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Research Article

EXPLAINABLE AI FOR DETECTING INSIDER THREATS IN HEALTHCARE SYSTEMS

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Abstract

A high-risk concern is the presence of healthcare insider threats: through which authorized users purposefully or accidentally expose or steal electronic health record (EHR) data, the attackers already have a credential, clinical context and workflow permissions that enable the abnormal behaviour to be invisible and hard to detect as such and legitimate care delivery. The paper proposes a principled architecture of an Explainable AI (XAI) which can assist in detecting such insider threats and also produce audit-ready explainable and causally-oriented explanations that may be utilized by the compliance team and investigators. We do it in a hybrid manner, where feature engineering by clinical-workflow awareness, inherently interpretable model families (e.g. rule lists, GAMs), a causal layer into which feature query counterfactual questions about clinical legitimacy are asked, and an evidence-packaging subsystem to produce tamper-evident investigation bundles. We evaluate the design objectives on three scales: detection utility against severe class imbalance and distributional shift, explanation fidelity and causal defensibility and human auditor effectiveness (triage accuracy, time and trust). It has been shown by simulation and clinician in the loop experiments that causal and counterfactual accounts reduce the false positives due to valid-but-infrequent clinical episodes, and material increase the speed of auditor triage without a loss of recall. The contributions publish (1) a stricture of XAI architecture of healthcare insider identification; (2) a system of justification that gives alert to compliance evidence levels; and (3) an assessment system by incorporating an adversarial stress test and human factors measurements.

Keywords: Insider threat, Healthcare security, Electronic health records (EHR), Explainable AI (XAI), Causal explainability, Counterfactual explanations, Auditability, Fairness, Uncertainty calibration.

1. INTRODUCTION

The medical systems are highly data intensive and stakes intensive. Clinicians, nurses, technicians, billing staff, contractors, all of them are interacting with electronic health records (EHRs) and related clinical systems on a regular basis; any of the insiders can look at the information about the patient out of the context of providing care, and the consequences can be devastating: patient privacy, reputation, fines, and, most importantly, patient trust can be lost. In their turn, the insiders are already authenticated and familiar with the context (list of patients, typical workflow), but external attackers lack this information and can therefore be difficult to notice: unauthorized/abusive accesses will often appear (on the face of it) as regular care procedures. The investigations of the mass breach and audit-log analytics studies show that the cases of insiders continue to be a puzzling and thorny problem to healthcare organizations. The research question within the scope of this paper is the following: How can we develop an AI system that could be relied upon to produce high risk insider behaviour flags within healthcare, as well as provide explanations that can be comprehended, be legally interpreted and practically utilized by auditors and compliance teams? Our suggested condensed response is to combine clinical-workflow contextualization, interpretable modeling, causal reasoning to validate legitimacy, and compliance grade evidence packaging into a unified functional pipeline - and evaluate it no longer in isolation on the basis of accuracy but also on the outcomes of human decision-making, audit readiness and fairness.
We define some important terms employed in the manuscript below and summarize the high-level scope.

1.1 Definitions of key terms

- **Insider threat (healthcare):** Any instance where an authorized user of healthcare IT systems accesses, modifies, or exfiltrates protected health information (PHI) in a manner that is unauthorized, malicious, or negligent relative to their legitimate duties and institutional policies. Insider threats include curiosity-driven snooping, revenge or opportunistic disclosures, credential sharing, and careless disclosure due to poor hygiene.
- **EHR audit logs:** Time-ordered records that document user interactions with electronic health records and related systems (who accessed which record, what action was performed, on what device, and when). Audit logs are a primary data source for retrospective insider investigations and for training detection models.
- **Explainable AI (XAI):** A family of methods and practices that aim to make machine learning model outputs understandable to humans. XAI techniques include inherently interpretable models (e.g., rule lists, GAMs), post-hoc attribution (SHAP, LIME), counterfactual explanations, and causal inference methods that attempt to expose not just correlations but plausible cause–effect relationships. In healthcare, XAI is crucial because model decisions can affect patient privacy, clinician careers, and regulatory compliance.

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- **Counterfactual explanation (in XAI):** A localized explanation that answers "what minimal change to inputs would have changed the model's prediction?" Counterfactuals are useful for auditors because they offer actionable, contrastive statements (e.g., "If the clinician had had a documented encounter with the patient that day, the access would not be anomalous"). However, counterfactuals generated from predictive models do not, on their own, establish causal relationships; integrating them with causal domain knowledge improves defensibility.
- **Audit-ready evidence bundle:** A structured, tamper-evident package containing raw logs, feature derivations, model scores, explanation artifacts (e.g., counterfactuals, rule traces), and investigator access logs. Such bundles are crafted to meet internal HR thresholds and, where necessary, legal evidence standards.

1.2 Motivation and unique challenges

Three interdependent features of healthcare make insider detection and explanation particularly hard:

1. **Clinical legitimacy confounds anomalies.** Many accesses that *look* unusual (off-shift access, accesses to high-profile patients, cross-departmental access) are perfectly legitimate when situational context is considered — e.g., emergent consultations, on-call transfers, telehealth visits and naive anomaly detectors generate many false positives as a result. A detection system must therefore reason about clinical context, not just statistical rarity. P
2. **High cost of false positives.** False alerts can interrupt care, waste investigator time, diminish clinician trust, and — if mishandled damage careers. Thus thresholds, uncertainty quantification, and human adjudication pathways are essential design elements. Human factors research shows poor UX and alert overload reduce the effectiveness of security systems in health settings.
3. **Regulatory and evidentiary requirements.** Audit logs must support compliance investigations (e.g., OSHA/HIPAA frameworks and organizational policy actions). Explanations must therefore be more than intuitive: they should map to evidence tiers and preserve provenance, immutability, and versioning. Recent literature on AI auditability and XAI in healthcare highlights the need for methods that are not only interpretable but also auditable and aligned with regulatory needs.

1.2 Scope and contributions

This manuscript develops a design and evaluation blueprint for an Explainable AI pipeline that: (a) ingests heterogeneous healthcare logs and contextual clinical data; (b) generates interpretable predictions using hybrid modeling (interpretable models + causal checks); (c) produces counterfactual and rule-based explanations mapped to compliance evidence tiers; and (d) measures system utility via detection metrics and human auditor outcomes. Specifically, we contribute:

- A clinical-workflow aware feature taxonomy for insider detection.
- A modeling stack that couples interpretable learners with a causal legitimacy layer and uncertainty calibration (Section 8).
- An explanation and evidence packaging specification tailored for auditors and compliance.
- A rigorous evaluation protocol combining adversarial stress tests, distributional-shift experiments, and human factors studies that quantify both algorithmic and organizational performance.

2. RELATED WORK

Insider threat detection in healthcare sits at the intersection of three distinct research streams: (1) healthcare audit-log analytics, (2) insider threat detection and anomaly modeling, and (3) explainable and causal AI for high-stakes environments. Despite progress in each area, few approaches jointly deliver *clinical context awareness*, *interpretable detection*, and *compliance-grade evidence generation*. This gap motivates the unified framework in this paper.

2.1 Healthcare Audit-Log Analytics and Insider Threats

The use of audit logs to detect insider threats in a prospective manner is a more recent development, whereas healthcare organizations have always used audit logs to run retrospective investigations. The initial research made use of heuristics that are rule-based (e.g., identifying accesses to unassigned departments or high profile patients), and discovered that these rules were plagued with too many false positives because of the variability of clinical workflows. An overview of audit-based surveillance in health systems has indicated that frequency does not imply legitimacy since infrequent actions are usually clinically warranted (Chen *et al.,* 2022). There have since been more advanced behavioral profiling methods. The recent massive studies of EHR access patterns show that relational signals, i.e. documented patient-clinician interaction, presence of a treatment team co-member, proximity to clinical events, significantly minimize false alerts over log-only anomaly detection (Hwang & Lee, 2023). These studies, however, mostly focus on detection as a statistical modeling issue, and little has been done to investigate interpretability or usability by the investigator. An analogous body of knowledge examines the environmental issues of healthcare log information. Several reports detail disintegration among EHR vendors, absence of single identity management, the absence of provenance metadata, and incomplete information exchange between clinical units (Nguyen *et al.,* 2023). These operational gaps leave the investigations of the insiders blind in information and makes generalization of AI models difficult in institutions.

Insider Threat Detection beyond Healthcare

General insider threat detection has evolved away form signature based techniques to machine learning, with behavioral modeling becoming the prevailing paradigm. Patterns that are likely to be detected as anomalies, clustering, graph analytics, and sequence

modeling are usually applied to the actions of users within an enterprise environment (Liu *et al.,* 2021). Nevertheless, enterprise insider behavior is not the same as clinical behavior: corporate users are likely to have well-defined access boundaries whereas clinicians do not deal with static and rigid information demands based on patient care. The popularity of risk scoring methods is explained by the possibility to bring together heterogeneous signals (access histories, device logs, network flows, HR risk indicators, etc.) into single profiles (Rashid & Li, 2022). Although useful, such scores can be causally ungrounded and lack sufficient transparency into the reasons a user was flagged, which is essential in healthcare, and why an investigator must explain their choices to compliance boards or other regulatory auditors. Adversarial analyses also indicate that behavior based detectors are susceptible to mimicry insiders having knowledge of baseline behavior can then evade simple anomaly detectors strategically (Kumar *et al.,* 2023). This has resulted in a tendency towards hybrid models which include contextual signals, organizational rules as well as psychological risk indicators. However, such improvements tend to make models more complex and less interpretable, which is an unsustainable tradeoff in healthcare institutions where the consequences of making a decision could be more severe than just professional or legal.

2.3 Explainable AI in High-Stakes Domains

Explainable AI has expanded exponentially as a result of audits, the changing regulation, and lack of trust in black box decisions by people. This is because XAI methods can be broadly classified into two major categories: the intrinsically interpretable models (e.g., decision trees, generalized additive models, rule lists) and the post-hoc explanations to more complex learners (e.g., SHAP, LIME, saliency scores) (Gunning *et al.,* 2023). In the medical domain, XAI implementation has exceeded security applications of use, mostly in clinical diagnostics and treatment assistance. Research suggests that interpretations should be clinically rationalized, multi-modal, uncertain, and consistent with human sensemaking to prevent automation bias or blind belief (Jha and Topol, 2023). Notably, the studies involving users demonstrate that structured reasoning chains are much more appreciated by physicians and auditors than feature importance scores alone (Ribeiro and Singh, 2022). This realization directly translates to investigation of insider threats: raw scores of anomalies or weights of features cannot be used without explanation. Counterfactual explanations have been brought to focus on their ability in assisting decision recourse -e.g. how an alert could have been avoided. Nevertheless, recent criticisms emphasize the fact that counterfactual plausibility is not the same as causal validity; under the absence of domain restrictions, counterfactual can be used to make unrealistic explanations (Karimi *et al.,* 2024). Based on this, the emerging literature suggests using a combination of counterfactual generation and causal graphs or domain invariants to increase validity - a strategy that is very applicable in the case of having clinical legitimacy models. Outside the clinical AI, AI audit trails have grown up. The new paradigms believe that explanations should be versioned, immutable, and reproducible to be used in an organizational evidence (Brundage *et al.,* 2024). All these frameworks are mostly theoretical without many implementations being specific to healthcare insider investigations.

2.4 Human Factors and Auditor-Centered Evaluation

A common topic in sociotechnical security studies has been that the failure of detection systems is not one of scoring, but of human interpretation and organizational response. Research at security operations centers (SOCs) indicates that alert fatigue, insufficient quality of explanations, and threat queues prioritization diminish accuracy of the investigators and slow incident response (Park *et al.,* 2022). In the field of healthcare, the role of investigators is not that of career security analysts, but practices part-time as compliance officers, privacy teams, or clinical informatics employees on security cases. A literature review on the security usability in hospitals shows that researchers focus more on aspects to be clear, provenance, and clinical legitimacy rather than the novelty of the algorithm (Martinez & Gilbert, 2023). Evidence triage in a timely way is more important than tedious modeling and explanation should be backed by fast judgment and not statistical savvy.

2.5 Gaps in the Literature

Despite progress, existing research falls short in five integrated areas:

i. Clinical context-aware legitimacy reasoning: many models flag anomalies without encoding *why the access may have been appropriate*.
ii. Causal interpretability: attribution methods often lack grounding in clinical cause-effect relationships.
iii. Compliance-grade evidence generation: few systems produce forensically robust, tamper-evident audit packages.
iv. Human auditor evaluation: technical accuracy is often measured, but *decision quality, speed, and cognitive load* are rarely assessed.
v. Harm-aware deployment: little attention is given to role-based false positive rates, career impact, accountability, or model misuse prevention.

2.6 Positioning of This Work

This paper differentiates itself by unifying:

- Clinical-workflow modeling to reduce false flags rooted in legitimate care activity,
- Causal and counterfactual XAI to justify decisions beyond correlational evidence,
- Compliance-oriented evidence generation to support investigations,
- Human-in-the-loop evaluation emphasizing auditor decision performance,

- Fairness, uncertainty quantification, and governance to mitigate institutional harms.

Rather than treating insider detection as purely a machine learning task, we frame it as a sociotechnical forensic decision-support system whose outputs must withstand scrutiny by auditors, clinicians, HR committees, and potentially, legal review.

3. THREAT MODEL, STAKEHOLDERS, AND SYSTEM REQUIREMENTS

Insider threat detection in healthcare is not a monolithic security challenge — it is a collision point of clinical urgency, privacy law, institutional risk, and human behavior. This section grounds the rest of the paper by defining who the adversary is (and often isn't), who bears the consequences, and what the system must guarantee beyond detection accuracy.

3.1 Threat Model: Who the Insider Is, and Isn't

In healthcare, an *insider* is less a shadowy exception and more an everyday user: clinicians glancing at charts, schedulers verifying appointments, technicians updating scans, residents documenting overnight care. Threat modeling must therefore begin with an uncomfortable truth most individuals who trigger an alert are not malicious, yet the system must still surface the rare harmful behaviors buried within.

We categorize insider threats along two axes: intent and harm modality.

3.1.1 By intent

Table 1. Insider Threat Categorization by Intent, Behavior, Motivation, and Risk Profile

Intent Type	Example Behavior	Typical Motivation	Risk Profile
Malicious	Selling celebrity health records, unauthorized data export, credential sharing with bad actors	Financial gain, revenge, external pressure	High harm, often premeditated, low frequency
Curiosity-driven abuse	Viewing a neighbor's or colleague's medical record without care involvement	Social gossip, curiosity, personal connection	Medium harm, impulsive, socially influenced
Negligent / risky	Shared workstation login, unsecured screen, carelessness with patient lists	Time pressure, workflow shortcuts	Often systemic, high prevalence, indirect harm
Unintentional errors	Accessing the wrong patient chart due to identical names or UI misclicks	System design flaws, fatigue	High volume, low malicious intent

The first two categories are traditional "insider threats." The latter two behave more like safety failures than hostile attacks, yet still create regulatory risk and privacy exposure. Importantly, the model must avoid pathologizing normal clinical behavior and distinguish *harmful intent* from *harmful outcomes*.

3.1.2 By Adversarial Capability

Table 2. Insider Threat Categorization by Adversarial Capability and Distinguishing Traits

Capability	Distinguishing Traits
Naïve opportunists	No evasion strategy; detectable via simple heuristics
Adaptive insiders	Mimic routine patterns, spread actions over time, avoid thresholds
Privileged insiders	IT administrators, EHR superusers, or clinicians with elevated access
Collusive pairs/groups	Credential sharing, coordinated chart access, distributed exfiltration

Adaptive and privileged insiders pose the highest detection difficulty, as their behavior blends seamlessly into baseline activity unless specialized modeling is applied.

3.2 Assumptions and Out-of-Scope Scenarios

3.2.1 Assumptions

- The system can accessverified identity logs, EHR audit trails, and structured clinical metadata (care team assignments, encounter history, department rosters).
- Logs are append-only, cryptographically verifiable, and timestamp-synchronized across systems.
- The institution can detect threats without compromising clinician trust or care quality.

3.2.2 Out of Scope

- External attackers without legitimate credentials
- Physical theft of devices or records
- Intent inference from psycholinguistics, personality profiling, or biometrics (due to proportionality and ethics considerations)
- Automated disciplinary actions without human review (system is investigative support, not adjudication)

3.3 Stakeholders and Competing Incentives

Real-world deployment is an exercise in trade-offs. The key stakeholders rarely optimize for the same outcomes.

Table 3. Stakeholders in healthcare insider threat detection and their competing incentives

Stakeholder	Goals	Primary Concerns
Patients	Privacy, confidentiality, trust	Unauthorized access, data leaks
Clinicians	Fast access to patient data, minimal workflow friction	Wrongful flags, reputational harm, surveillance culture
Compliance officers	Regulatory alignment, demonstrable investigations	Evidence defensibility, audit trails, accountability
Security teams	Threat detection, incident response	Evasion risk, blind spots, scalability
Hospital leadership	Institutional risk reduction, public trust	Legal exposure, staffing impact, public relations
IT/EHR administrators	System availability, integration, reliability	Technical complexity, performance overhead

A successful XAI insider threat system must therefore act less like a punitive detector and more like an organizational immune system: catching genuine harm early while tolerating expected clinical variability.

3.4 System Requirements

We define five classes of requirements: security, explainability, clinical contextualization, human usability, and governance.

3.4.1 Security & Detection Requirements

- Detect unauthorized access with high recall under extreme class imbalance
- Resist evasion by adaptive/mimicry attacks
- Support temporal, peer-group, and role-based baselines rather than static thresholds
- Quantify uncertainty to support tiered alert escalation
- Consume multimodal signals: audit logs, scheduling data, treatment team graphs, device context, anomalous session patterns

3.4.2 Explainability & Interpretability Requirements

- Provide human-readable causal narratives, not just risk scores
- Generate counterfactuals grounded in clinical validity (e.g., care relationships, scheduled encounters)
- Trace every alert to verifiable audit evidence, not latent model intuition
- Support explanation mutability audits (who viewed, generated, or edited an explanation and when)

3.4.3 Clinical Context Awareness

- Encode care legitimacy through encounter history, provider assignments, handoffs, and on-call schedules
- Understand exceptional yet valid clinical patterns (emergencies, rapid consults, cross-department transfers)
- Adapt to department-specific workflows (ICU, radiology, pharmacy, emergency psychiatry)

3.4.4 Human Auditor Support

- Prioritize alerts by investigative value, not anomaly magnitude alone
- Provide drill-down evidence views with chronological reconstruction
- Output conclusions in compliance-ready narrative form, with technical appendices attached
- Minimize analyst cognitive load through structured arguments, not probabilistic ambiguity

3.4.5 Governance and Ethical Guarantees

- Prohibit identity-based risk scoring tied to protected attributes
- Monitor and correct role-based false positive disparities (e.g., overflagging emergency clinicians or night staff)
- Maintain tamper-evident logs of model decisions and explanation versions
- Require human review for all escalations with documented decision overrides
- Support post-hoc audits for model drift, fairness, and alert validity

3.5 Key Design Tensions

We highlight three unavoidable design tensions and how this work approaches them:

Table 4. Key Design Tensions in Explainable AI for Insider Threat Detection and Proposed Mitigation Strategies.

Tension	Common Failure Mode	Mitigation Strategy
Detection vs. false accusations	Overly sensitive heuristics flag clinically normal behavior	Causal legitimacy modeling + uncertainty thresholds
Model power vs. interpretability	Black-box models outperform but lack defensibility	Hybrid design: interpretable core + causal module
Surveillance vs. clinician trust	Creates hostile workplace culture	Transparent evidence, clinician-contestable explanations

These tensions frame the central thesis of this paper: a technically accurate model that cannot justify its decisions in human terms is operationally unsafe in healthcare.

4. CLINICAL WORKFLOW REALISM AND CONTEXT-AWARE MODELING

Detecting insider threats in healthcare without modeling clinical reality is like judging flight anomalies without understanding weather, air traffic, or flight plans. Both yield technically "detectable" outliers — and both flood operators with false alarms unless operational context is treated as signal, not noise. This section reframes insider detection not as anomaly scoring over log entries, but as clinical-contextlegitimacy modeling: differentiating what is *unusual* from what is *inappropriate*.

4.1 Why Healthcare Behavior Defies Traditional Baselines

Traditional insider detection assumes relatively stable job boundaries and predictable access surfaces — an engineer works in certain repositories, finance reviews certain ledgers, HR accesses certain personnel records. Healthcare breaks every one of these assumptions:

- Care teams are fluid, restructuring around shift changes, emergencies, and consults.
- Access urgency outweighs hierarchy — junior clinicians may justifiably access records of patients they were never formally assigned.
- Care events propagate access chains (e.g., radiology → oncology → surgery → pharmacy).
- Temporal patterns are irregular — night shifts, rapid paging responses, and overlapping roles create nonstationary access behavior.

This is why pure statistical abnormality correlates poorly with wrongdoing in healthcare. Prior audit analytics studies confirm that many high-rarity events are clinically legitimate, which is why contextual signals drastically outperform frequency-based detectors (Hwang & Lee, 2023; Chen *et al.,* 2022).

4.2 Clinical legitimacy: From implicit assumption to explicit model variable

We introduce clinical legitimacy as a first-class modeling construct.

Definition (Clinical Legitimacy): An access event is *clinically legitimate* if it can be causally justified by a documented, reasonable, or imminently necessary care relationship between the user and the patient at the time of access, given institutional norms for timeliness, coverage, and role delegation.

Legitimacy is not binary from the standpoint of evidence; it exists on a spectrum:

Table 5. Clinical legitimacy levels and corresponding evidence tiers

Legitimacy Level	Interpretation	Typical Evidence
L1 — Explicitly legitimate	Directly documented care relationship	Encounter record, assigned care team, procedure note
L2 — Implicitly legitimate	Strong inferred care relationship	Internal referral chain, co-treatment pathway, cross-covered shift
L3 — Contextually reasonable	Plausible, but indirect justification	Pager log, on-call list, emergency department overflow
L4 — Weakly justified	Requires human review	Proximity in time/department but unclear role
L5 — Unjustified	No clinical or operational explanation	No relational or temporal basis in system

A key argument of this work is that L1–L3 accesses should rarely trigger high-severity alerts, while L4 requires explanation, and only L5 should escalate rapidly. This tiering structure prevents wasting investigative capacity on clinically valid exceptions.

4.3 Context primitives: Building blocks of workflow-aware reasoning

To operationalize legitimacy, models must reason over *context primitives* — structured representations of latent clinical workflows that usually exist only as dispersed logs or institutional knowledge.

4.3.1 Temporal Primitives

Rather than only modeling "access at 2:13 AM," useful primitives include:

- *Access within X minutes of a documented clinical event*
- *Access during sanctioned on-call intervals*
- *Follow-the-patient access cascades* (a clinician accessing a record shortly after a specialist consult is initiated)

Temporal adjacency to care events is a powerful legitimacy signal. Research shows that hour-of-day anomalies have weak separability without clinical sync points (Nguyen *et al.,* 2023).

4.3.2 Relational Primitives

These encode *who is clinically connected to whom*:

- Patient–provider graphs
- Treatment team overlaps
- Handoff relationships
- Consult and referral chains
- Co-charting frequency (soft team affinity signal)

Graph-based relational features consistently outperform isolated user statistics in insider threat tasks involving shared work contexts (Liu *et al.,* 2021).

4.3.3 Role-Expectation Primitives

Different care roles have qualitatively different access signatures. For example:

- Pharmacists → high volume, narrow scope
- ED clinicians → low patient revisit rate, high urgency
- Surgeons → clustered pre/post-op bursts
- Radiologists → modality-linked worklists, indirect patient contact

Without role-adjusted baselines, alerts disproportionately surface against clinicians in high-volatility specialties, amplifying fairness risks (Martinez & Gilbert, 2023).

4.3.4 Environmental Primitives

- Workstation location vs. unit location
- Device mobility patterns
- VPN or remote access during off-site care delivery
- Shared workstation clusters (common in nursing stations)

These are often mistaken for anomalies unless institutional workflow is encoded (Chen *et al.,* 2022).

4.4 Modeling legitimate exceptions without memorizing them

A recurring challenge is balancing generalization (recognizing legitimate exceptions) with overfitting (memorizing past exceptions as future rules). We propose three principles:

1. Model the *mechanism*, not the instance: Systems should learn *why* overnight access was legitimate (e.g., shift coverage), not that *2:00 AM is normal for Dr. X*.
2. Prefer causal signals over correlational regularities: A patient consult explains *access because care was required*, whereas a frequent-access cluster only says *access often happened*.
3. Encode invariants, not habits: "Clinician must have a treatment or coverage relationship" is an invariant. "Clinician tends to access cardiology charts at night" is a habit.

This approach aligns with research showing that causal and invariant representations transfer better under distributional shifts than behavioral aggregates (Karimi *et al.,* 2024).

4.5 Case Illustration: Same Behavior, Different Legitimacy

Consider the same event:

A cardiology resident accesses a patient chart at 1:47 AM without prior direct assignment.
Three contexts produce three different legitimacy interpretations:

Table 6. Case Illustration of same access behavior with different clinical legitimacy interpretations

Context	Interpretation
Rapid-response code paged at 1:45 AM	L2 — Implicitly legitimate (emergency care)
Cross-covering colleague on scheduled night shift	L3 — Reasonable (institutional coverage pattern)
No clinical event, no coverage duty, patient is a public figure	L5 — Unjustified access, high risk

From the access log alone, these are indistinguishable. With contextual modeling, they diverge sharply.

4.6 System requirements derived from context modeling

To effectively represent workflow legitimacy, a compliant insider threat system must:

1. Represent clinical relationships as time-bound graphs, not static tables
2. Ingest auxiliary signals (consult orders, handoffs, scheduling, paging, care overflow)
3. Model exceptions explicitly, not as noise
4. Ground alerts in contextual disproof of legitimacy, not mere statistical rarity
5. Generate explanations like investigative reasoning, not anomaly descriptions

The explanation standard shifts from: *"This access is suspicious because it is statistically rare for this user at this hour."* to: *"No documented or inferred clinical relationship to the patient existed within 72 hours, and no coverage or consult pathway explains the timing of access."* The latter is *actionable, falsifiable, and audit-ready*.

5. DATA ECOSYSTEM, FEATURE ENGINEERING, AND LABELING STRATEGIES

EHR audit logs alone cannot be used to develop clinical-context aware insider identification. The signal needed to differentiate between policy-violating access and lawful care is dispersed among various data sources, each of which is flawed, lacking, or produced for non-security-related reasons. This section describes labelling techniques that steer clear of typical ground-truth pitfalls in insider threat research, maps the data topography, and presents clinical-first feature taxonomy.

5.1 The Healthcare Insider Detection Data Landscape

A production-ready insider threat model must synthesize at least five complementary data strata, each answering a different implicit question about an access event.

Table 7. Data ecosystem for healthcare insider threat detection

Data Layer	Core Question Answered	Example Artifacts	Known Limitations
EHR Audit Logs	*What happened?*	Record viewed, timestamp, user ID, patient ID, workstation	Lacks context of *why* access occurred
Clinical Activity Logs	*Was care delivered?*	Orders, notes, medication actions, charting events	Sparse for indirect roles (e.g., consult review without note)
Workflow & Scheduling	*Who was supposed to be involved?*	Shift schedules, on-call lists, team rosters, bed assignments	Imperfect compliance, late updates, informal handoffs
Communication Traces	*Was interaction requested?*	Paging records, internal call systems, secure messaging	Not always retained or linked to patient IDs
System Environment Data	*From where and how?*	Device fingerprints, badge login, network segments, session length	Shared devices obfuscate user behavior

Prior studies repeatedly highlight that healthcare insider incidents are rarely detectable from any single log domain in isolation (Nguyen *et al.,* 2023; Chen *et al.,* 2022). Detection quality improves sharply when signals are fused into temporally aligned patient–provider context graphs (Hwang & Lee, 2023).

5.2 Feature taxonomy: Clinical context as primary signal

Rather than feature engineering around *user outlyingness*, we structure representations around evidence for or against clinical legitimacy. Features fall into six interpretable families:

5.2.1 Care Relationship Evidence

- Documented provider–patient encounters (binary &recency-weighted)
- Care team membership at time of access
- Referral chain distance (graph shortest path in consult network)
- Departmental patient overlap score (ratio of shared service pathways)

5.2.2 Temporal-Causal Alignment

- Time delta between access and nearest charting, order, or consult event
- Ordering → viewing → charting sequence validity (common clinical patterns)
- Access within escalation window of emergency events (e.g., code blue within 30 min)

5.2.3 Coverage & Delegation Cues

- On-call status at access time
- Shift overlap with primary clinician

- Handoff-window proximity (e.g., 1 hour before/after shift transition)

5.2.4 Environment and Device Appropriateness

- Access from departmentally associated clinical workstation
- Roaming device usage consistent with role (e.g., WOW carts in nursing units)
- Shared workstation risk flag (co-login proximity patterns)

5.2.5 Patient Sensitivity & Risk Tier

- VIP flag, public figure indicators
- Behavioral health or reproductive health sensitivity tags
- Recent media coverage or legal holds (correlated external risk modifiers)

5.2.6 User Behavioral Context (non-punitive baselines)

- Peer-group normalized access profiles (same specialty, same shift type)
- Specialty-consistent patient revisit rates
- Burstiness metrics tied to clinical workload peaks, not anomalies alone

This taxonomy constrains the model to reason in *clinically meaningful primitives*, improving both performance and explanation integrity (Ribeiro & Singh, 2022; Jha&Topol, 2023).

5.3 Constructing Context Graphs for Relational Reasoning

Feature vectors alone cannot represent clinical interdependencies. We additionally construct temporal patient–provider graphs where edges encode:

- "Treated by" (timestamped clinical encounter evidence)
- "Consult requested by"
- "Coverage for"
- "Co-treated with" (shared event participation)
- "Location co-presence" (same unit, overlapping shifts)

Graph representation learning has shown superior capability to model insider context without overfitting to individual user history (Liu *et al.,* 2021). Importantly, edges are *time-sensitive* to prevent historical relationships from being mistaken as active justification for current access.

5.4 Labeling Strategies: Overcoming the Ground Truth Paradox

Unlike general classification tasks, insider threat detection suffers from non-exhaustive, delayed, and institutionally filtered labels:

- Only a fraction of true violations are ever investigated
- Not all investigations conclude definitively
- Confirmed cases are often systematically different from undiscovered ones
- Labels reflect *organizational enforcement*, not objective guilt

This creates a positive class that is sparse, biased, and non-representative, a known limitation in insider threat datasets (Kumar *et al.,* 2023).

5.4.1 Multi-tier label framework

We propose replacing binary labels with a structured evidence hierarchy:

Table 8. Multi-tier label framework for insider threat ground truth

Label Tier	Meaning	Supervisory Use
T0 – Unknown	Access never reviewed	Unlabeled pool
T1 – Likely legitimate	Verified clinical justification	Negative training anchors
T2 – Suspicious but unresolved	Insufficient evidence to clear or convict	Semi-supervised learning
T3 – Policy violation	Confirmed unauthorized access, no malicious proof	Positive class (weak)
T4 – Malicious insider	Confirmed intent to misuse or exfiltrate	Positive class (strong)

Models trained only on T4 are unrealistically narrow. Models trained on T3+T4 generalize better, but must explicitly account for label noise through probabilistic labeling or positive–unlabeled (PU) learning (Liu *et al.,* 2021).

5.4.2 Weak Supervision via Clinical Consistency Rules

To expand training signal without manual adjudication, we generate provisional labels using logic such as:

- Likely legitimate if explicit encounter exists within 24 hours
- Likely unjustified if no encounter, no coverage, no referral path, no team overlap, and patient is high-sensitivity
- Ambiguous if partial relational evidence exists but justification incomplete

These heuristic labels are not treated as truth, but as noisy supervision with quantified confidence, a technique shown to stabilize insider models under sparse ground truth (Rashid & Li, 2022).

5.5 Privacy-Preserving and Auditable Data Engineering

Because this domain operates directly on PHI and workforce behavior, data pipelines must enforce:

1. Purpose-limited feature extraction (e.g., "care relationship exists" instead of storing diagnosis codes)
2. Attribute exclusion for protected traits (race, ethnicity, gender should never influence access risk features)
3. Differentially partitioned investigator views (auditors see justification artifacts without raw patient details unless escalated)
4. Feature provenance tracking (every feature must link back to a source log and timestamp for evidentiary reconstruction)

Secure audit trails for model decisions are now recognized as a core requirement in high-stakes AI governance (Brundage *et al.,* 2024).

5.6 Summary

This section establishes that:

- Insider detection depends on context fusion, not anomaly isolation
- Features must encode legitimacy evidence, not just statistical deviation
- Graph structures enable reasoning over clinical relationships essential for explanation quality
- Labels must be tiered, probabilistic, and noise-aware, not binary
- Data engineering must embed privacy, fairness, and evidentiary traceability

The resulting design shifts modeling from *"who behaves strangely?"* to *"what access is unjustified when examined against clinical reality?"*

6. EXPLAINABLE MODELING APPROACHES: INTERPRETABLE, CAUSAL, AND HYBRID DESIGNS

6.1 Explanation Expectations in Healthcare Investigations

Unlike typical ML explainability use cases, healthcare insider investigations require explanations that are:

1. Causally grounded – not merely correlational
2. Clinically contextualized – referencing care events and legitimate workflows
3. Individually falsifiable – investigators must be able to confirm or reject the narrative
4. Traceable to source evidence – every claim must link to an auditable log
5. Counterfactual-aware – able to state what *would have made the access legitimate*
6. Non-accusatory in structure – explaining behavior without asserting intent prematurely

A model that identifies risk without satisfying these conditions might still be *accurate*, but it would not be *usable* in practice.

6.2 Taxonomy of Explainable Modeling Approaches

We categorize approaches into four groups, evaluated against healthcare requirements:

Table 9. Taxonomy of explainable modeling approaches evaluated against healthcare requirements

Approach	Example Methods	Pros	Key Limitations in Healthcare
Intrinsic Interpretable Models	Rule lists, GAMs, decision trees	Transparent logic, easy to audit, minimal post-hoc translation	Can lack expressive power for complex relational workflows
Post-hoc Explanations	SHAP, LIME, attention heatmaps	Works with high-capacity models, flexible	Often unstable, not causal, hard to tie to compliance evidence
Causal Models	Structural causal models (SCMs), causal graphs, do-calculus reasoning	Supports counterfactual legitimacy testing, aligned with investigative reasoning	Requires domain knowledge graphs; harder to scale
Hybrid Models	Interpretable core + causal constraints + uncertainty calibration	Balances performance and investigability	More components to govern and validate

Recent analyses show that while post-hoc methods can support intuition, they fail compliance needs because they explain *the model*, not *the event* (Gunning *et al.,* 2023; Karimi *et al.,* 2024). Therefore, healthcare insider XAI must prioritize event-level causal narratives over model-centric feature scores.

6.3 Why purely predictive models fall short

Consider a gradient-boosted model flagging this access:

At 02:11 AM, Clinician X accessed Patient Y's chart from an ICU workstation.
A typical model explanation might yield:

- 31% contribution: accessed outside usual hours
- 22% contribution: not primary department
- 17% contribution: patient under VIP tag
- 11% contribution: high-sensitivity record

This explanation is statistically valid yet investigatively useless. It answers *what influenced the model*, not *whether the access had clinical justification*. There is no mention of:

- Emergency consults
- Cross-coverage duty
- Paging events
- Care handoffs
- Treatment relationships

Compliance teams routinely reject explanations that lack situational causality, even when risk scores are high.

6.4 Causal Legitimacy Modeling: A Better Framing

We formalize insider justification as a causal inference problem rather than an anomaly score. Let:

- **A** = Access event
- **C** = Documented or inferred clinical care relationship
- **W** = Workflow obligation (coverage, consult, emergency trigger)
- **R** = Institutional role permissions
- **L** = Legitimacy of access

The investigation question becomes: *Would the access A still have occurred in the absence of a clinical care justification (C or W)?*

Using counterfactual logic: $P(L = 1 \mid do(C = 0), do(W = 0), R) \approx 0 \Rightarrow$likely unjustified

This moves explanation from: "The model found this access unusual." to: "No care, coverage, or workflow condition existed that would have required this access at that time." This phrasing is causal, falsifiable, and procedurally aligned to investigations, mirroring how human auditors reason (Ribeiro & Singh, 2022).

6.5 Toward a hybrid architecture

We propose a three-layer modeling design:

Layer 1 — Interpretable Risk Scoring (Detection Layer)

- Models: Rule lists, Explainable Boosting Machines (EBMs / GAMs)
- Goal: Flag suspicious cases using transparent logic
- Output: Human-readable risk factors, confidence scores

Layer 2 — Causal Legitimacy Filter (Justification Layer)

- Models: Structural causal graph representing care, coverage, and delegation pathways
- Goal: Test whether a valid clinical mechanism could have plausibly caused access
- Output: Counterfactual legitimacy statement (e.g., *"If no consult path existed, this access would not be explained."*)

Layer 3 — Evidence Compiler (Audit Layer)

- Not a model, but a reasoning assembly system
- Goal: Convert model and causal results into compliance-ready investigative text
- Output: Timestamped evidence chain + explanation narrative (immutable, traceable)

This design enforces that: A record flagged by the predictor **must fail the causal legitimacy test** before being escalated. This dramatically reduces false positives triggered by rare-but-valid clinical scenarios.

6.6 Explanation Template Generated by the Hybrid System

A compliant explanation should resemble:

"No documented clinical encounter, consult pathway, or coverage assignment connects the user to the patient within 72 hours of access. The user was not on scheduled duty, nor affiliated with the patient's treatment team. A simulated counterfactual shows that if a consult request or coverage relationship had existed, the access would have been classified as clinically justified. No such evidence was found in EHR, paging, or roster systems. Source logs reviewed: encounter DB (null), coverage system (null), consult graph (null), workstation location (ICU, non-assigned unit)."

This explanation:

- Uses clinical reasoning, not statistical rarity
- Is falsifiable (auditor can check each claim)
- Contains counterfactual logic
- Cites data sources explicitly
- Avoids speculative statements about intent

6.7 Uncertainty Calibration: When to Say "We Don't Know"

A model must also know when evidence is incomplete. We enforce:

Table 10. Uncertainty calibration policies for handling incomplete or contradictory evidence

Uncertainty Condition	Policy
Missing audit sources	Defer to manual review, mark "evidence gap"
Contradictory workflow signals	Generate ambiguous classification, not high-risk
Insufficient causal resolution	Report "legitimacy indeterminate" rather than "suspicious"
High model disagreement	Trigger secondary human adjudication

This prevents algorithmic overreach — a major failure mode in high-stakes XAI systems (Brundage *et al.,* 2024).

7. FAIRNESS, BIAS, AND HARM-AWARE SAFEGUARDS

A particularly sensitive dual-risk AI surface is introduced by healthcare insider-threat detection: the system must safeguard patients and institutions without posing additional risks to medical professionals, employees, or under-represented groups. Errors here have therapeutic, career, regulatory, and legal ramifications, unlike credit scoring or content moderation. In addition to misclassifying, a biased model might unfairly endanger livelihoods, undermine confidence in hospital management, and discourage appropriate therapeutic practice. This section presents quantifiable safeguards specific to the healthcare industry after framing insider-threat fairness as a matter of equity, proportionality, and procedural safety.

7.1 What Fairness Means in Clinical Security Contexts

Traditional ML fairness definitions—demographic parity, equal opportunity, equalized odds—are necessary but incomplete here. Healthcare security AI must satisfy four additional domain-specific fairness axes:

Table 11. Four Domain-Specific Fairness Axes for Clinical Security AI

Fairness Dimension	Requirement	Failure Mode if Violated
Contextual Equity	Similar clinical situations must be treated similarly	ICU night-shift staff flagged more often due to workflow norms
Role Normalization	Risk baselines adjusted to job function, not individual history alone	ED physicians flagged for urgent chart reviews
Exposure Minimization	Minimize unnecessary identity exposure during investigations	Analysts seeing patient identities during preliminary review
Procedural Justice	Every alert must be contestable, evidence-linked, and reversible	"Black box guilt by algorithm" outcomes

These extend fairness from "statistical equality" to organizational justice in sociotechnical systems (Green & Chen, 2023).

7.2 Unique Bias Vectors in Healthcare Insider Detection

Healthcare generates several structural bias channels often invisible in traditional security ML:

7.2.1 Shift-Based Behavioral Bias

Night-shift clinicians access records in burst patterns, respond to emergencies, and cross-cover multiple wards. Outlier-based anomaly detectors can misinterpret this as suspicious access.
Example: A resident physician covering 5 wards at 2 AM may legally access dozens of charts rapidly—behavior statistically abnormal but clinically correct.

7.2.2 Role-Dependent Graph Centrality Bias

Specialists (e.g., infectious disease or radiology) are linked to large patient graphs, whereas community practitioners have narrower access scopes. Graph models may disproportionately flag highly connected nodes.

7.2.3 Digital Familiarity Bias

Clinicians differ in documentation style. Efficiency-driven users with sparse charting ("minimal note" physicians) may appear to have less explanatory evidence tying them to records, increasing false suspicion.

7.2.4 Institutional Hierarchy Bias

Junior staff may rely on informal delegation (verbal handoffs, hallway consults), which leave weaker digital traces than attending-level workflows. Without adjustment, models penalize less documented but legitimate care. These biases demonstrate that data completeness is confounded with organizational hierarchy, not intent.

7.3 Harm Auditing Beyond Accuracy

Fairness evaluation must treat *harm asymmetrically*. A false positive insider alert is not equivalent to a false negative missed threat. Institutions must transparently define acceptable tradeoffs, e.g.: $HFP > HFN$ for workforce safety, morale, and legal risk

Harm auditing includes:

- Clinician impact simulations (career, credentialing, psychological safety)
- Operational disruption analysis (staff turnover, investigation burden)
- Chilling effect measurement (slowed chart access, care delays)
- Disparate alert rate testing across specialties, shifts, seniority tiers

This shifts evaluation from ML metrics to organizational health outcomes (NIST, 2024; Green & Chen, 2023).

7.4 Algorithmic Guardrails and Mitigation Strategies

7.4.1 Role-Aware Baselining

Instead of a single global model, compute risk relative to peer reference cohorts:

- Same clinical specialty
- Same shift category (day, night, rotating)
- Same unit type (ED, ICU, outpatient)
- Similar coverage load distribution

This prevents privilege normalization bias where the "average user" becomes the implicit gold standard.

7.4.2 Legitimate-Access Coverage Priors

Before labeling access as anomalous, models must test for implicit legitimacy signals, e.g.:

- Was the unit short-staffed at that hour?
- Did emergency volume exceed threshold?
- Was the case likely escalated (ICU transfer, trauma intake, rapid response event)?

These work as *exculpatory priors*, minimizing wrongful suspicion.

7.4.3 Progressive Evidence Reveal

To prevent over-exposure of PHI or staff identity during investigations:

Table 12. Progressive evidence reveal stages to minimize identity exposure during investigations

Stage	Visible Information
Alert Triage	No clinician name, no patient identity, contextual justification only
Preliminary Review	Timestamped evidence, role type, department (not identity)
Escalation	Identities revealed only if evidence remains unexplained

This applies the principle of least investigative privilege.

7.4.4 Right to Contest & Algorithmic Appeals

Each alert must be reversible via structured rebuttals such as:

- *"I was covering for Dr. X (schedule updated late)"*
- *"Case escalated orally during code response"*
- *"Consult initiated outside EHR system"*

Appeal outcomes must flow back into model retraining to close feedback loops.

7.5 Quantitative Fairness Tests for Healthcare Security AI

Table 13. Quantitative fairness tests for healthcare security AI

Test	Purpose	Pass Condition
Shift Parity Gap	Ensures night shifts not disproportionately flagged	Δ alert rate < 8% vs. day shift
Role Alert Balance	Controls by clinical specialty	No role >1.5× baseline risk
Context Completeness Bias	Ensures sparse documentation isn't penalized	Risk score not inversely correlated with documentation volume
Clinical Justification Recall	Measures capture of legitimate care signals	>95% of audited legitimate accesses traceable to causal evidence

Metrics must be monitored continuously because institutional behavior drifts over time.

7.6 Sociotechnical Safety Nets

Even well-calibrated AI cannot fully eliminate structural ambiguity. Therefore, safe deployment requires:

1. Human adjudication panels, not individuals, to avoid confirmation bias
2. Non-punitive early review, separating investigation from disciplinary pathways
3. Transparent clinician communication, including examples of acceptable vs flagged access
4. Wrongful alert moratorium thresholds (auto-pause model if FP rate exceeds safety ceiling)
5. Protected incident learning, where overturned alerts improve policy, not punish staff

These measures align with responsible AI governance frameworks (NIST, 2024; WHO Digital Health Report, 2023).

7.7 Redefining "Suspiciousness" as "Insufficiently Explained"

A crucial paradigm shift: *Alerts should not indicate presumed wrongdoing, but insufficient documentation of justification.* This reframing reduces stigma, increases cooperation, improves data quality, and invites resolution rather than accusation.

8. SYSTEM ARCHITECTURE AND SECURE DEPLOYMENT IN CLINICAL ENVIRONMENTS

8.1 Overview of the Layered Architecture

We propose a modular, layered architecture designed to balance accuracy, interpretability, auditability, and human oversight:

- Data Ingestion and Harmonization Layer
- Contextual Feature Engineering Layer
- Risk Scoring and Predictive Modeling Layer
- Causal Legitimacy and Explanation Layer
- Evidence Compilation and Audit Layer
- Human-in-the-Loop Review Layer
- Governance, Logging, and Feedback Layer

8.1.1 Data Ingestion and Harmonization Layer

Purpose:

- Consolidate heterogeneous sources (EHR audit logs, scheduling, communication, device data)
- Ensure temporal alignment, user identity normalization, and log integrity
- Apply privacy-preserving transformations (hashing identifiers, minimizing PHI exposure)

Best practices:

- Use append-only immutable storage for audit logs
- Enforce end-to-end encryption during transit and at rest
- Maintain source provenance metadata for every record
- Integrate automated data quality checks to handle missing, delayed, or corrupted logs

8.1.2 Contextual Feature Engineering Layer

Purpose:

- Transform raw signals into clinically interpretable features representing relational, temporal, and environmental context
- Construct temporal patient–provider graphs and coverage mappings
- Compute peer-normalized and role-specific baselines to mitigate workflow bias

Key design considerations:

- Feature vectors should capture both legitimacy evidence and potential anomalies
- Ensure features remain auditable and reproducible for compliance review
- Retain traceability to source logs for each graph edge and attribute

8.1.3 Risk Scoring and Predictive Modeling Layer

Purpose:

- Flag potentially suspicious events using interpretable machine learning models
- Examples: Rule lists, Generalized Additive Models (GAMs), Explainable Boosting Machines (EBMs)
- Incorporate role- and shift-aware normalization to prevent systemic bias

Outputs:

- Risk score per access event
- Confidence intervals or uncertainty estimates
- Primary explanatory factors contributing to the score

8.1.4 Causal Legitimacy and Explanation Layer

Purpose:

- Determine whether flagged access events can be causally justified by documented or inferred clinical workflows
- Leverage structural causal models (SCMs), temporal graphs, and counterfactual reasoning
- Generate human-readable explanations aligned with investigation procedures

Key features:

- Counterfactual narratives: “Had the consult not existed, access would have been unjustified”
- Evidence linking: all reasoning backed by source logs, schedules, or encounter metadata
- Confidence scoring for explanation reliability

8.1.5 Evidence Compilation and Audit Layer

Purpose:

- Transform model outputs and causal justifications into compliance-ready investigative reports
- Maintain immutable, versioned audit trails for each alert
- Support structured queries and drill-downs by auditors or compliance officers

Outputs include:

- Chronologically ordered evidence chains
- Event-specific justification narratives
- References to source logs and derived features
- Explanation of any counterfactual or causal assumptions used

8.1.6 Human-in-the-Loop Review Layer

Purpose:

- Allow compliance officers, privacy officers, or designated clinicians to review, validate, and contest alerts
- Integrate manual adjudication into model retraining cycles
- Support multi-stage escalation: initial triage, secondary review, formal investigation

Design principles:

- Tiered access to sensitive information (least privilege)
- Structured feedback capture to improve model performance
- Integration with internal governance and reporting tools

8.1.7 Governance, Logging, and Feedback Layer

Purpose:

- Ensure ethical, legal, and procedural compliance
- Monitor model drift, fairness metrics, and alert distributions
- Record investigator decisions, model overrides, and feedback for continuous improvement

Key mechanisms:

- Regular fairness and bias audits (shift, role, specialty)
- Tamper-evident logs for all model outputs and explanations
- Integration with policy and regulatory reporting frameworks
- Feedback-driven retraining pipelines to incorporate resolved cases

8.2 Deployment Considerations in Clinical Environments

Healthcare systems present unique operational constraints:

8.2.1 Privacy and Regulatory Compliance

- Compliance with HIPAA, GDPR, and local health privacy laws
- Ensure data minimization: expose PHI only when required
- Encryption and access control for every layer

8.2.2 Integration with Clinical Workflows

- Non-intrusive alerting to avoid workflow disruption
- Support role- and shift-specific interfaces (e.g., night coverage dashboards)
- Ensure low-latency access to explanations for timely interventions

8.2.3 Resilience and Reliability

- Fault-tolerant ingestion for delayed logs or network interruptions
- Redundant storage and secure backup for audit evidence
- Monitoring for pipeline drift or failed causal inference scenarios

8.2.4 Human Factors and Training

- Train auditors and compliance staff on interpreting counterfactual explanations
- Provide decision-support dashboards with drill-down capabilities
- Include scenario-basedtraining for rare but high-impact insider events

8.2.5 Security of the Detection System

- Protect model weights, causal graphs, and audit trails from tampering
- Segment access: separate development, staging, and production environments
- Use role-based encryption to control access to sensitive model explanations

8.3 End-to-End Alert Lifecycle

1. Event occurs in EHR → logged in audit system
2. Data ingested, features computed → access graph updated
3. Interpretable model scores risk → uncertainty quantified
4. Causal legitimacy layer evaluates justification → generates counterfactual explanation
5. Evidence compiled → alert narrative produced
6. Human auditor reviews → escalates, resolves, or dismisses
7. Feedback captured → updates model, causal graph, and alerting thresholds
8. Immutable audit trail stored → for compliance and regulatory reporting

This closed-loop design ensures alerts are actionable, explainable, auditable, and ethically managed.

9. EVALUATION FRAMEWORK: METRICS, HUMAN-IN-THE-LOOP TESTING, AND COMPLIANCE ASSESSMENT

Evaluating explainable AI systems for insider threat detection in the healthcare industry is particularly difficult. High-stakes judgments require contextual performance indicators, fairness checks, and auditability verification; traditional machine learning metrics like accuracy, precision, and recall are essential but insufficient. A thorough review strategy that incorporates technical measurements, human-in-the-loop testing, and compliance-focused assessments is presented in this section.

9.1 Technical Metrics for Detection Performance

Insider threat detection is characterized by high class imbalance (rare true incidents) and heterogeneous data sources, necessitating specialized evaluation measures:

9.1.1 Classification Metrics

- Precision @ K: Fraction of true violations in the top K ranked alerts; critical for prioritizing investigative resources.
- Recall / Sensitivity: Ability to detect true insider events; high recall ensures few threats are missed.
- F1 Score: Balances precision and recall, useful under moderate class imbalance.
- Area Under Precision-Recall Curve (AUPRC): More informative than ROC AUC under extreme imbalance.

9.1.2 Temporal and Sequential Metrics

- Detection latency: Time between event occurrence and alert generation.
- Sequence consistency: Ability to detect multi-step or delayed insider actions spanning multiple shifts or departments.

9.1.3 Graph-Based and Relational Metrics

- Coverage detection: Fraction of events correctly contextualized within patient–provider graphs.
- Edge relevance accuracy: Percentage of causal links (e.g., consults, handoffs) correctly reflected in model explanations.
- Path-based alert precision: Correctness of relational reasoning pathways used to justify alerts.

9.2 Explainability and Causal Validity Metrics

Explainability is critical in healthcare security; evaluations should measure:

9.2.1 Fidelity of Explanation

- Counterfactual fidelity: Whether the explanation correctly predicts model output under hypothetical scenario changes.
- Causal plausibility: Degree to which explanations reflect actual clinical workflows.

9.2.2 Human-Understandability

- Readability metrics: Length, complexity, and clarity of narrative explanations.
- Human comprehension studies: Percentage of auditors correctly interpreting alerts and reasoning pathways.

9.2.3 Audit Traceability

- Evidence-link completeness: Fraction of explanation elements linked to verifiable source logs.
- Versioning integrity: Ability to reconstruct explanation evolution over time for compliance audits.

9.3 Fairness and Harm-Aware Metrics

Fairness evaluation must extend beyond traditional demographic parity to **workflow-aware, harm-sensitive metrics**:

Table 14. Fairness and Harm-Aware Metrics for Security AI Evaluation

Metric	Description	Acceptable Thresholds
Shift Parity Gap	Difference in alert rates between day/night shifts	$\Delta \leq 8\%$
Role Alert Consistency	Relative alert rates among different specialties	$\leq 1.5\times$ baseline
Documentation Bias	Correlation between access documentation density and risk score	$r \leq 0.1$
False Positive Harm Rate	Number of alerts likely to induce unnecessary investigation	Monitored continuously, target minimal

These metrics are evaluated continuously to detect drift and ensure sociotechnical fairness.

9.4 Human-in-the-Loop Evaluation

Human oversight is essential for validating model predictions, explanations, and mitigating operational harm. Key methodologies include:

9.4.1 Structured Auditing

- Randomized alert sampling for manual review.
- Comparison of human adjudicator decisions with model outputs.
- Feedback incorporated into retraining and causal graph updates.

9.4.2 Scenario-Based Testing

- Simulate emergency or high-volume access scenarios.
- Test whether alerts appropriately respect clinical exceptions.
- Evaluate auditor comprehension and response time.

9.4.3 Investigator Feedback Integration

- Capture structured feedback: “alert justified”, “alert explainable but false positive”, “alert unclear”.
- Use for continuous improvement of explanation templates and feature weighting.

9.5 Compliance and Regulatory Assessment

Healthcare institutions must satisfy audit, legal, and regulatory requirements, including:

- HIPAA and GDPR audit readiness: Ensure PHI minimization and traceable evidence for every alert.
- Documentation of alert rationales: All alerts linked to human-understandable explanations.
- Transparent escalation pathways: Demonstrable procedure for human review and resolution.
- Model validation reports: Periodic review of detection, fairness, and explanation metrics for regulatory submission.

Regulatory assessment metrics include:

- Completeness of justification documentation
- Timeliness of alert escalation
- Traceability of decision logic to source logs
- Evidence of bias mitigation mechanisms

9.6 Simulation-Based Stress Testing

Due to the rarity of insider threats, models must also be evaluated using synthetic or augmented datasets:

- Simulate coordinated access, credential sharing, or emergency override events.
- Inject anomalies mimicking real insider patterns, both malicious and negligent.
- Assess model robustness to unseen patterns and concept drift in workflow.

9.7 Evaluation Workflow

i. Offline evaluation: Metrics computed on historical logs, synthetic events, and known incidents.
ii. Controlled pilot: Alerts deployed to limited investigator groups with human-in-the-loop review.
iii. Continuous monitoring: Real-time metrics, fairness evaluation, and model recalibration.
iv. Periodic audit: Comprehensive compliance review and report generation for governance boards.

This multi-phase workflow ensures that detection accuracy, explainability, fairness, and operational safety are all validated before and during deployment.

10. DISCUSSION: INSIGHTS, LIMITATIONS, AND FUTURE DIRECTIONS

10.1 Key Insights

10.1.1 Contextualized Detection is Essential

Healthcare workflows are highly dynamic, multi-dimensional, and exception-prone. Simple anomaly-based detection fails to distinguish legitimate rare access from truly suspicious behavior. Integrating:

- Temporal care sequences
- Patient–provider relational graphs
- Coverage and shift assignments
- Environmental and device signals

Enables the system to capture clinically meaningful deviations rather than purely statistical outliers.

10.1.2 Explainability Must Be Causal, Not Statistical

Post-hoc feature importance alone cannot satisfy investigative or compliance requirements. The hybrid approach—combining interpretable risk scoring with causal legitimacy analysis produces:

- Audit-ready explanations
- Counterfactual reasoning
- Human-understandable narratives

This aligns the system with legal, ethical, and operational expectations, avoiding "black-box guilt by algorithm."

10.1.3 Fairness and Harm-Aware Design Are Non-Negotiable

High false-positive rates, bias against certain specialties, or workflow misinterpretation can cause career harm, trust erosion, and workflow disruption. Incorporating:

- Role- and shift-aware baselines
- Contextual priors
- Identity-limited alert exposure
- Structured appeal mechanisms

Ensures that fairness and procedural justice are integral, not peripheral, to the system.

10.1.4 Human-in-the-Loop Integration Amplifies Trust and Effectiveness

Even the most sophisticated models require auditor validation, iterative feedback, and scenario-based testing. Human-in-the-loop evaluation helps:

- Calibrate risk thresholds
- Validate causal explanations
- Capture exceptions not encoded in digital logs
- Reduce operational and psychological harm

This underscores that XAI is not a fully automated policing tool but a decision-support system embedded in organizational governance.

10.2 Limitations

10.2.1 Data Sparsity and Label Scarcity

- True malicious insider incidents are extremely rare.
- Labels are often biased, incomplete, or delayed.
- Probabilistic labeling, weak supervision, and synthetic scenario generation mitigate but do not eliminate this limitation.

10.2.2 Generalization Across Institutions

- Workflows, roles, and care pathways differ by institution.
- Graph-based causal models require institution-specific configuration.
- Transfer learning or federated approaches may help but introduce complexity in governance and privacy.

10.2.3 Complexity and Operational Overhead

- Multi-layered architectures (feature engineering, causal reasoning, human review) are resource-intensive.
- Smaller hospitals or clinics may face challenges in maintaining data pipelines, graph structures, and auditing infrastructure.

10.2.4 Ethical and Legal Ambiguity

- Despite safeguards, algorithmic alerts could influence disciplinary decisions, raising potential legal liability.
- Misinterpretation of counterfactual explanations may occur if auditors lack sufficient training.
- Continuous governance and policy alignment are essential to mitigate these risks.

10.3 Future Directions

10.3.1 Federated and Privacy-Preserving Learning

- Multi-institution collaborations could improve model robustness.
- Federated learning allows knowledge transfer without sharing PHI, supporting wider adoption.

10.3.2 Integration with Workflow Automation

- Linking alerts to workflow management systems could preemptively suggest coverage adjustments or resource reallocation.
- AI could support proactive, non-punitive interventions rather than reactive flagging.

10.3.3 Advanced Causal Graphs and Simulation

- Incorporate dynamic, multi-layered graphs capturing patient–provider interactions over time.
- Use simulation environments to stress-test rare insider scenarios, including collusion and adaptive strategies.

10.3.4 Continuous Fairness Monitoring

- Deploy real-time fairness dashboards for auditors and compliance teams.
- Track drift, role-based disparities, and unintended bias across shifting hospital policies or care patterns.

10.3.5 Explainability-Driven Training

- Future models could optimize detection and explainability jointly, e.g., maximizing both risk detection accuracy and counterfactual fidelity.
- Research in causally regularized interpretable models can further reduce false positives while enhancing audit trust.

10.4 Organizational and Ethical Considerations

- Deployment requires cultural sensitivity, clear communication with clinicians, and well-defined escalation protocols.
- Alerts should be framed as missing justification, not accusations, maintaining trust and morale.
- Continuous training for auditors is critical to interpret causal explanations correctly and consistently.

10.5 Summary

- Explainable AI for insider threat detection in healthcare is technically and ethically complex.
- Success requires integration of clinical context, causal reasoning, fairness safeguards, and human oversight.
- Limitations include data scarcity, institutional specificity, operational complexity, and ethical ambiguity.
- Future work should focus on privacy-preserving learning, simulation-based stress testing, fairness monitoring, and explainability-driven model optimization.

In sum, this work demonstrates that robust, interpretable, and context-aware AI systems are both feasible and necessary to detect insider threats while preserving patient privacy, clinician trust, and regulatory compliance.

11. CONCLUSION

The emergence of electronic health records (EHRs), telemedicine, and networked hospital environments has drastically amplified the vulnerability of insider attacks, malicious and careless alike, to the healthcare industry. The existing anomaly-based methods of detection, although highly capable of identifying abnormal access patterns, do not take into consideration the complexity, variability, and legitimacy of clinical workflows, which results in a large number of false-positive outcomes, operational interference, and even harm to clinicians. This paper has provided an in-depth explainable AI (XAI) framework in insider threat detection with a focus on clinical-context modelling, causal legitimacy rationale, safety and equity, and safe deployment. Among the major contributions and findings, there are:

1. **Contextualized Detection**: Alerts are guaranteed to represent actual risk rather than just statistical rarity when temporal, relational, and environmental factors are modelled. Nuanced comprehension of intricate care workflows is made possible by patient-provider graphs and coverage-based relational reasoning.
2. **Explainability through Causal Reasoning**: Counterfactual explanations, traceable proof, and audit-ready narratives are made possible by hybrid architectures that combine interpretable prediction models with structural causal models. This guarantees that warnings are reasonable, actionable, and legally defendable.
3. **Fairness and Harm Mitigation**: Role-aware baselines, shift normalization, exculpatory priors, and structured appeal mechanisms reduce bias and prevent undue harm to clinicians. Alerts are framed as *insufficient justification*, not presumptive malfeasance, fostering trust in the system.

4. **Secure, Modular Architecture**: Layered design—including data ingestion, feature engineering, causal reasoning, audit, human-in-the-loop review, and governance—supports resilient deployment while maintaining privacy, compliance, and operational safety.
5. **Comprehensive Evaluation Framework**: Technical metrics, human-in-the-loop assessment, fairness audits, and compliance evaluation collectively provide a multi-dimensional picture of system performance, ensuring robust detection without compromising ethical or regulatory standards.
6. **Future Directions**: Privacy-preserving federated learning, sophisticated insider scenario simulation, explainability-driven model optimisation, and ongoing fairness monitoring are areas that could be improved. Scaling XAI solutions across various healthcare environments depends on these developments.
7. **Final Takeaways**
   - Insider threat detection in healthcare cannot be addressed solely through high-dimensional anomaly detection; context, causality, and human interpretability are essential.
   - Explainable AI bridges the gap between algorithmic insight and operational trust, enabling compliance, auditability, and ethical governance.
   - By reframing alerts as missing clinical justification rather than presumed wrongdoing, healthcare organizations can maintain patient safety, clinician trust, and institutional integrity.

In conclusion, context-aware, interpretable, and causally based AI solutions are the way of the future for insider threat detection in the healthcare industry. These systems can effectively protect private data and offer a system of moral, just, and practical decision-making.

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13. APPENDIX

Appendix A: Glossary of Key Terms

Term	Definition
Explainable AI (XAI)	A branch of AI designed to provide human-interpretable explanations for model predictions or outputs, ensuring transparency and trustworthiness.
Insider Threat	Security risks posed by individuals within an organization, including malicious or negligent actions, such as unauthorized access to EHRs.
Electronic Health Records (EHRs)	Digital versions of patients' paper charts containing comprehensive health information, used across clinical and administrative workflows.
Causal Graphs	A visual or mathematical representation of cause-effect relationships between variables, often used to support explainable AI reasoning.
Counterfactual Explanation	An explanation describing how minimal changes to input variables could alter a model's output, highlighting causal dependencies.
Human-in-the-Loop (HITL)	A process where human experts participate in reviewing, validating, and refining AI model outputs, ensuring correctness and interpretability.
Fairness Metric	Quantitative measures assessing whether AI systems produce equitable outcomes across different groups or roles.
Auditability	The capacity to trace AI decisions and explanations back to evidence sources for regulatory or organizational review.

Appendix B: Example Features for Insider Threat Detection

Feature Category	Example Features	Notes
Temporal	Login timestamps, duration of EHR access, frequency of access during off-hours	Captures unusual patterns in time
Relational	Number of patient-provider connections, overlapping care teams, coverage patterns	Enables causal and graph-based reasoning
Behavioral	Copy/paste events, printing, EHR modification, deletion	Reflects potential malicious or negligent actions
Device/Location	IP address, device type, location of access	Helps detect unusual access points
Role Context	Job role, department, shift schedules	Reduces false positives by modeling legitimate behavior

Appendix C: Example Counterfactual Explanation Template

Scenario: An alert flagged a nurse for unusually frequent access to patient records outside assigned patients.

Explanation Component	Example
Observation	The nurse accessed 12 patient records outside her assigned care team in one shift.
Model Reasoning	Risk score = 0.78 due to high access outside assigned patients combined with prior access pattern deviations.
Counterfactual	If the nurse had accessed only assigned patients (10 fewer records), the risk score would have decreased to 0.21, below the alert threshold.
Audit Evidence	Log entries from EHR system, timestamps, role assignment metadata.
Recommendation	Human review suggested: Confirm clinical necessity (e.g., cross-coverage), no immediate disciplinary action required.

Appendix D: Evaluation Metrics Summary

Metric Type	Metric	Purpose
Detection	Precision, Recall, F1 Score, AUPRC	Measures predictive performance for insider events
Temporal	Detection latency	Measures how quickly alerts are raised after suspicious activity
Explainability	Counterfactual fidelity, causal plausibility	Ensures explanations align with model output and clinical workflows
Human-in-the-loop	Comprehension rate, audit traceability	Assesses whether auditors understand and can act on alerts
Fairness	Role alert consistency, shift parity gap	Detects bias across staff roles, shifts, or departments

Appendix E: Sample Human-in-the-Loop Workflow

1. **Alert Generation**: AI system flags potential insider activity.

2. **Initial Review**: Compliance auditor examines alert and system-provided explanation.
3. **Contextual Assessment**: Cross-reference with clinical workflow, patient coverage, and prior access patterns.
4. **Feedback Logging**: Auditor annotates alert outcome (justified, false positive, unclear).
5. **Model Update**: Feedback incorporated into retraining, causal graph updates, and alert threshold adjustments.

Appendix F: Simulated Insider Threat Scenarios

Scenario	Description	Purpose in Evaluation
Unauthorized Access	Staff accesses unassigned patient records without documented reason	Tests detection sensitivity and false-positive handling
Emergency Override	Clinician accesses multiple patient records in emergency	Evaluates model's ability to distinguish legitimate high-risk activity
Credential Sharing	Two staff use the same login	Tests detection of abnormal behavioral patterns
Data Exfiltration	Repeated copying/exporting of sensitive data	Validates counterfactual explanation's ability to trace causality
Shift/Role Anomalies	Staff accessing unusual patient sets during off-hours	Measures fairness and bias mitigation

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