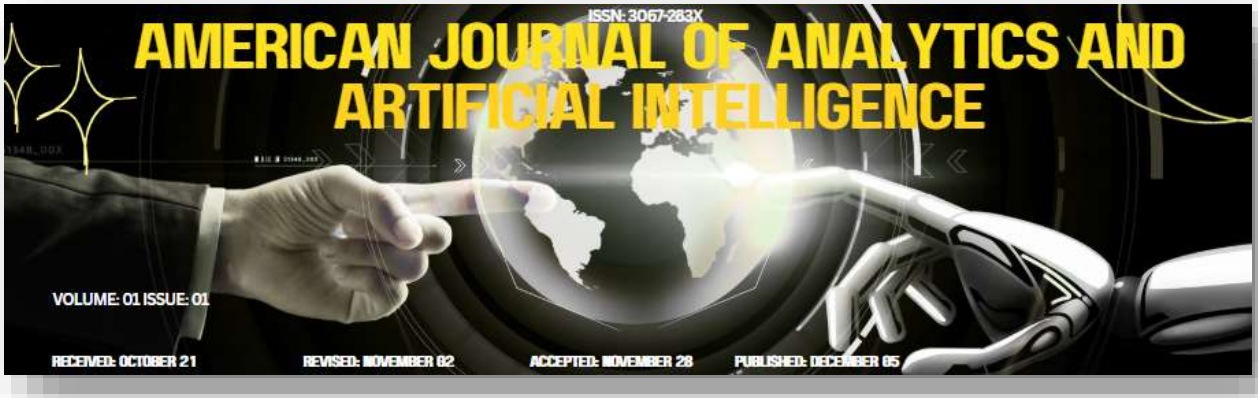

Hybrid AI for Insurance Fraud Detection

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Abstract

Fraud poses ongoing operational and financial challenges to the insurance industry, which rely on expert knowledge to prepare for and react against ever-evolving attacks. Beyond discrimination of potential fraud scenarios, future detection systems must therefore support the synthesis of training data for evolving patterns, surface latent signals for unseen forms, propose tests for the detection of adaptative fraud patterns and scenarios for benchmarking, and automatically adapt to changes. Recent advancements in the fields of Generative AI and Autonomous Decision making propose highly complex agents able to reason around natural language, map textual to 3D spaces, and learn new object categories from a few examples. Such models can find application to these aspects, and a study plan explore the hybrid integration of Generative and Agentic AI.

The research takes the shape of a Do-Observe-Learn cycle, with the first cycle concentrating on Detect, along with Detect processes for Synthesis, Adaptation, and Quality Layer, thus applying the original focus of fraud detection to the new context, identifying the critical elements from which new decisions can be made, concluding with the resulting TDCC basis for realisation. An analysis on how evolving patterns can influence the design is also performed, targeting integration path of the hybrid design, with the generative component directly involved in detection pipeline in layer supporting adaptation. One important instance of integration focuses on the Data Quality Layer, combining external knowledge with the concept of absolutely difficult-to-detect forms for fraud detection, thus synthesizing signals that should be present in the data for the adapted detector to generalise the aspect.

Keywords: Insurance Fraud Detection, Generative AI for Fraud, Agentic AI Systems, Adaptive Fraud Detection, Fraud Pattern Synthesis, Autonomous Decision Systems, Hybrid AI Architectures, Fraud Signal Discovery, Synthetic Training Data, Data Quality in Fraud Detection, Fraud Scenario Simulation, Evolving Fraud Patterns, Fraud Detection Pipelines, Anomaly Detection in Insurance, AI-Driven Risk Detection, Do-Observe-Learn Cycle, Fraud Benchmarking Models, Intelligent Fraud Analytics, Self-Adaptive Detection Systems, Advanced Fraud Prevention.

1. Introduction

Fraud in its myriad forms has plagued the insurance industry since its inception. The matched growth of fraud and detection has been defended as a prerequisite for a healthy market. It has also been flagged as evidence for fraud becoming endemic, devastatingly impacting both insurers and insured. Data-hungry AI-based methods are applied in increasingly innovative ways to detect cases. Commercial advertising touts success rates above 90%. Yet resourcing continues to fall far short of levels adequate to challenge even a small fraction of detected cases. Performance gains claimed by machine learning approaches remain hard to quantify. Focus on fraud detection thus remains a mixed narrative, where mainstream governmental and academic publications lament the purported failure of these techniques to displace traditional hardcoded rule-based approaches. Adaptive frameworks that can defeat evolving fraud patterns have become essential.

Research applying technological innovation to improve advanced fraud detection remains laudable. The deployment of hybrid systems of Generative and Agentic AI within primary operations presents obvious associated operational advantages. Such approaches are rightly still suggested as ground-breaking, frontier research. These advances reflect the gradual integration of fully-fledged Causative AI into existing systems in a sensible manner. Building on these foundations, careful exploration of prospective frameworks for the incorporation of these techniques into the daily workings of insurance fraud investigation – and the development of new detection systems – is timely, relevant and worthwhile.

2. Foundations of Fraud Detection in Insurance

Effective fraud detection in insurance relies on understanding the nature of fraud itself and the various ways fraudsters may attempt to deceive insurance companies. The insurance definition of fraud encompasses various fraudulent behaviours: fraud committed against an insured party; fraud committed by the insurer, e.g., payment of false claims; and fraud by third parties not related to the contract. The following discussion focuses on the third type—fraud attempted against an insurer by the insured or other parties. Detection challenges arise from a substantial lack of fraud awareness on the part of insurers and insureds alike, leading many insurers to regard fraud as a cost of doing business. As long as insurers consider fraud only a cost of doing business, the fraudster is afforded an advantage, since a fraudulent claim has a fair

chance of being paid. This is compounded by the hidden nature of fraud and the error–loss perspective of fraud, i.e., the fact that it is impossible to prove a negative.

Indeed, fraud can be described as a fatal error-by-loss. Yet fraud detection is not merely the detection of contradictions in claim information. Elite fraudsters create convolutions in the truth to exploit the hidden nature of fraud; often, the more elaborate the con the more unchallengeable it appears. The most sophisticated fraud enhances the very risk that it seeks to exploit. These considerations are seldom factored into the design of fraud detection systems; detection is merely applied to past data as a forensic exercise rather than as a tool for proactively anticipating future frauds. Effective detection requires the construction of a realistic signalling environment that can be reached only through the application of an intelligence cycle in which hypotheses are generated and tested in an iterative manner. Only in this manner can an unsustainable advantage be removed from fraudsters.

2.1. Key Principles and Strategies for Fraud Detection

Several well-defined principles encapsulate the fundamental strategies for fraud detection in insurance. All aim to achieve reliable identification of true fraudulent cases, with their respective absence or distortion marking the flaws of purely rule-based approaches. These principles comprise:

- **Signal Synthesis**: The integrity of claims signals depends on the truthful behavior of policyholders, who provide essential information. Failure to comply creates an anomalous signal that should be flagged. Consequently, insurance policies must be framed to minimize adversarial actions. Despite the assessment of incoming signals derived from policyholders, threat agents—the perpetrators of fraud—remain indistinguishable based solely on the signals they generate. Modern solutions for detecting delinquency patterns focus on the inherent properties of policyholders' activities—i.e., substantiation throughout the life cycle and identity validation in insurance terms and exposures.

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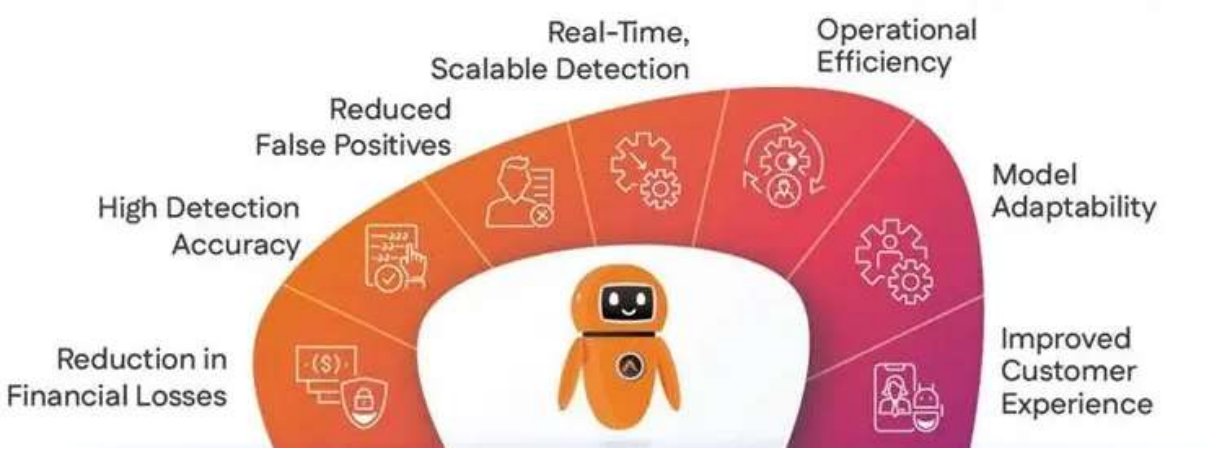

Fig 1: AI Anomaly Detection in Claims Fraud

- **Anomaly Detection**: Distinct from pattern recognition, anomaly detection aims to deliberately identify interesting points or patterns that do not conform to an expected or typical behavior—a behavior that, for the probation systems, cannot present the same high degree of confidence as the patterns associated with non-fraudulent activities. This is an aspect of endurance that signals "potential fraud." Signals must be internally coherent but deviate from the norm without being identifiable in pre-set patterns.

- **Fraud Risk Scoring**: Signal synthesis and anomaly detection address the probability of a claim being fraudulent. However, this dimension is not sufficient to manage the high daily flow of claims in a timely manner. A fraud risk score must also be implemented. The higher the tendency of a signal to be fraudulent, the closer the risk score is to +1. Conversely, the lower the tendency, the closer the score is to -1. Early signals satisfy the pattern identification maturity condition as a consequence of the fraud risk score. For claims with a higher risk score, the Auditor module automatically becomes involved in the decision-making process.

- **Explainability**: As a result of a fraud risk score, such a score represents a decision-making support module. In this context, it is similar to a credit scoring module that enables a scoring system to conduct large-volume evaluation tests for any type of business. At the same time, any decision taken by the fraud detection system must be explainable, and it must be

possible to build an explainable knowledge base to cope with claims sharing sensitive information with external entities.

- **Auditability**: Auditors are responsible for the post-decision-making review of fraud cases based on a test check of fraud pattern detection. All decisions, together with their explanations, can be audited and the reasons for not following the recommendations maintained in the system.

3. Methodology

A mixed-methods design combines quantitative and qualitative data sources to investigate the problem in an adaptive and integrative way. Dedicated data pipelines gather disparate datasets covering multiple aspects of insurance fraud detection, including claims, historical fraud, conversations, images, audit evidence, external information sources, and underlying legal texts. Core model integration links hybrid generative and agentic AI architectures to enable several key applications for the training and operation of online fraud detectors.

The data ecosystem encompasses multiple domains, and input data spatio-temporal accidents may be unfeasible. Experimental model pipelines enable an ambulatory topographic template for these datasets to facilitate the generation of both simple and complex frauds around the evaluation business scenario. A second model pipeline enables testing dimensional syntesis by detecting low-dimensional frauds to best recent detection. Support for counterfactual generation and testing is partly covered by the embedding vector augmented data pipeline, while the practical test for agents and persistent fraud models is outside the scope of the workshop. Nevertheless, the conceptual system is based on a dedicated online concept-drift benchmark detection that can continuously compare all permanent and persistent fraud models.

In a deep hybrid implementation continuous risk-scoring or case-creation detect models are persistently compared to the general properties of the fine-tuned engines and agents or indeed any type of unbenchmarked classifier. The capability of all these models contributing to feature provenance is the speciality of any adaptive embedding with a powerful generative model using the conditional augmented diffusion in the reverse direction for successful local-data failure.

Table 1. Main components of the proposed fraud-detection ecosystem

Layer / Module	Role in the article	Typical input	Typical output	Why it matters
Data Quality & Provenance Layer	Validates source reliability, lineage, integrity, and compliance	Claims, images, text, audits, external feeds	Trusted integrated data	Prevents weak or biased fraud signals
Signal Synthesis	Combines raw evidence into usable fraud indicators	Cleaned multi-source data	Feature vectors / signal set	Converts scattered observations into model-ready evidence
Generative Models	Synthetic data generation, counterfactuals, scenario creation, adversarial testing	Fraud and non-fraud samples, prompts, conditions	Synthetic claims, embeddings, scenarios	Helps with rarity of fraud and evolving patterns
Fraud Detector / Risk Scorer	Classifies or ranks suspicious cases	Feature vectors, anomaly outputs, generated evidence	Fraud probability / risk score	Core detection engine
Agentic Layer	Goal formulation, action policy, decision execution, autonomy control	Detector outputs, drift alerts, operational context	Retraining requests, escalations, workflow actions	Makes the system adaptive and operational
Drift / Online Learning Layer	Detects change in data distribution and updates models	Streaming batches, prediction performance	Updated parameters / retraining trigger	Keeps model relevant as fraud evolves

Layer / Module	Role in the article	Typical input	Typical output	Why it matters
Governance / Explainability / Auditability	Makes decisions transparent, reviewable, compliant	Scores, features, model decisions	Explanations, logs, audit traces	Essential for regulated insurance workflows
Case Management	Supports investigators and alert prioritization	Alerts, scores, explanation packets	Bundled cases, next-best actions	Turns model outputs into operational action

3.1. Integrating Generative Models in Fraud Detection Strategies

Generative models augment discriminative fraud detectors by enhancing training data, enabling counterfactual analysis, supporting the creation of synthetic scenarios, and facilitating adversarial testing. Data expansion for augmenting detector training often draws on probabilistic generative models representing either the target data distribution or relevant conditioning distributions. Generative adversarial networks, variational autoencoders, and diffusion models focus on synthesising training data, while language models support the structured generation of scenarios appealing to humans, as in the textual description of insurance claims. Besides data expansion, generative models also play a key role in fraud detection strategies that target data- or feature-space anomalies, risk assessment, and explainability.

Probabilistic data representations are instrumental in counterfactual analyses. When capable of modelling background distributions, generative methods allow the realistic modification of samples according to a given conceptual label. Stratified conditional generative models can simulate label-conditional parts of the joint distribution, paving the way for anomaly detection and risk-scoring systems. Procedures that use these techniques to synthetically create normal instances around any feature-vector combination can also guide other detectors. Moreover, synthetic samples can assist in producing tests that target fraudsters' weaknesses via adversarial search.

Equation 1. Representation of an insurance claim

Let

$$x = [x_1, x_2, x_3, \dots, x_d]^\top \in \mathbb{R}^d$$

where each component may represent:

$$x = \begin{bmatrix} \text{claim amount, claim timing, policy history, text embedding, image embedding, audit flags,} \\ \text{external risk indicators, ...} \end{bmatrix}$$

Derivation

1. A case contains many heterogeneous signals.
2. A model needs a unified mathematical object.
3. Therefore all signals are encoded into a vector x.
4. This makes downstream scoring possible.

So the claim representation is:

$$\boxed{x \in \mathbb{R}^d}$$

4. Objective of the Study

The study aims to improve adaptive fraud detection for insurance applications by unifying hybrid generative and agentic AI architectures. Fusion is pursued in two channels: first, integrating data-driven generative components within a broad class of fraud detector designs, accommodating Generative Adversarial Networks, Variational Autoencoders, Diffusion Models, and more; second, adaptation to evolving insurance fraud patterns by embedding online learning mechanisms for continuous model updating and concept-drift accommodation.

Two explicit hypotheses formulate a precise testable objective. The first posits that the integration of generative models will enhance detection performance metrics and enable the implementation of principles, including explainability, auditability, and the synthesis of explainable outlier behavior patterns. The second relates to enabling agents to learn, dominate, and manage fraud detectors, automatically identifying degradation modes and initiating model

retraining. Success will provide practical frameworks for bridging the generative–agentic paradigm gap in fraud detection in insurance ecosystems.

4.1. Defining the Study's Goals and Aspirations

The work aims to illustrate how hybrid architectures combining generative and agentic models can serve as a foundation for adaptive fraud-detection solutions in modern insurance ecosystems. Of particular interest is the implementation of online, continual, and active learning for detection systems exposed to drift-prone fraud patterns driven by innovative new fraud methods, shifting socioeconomic conditions, and periodic changes in insurance coverages. In line with this agenda, the study proposes a dual-generative, multi-agent architecture. General expressions of the system's primary components are established, and the use of any architecture for the development of the constituent agentic components is presented. Research hypotheses targeting the hybrid detector and making explicit its underlying experimental design are also clarified.

A successful detector architecture able to adapt to evolving fraud patterns without complete retraining would allow for a more sustainable usage of data resources, and could potentially reduce fraud losses that evade discovery for long periods. Exploration of the facilitation of such a detector through the use of generative models supported by other hybrid AI architectures—such as data- and task-driven combinations of VAEs, diffusion and LLMs—would thus represent a meaningful extension to both the application of hypergenerative AI within fraud detection, as well as the hybridisation of generative and agentic models across diverse use cases.

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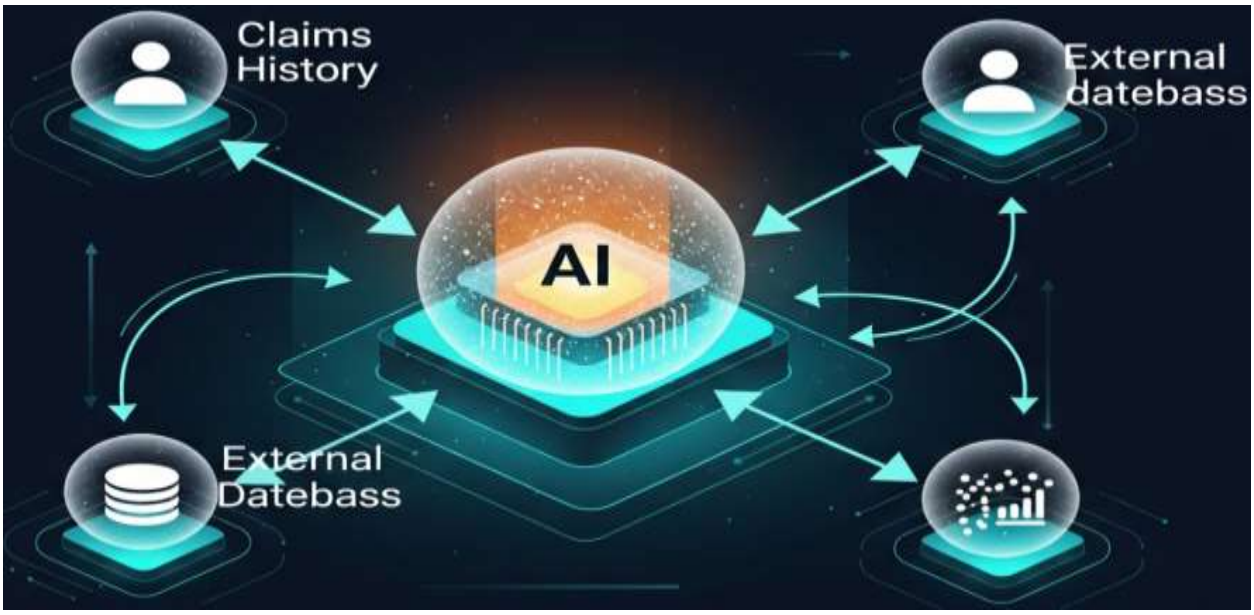

Fig 2: AI-Powered Fraud Detection in Insurance

5. Research Summary

Insurance fraud detection is a challenging problem that has attracted considerable academic and industrial efforts. Many detection systems are deployed within active insurance ecosystems. Clear objectives are provided by the stakeholders, and extensive data is generated during policy underwriting, risk assessment, claims processing, and operational decision-making. The detected cases of fraud can also allow for performance feedback. The question being explored is whether trustworthy hybrid generative and agentic AI models can be developed and deployed within such an insurance ecosystem in a way that enhances operational fraud detection.

Fraud detection benefit from a lab–lab simulation setup, where two principal components of a realistic operational detection pipeline are constructed independently—the core fraud detection engine and the surrounding operational context—and then integrated and evaluated. Preliminary work revealed the essential properties that any fraud detection engine should possess in order to be truly effective and operationally relevant.

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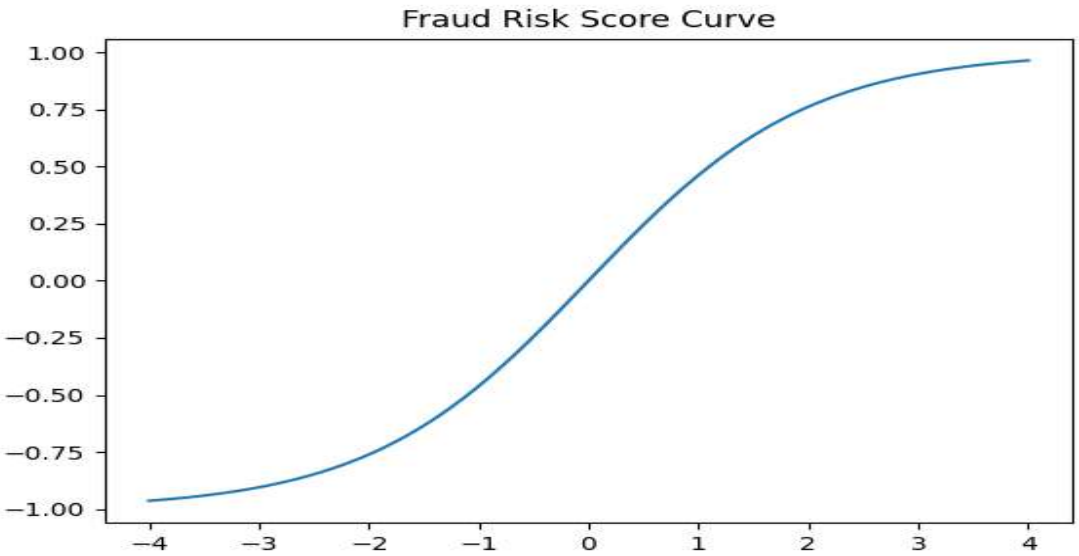

5.1. Integration of Hybrid Generative and Agentic AI Architectures

Hybrid generative–agentic AI models at the highest conceptual level. Like so, each technique employed follows a layered approach that dictates how types are integrated and coordinated. In this light, environments utilize multiple agents, each model encompassing both a strategic supervisory level and a procedural low level of different competence, with one layer controlling multiple system components according to a broader goal set, and allowing parallel exploration of the task space, for instance, while ensuring consistency of action and result of interacting modules underneath. Furthermore, ongoing research covers automatic governance, safety, and alignment mechanisms for artificial intelligence. Other conceivable safety measures propose a regulatory layer for complex environments running multiple generative–agentic AI models and/or agents.

Generative components and agentic modules are interconnected through the definition of goals that these latter will pursue—the goals might be defined as meta-dynamics for the overall architecture or for a specific agent at any level—and that shape exploration policies according to the foundations of agency. Safe exploration is ensured by providing a dual role for the generative model or supporting module: on one side, it formulates the behaviour of the agent considering its

goal or role in the environment, on the other side, it monitors the actions undertaken by the hidden layer of the generative–agentic AI architecture, generating warnings and defining switches of phase when the coordinated dynamics allows it.

6. Hybrid Generative and Agentic AI: Concepts and Architectures

An insurance organization typically consists of several departments, from product development to claims, supported by different functions providing solutions: compliance, operations, anti-money laundering (AML), fraud investigation, risk control, underwriting, pricing, etc. Most systems in these departments chiefly rely on discriminative AI for analysis, prediction, or classification. Fraud detection typically constitutes a complicated non-discrete adversarial RMS where digital agents and human investigators respond to the actions of policyholders and external actors trying to bypass detection. Fraudsters strive to alter the fraud signal so that it resembles legitimate behavior, while systems create detectors seeking to distinguish between legitimate use and fraudulent abuse.

Fraud patterns are not constant. Actors continuously adapt to diketions to reduce the probability of being detected. New situations that increase the probability of fraud (e.g., sudden change in tourism patterns) or types of claims begin to attract a more fraudulent attention. Discriminative models may have their behavior altered by DL techniques to synthesize a fraud detection sigma—training using pool teiling or help defeat a criminal environment whose criminal activity is not mined by scoring agents, allowing adaptation to concept drift. However, such augmentation is nontrivial and extremely expensive to maintain at a large scale. A novel approach considers different types of signal enrichment and augmentations as part of a coordination plan that controls and manages the experimental setup for an insurance organization using hybrid generative and agentic AI enabled by simulated data pipelines and distributed experiments.

Equation 2. Signal synthesis function

Define a synthesis function:

$$z = \phi(x)$$

where:

- x = raw integrated claim data,
- $\phi(\cdot)$ = feature engineering / embedding / fusion function,
- z = synthesized fraud signal.

If there are multiple data sources $x^{(1)}, x^{(2)}, \dots, x^{(m)}$, then:

$$z = \phi\left(x^{(1)}, x^{(2)}, \dots, x^{(m)}\right)$$

Derivation

5. The paper says data come from multiple pipelines.
6. Those sources must be combined before scoring.
7. So we introduce a fusion mapping ϕ.
8. The output z is the feature-space used for anomaly detection and fraud scoring.

Thus:

$$\boxed{z = \phi(x)}$$

or for multiple sources:

$$\boxed{z = \phi\left(x^{(1)}, x^{(2)}, \dots, x^{(m)}\right)}$$

6.1. Generative Models in Fraud Detection

Generative models serve specific roles in fraud detection, including data augmentation, counterfactual analysis, synthetic scenario generation, and adversarial testing. These applications extend to visual, textual, and audio-visual modalities; key types include variational autoencoders, diffusion models, and language models. Typical requirements involve supervised datasets with one or more data axes significantly affected by fraud. Model training follows standard paradigms, while evaluation often centres on quality metrics for generated data or, indirectly, for models using the generated data.

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Fraud is inherently rare, leading to sparse samples for rule or detector training, and hinders thorough testing. Novel incidents formulated as open problems offer significant potential for supervised learning using generative models specially designed for augmentation and counterfactual use. Proliferating synthetic scenarios support black-box detection components by enabling extensive, fully controlled explorations; diffusion models in particular represent an appealing option for realistic multimodal scenes. Generative AI technologies permit rapid prototyping of fully auditable misused capabilites, enabling cyber-resilience without policing all uses.

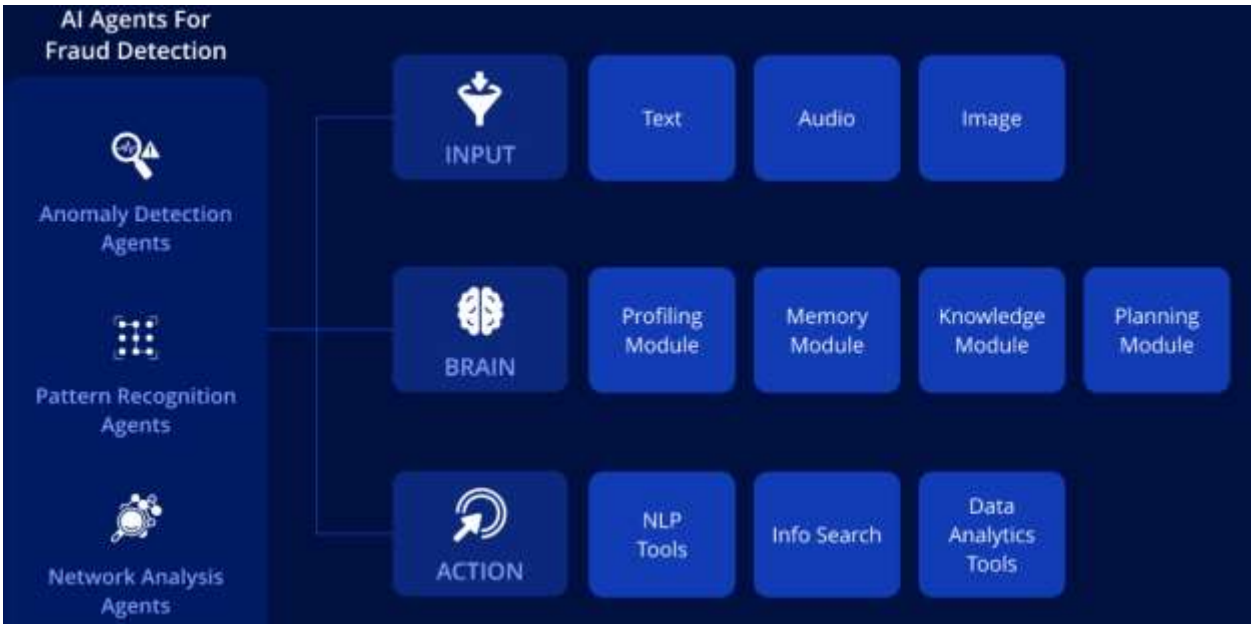

Fig 3: AI agents for fraud detection

6.2. Agentic Systems and Autonomous Decision-Making

Agentic components are concerned with performing specific actions in the world. More formally, an agentic architecture receives an environment observation as input; it defines a goal to be pursued in the environment and subsequently produces a sequence of actions to maximize the expected reward obtained while following it. These components typically comprise at least the following four high-level modules:

• Goal formulation. This module is responsible for breaking down the high-level objectives of the entire fraud detection ecosystem into specific, actionable tasks. It operates in a nested fashion, with higher-level modules defining more abstract and longer-term goals that are further decomposed by their submodules. An example of an organization-level goal is the detection of emerging fraud patterns; an example of a supporting goal is the identification of previously undetected clusters of suspicious events based on ontologies. These goals can then be transformed into queries about the fraud detection system's knowledge base, aimed at the data-gathering hybrid models.

• Action policy formulation. This module produces an action policy (i.e., a mapping from environment observations to actions) based on the current environment state and a specific goal. Considering the nature of the environment, such a policy can be constant or state-based. In the real-time anti-fraud scoring scenario (see Section 15.1), the action policy would inherently be constant. Conversely, in the case-management scenario (see Section 15.2), a case analyst would explore the environment using the action-recommendation policy to identify the next best action to take on an active investigation.

• Decision-making. This module collects the current environment state and a previously defined action policy, performs the corresponding action, receives the next environment observation and reward, and iteratively executes the policy until the specified goal is achieved (i.e., the task is accomplished).

• Autonomy boundaries. The autonomy boundaries of agentic modules define an additional coordination layer between human users and the autonomous agents built into the ecosystem. Such a layer indicates the type of activities that require human supervision and control, but also the specific actions or tasks that can or should be executed by the agents without human intervention, thus allowing the latter to focus on the higher-level, less frequent but more valuable decisions.

Table 2. Generative vs agentic vs governance responsibilities

Category	Explicit roles stated or strongly implied by the article	Count used in bar chart
Generative functions	Data augmentation, counterfactual analysis, synthetic scenario generation, adversarial testing	4

Category	Explicit roles stated or strongly implied by the article	Count used in bar chart
Agentic functions	Goal formulation, action policy formulation, decision-making, autonomy boundaries	4
Governance / quality functions	Explainability, auditability, privacy, compliance, fairness	5

7. Adaptive Detection for Evolving Fraud Patterns

Fraud continues to evolve, as individuals motivated by greed or financial necessity react to measures imposed by insurers, resulting in new fraud patterns. Adapting to these changes demands a combination of learning, evolvability, and change; these can be incorporated if appropriate operational modalities are adopted and sufficient data are acquired. Purely discriminative models, as discussed earlier, are not inherently capable of these attributes, but regulation on structure and data sources enables a variety of strategies that approximate these needs.

Concept-drift adaptation involves models that are already deployed being updated to reflect new data distributions. Recent developments in online learning permit continual training with small batches. The OpenWorld paradigm allows classifiers to grow beyond their initial set of classes without incurring a catastrophic loss in performance and is especially relevant for visual anomaly detection via one-class classifiers whose internal models of novelty are stored in VAEs. Data-efficient updates need to balance fraud-mitigation needs with the costs of retraining; balance is achieved by combining a reduced supply of false negatives with a generous resample interval.

For recurring events such as major storms, fraud emerges not from individual transactions but from aggregated patterns. Although fraud scoring systems need to learn such relationships, general architecture permits the definition of reservoirs for repeat detection. In contrast, surveillant model-based evaluation of term patterns requires extensive resampling support. An alternative constituted by discrete-event simulation allows insurers to replay the last five or six years of claims data and introduce artificial events at almost any level of granularity. New-model maintenance is thus an operational necessity for major changes in the data

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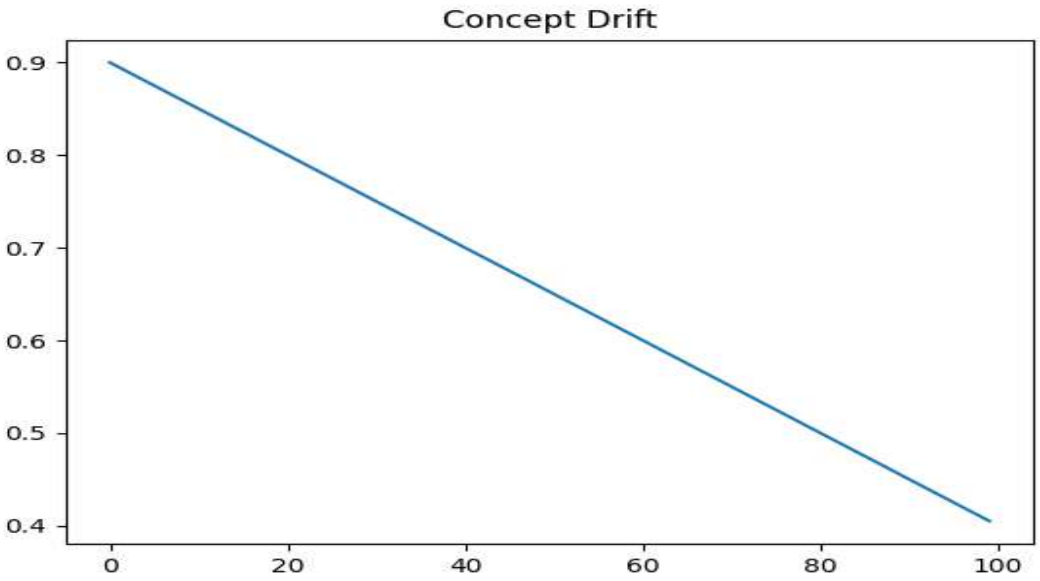
distribution. Evaluation planning enables design of experiments that examine specifically defined questions and produce the data required for sound conclusions.



7.1. Online Learning and Concept Drift Adaptation

New fraud techniques can develop quickly, requiring constant adaptation by discriminative detection models trained on static data distributions. Drift can arise not only in the distribution of the cases instantiating them but also in the fraud signal produced for other cases. Online learning using gradient descent or similar methods on recent batches prevents overall performance degradation, while tracking drift to adjust the data distribution. Specific detectors can thus capture drift by focusing on different components of the overall risk signal. This approach requires reinforcement of association rules by specialized components using few samples of the drifted fraud type or signal, at the expense of occasional false negatives for the other components. The resulting model operates discretely or continuously within a periodical retraining cycle, benefiting from gradual changes in the source of drift. Such a hybrid online

context-aware continuous learning paradigm actively and passively detects component relevance and brittle patterns.

Adaptive exploitability-attack drones in corporate networks can facilitate investigation or incident response, but their detection remains a challenge. Online learning on shadow or mirrored systems using moving-average smoothing can capture temporal data variations. Supervised classification provides an attractor for decision boundary shaping, while co-training aligns unlabeled data from an independent domain. Continuous or periodic updating of a supervised classifier to discriminate a new class, followed by class exclusion, allows expansion to include rare patterns with drifting features without catastrophic forgetting of other classes. Creation of component detectors supports redundancy and adaptability, enabling detection even when only a small set of behavioral rules is evident.

Equation 3. Anomaly score

A simple general anomaly score is:

$$A(x) = d(\phi(x), \mu_{\text{normal}})$$

where:

- μ_{normal} = centroid or reference of normal claims,
- $d(\cdot,\cdot)$ = distance function.

If Euclidean distance is used:

$$A(x) = \|\phi(x) - \mu_{\text{normal}}\|_2$$

Derivation

9. Fraud is described as “deviation from expected behavior.”
10. Expected behavior is represented by normal data.
11. The farther a claim is from normal, the more anomalous it is.
12. Therefore anomaly score = distance from normal profile.

So:

$$\boxed{A(x) = \| \phi(x) - \mu_{\text{normal}} \|_2}$$

7.2. Continual Learning and Model Maintenance

Hidden changes in the distribution of historical insurance data introduce new patterns not previously represented in training datasets. Adaptive external data augmentation allows external data to be incorporated throughout the detection system's life cycle. However, it is also essential to adjust internal model components in order to stabilize predictive performance. Several options can be considered for continually retraining the internal detection models along with the incoming new data:

1. **Self-Training with Automatically Labeled New Data**: When new unlabeled external data become available, labeled new data arising internally may be used to leverage the unlabelled data for knowledge transfer. Initially, the new data will be automatically labeled with the discriminator model from the previous stage.

2. **Knowledge Distillation**: Creating and continuously maintaining large, complex models will lead to long training times and large inference latencies. These expensive-to-train models may be used to periodically train a simpler model using knowledge distillation so that it can produce similar outputs while requiring less time for either training or inference.

3. **RF-C for Adapting a Committee of Descriminators**: Model adaptivity for concept drift, where the underlying distribution of labelled data changes, can also be achieved for the committee model using Relaxed Forgetting in a Continual learning setting.

8. Data Ecosystems and Privacy Considerations

Insurance fraud detection relies on external data sources for enriching risk signals, supporting external audit capabilities, and ensuring explainability and fairness in the detection process. Detecting concept drift in the fraud-scoring models and private data used to create new models or actors and monitoring fraud-feeding actors using risk-based alert systems are crucial for adaptive fraud-detection capability in the enterprise.

Achieving the right trade-off between value and privacy in data-sharing ecosystems requires robust technical and legal safeguards able to govern and manage who can use what data, under which conditions, and for how long. Detecting relevant signals, discerning the sources that shape them, and assessing signal quality result in the appropriate technical capacity for producing integrated signals aligned with model expectations.

8.1. Data Quality, Provenance, and Integration

Data provenance and integration into a unified detection framework represent critical aspects. Provenance encompasses the data history from source to consumer; knowing its origin enhances trust in AI models, justifying decisions, and conforming to regulations such as GDRP or CCPA. AI application introduces unprecedented volumes of data and correlations across a company's landscape, an evolution that calls for an integrated view for consistent and coherent detection signals. For instance, a voice call where the speaker pretends to be an insurance vendor might seem innocuous; however, if details of a specific customer-subscribed insurance product are scraped from a social network and made accessible by a fraudster, the call acquires a Fraud Risk Score closer to 1 and should be flagged as a fraudulent action.

Fraud detection models should know their data sources and be aware of both explicit and latent relationships to avoid shortage, imbalance, poor label quality, and biased decisions. Narrow signals from a single detector are prone to multiple false positives; hence, detectors should interact to compose a Fraud Risk Score instead of allowing binary answers. A price tag on visualization, prevention, and detection models is often greater than an insurance product cost, but the financial sector protects against data loss and bad actors, making pervasive model deployment justifiable. State-of-the-art detectors are enabled by massive labeled datasets; financial institutions also produce huge amounts of data for training private models.

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Fig 4: Generative AI Use Cases in Insurance

8.2. Privacy, Compliance, and Fairness

Privacy-preserving approaches should be considered when personally identifiable information is at stake or when models could learn discriminatory biases from the data. Federated learning can enable the shared training of components across cloud resources without exposing the raw data to third-party organizations. Monetizing access to a trained model is beneficial when a lack of data hampers the use of pure rule-based detection. In such scenarios, companies could potentially share their knowledge and expertise through the provision of model-inference APIs.

Model fairness is particularly difficult to validate and guarantee in fraud-detection tasks because the frequency of fraudulent behavior in insurance datasets is normally very low and positive cases are usually collected in a non-representative manner (e.g. only confirmed-fraud cases are analyzed). Nevertheless, improper model predictions can lead to unfair and inappropriate treatments of specific groups or types of clients. To guarantee fairness, categorical-sensitive attributes can be removed from the data before training or inference. In the first case, detection performance should be carefully monitored, while in the second case, it should be validated that protected groups receive a similar treatment.

Table 3. Core performance metrics for fraud detection

Metric	Formula	Meaning in fraud detection
Precision	TP / (TP + FP)	Of all flagged claims, how many are truly fraud
Recall	TP / (TP + FN)	Of all actual frauds, how many are caught
F1-score	2PR / (P + R)	Harmonic balance of precision and recall
Specificity	TN / (TN + FP)	How well legitimate claims are not falsely flagged
Fraud Probability	$p(y = 1 \mid x)$	Model-estimated chance of fraud
Risk Score	$s = 2p - 1$	Scales fraud tendency to the article's $[-1,1]$ idea
Drift Signal	D_t	Measures distribution/performance change over time

9. Risk Management, Governance, and Explainability

Fraud detection is a safety-critical function that is often regarded as a high-stakes domain. Therefore, the consequences of suboptimal decision-making are a concern for the operational team and system owners. Additionally, the resulting output may directly impact individuals: the risk score allocated to a transaction or the decision made about it (e.g. approval, release for investigation) could affect the client experience by causing unnecessary friction during a transaction or delaying claims payments. It is thus very important for fraud detection systems to be audited and monitored properly. The accuracy and fairness of the fraud detection models, as well as how their predictions contribute to the decisions taken on transactions, must also be communicated transparently to the operational teams and end users.

Model risk management is concerned with evaluating models to ensure that they perform as intended and adhere to all relevant regulations. This process is typically formalized in a model governance framework. Auditability and explainability give a handle on model risk: the fraud detection models should be testable externally via third-party data and the predictions made by the models should be interpretable (e.g. for regulators, the compliance team) and network (operational team, investigators) users. A variety of approaches may be used to achieve these aims. These principles and activities enhance the reliability of the fraud detection process and reduce the likelihood of stakeholders being harmed through poor performance of the models.

9.1. Model Governance in Insurance Ecosystems

Successfully applied detection models impact at both the operational and strategic levels. Sound decisions taken by front-line users or automated systems protect the institutions' resources and reputation while safeguarding customer interests. Conversely, failures can have serious consequences. In the worst cases, institutions may suffer sanctions for non-compliance with regulatory requirements. Consequently, model risk and governance considerations tailored to insurance fraud detection infiltrate all parts of the system's architecture and should not be treated as an afterthought. However, specific literature guidelines are scarce. The need for reliable systems that are unstructured and high-dimensional without an underlying mathematical model, and that have been implemented on rich and complex datasets, heightens the demand for model oversight.

Key components of an insurance fraud-detection environment have already been delineated, along with the principles for their effective operation. A well-structured insurance fraud-detection environment, and the elaboration of those critical aspects of model governance that take high-dimensional data into account, should assist all those institutions that rely increasingly on detection systems but lack the know-how to audit and govern them properly.

Equation 4. Probabilistic fraud classifier

$$p(y = 1 \mid x) = \sigma(w^{\top} z + b)$$

where:

- $z = \phi(x)$,
- w = learned weights,
- b = bias,
- $\sigma(u) = \frac{1}{1+e^{-u}}$ is the sigmoid.

Step-by-step derivation

Start with the linear decision variable:

$$u = w^{\top} z + b$$

This value can be any real number.
To convert it into a probability between 0 and 1, apply sigmoid:

$$\sigma(u) = \frac{1}{1 + e^{-u}}$$

Substitute $u = w^{\top} z + b$:

$$p(y = 1 \mid x) = \frac{1}{1 + e^{-(w^{\top} z + b)}}$$

Thus:

$$\boxed{p(y = 1 \mid x) = \frac{1}{1 + e^{-(w^{\top} \phi(x) + b)}}}$$

9.2. Explainable AI for Fraud Detection

Explainability of fraud detection models is indispensable for audits and investigations in insurance fraud management ecosystems. Insurance is a heavily regulated industry. Insurance companies need not only to comply with regulations but also to ensure that models can be audited by stakeholders and trusted by investigators with limited data science expertise. Therefore, secondary fraud detection models such as models producing risk scores must provide adequate explanations for the underlying predicted decision to meet auditor requirements.

Towards explainability, explainable AI can be integrated with machine learning models used in the insurance fraud detection ecosystem. For instance, LIME or SHAP can be applied to obtain explanations for the predictions of black-box machine learning models, such as individual fraud detectors. These calculations can be done in batch mode instead of in real-time. Explanations can be generated for all prediction requests received over a given time window, therefore avoiding overhead during real-time detections. Detecting explanations in batch mode for a historical batch of predictions also allows focusing on the most important predictions for auditing.

10. Deployment Scenarios and Operational Impacts

Adoption of Hybrid Adaptive Detection in Modern Insurance Ecosystems can enable the integration of detection capabilities with case management systems and orchestrated workflows, thereby directly supporting investigator operations. Supporting system-wide risk-scoring pipelines for transactions undergoing automated underwriting, claims settlement, or payment processing functions further aligns the detection process with operational workflows. Such setups permit dedicated detection source system within the fraud-surveillance connected to specific areas of risk.

Configured traffic on these operational pipelines are scored through the fraud models, typically on a transaction basis. Detected transactions that score highly on the risk metric trigger a higher level alert for action by investigators. A real-time scoring capability integrated into the operational platform is often needed, so that scoring does not become a bottleneck in these delayed time-sensitive transactions. Integration with the operation system provides an easy avenue for the scores to be used. Blast-its-level alerts reduce the service risk to the organization as the bad-deals are detected and intercepted early, before a large exposure occurs.

10.1. Real-Time Fraud Scoring and Decisioning

Deploying adaptive fraud detection capabilities within an insurance ecosystem is not only about building effective models for detecting fraudulent behaviours in the data. The extended hybrid generative and agentic AI architecture enables real-time operational fraud detection as an additional layer of aggregation for all fraud-related activity in the system. As such, both agentic and generative components can be hooked to outlet controllers that feed into one or more online scoring engines, specifically designed for rapid deployment in cloud or edge environments.

The scoring engines can be used to process incoming transactions and classify them as either suspicious or clean in real time. This refers to the process of auto-tagging transactions, individual customers or other parameters with expected risk-level indicators. For example, a potential policyholder can be evaluated when they apply for a policy, with predictions being based on information readily available in the initial application. Novelty detection algorithms, such as ADWIN or DDM, can be run in parallel, and if they raise an alarm, the agents can be activated to evaluate the case in more detail. Alongside the dashboard, a fraud risk score can also be assigned to the transaction, signalling to the incoming transaction management team the appropriate degree of scrutiny to apply to the case before acceptance.

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Fig 5: Adoption Strategy for Agentic AI in Insurance

10.2. Case Management and Investigator Workflows

The classic antifraud model resembles a multilevel framework combining detection and investigation. Indicators or scores may trigger more involved case analysis. Typically, such deeper investigations require human analysts, especially for complex, high-stake cases. The expertise of investigators and their motivation to dig deeper into low-risk cases can be crucial. Experimental results have shown that a case management module can complement a scoring system well, increasing the fraction of frauds scored at very high confidence. Workflow modeling and automation can boost investigator productivity significantly.

Contemporary approaches focus on keeping fraud-detection investigators in the loop. They seek to empower fraud investigators as fraud deterrents. Although detection systems are very effective at flagging a large volume of unusual claims, the amount is often unmanageable for the investigation team. The goal is to direct the analysts toward the small number of potentially big losses that require greater scrutiny. To enhance the productivity of the investigation team, the alerts given to the investigators must be refined, allowing them to focus on the higher-stake cases that are most likely to be fraud. Empirical results support such an approach: although classic antifraud models are very good at predicting fraud with a high precision and recall, their alerts overwhelm analysts in the field.

Three key aspects can drive the design of a promising Case Management module, facilitating the seamless use of investigation semantics across various detection systems: developing alert bundling methods; devising SIPs; and enhancing investigators' productivity through tailored tools. A simple first approach to bundling alerts can be based on entity resolution. First, the unbundled alerts need to be associated with claims and claimants. For each of these claimants, alerts can be bundled under a single alert for that claimant. The next level of bundling can take other entities into account. The result of this approach is a case matrix—alerts bundled around claimants who are identified as actors in the case. The notion of Situation Impact Predictor (SIP) can channel information from various fraud-detection systems in a unified manner, ensuring that alerts can be presented in a way that drives the investigator toward the most impactful actions. While SIPs may be considered proxies for FRs, such as Drop-, Process-, and Reward-SIPs, they indeed permit a wider view of the alerting space.

11. Evaluation Methodologies and Benchmarking

Evaluation of fraud detection capabilities ideally considers multiple performance aspects, yet natural constraints often narrow the focus. A metric taxonomy and suitable benchmarking datasets provide the basis for capabilities assessment according to a practical experimental protocol. Among standard detection metrics, precision and recall are fitted to tasks involving detection of, and control over, False Positive and False Negative Rates.

Detection in the insurance domain and other unbalanced ecosystems is particularly challenging due to the typically low proportion of fraud cases. Benchmarks need to be based on optimally chosen partitions of well-structured datasets. Care should be taken to ensure effective sampling from the entirety of the training dataset to avoid undetected edge cases during testing. Available datasets largely lack comprehensive labelling and curated synthetic data could enhance evaluative performance testing, although excessive artificiality may hinder evaluation of more generalised capabilities.

Table 4. Stepwise adaptive workflow

Step	Operation	Mathematical view
1	Collect claim and context data	$x \in \mathbb{R}^d$
2	Validate provenance and quality	$q(x)$ quality checks

Step	Operation	Mathematical view
3	Generate extra fraud evidence	$\tilde{x} \sim p_\theta(x \mid c)$
4	Compute anomaly / classifier signals	$A(x),\ p(y = 1 \mid x)$
5	Fuse evidence into one score	$s(x)$
6	Threshold for alerting	alert if $s(x) \geq \tau$
7	Explain and log the decision	explanation vector / audit record
8	Monitor drift	$D_t > \delta$
9	Adapt model online	$\theta_{t+1} = \theta_t - \eta \nabla L_t$

11.1. Metrics for Fraud Detection Performance

Various metrics assess the effectiveness of fraud detection strategies across different architectures and applications. In supervised models (including credit scores), prediction quality quantifies model performance from the perspective of the target classes. Common measures include precision (PPV), recall (sensitivity), F1 score, specificty (TNR), ROC AUC, and PR AUC. Unsupervised detectors are commonly evaluated using precision-recall curves for ranked anomaly lists, though properties such as empirical false positive rate are also relevant. Techniques such as one-class classification, novelty detection, and anomaly detection have also been applied in semi-supervised scenarios, with benchmarks often relying on real data with injected anomalies.

Performance evaluation may not suffice for a production-grade fraud-detection service. An operational quality assessment also involves the downstream operational workflow of fraud detection and response in a case management system. For example, a scoring function may assign an operational score on which the case management system relies for managing the resources assigned to investigating the flagged cases. Indeed, an operational task may perform the scoring based on a mixture of supervised and unsupervised methods indicating the current status of ongoing claims. This information may help improve the relibaility of the predictive scoring function in a resource-efficient manner, which is critical in real-world applications of fraud detection.

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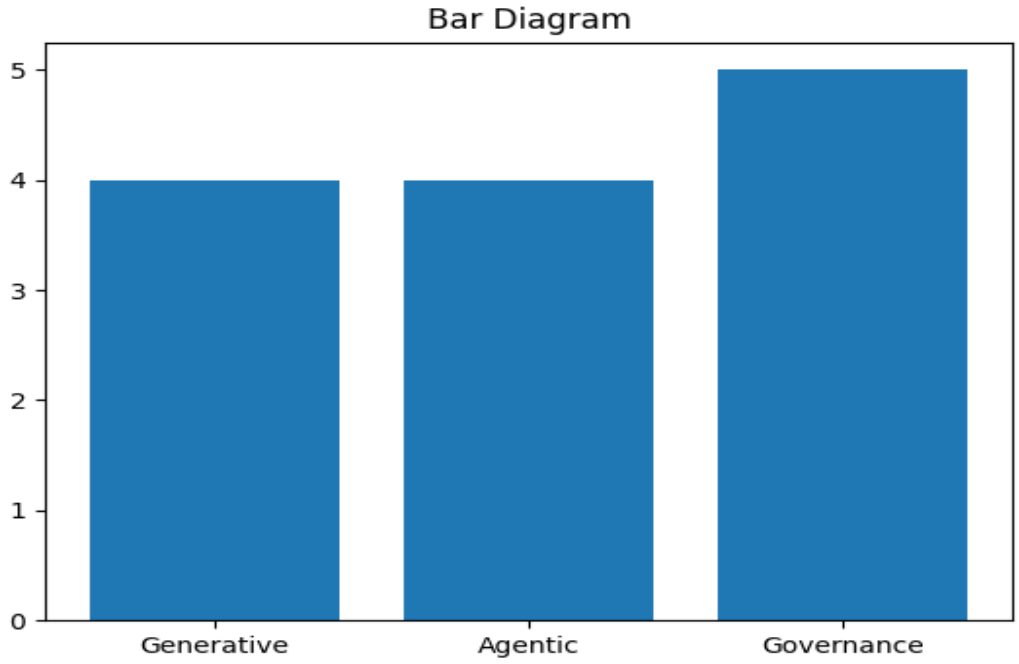

11.2. Benchmark Datasets and Experimental Protocols

Detective schemas and sub-schemas need to be built and evaluated within a well-established framework from both within and outside the typical insurance zone (e.g. investing gambling fraud, lending fraud, online transactions fraud), making use of concepts such as zero-shot learning to expand to other classes. The proof of concept focuses on one of the major fraud types: motor insurance fraud. In terms of practical coverage, a dataset used for spatial-temporal classification of traffic accident hotspots was chosen as the origin dataset, as this is one of the most studied case types in the domain. Expanding the detection requirements beyond patching existing problems means performing an experiment on traffic accident hotspots in order not to duplicate these studies already present in the literature. The first experiments will use Deep Neural Networks and Random Forests to check the behaviour of these architectures in detecting insurance fraud by creating two different types of posteriori detectors: an anomaly detector using

the previous dataset as a normality basis and a risk scoring system based on a supervised learning paradigm.

For more complex detections and other incidences not covered by the physical and socio-environmental characteristics of the proposal, transfers to the automobile domain are planned using data from gambling, investing and lending areas to create new schemas able to cover as many use evolution as possible. These other applications are then intended to base the final design applying a generative model that combines information from different types of fraud and covering broad knowledge bases to allow the fraud detectors in the insurance zone to work without extensive training and generation processes adapted to all the possible engines eventually detected. The final model drainings will use VAEs and diffusion models in order to create specific and centred driving engines and generators.

Equation 5. Fraud risk score on the article's $[-1, 1]$ scale

- closer to $+1$ means more fraudulent,
- closer to -1 means less fraudulent.

If classifier probability is $p \in [0,1]$, map it linearly to $[-1,1]$.

Let score s satisfy:

- $p = 0 \mapsto s = -1$
- $p = 1 \mapsto s = +1$

Assume a linear form:

$$s = ap + c$$

Use the two boundary conditions.

For $p = 0$:

$$-1 = a(0) + c \Rightarrow c = -1$$

For $p = 1$:

$$1 = a(1) - 1 \Rightarrow a = 2$$

Therefore:

$$s = 2p - 1$$

Substitute $p(y = 1 \mid x)$:

$$s(x) = 2\,p(y = 1 \mid x) - 1$$

So:

$$\boxed{s(x) = 2\,p(y = 1 \mid x) - 1}$$

and with sigmoid:

$$\boxed{s(x) = 2\left(\frac{1}{1 + e^{-(w^{\top}\phi(x) + b)}}\right) - 1}$$

12. Results

The research contributes a comprehensive synthesis of diverse elements of adaptive fraud detection based on hybrid generative-ai and agentic-ai paradigms, with explicit, architecturally consistent, online-learning-oriented operationalization. Architecturally agnostic, family-independent, and not confined to the insurance domain, the results combine theoretical consolidation with concrete and coherent descriptions of the design and deployment of adaptive fraud-detection systems.

The core idea is straightforward: key components of adaptive fraud analysis—the capacity for detection, the ability to form hypotheses, and the capability to check hypothesis validity—are best separated and executed by different structures, which may be generative or agentic for detection, hypothesis formulation, or hypothesis validation, and might not even belong to the same family of models, such as discrete or continuous. Nevertheless, best results necessitate clear control and interface specifications, as well as a consistent underlying cognitive architecture.

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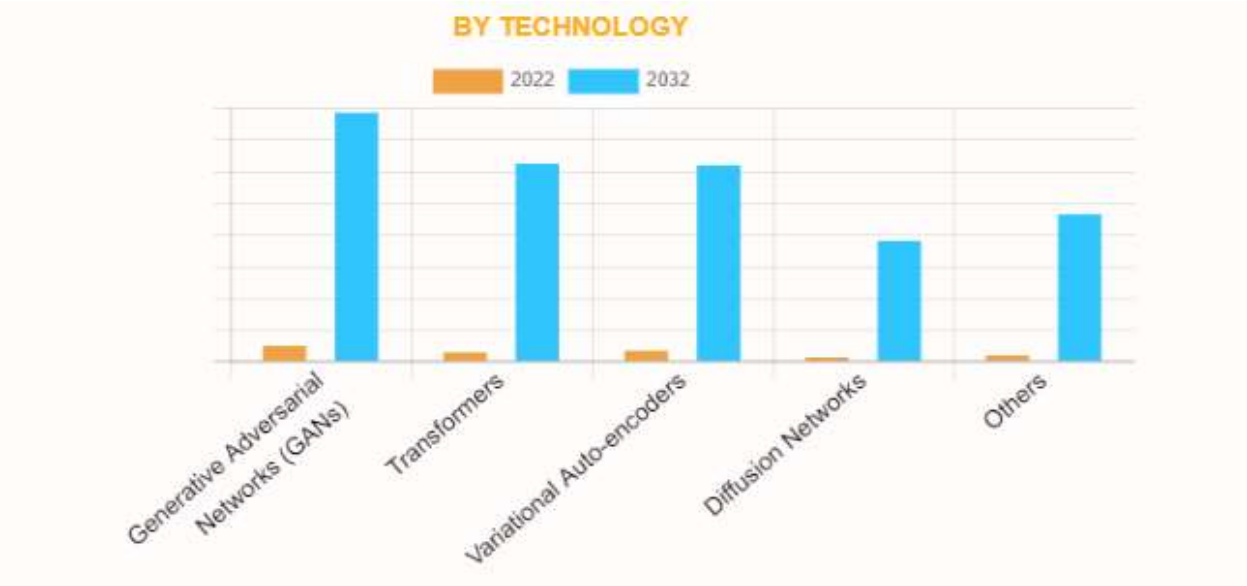

Fig 6: Generative AI in Insurance Market

13. Conclusions

Utilizing hybrid generative and agentic models for adaptive detection of insurance fraud is useful in continuously implementing the full Fraud Detection Lifecycle. Knowledge of the implicit Data Ecosystem is essential for identifying the sources required by the models and determining the Data Quality, Provenance, and Integration. Privacy, Compliance, and Fairness must be embedded in the Fraud Detection Lifecycle, especially designing a Differentially Private data-sharing mechanism. Model Governance gives assurance to stakeholders that the insurance ecosystem relies on a robust and well-managed tooling portfolio. The Fraud Detection Lifecycle needs Explainable AI as an essential component for both risk assessment and control.

The sum of these considerations shows that Fraud Detection Risk Management needs to provide clear answers to the following questions: Which fraud signals are detected? How is the detection management governed? What is the expected explainability level? These inquiries support and define the operational impact of Fraud Detection tooling: Real-Time Fraud Scoring

and Detection along with Case Management and Investigator Workflows are fundamental scenarios that can benefit from integrating Fraud Detection with a Data Ecosystem.

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