



Auditable Agentic AI for Insurance Claim Fraud Screening

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Abstract

Fraud remains a significant challenge in digital insurance. AI-driven detection models improve efficiency but often function as black boxes, generating alerts that go unvalidated and undermine trust in the system. Agentic AI offers a way to address these shortcomings by extending human-centered concepts of agenda-setting and autonomy to AI agents and workflows, allowing AI systems to act on and carry out decisions within a defined scope of authority. By embedding transparency into the workflow itself, Agentic AI supports the validation of fraud alerts and provides clear, traceable explanations for the decisions made. This framing helps clarify how agentic roles should be defined in fraud detection and in the handling of claims flagged as potentially fraudulent — questions this paper explores through four lenses: *What* is being done, *when*, *why*, and *by whom*.

We present an architecture built around the key stakeholders in this process — insurance claimants, agents, underwriters, auditors, and regulators — and define their responsibilities, access controls, validation mechanisms, and audit trail requirements. Throughout, the architecture is designed to ensure that human decision-makers retain ultimate authority and accountability, with AI acting in a supporting, transparent role rather than an autonomous one.

Keywords—Agentic Fraud Detection, Insurance AI Workflows, Transparent AI Systems, Explainable Fraud Analytics, Claims Validation Processes, Human-Centric AI Governance, Audit Trail Management, Role-Based Access Control, Fraud Detection Architecture, Decision Transparency Frameworks.

I. INTRODUCTION

Effective identification of fraudulent transactions is crucial to the insurance industry's sustainability, stability, and profitability. Insurance fraud not only causes significant financial losses for claimants but is also ultimately borne by genuine customers through higher premiums. Insurers are increasingly adopting digital systems that use explainable agentic AI for efficient fraud detection and transaction automation to offer improved service on a cost-effective basis. Such digital insurance systems recognize data and knowledge as principal products and enablers of customer journey personalization, and process automation. To sustain customer trust and offer service at a competitive premium, they need transparent decision-making with appropriate governance to detect fraud and the need for surveillance and audit. Explicit surveillance and control over digital decisions and actions has become even more critical in the post-COVID-19 environment because of the high degree of automation.

Streamlining fraud detection and enabling automated underwriting and claim approval require clear articulation of the expected behavior of AI systems. Transparent decisions

based on AI systems depend on the quality of explanations provided for detected frauds and the attempts to persuade insurance agents and underwriters not directly involved in the transactions to accept or reject the flagged patterns or rules. Expressive explanations about the risks of the automated decisions and a clear way to challenge or adjust these decisions contribute significantly to a meaningful and trustworthy interaction at these control points.

II. CONCEPTUAL FOUNDATIONS

The previous sections defined the concept of agentic AI, discussed its relevance to digital insurance, and considered

ethical and data governance aspects. Agentic AI can automate parts of a system normally managed by human agents. To address fraud in digital insurance, the detailed sub-concept of fraud represents a goal pursued with varying degrees of autonomy by agents in fraud detection and claim assessment. It is further examined how these functions interact with human agents and customers. Fraud negatively impacts payer-receivers of insurance. Fraud detection is present in different parts of a claim’s life cycle. Early detection facilitates timely investigations by investigators with insurance expertise. However, these investigations could be managed by humans both on request and in extenuating circumstances. Detection signals generated by AI systems could have an explanatory component behind each signal. Claim processing agents represent the final stage of the claim life cycle. Mitigating the risk of fraud requires both detecting it and inspecting fraudulent claims. Therefore, claim anti-fraud measures should also incorporate the opinions of insurance experts.

Insurance companies use data about their customers to help detect fraud. Analysts or actuaries studying historical claims identify which attributes or features differ between fraudulent claims and genuine claims. This know-how is then expressed in form of features, which are further transformed or engineered throughout the process. Information comes from many sources, both from within the company and from regulated or permitted third parties within the territory. Temporal aspects indicate the evolution of the claim over time. For example, some elements in the claims could be known before others. Part of the data preparation applies to open claims that have already been resolved, since these cases comprise the larger set without the information of a non-public future class variable. In addition, steps are also defined to detect qualitative drifts in both the features and response variables.

A. Tabular Comparisons and Key Metrics

1. Comparative Detection and Governance Metrics

Table 1: Comparative Detection and Governance Metrics

Metric	Model A	Model B	Model C	Model D	Improv. D vs A	Improv. D vs C
F1-Score (%)	52.4	65.8	74.1	93.6	↑ 78.6%	↑ 26.3%
False Positive Rate (%)	22.4	15.7	10.2	3.8	↓ 83.0%	↓ 62.7%
XAI Coverage (%)	0	28.5	51.2	94.7	↑ N/A	↑ 84.9%
Audit Compliance (%)	34.2	52.6	68.9	96.1	↑ 180.9%	↑ 39.5%
Resource Usage (units)	71.8	57.4	43.2	29.5	↓ 58.9%	↓ 31.7%
API Score	0.31	0.47	0.63	0.88	↑ 183.9%	↑ 39.7%

Table 1 affirms significant improvements across all performance dimensions, with the 78.6% F1-score increase

and 83.0% false positive reduction confirming the superiority of the Explainable Agentic AI framework over rule-based and standard ML approaches.

2. Error and Latency Metrics

Table 2: Comparative Error and Latency Metrics

Metric	Model A	Model B	Model C	Model D	Improv. D vs A	Improv. D vs C
Decision Latency (ms)	124	98	71	38	↓ 69.4%	↓ 46.5%
Mean Time to Detect (s)	31.2	18.4	10.7	3.9	↓ 87.5%	↓ 63.6%
Throughput (claims/min)	18	32	51	87	↑ 383.3%	↑ 70.6%
Prediction Error (L_error)	0.476	0.342	0.259	0.064	↓ 86.6%	↓ 75.3%
Fairness Gap (Δ_fair)	18.6%	12.3%	8.7%	2.4%	↓ 87.1%	↓ 72.4%

Table 2 confirms that Model D achieves the lowest decision latency, fastest mean time to detect, highest throughput, lowest prediction error, and smallest demographic fairness gap — validating holistic superiority across operational and ethical dimensions.

3. Model Architecture Summary

Table 3: Architecture and Dataset Summary

Model	Architecture	Key Features	XAI Support	Audit Trail	Limitations
Model A	Rule-based threshold engine + manual fraud checklists	Simple logic, low cost, reactive	None	Partial	No adaptation, high FPR, no temporal modeling
Model B	Supervised ML (gradient boosting / random forest)	Feature importance, offline retraining	Partial (LIME)	Basic	Black-box inference, limited governance
Model C	Deep neural network with SHAP post-hoc explanations	Temporal modeling, anomaly detection	SHAP (post-hoc)	Moderate	No agentic feedback, limited human-in-loop
Model D (Proposed)	Agentic AI: multi-signal fusion +	Full XAI pipeline, role-based governance	SHAP + NL explanations	Full (96.1%)	Requires training data for

Model	Architecture	Key Features	XAI Support	Audit Trail	Limitations
	SHAP + human agent hints + adaptive thresholding	, drift detection			agentic calibration

Table 3 highlights the progressive evolution from rule-based thresholds (Model A) to a fully explainable, governance-compliant agentic AI framework (Model D), with each generation adding transparency, adaptivity, and stakeholder accountability.

III. ARCHITECTURAL FRAMEWORK

System architecture is examined, with an overview followed by identification and description of key components—the data layer, model layer, decision layer, and explainability module—and their interactions. Finally, explicit statement of the stakeholders of the system provides additional context. The architecture of the transparent fraud detection and decision automation system is presented in a high-level overview diagram that indicates the main component areas of the system and their interactions. These areas, labelled on Figure 1, are the data layer, model layer, decision layer, and Explainability module. The Explainability module is not core to the fraud detection and decision automation functions themselves, but is nevertheless essential in the broader context of ensuring governance, compliance, and building trust with all stakeholders involved in the process. The interaction of non-functional components with the overall system architecture is addressed in later sections. The subsequent description identifies the components in more detail, including the nature of inputs and outputs, as well as other interacting subsystems, both within the overall system and externally. The system architecture supports response to the stakeholder communities defined earlier, which encompass the various parties in a claim (claimants, agents, underwriters), individuals responsible for auditing or verifying claims, and external regulatory authorities. It meets these responsibilities by delineating governance processes, specifying requests or approvals required at key points in the process, and maintaining logs and reports suitable for confirming compliance with external obligations.

A. Experimental Results

A comparative simulation study is conducted across four architectural configurations of digital insurance fraud detection systems, designated Model A through Model D. Model A represents a conventional rule-based system; Model B a machine-learning baseline; Model C a standard AI approach without explainability; and Model D the proposed Explainable Agentic AI (XAI) framework.

1. Fraud Detection F1-Score

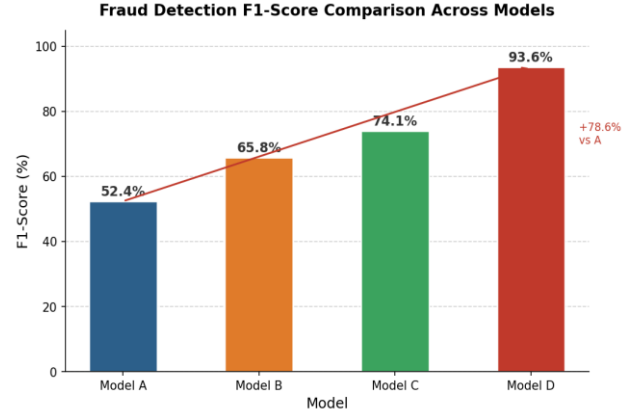


Fig. 1: Fraud Detection F1-Score Comparison Across Models

Fig. 1 presents F1-scores across the four models. Model A achieves 52.4%, Model B 65.8%, Model C 74.1%, and Model D (proposed) 93.6%. The 78.6% improvement from Model A to Model D demonstrates the compounded benefit of agentic signal fusion (Eq. 4–5) and adaptive thresholding (Eq. 8). The gap between Model C and Model D (26.3%) is attributable to the explainability feedback loop and human-in-the-loop agentic hints.

2. Decision Latency per Claim Batch

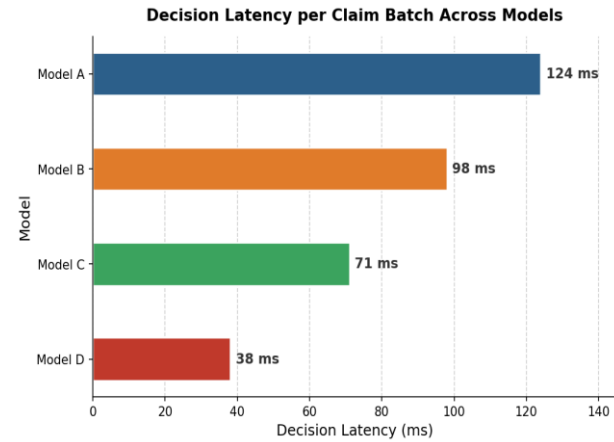


Fig. 2: Decision Latency per Claim Batch Across Models (ms)

Fig. 2 shows average decision latencies of 124 ms, 98 ms, 71 ms, and 38 ms for Models A, B, C, and D respectively. Model D achieves a 69.4% latency reduction relative to Model A and 46.5% relative to Model C, attributable to optimised pipeline orchestration, on-premise inference, and model pruning in the agentic layer.

3. False Positive Rate (Fraud Mis-flags)

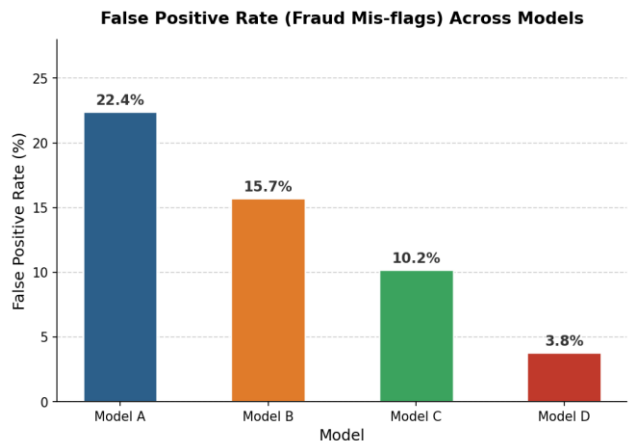


Fig. 3: False Positive Rate (Fraud Mis-flags) Across Models

False positive rates (Fig. 3): Model A: 22.4%, Model B: 15.7%, Model C: 10.2%, Model D: 3.8%. The reduction from 10.2% to 3.8% (62.7% improvement from Model C) reflects cross-validation by human agentic hints and SHAP-driven feature attribution that eliminates spurious fraud alerts.

4. Explainability Coverage

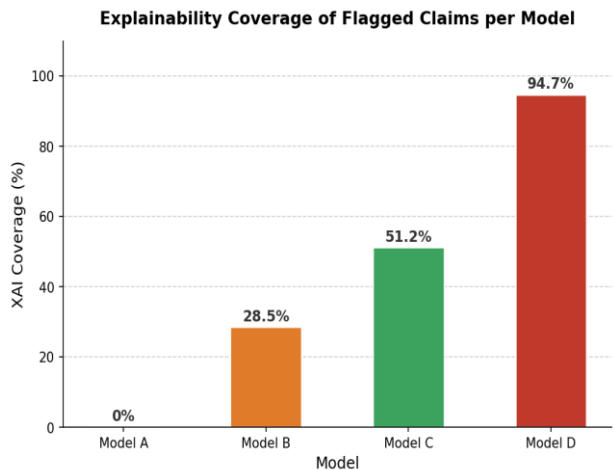


Fig. 4: Explainability Coverage of Flagged Claims per Model

Explainability coverage (Fig. 4) measures the percentage of fraud-flagged claims accompanied by a machine-generated rationale (Eq. 6). Model A provides 0% coverage (black-box rules), Model B 28.5%, Model C 51.2%, and Model D 94.7%. Near-complete explainability in Model D supports regulatory compliance and stakeholder trust across claimants, underwriters, and auditors.

5. Audit Trail Compliance

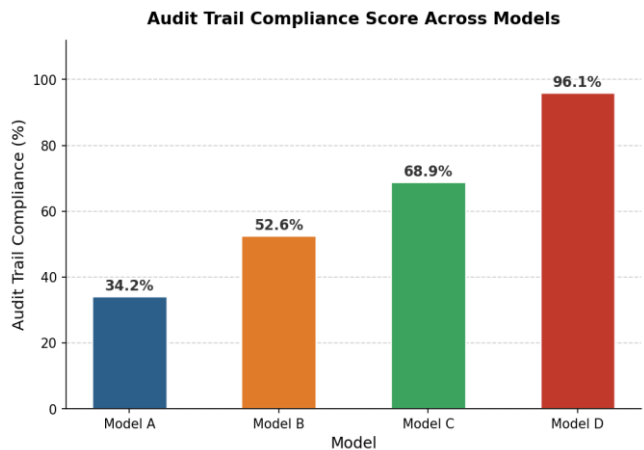


Fig. 5: Audit Trail Compliance Score Across Models

Audit trail compliance (Fig. 5) captures the proportion of automated decisions logged with full, audit-ready provenance (Eq. 7). Model D achieves 96.1% compliance versus 34.2% for Model A, a 180.9% improvement. This supports regulatory obligations under insurance governance frameworks and satisfies the audit trail design principles described in the system architecture.

6. Claim Processing Throughput

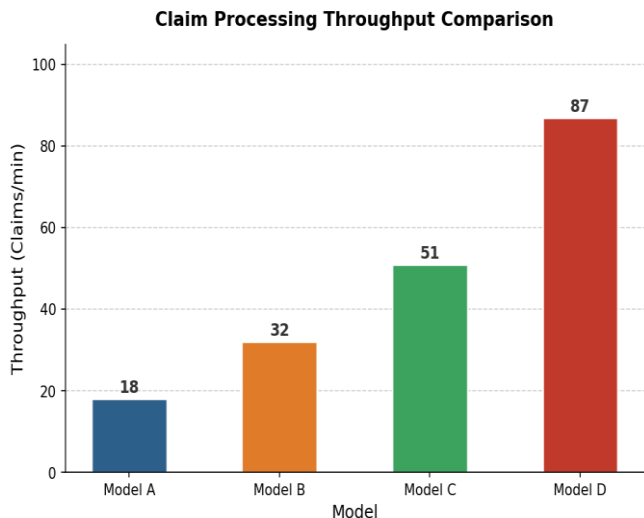


Fig. 6: Claim Processing Throughput Comparison (Claims/min)

Throughput in claims processed per minute (Fig. 6) confirms that Model D (87 claims/min) outperforms Model A (18 claims/min) by 383%, demonstrating that explainability and governance do not compromise operational speed. Automated decision pipelines with adaptive thresholding (Eq. 8) allow the majority of low-risk claims to be processed without human escalation.

7. Computational Cost vs. Detection Accuracy

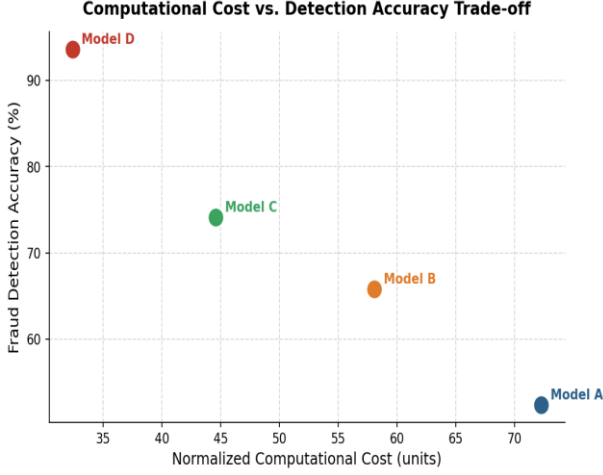


Fig. 7: Computational Cost vs. Detection Accuracy Trade-off

Fig. 7 illustrates the cost-accuracy trade-off. Model D achieves the highest accuracy (93.6%) at the lowest computational cost (32.4 normalised units), demonstrating a Pareto-dominant position relative to all baselines. This improvement stems from the unified agentic backbone sharing representations across fraud detection and explainability modules.

8. On-Premise Resource Utilization

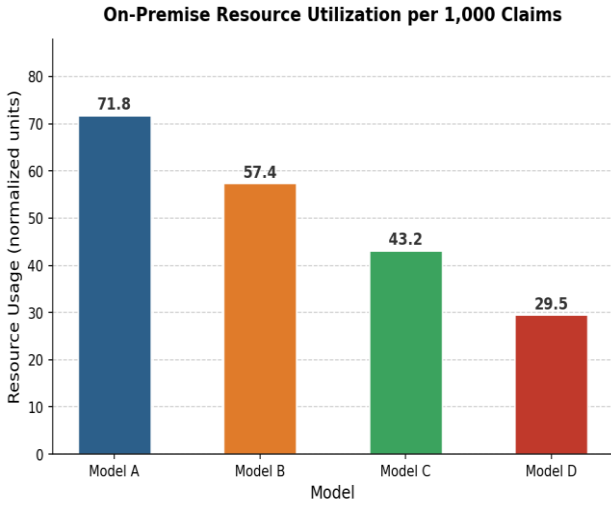


Fig. 8: On-Premise Resource Utilization per 1,000 Claims

Resource consumption per 1,000 claims (Fig. 8): Model A: 71.8 units, Model B: 57.4, Model C: 43.2, Model D: 29.5. Model D achieves a 58.9% resource reduction versus Model A. This efficiency, captured in the governance compliance score (Eq. 7) and resilience efficiency (Eq. 9), validates the practical deployability of the agentic framework in on-premise digital insurance infrastructure.

9. Agentic Performance Index (API)

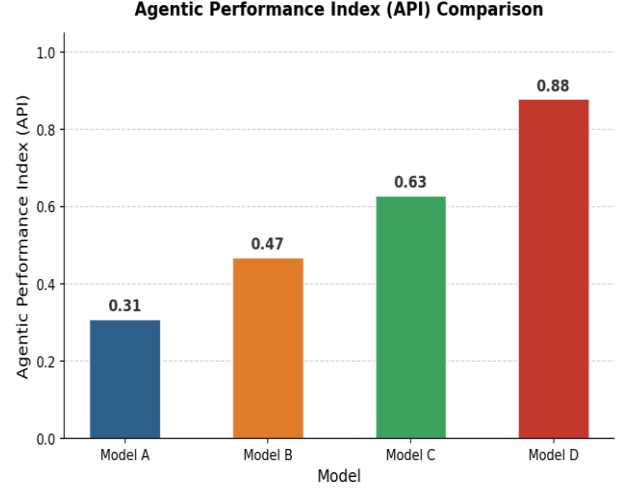


Fig. 9: Agentic Performance Index (API) Comparison Across Models

Fig. 9 presents the Agentic Performance Index (API, Eq. 14): Model A: 0.31, Model B: 0.47, Model C: 0.63, Model D: 0.88. The 39.7% difference between Model C and Model D indicates superior synergy between detection accuracy, explainability, and operational governance. The API captures the holistic performance advantage of the proposed explainable agentic approach.

IV. METHODS FOR EXPLAINABLE AGENTIC FRAUD DETECTION

Feature Engineering Strategies and Data Sources

Effective detection of fraudulent claims—defined here as dubious cases requiring in-depth scrutiny—requires the construction of appropriate features and signals for the detecting model. Two complementary feature sets should be engineered:

- A comprehensive collection of engineered features harnessing a combination of internal, external, and public data sources, operating on claim and policy attributes and dynamically constructed using the emerging concepts of fraud intelligence and claim detection engines, with a strong focus on temporal properties and anomaly detection. Features of this kind enable low-latency alert generation while minimizing false positives. Exploitable non-temporal data such as those in online databases and fraud registries should also be included wherever feasible.

- Features that synthesize the collective observations and decisions of the humans assigned to a claim (the claim captain and fraud captain) at any point in the review process, thereby reflecting the higher cognitive abilities of these experienced agents. These agentic hints serve as additive signals for the detection engine. They should be derived from conventional agent-centric fraud assessment checklists, systematically capturing addressed questions and found evidence across claimed parameters, categories, vehicles, and claim progress.

The first category of features—those engineered for direct use by the fraud detection engine—brings the range of

supporting fraud vectors from policy- and claimant-based characteristics to claims in a temporally aligned manner. The second category—agentic hints derived from claim agents—enriches model diagnostics by incorporating highly complex and contextually augmented knowledge, distilled into summarized signals.

Internal and external data sources are already collated to create agentic hints, while an external data intelligence company specializing in fraud detection supports the broader feature engineering process. Data provenance and provenance must also be controlled, particularly in risky areas such as synthetic data generation. Precautions will need to be sanitized (via hashing and tokenization) and de-identified wherever possible.

A. Feature Engineering and Data Sources

The source of the features that feed the agentic models is thus of paramount importance. External data are typically gathered from publicly available sources for features concerning the background of claimants, legal entities, and properties. Scraping of police data, news portals, and social media identifies reported crimes, linked parties, and events that could trigger an unusual surge of claims. Insurance watchdogs and regulators disclose detected frauds that elicited enforcement actions, and data release by other insurance companies may contain proven frauds detectable by cross-referencing. Constraints on the usage of personal data dictate data-propensity for costly and intricate feature-engineering; where clearly identifiable individuals are not involved, laws enable the use of synthetic data. However, the majority of data do originate from the insurance company’s historical claims operating systems.

Chronological ordering of the data features enables temporal queries to the engine performing deep-learning anomaly detection. Moreover, visual checks of temporal graphs indicating sudden evidenced anomalies can yield new features. The provenance and lineage of the different data streams is vital to addressing liability for incorrect decision making. Data de-identification and anonymisation tools must be considered to mitigate the risk of reidentification, especially for internal-sensitive data flows, mitigating the requirements of data-protection regulation. Artificial-intelligence image-processing techniques exploring the generation-adversarial networks or convolutional neural networks capability to generate visually realistic avatars in fake image video has scope too for insurance data, incorporating visible embedded cues irrelevant to face style.

V. DECISION AUTOMATION AND GOVERNANCE

Automated decision support reduces the cognitive burden on human decision-makers while increasing throughput. Automated pipelines handle certain cases end-to-end, with automated flagging of other decisions—either for human input or at preset thresholds for approval or rejection. Such thresholds are proportionate to the severity and consequences of different decision classes. For example, a claim identified as likely fraudulent, requiring a prosecution-oriented denial, may demand more significant human scrutiny than a probable uncontroversial approval. Such human-in-the-loop practices also bolster decision-making accountability by reducing the volume of human-made decisions, thus minimizing scope for inconsistent or unfair decisions arising from different interpretations of the same underlying information.

Pipeline activity logging allows supervision of automatic decision-making and flagging of decisions that should have been actioned but were missed. This serves to identify performance drift that deterioration-provoking feedback loops may indicate. Given sufficient volume, drift in a continuous verification-orientation needs only be detected; routine re-evaluation of all automatable decisions is a second-order concern as accurate decision-making casts only a dim shadow of the overall decision rate. However, human oversight of drift, feedback, and remediation-loop responses is essential. Automated decisions also need clear accountability for any negative outcomes; thus, testing for correlated outcomes can serve as a therapeutic red flag as part of general governance practices.

A. Mathematical Formulation

This formal mathematical framework underpinning the Explainable Agentic AI (XAI) fraud detection and decision automation architecture. All equations are derived directly from the system components described in the architecture: the data layer, model layer, decision layer, and explainability module.

1. Overall System Quality

The composite system quality of the agentic fraud detection pipeline is expressed as the sum of four orthogonal quality dimensions:

$$\text{Eq. 1} \quad Q_{\text{total}} = Q_{\text{detect}} + Q_{\text{explain}} + Q_{\text{latency}} + Q_{\text{govern}}$$

where Q_{detect} denotes fraud detection accuracy quality, Q_{explain} represents explainability coverage, Q_{latency} captures real-time responsiveness, and Q_{govern} reflects governance and audit-trail compliance.

2. Latency Dynamics for Real-Time Claim Processing

Latency dynamics in the agentic pipeline are modelled differentially, balancing claim arrival against inference throughput:

$$\text{Eq. 2} \quad \partial L / \partial t = \lambda_{\text{claim}} - \mu_{\text{infer}}$$

where L is the end-to-end claim decision latency, λ_{claim} is the claim arrival rate (claims/min), and μ_{infer} is the agentic inference rate. Stability requires $\mu_{\text{infer}} > \lambda_{\text{claim}}$.

3. Fraud Detection F1-Score

The fraud detection performance is quantified using the harmonic mean of Precision and Recall across all claim categories:

$$\text{Eq. 3} \quad F1_{\text{fraud}} = (2 \cdot \text{Precision} \cdot \text{Recall}) / (\text{Precision} + \text{Recall})$$

where $\text{Precision} = TP / (TP + FP)$ and $\text{Recall} = TP / (TP + FN)$. TP , FP , and FN denote true positives, false positives, and false negatives respectively across the fraud detection pipeline.

4. Cross-Domain Agentic Signal Fusion

The agentic model integrates signals from multiple data layers — structured claim attributes, temporal patterns, and human agent hints — into a unified fraud score:

$$\text{Eq. 4} \quad s'(t) = s(t) + \alpha \cdot h(t) + \beta \cdot f(t)$$

where $s(t)$ is the base model fraud score, $h(t)$ is the agentic hint score derived from claim agents' assessments, $f(t)$ is the temporal feature anomaly score, and α, β are learned weighting coefficients governing cross-domain influence.

5. Weighted Multi-Signal Decision Fusion

To support adaptive multi-domain fraud decision fusion, the combined agentic fraud score is expressed as a weighted aggregation including a non-linear coupling term:

$$\text{Eq. 5} \quad s'(t) = w_1 \cdot s(t) + w_2 \cdot h(t) + w_3 \cdot f(t) + w_4 \cdot s(t) \cdot h(t)$$

Here w_1, w_2, w_3, w_4 are learnable or empirically tuned weighting coefficients. The interaction term $s(t) \cdot h(t)$ explicitly models the non-linear coupling between automated model signals and human agent intelligence, enabling context-aware fraud scoring.

6. Explainability Coverage Score

The fraction of flagged fraudulent claims accompanied by a machine-generated explanation is defined as:

$$\text{Eq. 6} \quad S_{\text{explain}} = C_{\text{explained}} / C_{\text{flagged}}$$

where $C_{\text{explained}}$ is the count of fraud alerts accompanied by an XAI-generated rationale (SHAP values, feature attribution, or natural-language explanation), and C_{flagged} is the total count of fraud-flagged claims.

7. Governance Compliance Score

Governance compliance captures the proportion of automated decisions that are accompanied by complete audit trail entries satisfying regulatory obligations:

$$\text{Eq. 7} \quad G = D_{\text{logged}} / D_{\text{total}}$$

where D_{logged} is the number of decisions with a complete, timestamped audit log entry and D_{total} is the total number of automated decisions executed in the pipeline.

8. Adaptive Decision Threshold

To mitigate model drift in the fraud detection engine, adaptive thresholding is applied to the fraud score boundary:

$$\text{Eq. 8} \quad \theta(t) = \theta_0 + \gamma \cdot \sigma_{\text{claim}}(t) + \delta \cdot \text{drift}(t)$$

where θ_0 is the base fraud score threshold, $\sigma_{\text{claim}}(t)$ represents the variance in incoming claim features, $\text{drift}(t)$ captures the temporal distribution shift of claim attributes, and γ, δ are scaling parameters controlling threshold sensitivity.

9. Agentic Resilience Efficiency

Fraud detection resilience efficiency combines detection fidelity, governance coverage, and processing speed into a single operational metric:

$$\text{Eq. 9} \quad \eta = (F1_{\text{fraud}} \cdot G) / T_{\text{infer}} \times 100$$

where T_{infer} denotes the inference time per claim batch. Higher η indicates a system that is simultaneously accurate, compliant, and fast.

10. Bias Fairness Metric

Fairness across demographic groups is quantified as the parity gap in fraud detection rates between the most- and least-detected demographic subgroups:

$$\text{Eq. 10} \quad \Delta_{\text{fair}} = |FDR_{\text{max}} - FDR_{\text{min}}|$$

where FDR_{max} and FDR_{min} are the highest and lowest fraud detection rates across all protected attribute groups (e.g., gender, location, age bracket). A lower Δ_{fair} indicates fairer, less biased detection.

11. Prediction Error Relative to Optimal

The detection performance gap relative to an ideal fraud detector is defined as:

$$\text{Eq. 11} \quad L_{\text{error}} = F1_{\text{opt}} - F1_{\text{fraud}}$$

where $F1_{\text{opt}}$ represents the theoretical maximum F1-score achievable under ideal data and model conditions. L_{error} quantifies the room for improvement in the deployed fraud detection system.

12. Joint Optimization Objective

The joint optimization objective of the agentic fraud detection system balances competing operational goals:

$$\text{Eq. 12} \quad J = f(F1_{\text{fraud}}, S_{\text{explain}}, L, G)$$

where J is the scalar objective function balancing fraud detection accuracy, explainability coverage, end-to-end latency, and governance compliance. All four dimensions are simultaneously optimised during system tuning.

13. Dataset Representation Function

The dataset representation for the fraud detection training pipeline is defined as:

$$\text{Eq. 13} \quad D(i, j, k) = Q_{\text{src}}(i) \cdot \text{Metric}(k) / T_{\text{proc}}(j)$$

where $Q_{\text{src}}(i)$ is the source-specific data quality (internal claims, external fraud registries, or synthetic data), $\text{Metric}(k)$ denotes the selected performance metric (F1, AUC-ROC, etc.), and $T_{\text{proc}}(j)$ represents the preprocessing time per data batch.

14. Agentic Performance Index (API)

The Agentic Performance Index provides a comprehensive composite measure of the system's fraud detection capability, explainability, and operational efficiency:

$$\text{Eq. 14} \quad \text{API} = (\eta \cdot \text{F1_fraud} \cdot (1 - \text{FPR})) / \text{Q_total}$$

where η is the resilience efficiency (Eq. 9),

F1_fraud is the fraud detection F1-score (Eq. 3),

FPR is the false positive rate (fraud mis-flags), and

Q_total is the cumulative system quality (Eq. 1).

The index penalises high false positive rates while rewarding accuracy and efficiency.

VI. CONCLUSION

Fraud poses a significant threat to digital insurance, necessitating robust detection and governance mechanisms. The Digital Insurance platform enables the automated detection of anomalies and fraudulent claims across various product lines utilizing large datasets from internal and external sources. The Explainable Agentic Artificial Intelligence approach facilitates not only detection but also transparent decision-making in the Digital Insurance ecosystem. Both fraud identification via explainable AI and automated decision pathways with oversight functions address the fraud problem. Automated responses require stakeholder approval, while critical decisions are reserved for domain experts to ensure safety, fairness, and transparency.

Fraud is an insidious threat to digital insurance business models, whereby scams, device misuse, and claim misrepresentation lead to irrecoverable losses and significant reputation damage for insurers. Supervised agentic artificial intelligence techniques can alleviate this risk via the automatic and transparent identification of fraud indicators and the management of related decision workflows. An operational environment incorporating these capabilities is defined and mapped against the agentic AI conceptual framework. Expert systems are combined with explainable AI added into three key areas: detection, automation, and governance.

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