



Adaptive Data Meshes for Claims Efficiency and Fraud Resilience

Dhanaraj Sathiri

Independent Researcher

dhanrajsathiri@gmail.com

Abstract

Cloud-based cognitive data fabrics—built on platforms such as Google Cloud, AWS, or Azure—enable intelligent, predictive, real-time big-data solutions for insurance claims processing and query handling. This work addresses two interdependent challenges: (1) optimizing the claims process through intelligent extraction, normalization, and automated response generation, and (2) building resilience against fraudulent behavior through adaptive analytics.

Cloud-scale cognitive capabilities support two core functionalities: claim-process optimization and fraud resilience. The underlying computation model operates across layers of reasoning and knowledge, supporting either localized (topic-specific) reasoning engines or a single, more advanced engine for global, cross-domain reasoning over complex events.

Three claim-optimization strategies are proposed: (1) extracting claims from unstructured data sources and automatically normalizing them into structured form; (2) using historical claim patterns to automatically respond to incoming service or insurance requests; and (3) detecting anomalous patterns in insurance queries and requests to identify, score, and reduce fraud risk.

Keywords: Cloud-Scale Data Fabrics, Cognitive Data Management, Intelligent Claims Processing, Fraud Detection and Prevention, AI-Driven Insurance Analytics, Real-Time Claims Optimization, Machine Learning for Fraud Resilience, Enterprise Data Integration, Predictive Risk Intelligence, Adaptive Decision Support Systems.

1. Introduction

The transformation of cognitive claims systems into a cloud-scale architecture based on cognitive data fabric is a critical topic in the development of cloud-scale cognitive solutions. Evidence-driven claims, service, and customer claims take advantage of artificial intelligence technologies on consolidated, integrated data. Enablers include the cognitive data fabric architecture and cloud-scale data fabrics with special provisions for intelligent orchestration and service/data provisioning. These ensure sufficient reliability where the underlying data sources are unreliable and manage the flow of information from a potentially large number of clouds.

The characterisation of claims processes as intelligent systems with heterogeneous data sources typically leads to cognitive systems-oriented studies. Claim elements are extracted from unstructured sources, normalised when necessary, and integrated into a structured claim schema. The constituency of claims becomes the basis of epistemic or behavioural anomaly analyses that allow an extensive exploration of dispersed customer services. Fine-grained sequence anomaly detection addresses risk in any sequence and at the individual customer level while assessing the fraud risk of the totality of claims at query time.

Mathematical Formulas:

1. Claim Extraction Score



$$CES_i = \sum_{j=1}^n w_j x_{ij}$$

Where CES_i is the extraction score of claim i , x_{ij} represents extracted claim features, and w_j is the feature weight.

2. Claim Normalization Function

$$CN_i = f(C_i, O, S)$$

Where C_i is the raw claim, O is the ontology mapping, and S is the standardized claim schema.

3. Cognitive Reasoning Score

$$CRS_i = \alpha Q_i + \beta R_i + \gamma A_i$$

Where Q_i is query formulation quality, R_i is retrieval relevance, and A_i is answer composition accuracy.

4. Claims Processing Optimization

$$CPO = \min(T_e + T_n + T_d)$$

Where T_e is extraction time, T_n is normalization time, and T_d is decision-processing time.

5. Fraud Anomaly Score

$$FAS_i = \frac{|B_i - \mu_B|}{\sigma_B}$$

Where B_i is the behavior score of claim i , μ_B is average normal behavior, and σ_B is behavior deviation.

6. Fraud Risk Probability

$$P(F_i) = \frac{1}{1 + e^{-z_i}}$$

$$z_i = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n$$

Where $P(F_i)$ represents the probability that claim i is fraudulent.

7. Trustworthiness Score

$$TS_i = 1 - FAS_i$$

Where TS_i represents the trustworthiness of the claimant or counterparty.

8. Real-Time Claim Decision Score

$$RCD_i = \lambda_1 CES_i + \lambda_2 CRS_i - \lambda_3 FAS_i$$

Where RCD_i supports real-time claim approval, review, or rejection.

9. Cloud Resource Efficiency

$$CRE = \frac{N_c}{R_t + C_u}$$

Where N_c is the number of processed claims, R_t is response time, and C_u is cloud resource usage.

10. Overall Fraud Resilience Index

$$FRI = \frac{TP + TN}{TP + TN + FP + FN}$$

Where TP , TN , FP , and FN represent true positives, true negatives, false positives, and false negatives in fraud detection.

A. Computation and Orchestration

Cloud-scale cognitive data fabrics rely on a broad set of governing policies and effective computation models that help maintain reasonable service levels across very large systems. These fabrics are cognitive in nature: data processed via the fabric can be managed and understood in a similar fashion to how humans manage and reason about real-world objects and situations. The orchestration



strategies implemented in a given data fabric control the external exposed features and capabilities of the cognitive functions. These capabilities provide layer-on-layer increase in machine learning, natural language processing, human-like reasoning abilities, and pattern mining. Other components—such as the latency for response generation, the required provisioned resources needed to carry out the processes, fault-tolerant features to mask occasional partial system failure, and the provisioned Cloud resources asked for by users—help understand the fabric's ability to provide cloud multi-tenancy and scale.

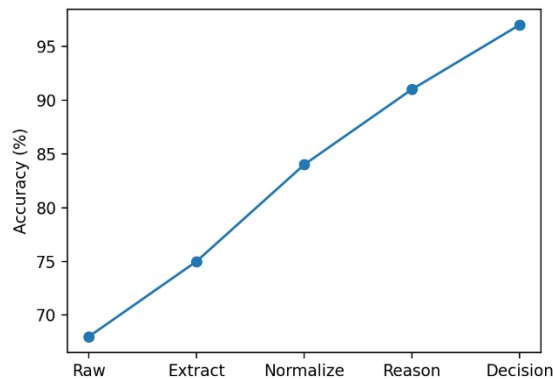


Fig 1: Claims Processing Pipeline Accuracy

Built using multi-orchestration capabilities, these cloud-scale cognitive data fabrics provide reliable, cognitive ML services within the models of OpenStack, Amazon, and Google clouds. The underlying platform-as-a-service (PaaS) being used is recognized as mentally capable of providing human-like reasoning over multimodal data. These cognitive data fabrics integrate logic programming principles for natural language processing and human-like reasoning, contributing additional scalability and broad accessibility of multilayer reasoning services. Cognitive services are operated on-demand, resisting any spurious reasoning activation when processes, services, and behavior models run under normal conditions.

2. Literature Review

Cloud-scale cognitive data systems have emerged due to the growing desire to unleash orchestration, management, and reasoning capabilities at a (near) infinity scale and in a (near) zero-cost manner. Cognitive data fabrics are able to optimize complex queries, robustly answer ad hoc requests, and provoke recommendations on the best next questions to ask. When applied to the claims business of an insurance company or a service provider, these approaches can minimize claims cycle time, driving high customer satisfaction, and detect and mitigate fraudulent behavior, reducing risk and loss.

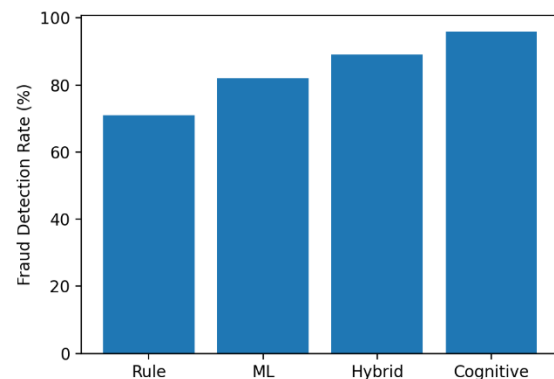


Fig 2: Fraud Detection Rate Comparison

Despite these promising developments, a coherent cognitive data system architecture that enables extremely low-cost cognitive capabilities has not yet been proposed. The literature on cognitive systems has focused mainly on a coarse classification of components, discussing only a limited subset of the main architectural dimensions.

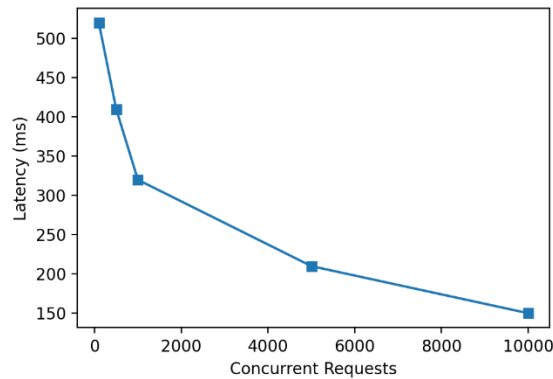


Fig 3: Cloud Scalability: Latency vs Concurrent Requests

A. Cognitive Reasoning and Reasoning Engines

Cognitive data systems offer a comprehensive set of resources that enable reasoning, which is central to intelligence. However, relatively little work has been done on reasoning engines. The existing paradigms for reasoning, their relative efficiency for distributed operations, and some refinements also demanding attention are explored.

Cloud-scale cognitive data fabrics can host an ecosystem of specialized distributed reasoning engines that implement various paradigms in a manner that satisfies different requirements. Cognitive intelligence is the ability to comprehend, analyze, evaluate, and synthesize information from sensory experiences and knowledge represented in different forms. Cognitive reasoning is the process of deriving answers through reasoning cycles. A reasoning cycle typically includes three main phases: query formulation, search-and-retrieve, and answer composition. The first phase forms a query that specifies the knowledge required who, what, when, where, how, why, or who, what, when, where, how, and why about an entity or a set of entities. The second phase searches for the knowledge by making inferences over the knowledge graph or performing knowledge graph completion. The last phase composes the answer by leveraging information from the knowledge graph

or storage system. The dimension of cognitive reasoning is the strategy employed to traverse the underlying knowledge graph. Existing reasoning paradigms include depth-first search, breadth-first search, best-first search, and distributed Lazy SAT solver.

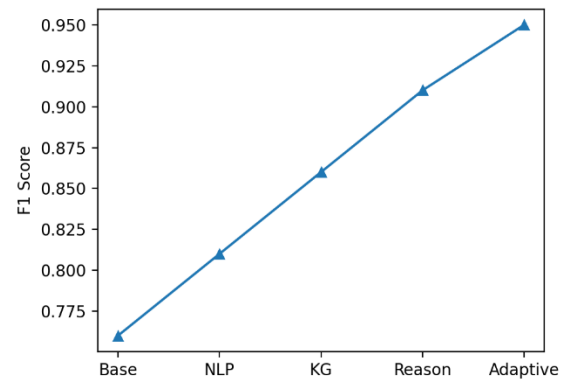


Fig 4: Cognitive Model Performance (F1 Score)

3. Architectural Foundations of Cloud-Scale Cognitive Data Fabrics

Core architectural foundations for cognitive data fabrics at cloud scale support hybrid models with multiple data-processing modes and styles. An architectural view highlighting essential principles, layers, and integration patterns shows how these characteristics enable cognitive capabilities.

Cognitive data fabrics integrate dedicated reasoning engines with data-processing engines designed for declarative, imperative, or operational query languages. As the orchestration of parallel, distributed query engines grows more sophisticated, the cognitive reasoning layer improves the overall service by performing tasks best done using reasoning paradigms such as description logics, knowledge representation, or agents. Cognitive reasoning, whether centralized or distributed, remains independent of query

routing and data transformation and is invoked when necessary within any of the query-processing engines. When located at edges or specialized nodes, these data-processing engines operate as low-latency, interactive, on-demand services.

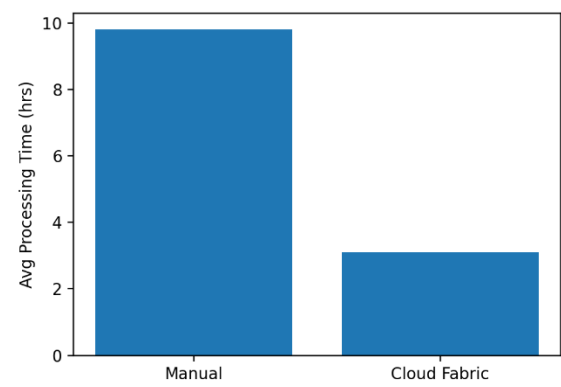


Fig 5: Claims Processing Time Comparison

The provided excess-bandwidth capacity is exploited to accommodate the cognitive reasoning layer. Cognitive reasoning engines are elastic in the cloud; they process simple queries concurrently—batch mode—and are reused for queries that generate the same plan. Alongside the standard data-processing engines, the cognitive reasoning services are invoked via an administrative interface that monitors the execution paths of incoming queries.

A. Data Layer and Storage Abstractions

Cloud-scale cognitive data fabrics often operate on unstructured or semi-structured data, requiring complex content analyses, extraction, and normalization steps. For unstructured data, space-efficient textual representations such as bag-of-n-grams or bag-of-trigrams can be extracted, enabling the detection of relevant terms and their significance; e.g., for insurance claims made on chatbot applications and subsequently handed over to agents for fulfilment, performed-term counts can be leveraged for

extraction. Given the diversity of clients or packages associated with a textual data source for extraction, human-labeled claim schemas or equivalent group hints can be used for determination of claim attributes. The results from these operations may be available for consecutive analyses via periodical publishes to distribution systems; however, initial non-periodical sources may require additional handling. One possible approach for document-type classification is based on training detection classifiers on previous labeled types, and concurrently applying their ranks to incoming sources until the assignment of sufficient support classes (normalization timing determined by a threshold).

For semi-structured data types, where extraction operations are directed towards definitions of data-schemas completed with sample support instances, the challenge revolves around identifying equivalent support synonyms across all variables. To assign normalized-valued schema instances to a label list or structure, existing schema names are mapped onto a customized package-hint repository based on word embeddings, synonyms lists, or BERT-based techniques, possibly employing a confidence threshold selection.

Table 1. Functional Layers of the Cloud-Scale Cognitive Data Fabric

Layer	Primary Components	Input Data	AI/Cognitive Functions	Output
Data Acquisition Layer	APIs, IoT, Documents, Emails	Structured & Unstructured Data	Data Collection	Raw Claims Data
Data Integration Layer	ETL, Data Fabric Connectors	Multi-source Data	Data Fusion, Schema Mapping	Unified Repository



Layer	Primary Components	Input Data	AI/Cognitive Functions	Output
Cognitive Processing Layer	NLP, Knowledge Graphs, Reasoning Engine	Integrated Data	Semantic Analysis, Reasoning	Contextual Knowledge
Claims Intelligence Layer	ML Models	Claims Repository	Claim Classification & Prioritization	Optimized Claims
Fraud Analytics Layer	Anomaly Detection, Pattern Mining	Claims History	Fraud Risk Prediction	Fraud Score
Decision Support Layer	Business Rules Engine	Risk & Claims Data	Automated Decisions	Approved/Rejected Claims

responses for both insurance claims fraud detection and insurance claims processing.

Table 2. Intelligent Claims Optimization Pipeline

Processing Stage	Technique Used	Objective	Output
Claim Extraction	NLP	Extract claim entities	Structured Claims
Data Normalization	Ontology Mapping	Standardize terminology	Normalized Records
Feature Engineering	Data Transformation	Generate predictive variables	Feature Dataset
Claim Classification	Machine Learning	Categorize claim type	Classified Claims
Risk Assessment	Predictive Analytics	Estimate claim risk	Risk Score
Decision Automation	Rule Engine	Generate claim decision	Final Claim Status

4. Intelligent Claims Optimization

An insurance claim or service claim encompasses loss or damage claims filed by customers with a service provider for compensation — for instance, medical claims filed by insurers with healthcare organizations for rendering health services to insured members, or suppliers' claims filed with manufacturers for defective parts being subordinate vendors' payments. These claims process entail handling unstructured or semi-structured source data originating from voice calls, faxes, e-mails, or SMS, as well as structured data from third-party vendors. Hence, aspects such as graphical and textual mining, natural-language processing, semantic web, mapping to ontologies, and big-data analytics should be utilized to derive the cognitive

Optimizing insurance or service-claims processes requires cognitive fabrics from both strategy and technical perspectives. A business-oriented view would prioritize strategies for increasing revenue, lowering expenses, improving customer service, ensuring compliance, enhancing product innovations, and reducing fraud risk. Technical considerations would include securing the data, standardizing data quality, reducing time to extract relevant information for claims decision-making, managing business rules for claims processing efficiently, and minimizing rule-processing time. Cognitive analytics can assist in these areas.

A. Claim Extraction and Normalization



Extracting claim elements from unstructured sources like incident reports—either internal, generated during the claim-handling process, or external, such as news reports and social media—is crucial yet challenging. Claim-relevant information is typically scattered or written in unstructured and sometimes ambiguous form. Claims may not use standardized terminology, even when mapped to an ontology. For instance, the term "collapsing bungalows" could relate to landslide damage, while "wildfires" could connect to claims for fire or smoke damage to properties. Such ambiguities create mismatches with constructed schemas, even as insurance companies employ unique nomenclature and terminology for similar items and services. Indeed, myriad companies worldwide handle damages due to various natural catastrophes, and terminology convergences across frequently partners and insurers remain rare.

Table 3. Fraud Detection Models and Performance Indicators

Fraud Detection Method	Input Features	Detection Capability	Expected Accuracy	Computational Cost
Rule-Based Detection	Business Rules	Low	Medium	Low
Statistical Analysis	Historical Claims	Medium	Medium	Medium
Machine Learning	Claims Features	High	High	Medium
Deep Learning	Complex Behavioral Data	Very High	Very High	High

Fraud Detection Method	Input Features	Detection Capability	Expected Accuracy	Computational Cost
Graph Analytics	Relationship Networks	Very High	High	High
Hybrid Cognitive Model	Multi-source Data	Excellent	Excellent	High

Hence, normalization is required to extract textual elements from incident reports and maps, generate claims based on templates, and subsequently prepare claims for processing/handling. Textual terms in claims must be normalized by checking with the ontology for standards/convergence. External documents also serve as informal sources as part of an anomaly-detection engine. To orchestrate, quality-control, and normalize claims from disparate sources, a parallel orchestration pipeline exploits annotation NLP models or generative-action pipelines to extract claims from both internal and external reports. Parallel orchestration with differentiator pipelines can aid in breach detection using claims filed by other companies, news-based breach indication, and land-sensing-data-generated alerts.

Table 4. Cloud Cognitive Reasoning Components

Component	Function	AI Technique	Benefit
Query Engine	Query Processing	Distributed Search	Faster Retrieval
Knowledge Graph	Relationship Modeling	Graph Analytics	Context Awareness
Reasoning Engine	Logical Inference	Symbolic AI	Intelligent Decisions



Component	Function	AI Technique	Benefit
NLP Module	Text Understanding	Transformer Models	Claim Interpretation
Pattern Mining Module	Behavioral Discovery	Sequential Mining	Fraud Identification
Decision Engine	Final Recommendation	Hybrid AI	Automated Processing

5. Fraud Resilience and Anomaly Detection

Fraudulent behavior negatively impacts businesses across virtually every industry, including finance, travel, telecommunications, and insurance. A cognitive data fabric can be used to discover fraud-relevant behavior patterns, build adaptive models that dynamically update a score of counterparty trustworthiness, and ultimately mitigate such risk. Cognitive behavioral analytics focus on detecting behavior changes in individuals or groups caused by some event or at a particular time. In the fraud context, the goal is to detect behaviors that may indicate fraud so as to help a company prevent fraud before it happens. The process typically involves the identification of behavioral indicators associated with fraud, the exploitation of behavioral sequences to discover abnormal behavior, the automatic extraction of anomaly scores from real-world behavior, and models for behavioral adaptation.

Data-exploration tools such as sequence mining algorithms can be used to mine frequent behaviors over time across a population, while event sequence pattern matchers can detect individuals expressing those behaviors and heuristic methods can further discriminate between normal and abnormal cases. For instance, certain types of insurance claims become more prevalent after specific weather events

(e.g., hurricanes). Such recurrent or sudden behavior changes can raise a fraud risk flag. Yet fraudsters do not usually behave like typical customers since they have a distinct goal: to exploit weaknesses in a system for personal gain. For that reason, they often over-exploit a system during a limited time frame. Scoring methods can model the level of abnormality of a counterparty's behavior for a specific product at that specific moment, thus creating a behavior-anomaly score.

Table 5. Performance Evaluation Metrics

Metric	Formula	Purpose	Desired Trend
Claim Processing Time	Total Time / Claims	Processing Efficiency	Lower
Claim Approval Accuracy	Correct Decisions / Total Decisions	Decision Quality	Higher
Fraud Detection Rate	Fraud Cases Detected / Total Fraud Cases	Detection Capability	Higher
False Positive Rate	Incorrect Fraud Alerts / Total Normal Claims	Reliability	Lower
Data Integration Accuracy	Correct Integrated Records / Total Records	Integration Quality	Higher
System Throughput	Claims Processed / Second	Scalability	Higher

A. Behavioral Analytics and Pattern Mining

The exploration of behavioral signatures that facilitate the detection and mitigation of undesirable actions represents another instance of cognitive process Web



interpretation within a cloud-scale cognitive data fabric. A firm or service provider possesses the historical records of a numerous clients' habit(s), and ideally observes normal activities over a sufficiently long period on a manifold constellation. Behavior forecasting is more tractable when process dynamics are sufficiently stationary, as otherwise similar activities produced by different people may depart significantly.

Table 6. Cloud Infrastructure Components

Infrastructure Component	Cloud Service	Purpose	Scalability
Object Storage	Cloud Storage	Document Repository	High
Data Lake	Distributed Storage	Raw Data Management	High
Stream Processing	Kafka/Event Hub	Real-Time Processing	High
AI Platform	ML Services	Model Training	Elastic
Knowledge Repository	Graph Database	Semantic Storage	High
Monitoring Dashboard	Analytics Platform	System Monitoring	High

From the above definition of goals and the procedures designed to achieve them, a learning perspective emerges. Solutions involving the discovery and utilization of behavioral signatures, whether with or without trained models, tackle a significant problem of behavioral fraud managing. It is acknowledged that human behavior is highly complex, and adaption models can significantly reduce fraudulent behavior.

6. Conclusion

Cloud-scale Cognitive Data Fabrics support intelligent claims optimization, fraud-resilience functions, and cognitive capabilities for a wider range of cloud applications. The underlying research tackled two of the most common and critical use cases—Cloud-scale Cognitive Data Fabrics support intelligent claims optimization, fraud-resilience functions, and cognitive capabilities for a wider range of applications. The underlying research tackled two of the most common and critical use cases—claims optimization and fraud detection—in the insurance and service domains, utilizing existing technology, proposing novel methods, and exploiting the specific nature of Cloud-scale Cognitive Data Fabrics.

The research provides an architecture for these functions, including an account- and role-based behavioral analytics engine for fraud mitigation. Many other interesting and valuable applications can be envisaged, making it important to shape the Cloud-scale Cognitive Data Fabrics. Limitations are discussed to lay the groundwork for future research.

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