/all/2024/health-care-fraud-and-abuse-control-program-report-fiscal-year-2023/. [Accessed August 14, 2025], 2024.

[29] Codoxo, "AI-driven healthcare fraud, waste, and abuse prevention with Fraud Scope," Retrieved: https://www.codoxo.com/healthcare-fraud-scope/. [Accessed August 14, 2025], 2024.

[30] Saxon AI, "Predictive analytics for hospital operations," Retrieved: https://saxon.ai/blogs/predictive-analytics-in-healthcare/. [Accessed August 14, 2025], 2023.

[31] C. Jones, J. Thornton, and J. C. Wyatt, "Artificial intelligence and clinical decision support: Clinicians' perspectives on trust, trustworthiness, and liability," *Medical Law Review*, vol. 31, no. 4, pp. 501-520, 2023. https://doi.org/10.1093/medlaw/fwad013

[32] Innovaccer Inc, "AI in healthcare: A beacon of hope amidst the great burnout?," Retrieved: https://innovaccer.com/resources/blogs/ai-in-healthcare-a-beacon-of-hope-amidst-the-great-burnout. [Accessed August 14, 2025], 2025.

[33] S. Mandal, A. B. Greenblatt, and J. An, "Imaging intelligence: AI is transforming medical imaging across the imaging spectrum," *IEEE Pulse*, vol. 9, no. 5, pp. 16-24, 2018. https://doi.org/10.1109/MPUL.2018.2857226

[34] S. Baluta, V. Suresh, M. Chmielowska, L. Smeesters, and J. Cabaj, "Improving clinical diagnostics and patient care through artificial intelligence and biosensor technologies," *ACS Omega*, vol. 11, no. 1, pp. 82–99, 2026. https://doi.org/10.1021/acsomega.5c06072

[35] Epic Systems Corporation, "Epic AI Charting rolls out alongside an expanding set of built-in AI capabilities," Retrieved: https://www.epic.com/epic/post/epic-ai-charting-rolls-out-alongside-an-expanding-set-of-built-in-ai-capabilities/. [Accessed February 4, 2026], 2026.

[36] K. Sundaram, S. Vinu, A. Ramamoorthy, and S. Venkatesan, *Optimizing hospital workflows through artificial intelligence. In Evaluation and assessment of AI-driven systems in hospitals*. Hershey, PA: IGI Global Scientific Publishing, 2026.

[37] M. Islam, M. A. U. Z. Khan, M. S. Rahman, S. Acha, and G. E. Isangadighi, "Predictive risk modelling and occupational hazard mapping in the United States healthcare sector: A data-driven safety surveillance study," *European Journal of Medical and Health Research*, vol. 1, no. 2, pp. 153-160, 2023. https://doi.org/10.59324/ejmhr.2023.1(2).24

[38] A. Khang, V. Abdullayev, A. V. Alyar, M. Khalilov, and B. Murad, *AI-aided data analytics tools and applications for the healthcare sector. In AI and IoT-based technologies for precision medicine*. Hershey, PA: IGI Global Scientific Publishing, 2023.

[39] Organization for Economic Co-operation and Development, *Artificial intelligence in society: Global trends in AI adoption*. France: OECD Publishing, 2023.

[40] H. Zhu, L. Liu, and Y. Shi, "Intelligent financial fraud detection practices in the post-pandemic era," *The Innovation*, vol. 2, no. 3, p. 100135, 2021.