Mitigating Revenue Leakage: An AI Framework for Connecticut Healthcare Organizations

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Abstract
This paper examined the impact of AI framework for mitigating revenue leakage in Connecticut Healthcare Organizations as a result of thin margins, strict state cost benchmarks, and complex regional payer dynamics that cause severe financial strain for the organizations. The Technology Acceptance Model (TAM) served as the theoretical roadmap for the review. Using a qualitative, non-empirical conceptual review framework and thematic synthesis, this review analyzed and synthesized healthcare literature from 2019 to 2026 across major databases. The methodology mapped data pipelines across the care continuum to isolate technical friction and deployment barriers. The review indicated that integrated AI frameworks deliver substantial financial protection across regional health networks. Specifically, clinical-grade NLP optimizes comorbidity capture from unstructured documentation, predictive analytics compute pre-bill risk scores to intercept billing errors, autonomous multi-agent systems execute closed-loop denial remediation, and the Patient Prism framework activates front-end appointment recovery within a 60-second window. It was concluded that AI protects revenue, but only if it fits daily workflows and protects data security. It was recommended that to lower alert fatigue, executives should use AI systems tailored to local health insurance data alongside simple, user-friendly dashboards. Also, hospitals should connect separate software systems using standard APIs. This removes manual workarounds, protects data, and keeps information flowing smoothly. Next-gen AI must use self-correcting networks that audit billing and automatically adapt to new regulations.

Keywords: *AI frameworks, Connecticut healthcare organizations, Mitigating Revenue Leakage*

Introduction

Administrative errors, missed billing, and broken processes cause systemic revenue leakage, costing healthcare organizations billions of dollars in unintended losses each year (Kain-Williams, 2026). Flawless workflows are critical to surviving the complex U.S. multi-payer system (Coley, 2026). Escalating documentation and prior authorization hurdles disrupt provider-payer dynamics, driving initial claim rejections past 10% (Leigh, 2022; Long et al., 2026). These systemic denials permanently drain capital rather than just delaying cash flow, eroding the operating margins needed to sustain clinical care and ultimately compromising patient outcomes (Dong, 2015). Hidden revenue leakage severely threatens national healthcare sustainability despite widespread focus on cost containment (Ejiofor, 2025).

Connecticut healthcare systems also face severe financial strain due to strict spending growth caps and heavy regulatory oversight, which legally prevent hospitals from raising billing rates to offset deficits (Golvala, 2026; Katy, 2026; Lisitano & Arden, 2022). Post-pandemic deficits at major networks like Yale New Haven Health and Hartford HealthCare compound this regulatory pressure, fueled by surging labor costs and fixed public insurance shortfalls

(Golvala, 2026; Katy, 2026). Manual audits fail to catch real-time errors, driving severe revenue leakage through claim denials and underpayments. Shifting to proactive financial management is now a necessity to safeguard operating margins. To stop revenue leakage, healthcare providers are embedding integrated AI frameworks directly into their Electronic Health Records (EHR) systems (Adeleke, 2023, 2026; Adeleke & Ajayi, 2024).

AI frameworks act as unified software environments, combining data pipelines and predictive models to continuously refine clinical and financial information (Garba, 2024). Instead of relying on isolated tools, these ecosystems deploy supervised learning for anomaly classification and explainable AI methods like SHAP and LIME to continuously optimize revenue cycle data while ensuring auditable decision transparency (Agbo et al., 2026). They also comprise advanced NLP and LLM frameworks to interpret unstructured clinical narratives and automate accurate billing codes, maximize charge capture, and verify insurance eligibility in real time (Siddiqua, 2026). Predictive analytics utilize historical payer behavior to prevent pre-submission denials, track underpayments, and enforce contract compliance. This end-to-end automation plugs operational leaks to preserve the financial sustainability of health systems navigating complex multi-payer environments (Ejiofor, 2025).

Scholarly research demonstrates that deploying comprehensive AI frameworks in revenue cycle management significantly mitigates financial losses in modern health systems in Connecticut (Ejiofor, 2025; Siddiqua, 2026). Specifically, integrating natural language processing and predictive analytics directly minimizes claim denials, maximizes charge capture, and strengthens overall institutional financial sustainability (Cass, 2026; Ejiofor, 2025; Manoharan, 2026). Conversely, legacy EHR barriers, algorithmic errors, and rigid regulatory caps can stall financial recovery and increase operational friction (Rall, 2024). This contradiction highlights a critical gap in understanding how these tools perform under specialized state oversight. Fixing this mismatch is crucial for showing tech leaders, policymakers, and executives how AI can strategically modernize healthcare billing (Alotaibi et al., 2020). Hence, this paper reviewed various literatures on AI framework for mitigating revenue leakage in Connecticut healthcare organizations.

1. Therefore, the two specific objectives of this review were to: examine the impact of various AI frameworks used for mitigating revenue leakage in Connecticut healthcare organizations; and
2. The challenges facing the use of AI frameworks for mitigating revenue leakage in Connecticut healthcare organizations.

Literature Review

Theoretical Foundation

The Technology Acceptance Model (TAM) offers a structured theoretical lens to evaluate how healthcare organizations adopt and integrate advanced automated systems to safeguard their revenue streams. This model was created by Fred Davis in 1989 and adapts the Theory of Reasoned Action to predict how users accept new computer technology. TAM states that tech adoption depends on two core factors: Perceived Usefulness (will it improve performance?) and Perceived Ease of Use (is it easy to learn?). Together, these two key factors shape a user's attitude and decision to actually use the framework (Davis, 1989). Over decades of research, these core factors have expanded from tracking individual psychology to predicting how entire organizations such as Connecticut healthcare system integrate new tech such as AI frameworks. In Connecticut's healthcare system and economy, strict cost-containment benchmarks from the Office of Health Strategy (OHS) force administrators to re-evaluate their financial tech. These external pressures act as catalysts that drive the health care organizations to adopt new systems to survive financially. TAM reframes AI from a basic IT upgrade into an operational environment where preventing financial losses depends on staff trust. Technical features alone

will not protect revenue. Instead, success hinges entirely on whether users find the software (AI frameworks) easy to use (PEOU) and financially valuable (PU) in their daily workflows (Davis, 1989; Lee et al., 2025).

TAM helps diagnose why financial automation succeeds or fails during daily billing routines. Here, perceived usefulness' implies the AI's actual ability to protect the bottom line by blocking claims denials, finding unbilled procedures, and spotting insurance underpayments. Meanwhile, 'perceived ease of use' looks at how smoothly the software fits into hectic, high-pressure shifts. If billing teams can quickly audit the AI's transparent algorithms without disrupting their current EHR systems, operational friction drops dramatically. Validating usefulness and usability shows how Connecticut health systems can swap manual audits for automated financial tools to survive long-term (Beraducci, 2025; Davis, 1989). A diagrammatic illustration is shown below:

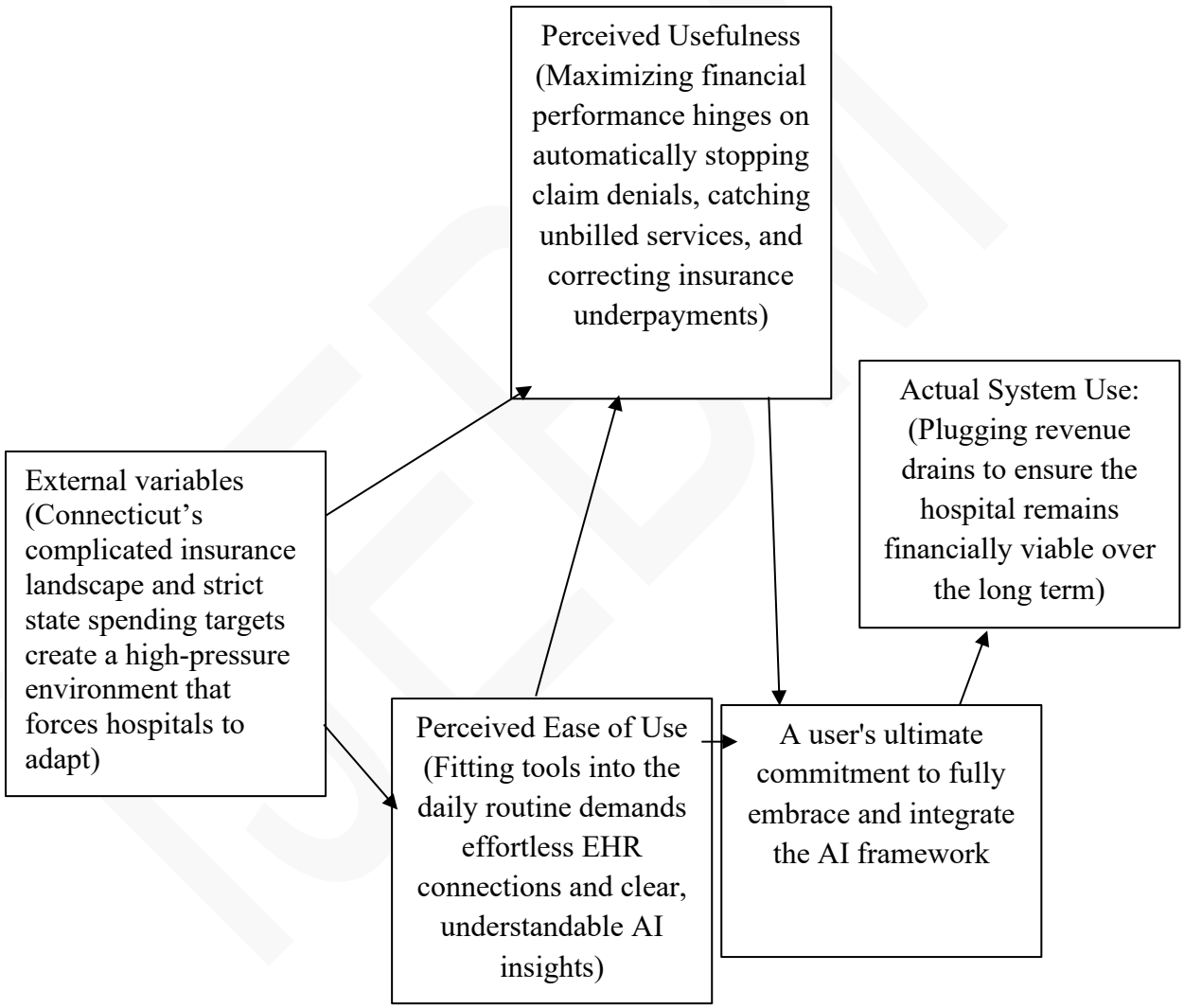


Figure 2.1: Modified Technology Acceptance Model (TAM) for AI Revenue Framework (Source: Author, 2026)

This adapted TAM framework shows how Connecticut's regulatory pressures force hospitals to adopt healthcare AI. These market conditions dictate whether the tech is financially useful and fits daily workflows, which ultimately drives the shift from manual audits to automated revenue protection.

Conceptual Clarifications

Healthcare Organizations

A healthcare organization is any public or private entity providing medical services, including hospitals, clinics, nursing homes, and rehab centers. The term covers any care setting where diagnostics take place, from private clinician practices to integrated hospital networks (Agency for Healthcare Research and Quality, 2025). Healthcare organizations provide resources and infrastructure to medical professionals like doctors and nurses to deliver high-quality, affordable care. Their core mission is to lower costs and expand access to services for as many patients as possible (Hilaris Publisher, 2026). Faced with rising costs, healthcare organizations are changing how they operate to improve medical care, safety, and rehabilitation. Because of this, their management is under close scrutiny to ensure their research, training, and services directly address local community health needs (WisdomLib, 2026).

Revenue Leakage in Healthcare Organizations

Revenue leakage occurs when hospitals fail to track, code, or collect payments properly across separate departments like registration and coding (Alpine Pro Health, 2025; Ullah, 2023). It is the quiet, preventable loss of earned income caused by administrative and operational gaps. It stems from missed billing charges, coding errors, denied insurance claims, and poorly managed medical inventory. Because these minor leaks occur diffusely across different departments, they easily go unnoticed. Over time, however, these small, daily losses compound into severe, irreversible budget deficits (Cheptora, 2026). Revenue leakage stems from minor gaps like billing typos, unbilled services, and contract noncompliance. Because these operational errors happen quietly at the ground level, high-level financial statements rarely catch them (Fardous, 2026). Hospitals lose potential revenue when clinical bottlenecks, administrative errors, and unchallenged insurance denials prevent full payments (Ejiofor, 2025; Rackley, 2025). Fragmented workflows allow these losses to slip past traditional audits unnoticed. Lacking real-time visibility, organizations underestimate these compounding errors and fail to fix them proactively (Ejiofor, 2025).

AI Framework

An AI framework coordinates data flows and software systems to maximize financial performance across the billing cycle (Garba, 2024). This system uses Supervised Learning to flag billing anomalies and Explainable AI (XAI) to ensure audit transparency. Simultaneously, NLP and LLMs read unstructured clinical notes in real time to automate coding, maximize charge capture, and instantly verify insurance eligibility (Siddiqua, 2026). Predictive analytics shifts financial management from reactive dispute tracking into automated early prevention by auditing historical payer data before claims are submitted. These adaptive machine learning models uncover hidden leakage patterns, forecast denial risks, and spot undercoding vulnerabilities. Unlike rigid legacy software, the algorithms continuously learn from changing reimbursement trends to improve precision over time. By embedding these automated alerts directly into provider workflows, the system plugs operational revenue leaks, secures contract compliance, and protects long-term institutional survival (Ejiofor, 2025).

Methodology

This study uses a conceptual review and thematic synthesis to design an operational model that connects data science with healthcare finance. This paper applied systems engineering to evaluate AI integration in regional healthcare and its deployment obstacles. The method used literature reviews, process mapping, and friction analysis to deliver a legally sound strategy that isolates operational bottlenecks. Healthcare administration automation was systematically reviewed by searching databases like PubMed, IEEE, Google Scholar and healthcare provider

websites and other online resources. The search used specific strings combining terms like "revenue leakage" and "NLP medical coding" with local filters like "Connecticut Office of Health Strategy cost benchmarks. The final selection focused on peer-reviewed articles, health economics texts, and regulatory reports from 2019-2026. Criteria focused on machine learning, NLP, autonomous multi-agent networks, and patient prism AI frameworks designed to mitigate revenue leakages.

This review applied thematic synthesis to translate data theory into clinical workflows. Proactive pipelines mapped across all care stages demonstrate how real-time algorithms catch documentation gaps and errors early to stop financial waste. By shifting administration from reactive disputes to proactive revenue protection, it turns passive retrospective reporting into immediate recovery workflows. Simultaneously, the literature was analyzed to isolate the operational, ethical, and organizational barriers that slow down AI framework integration. The framework categorizes these friction points into algorithmic drift, legacy data silos, regulatory compliance risks, and physician alert fatigue. This analysis ensures the roadmap balances technical feasibility with the human and regulatory constraints of healthcare. The resulting template helps executives guide strategic AI deployment while meeting state cost benchmarks and health equity guidelines.

The Impact of Various AI Frameworks Used for Mitigating Revenue Leakage in Connecticut Healthcare Organizations

Mitigating revenue leakage is vital for the financial survival of Connecticut's healthcare sector. Deploying AI frameworks, like NLP, predictive analytics, and multi-agent machine learning, is essential to transform revenue cycle management across the state's medical network (Adeleke, 2026; Ejiofor, 2024; Nahar et al., 2025). Revenue leakage usually stems from documentation errors, administrative friction, and payer disputes. Historically, these compounding errors have cost regional health systems millions of dollars in unrecovered care margins (Manoharan, 2026). Research from 2019 to 2026 shows that AI's financial success depends on its technical setup, algorithmic maturity, and ability to handle local payer requirements. Viewed through the Resource-Based View (RBV), these advanced systems serve as unique organizational assets that secure capital and optimize hospital operations (Cass, 2026; Manoharan, 2026; Raths, 2026). A critical appraisal of recent literature reveals four primary themes for the use and impact of various AI frameworks for mitigating revenue leakage in Connecticut healthcare organizations.

Theme 1: Natural Language Processing (NLP) for Clinical Documentation Optimization

A major focus in recent health systems research is using deep NLP frameworks to capture mid-cycle revenue (Adeleke, 2026). Manual billing frequently misses secondary conditions, patient severity levels, and specific medical justifications hidden within unstructured clinical text (Adeleke, 2026; Adeleke & Ajayi, 2024). This blind spot causes systematic under-coding and incorrect DRG assignments (Adeleke, 2026; Manoharan, 2026). Advanced medical NLP software uses deep learning to review unstructured clinical notes on the fly. By instantly linking medical narratives to accurate ICD-10-CM and CPT codes, it catches human errors and ensures insurance claims match the exact level of care provided (Adeleke & Ajayi, 2024; HIMSS Market Scan, 2024; Manoharan, 2026).

Hartford HealthCare's deployment of an NLP mid-cycle automation framework across its seven Connecticut hospitals highlights the clear financial benefits of this approach. By syncing clinical charts with billing workflows, the system flagged missed charges and sped up documentation queries. This integration recovered $16 million in leaked revenue in just 90 days, proving that turning unstructured data into verifiable codes safeguards financial health

(Georgios et al., 2026). The figure below illustrates NLP for clinical documentation optimization.

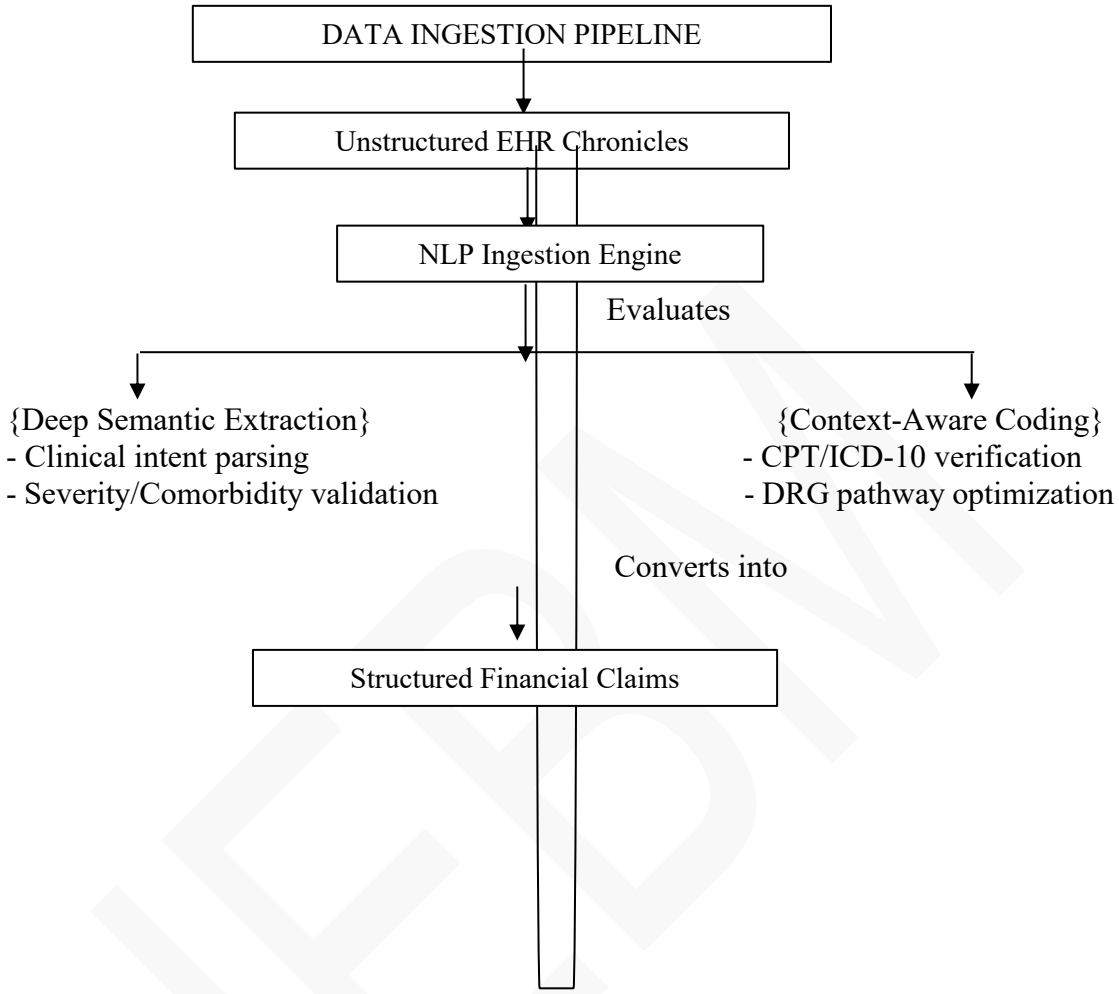


Figure 4.1: Illustration of NLP for clinical documentation optimization: A case of Hartford HealthCare, Connecticut (Source: Author's illustration)

Theme 2: Predictive Frameworks and Denial Prevention Engines

While NLP fixes mid-cycle documentation, predictive analytics plug front- and back-end revenue leaks. Denied claims drive the most losses for regional healthcare networks, as the heavy administrative cost of reworking them quickly drains tight operating margins (Adeleke, 2023; Cass, 2026; Raths, 2026). Predictive denial engines use machine learning to score a claim's financial risk before submission, stopping revenue loss at the source (Adeleke, 2023, 2026; Adeleke & Ajayi, 2024; Manoharan, 2026; Manoharan, 2026).

By analyzing historical transactions, clearinghouse data, and payer rules, these systems assign a real-world denial risk score to each pending claim (Manoharan, 2026). Claims exceeding a risk threshold—usually from bad code mixes, missing paperwork, or prior authorization errors—are flagged for instant human review (Adeleke, 2023, 2026; Adeleke & Ajayi, 2024). This shifts revenue operations from reactive recovery to proactive prevention—a vital strategy within the Yale New Haven Health System (Adeleke, 2026; Cass, 2026; Manoharan, 2026; Muzahidul & Aditya, 2024; Raths, 2026). To phase out rigid, rules-based billing, Yale New Haven Health System co-invested in a $51 million venture initiative to deploy advanced tools like the Arintra Platform, which checks millions in institutional claims to predict payer

rejections and uncover hidden variance patterns (Cass, 2026; Gleeson, 2026; Raths, 2026). This deployment drove a 5.1% boost in compliant revenue capture and cut coding denials by 43%, proving the financial value of automated, proactive risk profiling (Cass, 2026; Raths, 2026).
AI frameworks have established a measurable financial impact by systematically plugging Connecticut-specific leakage vectors (Patient Prism, 2026). Moving from generic risk models to localized, multi-checkpoint eligibility and prior-auth platforms lets regional providers catch administrative errors before they turn into expensive rejections (Muzahidul & Aditya, 2024; CodeBranch Team, 2026; Manoharan, 2026). Real-world data shows that tuning autonomous coding and predictive denial systems to local Blue Cross and HUSKY Health patterns turns billing friction into reliable, compliant cash flow (Adeleke & Ajayi, 2024; Cass, 2026; David, 2026; Raths, 2026). Under strict written governance, these systems turn raw EHR data into protected financial margins across the state's complex payer mix (Maddela, 2025; Manoharan, 2026).

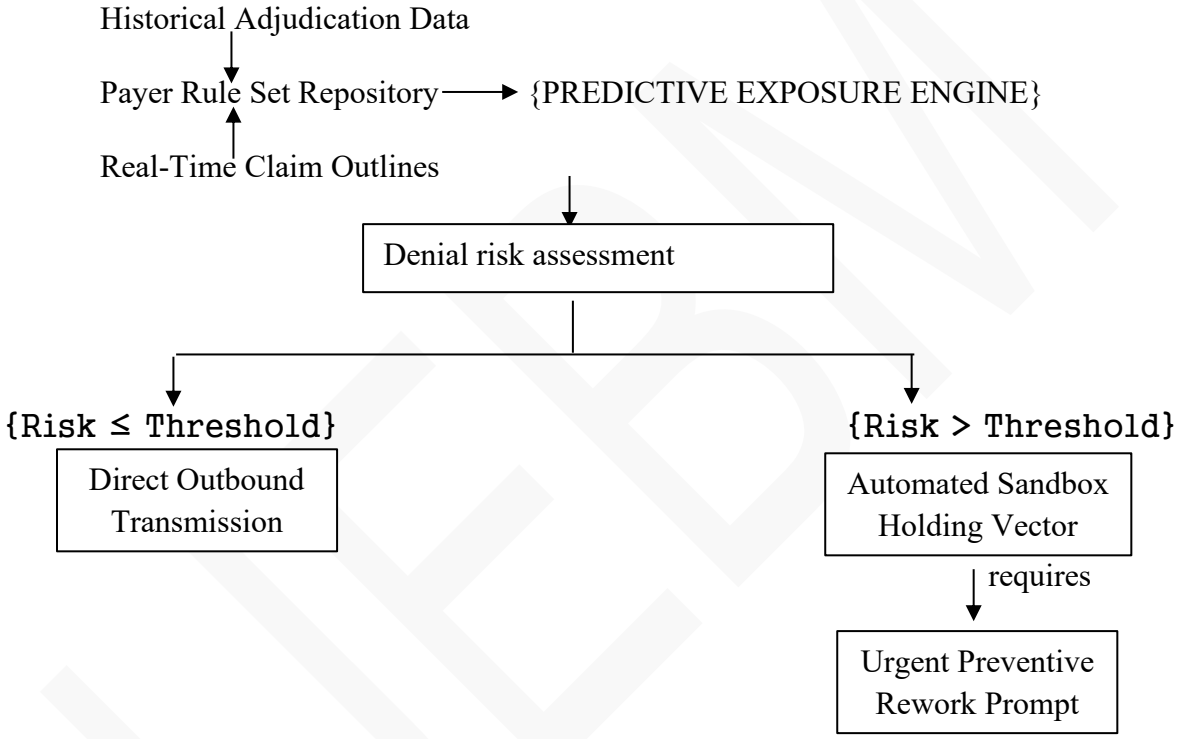


Figure 4.2: Illustration of Predictive Frameworks and Denial Prevention Engines: A case of Yale New Haven Health System, Connecticut (Source: Author's illustration)

Theme 3: Multi-Agent Systems and Localized Payer Calibration
This agentic architecture plugs revenue leaks by shifting directly from passive analytics to autonomous execution (Cass, 2026; Raths, 2026; Taware, 2025). When a network like Yale New Haven Health deploys Arintra's agentic AI, the system goes beyond flagging errors; it sends specialized digital agents to actively manage cross-functional workflows (Cass, 2026; Raths, 2026).

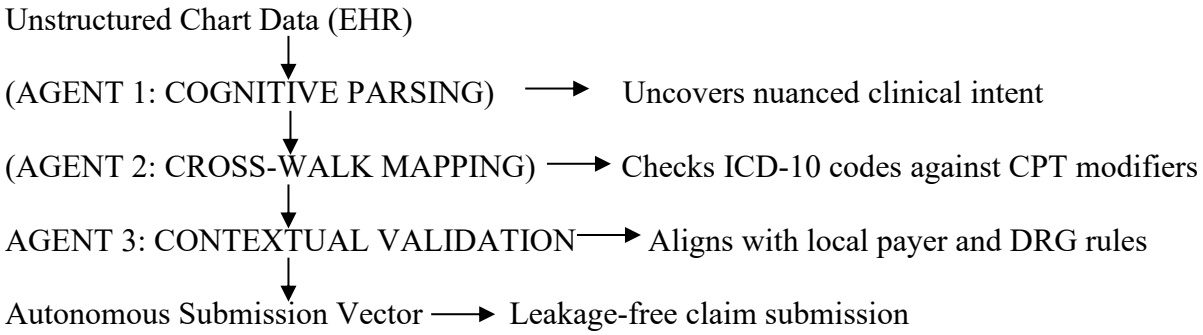


Figure 4.3: Multi-Agent Systems and Localized Payer Calibration (Author's illustration based on the works of Cass, 2026 and Raths, 2026)

This automated mitigation process operates via three tightly coupled operational phases:

i. **Autonomous Mid-Cycle Chart Ingestion:** Instead of waiting for a manual review, the system's NLP agent parses unstructured EHR files immediately upon patient discharge. By analyzing clinical context instead of static keywords, it extracts overlooked secondary comorbidities and complications (CC/MCC) to assign the highest compliant Diagnosis-Related Group (DRG) pathway (Cass, 2026; Raths, 2026).

ii. **Real-Time Payer Cross-Walking:** A second agent matches the file against local rules, catching the shifting prior-auth demands of Anthem Blue Cross and HUSKY Health (Cass, 2026; David, 2026; Raths, 2026). If a modifier or code combo is wrong, the agent uses APIs to pull historical intake files and insert the needed prior-auth token before submission (David, 2026; Patient Prism, 2026).

iii. **Closed-Loop Denial Remediation:** If a claim is rejected, a denial agent reads the specific reason code, pulls clinical proof from the EHR, drafts an appeal, and uploads it directly to the payer portal (Adeleke & Ajayi, 2024; Cass, 2026; Raths, 2026).

Arintra's agentic system for example connects clinical records directly to appeals, completely bypassing manual steps and clearing out billing backlogs (Cass, 2026; Raths, 2026). This automation cuts administrative friction, stops underpayments from turning into bad debt, and creates a strict compliance shield that protects tight hospital margins (Muzahidul & Aditya, 2024). With intense competition between heavyweights like Anthem, Aetna, and public HUSKY Health options, generic billing apps cannot handle Connecticut's unique healthcare market (Cass, 2026; Raths, 2026). Research highlights that multi-agent systems deliver superior results by assigning dedicated algorithms to handle specific local insurer rules (Adeleke & Ajayi, 2024; Kaur & Konstantin, 2025; Spieser et al., 2026).

This serverless architecture divides the work among specialized AI tools: one handles prior authorizations, another verifies local insurance coverage, and a third identifies underpaid claims. (Muzahidul & Aditya, 2024; Singhal et al., 2025). Since insurers modify payment and clinical guidelines without notice, these systems rely on local transaction data to constantly update (Adeleke & Ajayi, 2024; Manoharan, 2026). This strategy excels in local practices. For instance, Connecticut's Saisystems Health embeds machine learning directly into regional practice management software. Tuned to local insurance rules, these models fix front-end intake errors and back-end underpayments, saving smaller clinics from writing off lost revenue as bad debt (Adeleke & Ajayi, 2024; Saisystems Health, 2026).

Theme 4: Patient Prism and Revenue Leakage Detection

Patient Prism serves as an AI revenue framework that stops front-end leakage in Connecticut healthcare groups by capturing missed patient opportunities. Using DeepLens AI, the system spots stalled interactions and sends staff rapid recovery alerts within 60 seconds of a failed booking (Patient Prism, 2026).

Table 4.1: Summary of the various AI Frameworks for Revenue Leakage

AI Framework Type	Specific Use Case Area	Operational Impact Metrics	Case
Natural Language Processing (NLP)	Mid-cycle chart analysis and automated code assignment	Recovered $16M within 90 days Speed up clinical queries	Hartford HealthCare
Predictive Analytics Engines	Predictive claim scoring before submission	Yielded 5.1% higher revenue capture and reduced coding denials by 43%	Yale New Haven Health
Multi-Agent Networks	Segmented billing workflows and regional insurer rules	Live underpayment tracking and Instant front-end error checking	Saisystems Health
Patient's Prism	Streamlines patient intake across all communication channels	Clinics see a 15% to 30% jump in booked appointments within three months	Connecticut State Dental Association (CSDA)

(Source: Author's Compilation, 2026)

The Challenges facing the Use of AI Frameworks for Mitigating Revenue Leakage in Connecticut Healthcare Organizations

While these frameworks offer clear financial benefits, their success depends entirely on breaking down data silos and reducing workflow friction across the hospital (Cass, 2026; Raths, 2026). When deploying AI over legacy infrastructure, healthcare groups face poor EHR interoperability, messy clinical data, and missing data-sharing pipelines (Sully AI, 2026). These hurdles derail automated workflows and complicate backend systems (Adeleke & Ajayi, 2024; Cass, 2026; Raths, 2026; Patient Prism, 2026; Adeleke, 2026; Manoharan, 2026). Without native APIs, staff resort to manual workarounds like copy-pasting files between separate systems or entering updates by hand (Adeleke & Ajayi, 2024; Rockett, 2025). This operational disconnect makes the AI far less useful (Cass, 2026; Raths, 2026). Literatures reveal that when staff ignore automated tips, it stems from poor onboarding, clunky dashboards, or silos between clinical and finance teams (Adeleke, 2023, 2026; Adeleke & Ajayi, 2024; Patient Prism, 2026).

Furthermore, staff shortages and hectic shifts cause rushed, incomplete data entry during rounds. If providers skip secondary details to save time, the underlying data stream falls apart (Adeleke & Ajayi, 2024; Sully AI, 2026). By pairing private clouds with strict data-sharing agreements, local health networks protect patient files during automated financial reviews (Cass, 2026; Manoharan, 2026; Raths, 2026). Ultimately, AI tools only stop revenue drain when they are fully integrated with hospital staff and tailored to the local regulatory landscape (Adeleke, 2023, 2026; Adeleke & Ajayi, 2024; Cass, 2026; Manoharan, 2026; Raths, 2026).

Conclusion

Old-school, reactive billing models just cannot keep Connecticut health networks afloat in today's brutal financial and regulatory climate. This paper presents a framework combining data science and healthcare finance to show how integrated AI such as NLP, predictive scoring, and multi-agent systems stop revenue leakage. By replacing slow dispute resolution with automated, real-time prevention, this framework eliminates info gaps between payers and providers to protect revenue. This architecture gives regional healthcare executives a clear way

to maintain financial stability, boost efficiency, and meet state cost mandates without sacrificing patient care. However, AI adoption to stop revenue leakage is bottlenecked by poor EHR interoperability and a lack of native APIs, forcing staff into manual workarounds. Additionally, severe staff shortages and clunky dashboards lead to rushed data entry and ignored insights. Ultimately, AI cannot prevent revenue drain unless hospital technology, staff workflows, and local regulations are completely aligned.

Recommendations

On the basis of the objectives and conclusion of this review, the following recommendations are therefore proffered:

Deploying hospital-wide medical NLP to improve charts and accurately capture patient complications

Embedding clinical NLP into EHRs allows deep learning to parse complex physician notes and catch overlooked patient complications. This automates chart reviews, ensures accurate billing codes, and protects revenue without manual bottlenecks.

Using custom regional data models to track and match changing insurance rules automatically

Connecticut healthcare networks need AI calibrated to local insurance rules rather than generic billing software. By adapting in real time to shifting policies from plans like Anthem BCBS and HUSKY Health, the system catches errors and automatically inserts correct authorization tokens before claims are sent, blocking costly denials

Using pre-billing risk scores to catch and automatically fix insurance denials before they happen

Health networks must pair predictive analytics with automated denial fixes. By risk-scoring claims before submission, high-risk bills are isolated for human review. If a denial happens, backend agents instantly pull clinical proof from the EHR and automatically submit a targeted appeal packet directly to the insurer.

Using real-time patient check-in updates to secure and verify revenue at the front desk

To prevent front-end revenue loss, practices must use real-time intake tracking tools like Patient Prism's DeepLens AI to monitor calls and texts. If a patient leaves without booking an appointment due to scheduling or pricing hurdles, the system sends an alert to front-desk staff within 60 seconds. This fast notification gives the team the immediate context and talking points needed to contact and win back the patient.

Building strategic plans to fix systemic tech issues and overcome staff resistance to new software

AI success depends on breaking down legacy data silos and managing staff friction. Hospitals must use native APIs to replace messy, manual file-copying. Additionally, introducing structured onboarding and user-friendly dashboards helps stop alert fatigue and staff resistance. Bridging the gap between clinicians and finance teams ensures AI tips are actually adopted to protect long-term financial margins.

Future Directions

Transitioning to self-adjusting AI networks with multiple specialized agents: Future healthcare systems must use serverless AI agents to automate workflows and update claims. These tools automatically update their own models based on real-time audit trends rather than relying on old reports.

Setting up ongoing checks to monitor and update hospital AI models: Strict oversight frameworks must regularly audit financial AI models to prevent bias, drift, and billing compliance errors.

Connecting disconnected systems using standardized APIs to break down data silos: Hospitals must mandate standardized EHR integrations to eliminate manual file-copying and keep data streams secure and compliant.

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