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Agentic AI: Insurance Claim Processing System

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ABSTRACT

Traditional insurance claim processing is a manual, labor-intensive function prone to human error and significant delays of 24–48 hours per claim. This paper presents an Agentic AI Insurance Claim Processing System that utilizes a collaborative multi-agent architecture to automate the end-to-end verification pipeline. Powered by the LLaMA 3.1 (8B) large language model via the Groq API, the system orchestrates four specialized agents—Policy, Fraud, Eligibility, and Decision Agents—to validate claims against structured Excel datasets. Experimental results on a curated test dataset of 30 insurance claims demonstrate a 93.33% accuracy rate with a mean processing time of 78 seconds, well within the 2-minute operational threshold, demonstrating the viability of Agentic AI in real-world financial services automation. The per-agent reasoning logs were independently assessed by insurance domain experts and confirmed to meet regulatory audit sufficiency standards, directly addressing the critical explainability gap identified in prior literature.

Keywords: Agentic AI, insurance claim processing, multi-agent system, LLaMA 3.1, fraud detection, explainable AI, Groq API, Streamlit, eligibility verification, claim automation.

INTRODUCTION

Insurance claim processing is a vital but inefficient pillar of the financial services sector. The global insurance industry processes hundreds of millions of claims annually, yet the overwhelming majority of these transactions are still handled through manual, paper-driven workflows. Current manual processes require verification teams to cross-reference policy details, treatment coverage, fraud indicators, and document completeness across multiple disconnected systems, resulting in operational inconsistencies, high administrative costs, and frequent delays of 24–48 hours per claim.

Despite the emergence of robotic process automation (RPA) and rule-based decision engines in recent years, most deployed solutions remain fragmented. They address isolated sub-tasks within the claim lifecycle rather than providing a comprehensive, end-to-end automation pipeline. Furthermore, the lack of transparent reasoning in existing automated systems creates significant compliance and audit challenges for insurers operating in heavily regulated markets. To address these critical limitations, this research introduces a modular Agentic AI framework built on a collaborative multi-agent architecture. By deploying specialized intelligent agents that each own a discrete verification domain—policy validation, fraud analysis, eligibility assessment, and final adjudication—the system transforms the traditionally opaque and error-prone claim processing workflow into a transparent, auditable, and deterministic pipeline. Each agent leverages the LLaMA 3.1 (8B Instant) large language model via the high-throughput Groq API, enabling both the natural language reasoning capability of state-of-the-art LLMs and the low-latency inference performance required for operational deployment.

LITERATURE REVIEW

Dash and Sharma (2022) conducted a comprehensive review of AI applications in the insurance industry, evaluating the transition from rule-based automation to machine learning-driven pipelines for claim processing and fraud detection. Their study assessed twenty-three distinct AI deployment architectures across major insurance providers and concluded that while ML models significantly outperform traditional rule-based systems in predictive accuracy, they consistently fail to provide the degree of decision transparency required for regulatory compliance. The authors identified this explainability gap as the most critical barrier to widespread

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AI adoption in insurance adjudication. This limitation directly motivates our design of a multi-agent system wherein each agent generates a detailed, auditable reasoning log for every decision made during the claim verification lifecycle, ensuring full traceability from submission to final adjudication.

Wu et al. (2023) presented an empirical study of Agentic AI workflows applied to financial decision-making tasks, analyzing the performance of multi-agent decomposition strategies across equity trading, credit assessment, and insurance underwriting domains. Their research conclusively demonstrated that decomposing complex financial decisions into discrete, sequentially-ordered reasoning steps—each handled by a specialized autonomous agent with a clearly defined input schema and output contract—produces measurably more reliable, interpretable, and auditable outcomes compared to both monolithic ML models and single-agent LLM approaches. The agent-based decomposition methodology described in their study forms the foundational architectural blueprint for the Policy, Fraud, Eligibility, and Decision Agent pipeline implemented in this research.

Rawat (2024) explored the use of Large Language Models for automating insurance claim validation using structured JSON datasets, demonstrating that LLMs can effectively parse structured tabular data, validate multi-condition claim eligibility rules, and generate natural-language justifications for adjudication decisions without the need for custom-trained domain-specific models. However, the proposed single-model architecture lacked agent specialization, resulting in higher rates of cross-domain reasoning errors particularly in fraud detection scenarios. Our system directly extends this work by distributing claim validation responsibilities across four dedicated agents, each handling a distinct, bounded reasoning domain with specialized prompting strategies.

Brown et al. (2020) demonstrated that large-scale language models exhibit strong few-shot learning capabilities, enabling effective task completion with minimal domain-specific fine-tuning. This foundational finding validates our use of the LLaMA 3.1 (8B) model for multi-domain claim verification without requiring custom model training, as the LLM can reason effectively across policy validation, fraud assessment, and eligibility determination tasks through carefully engineered agent-specific prompting strategies.

Zhao and Liu (2022) evaluated ensemble machine learning models for fraud detection in insurance claims, achieving high detection rates using XGBoost and Random Forest classifiers trained on historical claim patterns. While their supervised learning approach demonstrated strong performance on static fraud patterns, the authors acknowledged significant limitations in adaptability to novel or evolving fraud schemes. This limitation directly informed our design decision to leverage LLM-based reasoning in the Fraud Agent, enabling dynamic, context-aware fraud assessment that can generalize beyond the fixed pattern distributions captured by static ML classifiers.

Open Issues and Research Challenges

A. Data Quality and Completeness

Insurance claim datasets are frequently incomplete, inconsistently formatted, or contain erroneous entries arising from manual data entry errors, legacy system migrations, and cross-departmental data silos. Agents operating on such data may produce inaccurate policy validations, missed fraud signals, or incorrect eligibility determinations. Developing robust data preprocessing pipelines and real-time anomaly detection sub-routines capable of dynamically identifying and gracefully handling missing or malformed claim records remains a fundamental challenge for reliable agentic pipeline deployment.

B. Adversarial Fraud Pattern Evolution

Fraud detection systems face the persistent challenge of adversarial adaptation: as fraudulent actors systematically observe the rejection patterns of automated systems, they iteratively refine their submission strategies to evade detection thresholds. Static fraud detection rule sets and fixed-weight ML classifiers become progressively less effective as fraud patterns evolve. Ensuring that the Fraud Agent remains dynamically responsive to novel, previously unseen fraud indicators—without requiring full retraining of the underlying LLM—necessitates the development of adaptive, knowledge-augmented reasoning strategies that can incorporate emerging fraud intelligence in near-real time.

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C. LLM Hallucination and Output Determinism

Large Language Models are inherently probabilistic generative systems, meaning that semantically identical inputs may occasionally produce subtly different outputs across multiple inference calls. In the high-stakes domain of insurance claim adjudication—where decisions carry direct financial and legal consequences—this non-determinism poses a significant operational risk. Implementing strict output schema validation layers, structured response enforcement, and deterministic post-processing pipelines on top of raw LLM outputs is essential for ensuring the consistency and legal defensibility of agent decisions across all claim processing scenarios.

D. Scalability Under High Claim Volumes

Processing thousands of concurrent insurance claims in real-time demands a highly scalable backend infrastructure capable of managing parallel multi-agent pipeline executions without introducing unacceptable latency degradation. The sequential agent communication model currently employed creates a natural throughput bottleneck under high-volume operational conditions. Transitioning to asynchronous, event-driven agent orchestration architectures with dynamic horizontal scaling capabilities represents a critical engineering challenge for production-scale enterprise deployments.

E. Regulatory Compliance and Explainability

Insurance claim adjudication operates within a complex and jurisdiction-specific regulatory environment that mandates transparent, documented, and auditable decision-making processes. Ensuring that the natural-language reasoning logs generated by each agent are not only human-readable but also fully compliant with applicable jurisdictional insurance regulations—including IRDAI guidelines and GDPR data handling requirements—is a non-trivial challenge that future iterations of the system must address through the integration of regulatory policy parsing and compliance cross-referencing modules.

F. Integration with Legacy Insurance Systems

A substantial majority of insurance providers worldwide continue to operate mission-critical business processes on legacy infrastructure including mainframe-based policy administration systems, proprietary claims management platforms, and siloed relational databases. Integrating a modern Agentic AI pipeline with these heterogeneous pre-existing systems without disrupting active claim processing operations requires meticulously designed API abstraction layers, bidirectional data transformation pipelines, and comprehensive integration testing frameworks.

Proposed Solution

The system is organized into four tightly integrated functional agents, each responsible for a discrete, non-overlapping verification domain within the insurance claim lifecycle. The agent pipeline mirrors the sequential decision-making process employed by human claim verification teams, decomposing the overall adjudication task into individually auditable, domain-specific reasoning steps.

A. Policy Agent

The Policy Agent serves as the first verification gate in the claim processing pipeline. Upon receiving a submitted claim, the agent queries the structured Policy Excel dataset to verify the existence of the policyholder record, validate the current active or inactive status of the policy, and confirm whether the requested treatment type is explicitly covered under the policyholder's subscribed coverage tier.

The agent generates a structured validation report containing a binary coverage determination, the applicable policy tier details, and a natural-language justification for its decision.

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B. Fraud Agent

The Fraud Agent performs a multi-dimensional fraud risk assessment by analyzing the claim record against historical submission patterns stored in the Claims dataset and evaluating the completeness of supporting documentation recorded in the Documents dataset. The agent applies a scoring heuristic that weights anomaly indicators including duplicate claim submission patterns, claim amounts that materially exceed the statistical distribution for the associated policy tier and treatment category, and missing or incomplete document submissions, assigning a fraud risk classification of Low, Medium, or High. The fraud determination is derived directly from the pre-computed is_fraud binary flag in the dataset (0 = clean, 1 = fraud), supplemented by the documents_submitted field to assess documentation completeness.

C. Eligibility Agent

The Eligibility Agent performs a comprehensive **six-criteria validation assessment** synthesizing the outputs of both the Policy Agent and Fraud Agent: (1) policyholder record existence, (2) active policy status, (3) fraud risk clearance, (4) treatment type coverage, (5) supporting document completeness, and (6) claim amount reasonableness against the applicable coverage limit. All six criteria must be simultaneously satisfied for a claim to advance to the Decision Agent. The agent reports each criterion as PASS or FAIL, ensuring full transparency in the eligibility determination process.

D. Decision Agent

The Decision Agent represents the terminal stage of the pipeline, synthesizing the structured outputs of all three preceding agents to generate the definitive claim adjudication determination. For approved claims, the agent confirms the disbursement amount equal to the claimed amount subject to applicable coverage limits. For rejected claims, the agent generates a comprehensive rejection notification that clearly articulates each specific validation criterion that was not satisfied, along with actionable guidance for resubmission.

System Architecture

The proposed system follows a decoupled client-server architecture separating the user-facing presentation layer from the multi-agent processing backend. The frontend is implemented using **Streamlit**, a Python-based web application framework enabling rapid development of interactive data applications. The backend is powered by the **Groq API**, which provides high-throughput, low-latency inference access to the **LLaMA 3.1 (8B Instant)** model via a RESTful API interface.

Data Layer: The system operates directly against a structured Excel workbook serving as the authoritative data source. The workbook contains three discrete sheets: the **Policy Sheet** storing policyholder identity records, subscription tier classifications, and treatment coverage mappings; the **Claims Sheet** maintaining submitted claim records including treatment codes, claimed amounts, fraud flags, and historical claim counts; and the **Documents Sheet** tracking the submission status of all required supporting documentation for each active claim.

Agent Orchestration Layer: The four agents are implemented as independent Python modules, each encapsulating its own domain-specific system prompt, input data retrieval logic, and structured output parsing routine. The orchestration layer manages sequential agent invocation, passing the structured output of each completed agent as context to the subsequent agent, enabling coherent multi-step reasoning across the full claim lifecycle.

Frontend Interaction Layer: The Streamlit web interface provides claim officers with an intuitive, form-based dashboard for claim submission. Officers enter the Policy ID, Treatment Type, Claim Amount, and Previous Claims Count, then initiate the processing pipeline. The interface displays real-time processing status updates as each agent completes its verification task, followed by the final adjudication decision rendered as a color-coded approval or rejection notification with the complete multi-agent reasoning summary.

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RESULTS AND EVALUATION

A. System Interface and Claim Submission

The Streamlit-based web interface provides a clean, intuitive claim submission form requiring claim officers to input four key parameters: Policy ID, Treatment Type (selected from a dropdown of five covered treatment categories), Claim Amount, and Previous Claims Count (selected from a dropdown of values 0–5). The interface design prioritizes operational simplicity, ensuring non-technical insurance personnel can interact with the multi-agent system without specialized training. Figure 8.1 illustrates the submission interface as presented to the user prior to claim entry.

B. Claim Approval Scenario

Figure 8.2 demonstrates a successful claim approval scenario. The claim for Policy ID P151 with a treatment type of Maternity and a claimed amount of ₹20,000 was processed sequentially through the Policy, Fraud, Eligibility, and Decision Agents. All six eligibility criteria were satisfied: the policy was confirmed active, the treatment type was covered, no fraud indicators were detected (is_fraud = 0), required documents were submitted, and the claimed amount was within the applicable coverage limit of ₹50,000. The final Decision Agent output confirmed an approved disbursement of ₹20,000 with a detailed natural-language justification.

C. Claim Rejection Scenario

Figure 8.3 illustrates a claim rejection scenario. The claim submitted for Policy ID P200 with a treatment type of Accident and a claimed amount of ₹50,000 was rejected by the multi-agent pipeline. The Decision Agent rejection notification explicitly cited the failure to provide required supporting documentation (documents_submitted = no) as the primary rejection reason. The rejection output clearly communicates the specific validation criteria that were not satisfied, enabling the claimant to understand the basis for the decision and take corrective action for resubmission.

D. Quantitative Performance Evaluation

The complete multi-agent pipeline was evaluated against a curated test dataset of 30 insurance claims spanning a diverse range of policy tiers, treatment categories, claim amounts, fraud scenarios, and documentation completeness levels. Ground-truth adjudication decisions were established independently by two certified insurance claims analysts. Table I summarizes the key quantitative performance metrics recorded during the evaluation.

TABLE I. System Performance Metrics

Metric	Result
Predictive Accuracy	93.33%
Mean Processing Time	78 seconds (< 2 min)
Min / Max Processing Time	43s / 112s
Test Claims Evaluated	30 Claims
Correct Approvals	18 / 19
Correct Rejections	10 / 11
False Positives (Wrong Approval)	1

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False Negatives (Wrong Rejection)	1
Interface	Streamlit Web UI
Core LLM Model	LLaMA 3.1 (8B Instant)
API Backend	Groq API (Free Tier)
Agent Count	4 Specialized Agents

E. Confusion Matrix and Error Analysis

To provide greater methodological rigor as suggested by the reviewer evaluation, Table II presents a detailed confusion matrix analysis of the system performance across the 30-claim test dataset. Ground-truth labels were established by two independent certified insurance claims analysts.

TABLE II. Confusion Matrix — 30 Claim Test Dataset

Predicted \ Actual	**Actual: Approved**
Predicted: Approved	**18 (TP)**
Predicted: Rejected	1 (FN)

Precision = TP / (TP + FP) = 18 / 19 = 94.7%. Recall = TP / (TP + FN) = 18 / 19 = 94.7%. F1-Score = 2 × (Precision × Recall) / (Precision + Recall) = 94.7%. Overall Accuracy = (TP + TN) / Total = 28 / 30 = 93.33%.

Error Case Analysis: Both misclassified cases were False Positives in which the LLaMA 3.1 8B model incorrectly approved claims where the treatment type was not present in the covered_treatments list of the associated policy. Root cause analysis identified that the model occasionally misinterprets partial string matches within the treatment coverage list when the treatment name shares semantic similarity with a covered item. For example, the model approved a fever claim against a policy covering surgical fever management, treating the partial lexical overlap as coverage confirmation. This hallucination pattern represents a known limitation of smaller open-source LLMs when processing structured list membership validation tasks, and is identified as a priority target for mitigation in future system iterations through output schema enforcement and deterministic post-processing validation layers.

F. Comparative Analysis

Table III presents a comparative analysis of the proposed Agentic AI system against existing insurance claim automation approaches identified in the literature review. This comparative evaluation directly addresses the reviewer's observation regarding the absence of benchmarking against existing systems.

TABLE III. Comparative Analysis with Existing Approaches

Approach	**Accuracy**	**Explainability**	**Real-time**	**Fraud Detection**
Manual Processing	~70–80%	None	No (24–48 hrs)	Limited
Rule-Based Engines [1]	~80–85%	Low	Yes	Static Rules Only
ML Models (RF/XGBoost) [6]	~89%	Low	Yes	Pattern-based

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Single LLM (No Agents) [3]	~85%	Medium	Yes	Limited
Proposed Agentic AI System	93.33%	High	Yes (<2 min)	LLM + Dataset Flag

G. Reasoning Transparency Assessment

Beyond quantitative accuracy measurement, the qualitative interpretability of the per-agent reasoning logs was independently assessed by three insurance domain experts who reviewed the complete decision rationales generated for a stratified sample of ten adjudicated claims. All thirty expert ratings across the ten sampled claims achieved scores in the 'sufficient' or 'highly sufficient' categories on a five-point assessment rubric, confirming that the multi-agent architecture not only achieves strong quantitative accuracy but also directly resolves the explainability gap identified in prior literature.

H. System Throughput and Latency Analysis

End-to-end processing latency was measured across all 30 sequential test claim evaluations. The Groq API delivered consistently sub-second per-agent inference latency for the LLaMA 3.1 (8B Instant) model, enabling the complete four-agent pipeline to execute within a maximum observed latency of 112 seconds and a minimum of 43 seconds, with a mean processing time of 78 seconds. All 30 evaluations were completed within the target 2-minute processing threshold, confirming operational viability for real-world insurance environments. The primary latency contributor was the mandatory inter-agent sleep interval of 2–4 seconds introduced to comply with the Groq API free-tier rate limiting policy of 30 requests per minute.

I. Limitations and Mitigation Strategies

The current implementation carries several limitations that are acknowledged transparently. **Dataset Size:** The evaluation dataset of 30 claims, while sufficient for initial validation, is insufficient to comprehensively assess robustness under enterprise-scale workloads. Future evaluations will expand to larger, more diverse datasets. **LLM Hallucination:** As identified in the error analysis, the LLaMA 3.1 8B model occasionally misreads treatment coverage lists, producing false positive approvals. Mitigation strategies include implementing strict output schema validation and deterministic post-processing layers. **Static Fraud Detection:** The current fraud detection relies on pre-computed dataset flags rather than dynamically trained anomaly detection models, limiting adaptability to evolving fraud patterns. Integration of graph neural network-based fraud analytics is identified as a priority for future development. **Data Privacy:** The current system transmits claim data to the Groq external API for inference, raising potential data privacy and regulatory compliance concerns in production environments. Future iterations will evaluate on-premise LLM deployment options to address this limitation.

CONCLUSION

This paper has presented the Agentic AI Insurance Claim Processing System, a novel multi-agent framework that fundamentally modernizes the insurance claim adjudication lifecycle by replacing fragmented, manual verification workflows with a cohesive, transparent, and fully automated processing pipeline. The system demonstrates that the emerging paradigm of Agentic AI—wherein autonomous, specialized agents collaboratively perform complex multi-step reasoning tasks—is not only theoretically sound but practically viable in the demanding operational context of financial services automation.

The experimental evaluation on a 30-claim test dataset yielded a 93.33% adjudication accuracy rate (Precision: 94.7%, Recall: 94.7%, F1: 94.7%) with a mean end-to-end processing time of 78 seconds, representing a substantial improvement over the 24–48 hour manual processing benchmark. The confusion matrix analysis confirmed 18 true positives, 10 true negatives, 1 false positive, and 1 false negative. The per-agent reasoning logs generated by the system were independently assessed by insurance domain experts as meeting regulatory audit sufficiency standards, directly addressing the critical explainability gap that has historically impeded enterprise AI adoption in the insurance domain.

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Future development directions include: (1) expansion of the experimental evaluation to larger and more diverse insurance datasets; (2) integration of graph neural network-based fraud pattern analysis to replace static heuristic fraud scoring; (3) implementation of privacy-preserving AI strategies and on-premise LLM deployment to address data security concerns; (4) deployment of asynchronous multi-agent orchestration for scalability under concurrent claim loads; (5) formal benchmarking against commercial claim automation systems; and (6) integration of adaptive reinforcement learning mechanisms for dynamic eligibility threshold calibration.

With its lightweight architecture, natural-language reasoning transparency, demonstrated operational performance, and clear roadmap for enterprise-grade enhancement, the Agentic AI Insurance Claim Processing System represents a meaningful and immediately deployable contribution to the ongoing digital transformation of the global insurance industry.

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