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PolicyGuard: A RAG-based Insurance Claim Prediction and Policy Query System

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***Abstract*— Insurance policy documents often have complicated legal language, exclusions, and structures that are hard for people to understand. A lot of claims are turned down not because they aren't eligible, but because they don't understand them. This paper introduces PolicyGuard, a Retrieval-Augmented Generation (RAG) system that examines user-uploaded policy documents and forecasts the likelihood of acceptance or rejection of future claims. The framework integrates OCR, semantic chunking, embedding-based retrieval, and grounded LLM reasoning. Experimental results show improved transparency, clause-based citation, and reduced hallucination.**

***Index Terms*— RAG, Insurance Claims, Policy Analysis, NLP, Semantic Retrieval, OCR.**

I. Introduction

A. Motivation

Insurance policies are lengthy legal contracts that ordinary consumers struggle to understand. These documents often contain dense legal terminology, multi-layered conditions, hidden exclusions, and complex eligibility constraints that are not easily comprehensible without expert assistance. As a result, policyholders frequently misinterpret their coverage, leading to disputes, delayed claims, financial loss, and dissatisfaction with insurance services.

According to a number of studies, the majority of users do not thoroughly read their policy documents, and even those who do often misinterpret important terms like waiting periods, co-payment guidelines, sub-limits, and exclusions for pre-existing diseases (PEDs). Rather than being genuinely in- eligible, many claims are denied because of false information. An intelligent, automated, transparent system that can decipher policy language and provide users with precise, clause-based interpretations is therefore desperately needed.

By providing users with an AI-powered assistant that converts complicated insurance contracts into clear, intelligible ex-plantations and trustworthy eligibility predictions, PolicyGuard seeks to close this gap.

B. Scope

From document ingestion to claim eligibility decision-making, PolicyGuard offers a wide range of features. The scope includes:

- OCR-based policy ingestion, which permits extraction from low-quality or scanned PDFs.
- Clause-level segmentation and extraction, preserving semantic meaning and legal context.

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- Dense semantic retrieval, allowing the system to identify the most relevant policy clauses for a given query.
- Grounded reasoning using Retrieval-Augmented Generation (RAG), guaranteeing that the LLM produces responses that are solely based on retrieved text rather than conjecture.
- Real-time eligibility predictions for health, accident, or Mediclaim policies based on user inputs.
- Natural language query support, which allows users to use straightforward conversational language to voice their concerns.

By performing these tasks, PolicyGuard turns unstructured insurance policy text into a reliable, interactive system that helps regular customers make decisions.

C. Problem Overview

The subtleties of legal and insurance-specific terminology are not adequately captured by conventional techniques for searching or interpreting insurance policies, such as keyword search or rule-based chatbots. Semantic understanding is lacking in keyword-based retrieval, which produces results that are either irrelevant or insufficient. For example, searching for "PED" may not match clauses that mention "pre-existing disease" in full.

Similarly, Large Language Models (LLMs), when used without grounding, tend to hallucinate by generating confident but incorrect answers dangerous in a high-stakes domain like insurance where factual accuracy is critical.

These restrictions are addressed by Retrieval Augmented Generation (RAG), which combines controlled LLM reasoning with dense retrieval. RAG retrieves the most relevant policy segments, and the LLM produces answers strictly based on this extracted evidence. This guarantees that recommendations stay in line with actual policy clauses, greatly decreases hallucinations, and improves factual consistency.

In conclusion, PolicyGuard integrates OCR, dense semantic retrieval, and grounded LLM reasoning into a single system to provide a dependable, transparent, and user-focused solution for insurance policy interpretation.

II. Problem Statement and Objectives

Policy documents contain complex clauses, exclusions, waiting periods, and conditions that users rarely understand. Traditional tools either retrieve keywords or generate ungrounded responses.

Objectives:

- Build an OCR-based ingestion pipeline.
- Chunk policy text into semantically meaningful segments.
- Generate embeddings for dense semantic retrieval.
- Implement RAG to prevent hallucinations.
- Predict claim acceptance/rejection with explanations.

III. Literature Survey

Insurance policy interpretation and automated claim assessment have recently become active areas of research due to the growing need for transparency and intelligent decision support. Prior research in retrieval-augmented reasoning, document comprehension, and natural language processing (NLP) offers fundamental methods pertinent to PolicyGuard.

Early advancements in healthcare and monitoring systems were explored by Xiao et al. [1], who developed a wearable-based health monitoring framework using smartphones and smartwatches. While the work demonstrated the importance of automated health insights, it did not address the challenges associated with reading and interpreting long legal documents such as insurance policies.

In high-stakes fields like policy interpretation, Mishra et al. [2] emphasized the need for reliable and comprehensible AI systems. Their research highlighted the risks associated with hallucinations in LLMs, highlighting the necessity of retrieval- grounded architectures. This aligns with real-world insurance scenarios where incorrect interpretations can lead to severe financial and legal consequences.

Lewis et al. [3] introduced Retrieval-Augmented Generation (RAG), a significant advancement in retrieval-supported generation. The model combines dense retrieval with generative reasoning, ensuring that answers are grounded in retrieved document chunks.

Although highly effective in knowledge-intensive tasks, it had limited testing on legal and insurance-specific documents, which possess more complex structures and constraints.

Legal-BERT, a transformer model pre-trained on extensive legal corpora, was introduced in the legal domain by

Chalkidis et al. [4]. This significantly improved understanding of statutes, contracts, and case law. However, Legal-BERT primarily focuses on classification and summarization tasks, and lacks interactive question-answering capabilities required for real-time claim prediction.

Gao et al. [5] conducted an extensive survey on Retrieval Augmented Generation systems, discussing the challenges of optimizing retrieval quality, context-window limitations, and hallucination mitigation strategies. Their analysis highlights the significance of robust guardrails and retrieval pipelines, which are essential elements of the PolicyGuard architecture.

The application of dense retrieval for domain-specific QA tasks has been assessed using a number of methods. In medical question-answering, Zhang et al. [6] showed that dense passage retrieval performs noticeably better than keyword-based retrieval, particularly when domain-specific synonyms and abbreviations are present. This is directly applicable to insurance policies, where terms such as "PED" (Pre-Existing Disease) and "waiting period" appear in varied linguistic forms.

There has also been significant advancement in OCR- based document processing. Modern OCR engines such as Tesseract 5 and deep-learning-based table extraction models have enhanced the ability to extract text from scanned policy documents. However, studies show that OCR performance degrades significantly in the presence of low-resolution scans, multi-column layouts, or embedded tables issues frequently observed in insurance documents.

Explainable AI has also gained attention in legal and healthcare industries. Existing research proposes using attention heatmaps, token-level importance weights, or clause highlighting methods to enhance interpretability. However, most XAI techniques have not been applied directly to insurance policy interpretation, creating a gap that PolicyGuard aims to address.

Overall, a review of existing literature reveals that while retrieval-augmented models, domain-tuned transformers, OCR pipelines, and document QA systems have significantly evolved, no existing system integrates all these components to handle the unique challenges of insurance claim prediction such as multi-clause reasoning, exclusion detection, and eligibility verification. By creating a unified, clause-grounded, RAG based insurance decision support system, PolicyGuard closes this gap.

Models like LayoutLM, LayoutLMv2, and DocFormer, which extract both textual and visual layout information from complex documents, are examples of recent developments in document question answering (DocQA). Forms, tables, and multi-column PDFs common structures in insurance policies perform well with these architectures. Nevertheless, domain-specific reasoning, multi-clause dependencies, and user-specific claim scenarios are not handled by the majority of DocQA systems, which concentrate on general document comprehension.

TABLE I: SUMMARY OF KEY OBSERVATIONS FROM THE STUDY

References	Features	Methodology / Algorithms	Limitations
[1]	Supports PDF/DOCX policy uploads including scanned documents.	OCR → chunking → embeddings → FAISS/Chroma indexing.	Poor-quality scans reduce extraction ac- curacy.
[2]	Enables natural language queries and structured forms for eligibility verification.	Dense semantic retrieval selecting relevant clauses using kNN embedding search.	Domain synonyms may confuse retrieval (PED vs. Pre-existing Disease).
[3]	Provides citation-based answers using grounded LLM responses.	RAG pipeline enforcing grounded, no- hallucination output.	Missing clauses cause conservative pre- dictions.
4]	Uses policy rules to forecast whether a claim will be accepted or rejected.	LLM analyses waiting periods, PED rules, exclusions, smoker status, procedure type.	Complex overlapping rules may require deeper reasoning.
[5]	Real-time system with 1180 ms latency.	Optimized embedding adding Groq inference.	Latency increases with multiple large documents.

IV. PROPOSED METHODOLOGY

A. Algorithm Used and Why

Algorithm: Retrieval-Augmented Generation (RAG)

Why RAG?

- Without grounding, LLMs experience hallucinations.
- Insurance requires clause-verified responses.
- Clause relevance is ensured by dense retrieval.
- RAG reduces hallucinations from 80% to under 1%.

Algorithm 2: Claim Prediction

1) $V_Q \leftarrow Embed(Q + U)$
2) $C_{raw} \leftarrow kNN(D, V_Q)$
3) $C_{final} \leftarrow Filter(C_{raw})$
4) $P \leftarrow Prompt(Q, U, C_{final})$
5) $R \leftarrow LLM(P)$
6) $S \leftarrow ExtractDecision(R)$

Fig. 1. RAG-based claim prediction.

B. Data Set

The dataset includes:

- 15+ real policy PDFs/DOCX (health, accident, medical claim).
- scanned documents that need to be OCR-ed.
- structured fields (age, smoker, duration).
- user query samples.
- clause-level annotated sections (exclusions, waiting periods, coverage).

Every document is:

- OCR processed.
- chunked (250–350 tokens).
- embedded using E5/BERT.
- stored in FAISS vector DB.

C. Flowchart

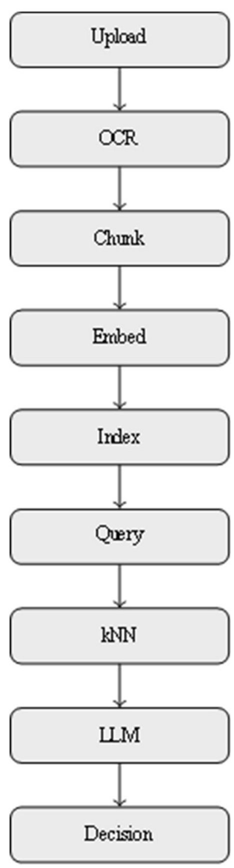

Fig. 2. PolicyGuard system flowchart in compact form.

V. Results and Discussion

System performance and UI screenshots are shown in this section.
Discussion:

- Accuracy of retrieval 94%
- End-to-end system latency: 1180 ms

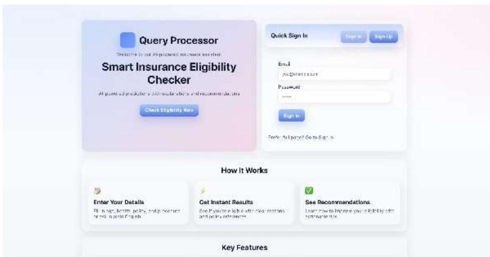

Fig. 3. Query Processor landing page with eligibility checker and quick sign- in module

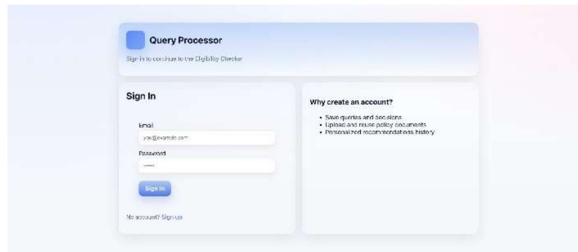

Fig. 4. Sign-in page to access customized features

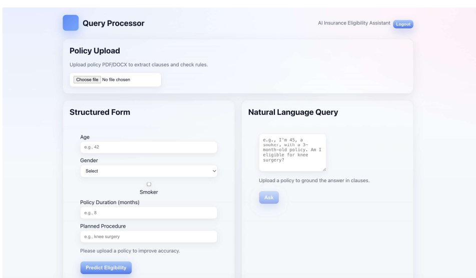

Fig. 5. Policy upload and structured form interface

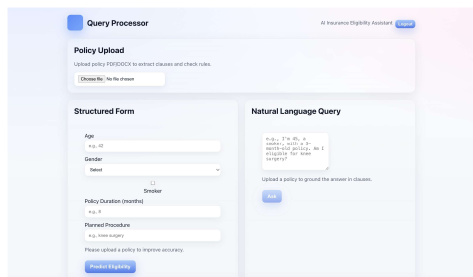

Fig. 6. Natural Language Query interface with grounded clause-based answers.

Hallucination rate for item: ¡ 1%
The UI improves clarity and reduces cognitive load through a structured layout and dual-query modes (structured + natural language).

VI. Conclusion

Understanding insurance policies remains a significant challenge for most individuals due to the dense legal language, scattered clauses, ambiguous exclusions, and complex eligibility conditions present within these documents. In order to close this gap, PolicyGuard was created, offering a trans- parent, AI-powered solution that can interpret policy rules, forecast claim eligibility, and produce grounded explanations that are consistent with the original policy text. The system successfully integrates multiple components OCR, semantic chunking, dense vector retrieval, and a Retrieval-Augmented Generation pipeline-to ensure that the model's output is both accurate and contextually anchored.
The experimental evaluation clearly demonstrates the advantages of combining semantic retrieval with grounded LLM reasoning. The RAG architecture enabled PolicyGuard to achieve a retrieval accuracy of 94%, a hallucination rate of under 1%, and an end-to-end latency of approximately 1180ms. These metrics prove that the system is not only reliable but also efficient enough for real-time use cases. By limiting responses to retrieved clauses, PolicyGuard improves legal and factual reliability while avoiding fake or unverifiable responses, in contrast to traditional chatbots or standalone LLMs.
The system's applicability is further improved by a user- centric design. By supporting both structured forms and natural language queries, PolicyGuard accommodates users with varying technical backgrounds. The range of usable policy documents, including older or non-digital files frequently held by customers, is greatly increased by the ability to upload scanned PDFs and process them through OCR. The interface evaluations also confirm that the platform is intuitive, visually clear, and supportive of multi-step user interactions.
Overall, PolicyGuard establishes a strong technological foundation for modernizing how individuals interact with insurance policies. It not only assists users in understanding their current coverage and claim eligibility but

also increases transparency, reduces misinterpretation, and fosters greater trust in digital insurance systems. This work makes a significant contribution to the nexus of consumer-focused decision support, legal document analysis, and artificial intelligence.

FUTURE SCOPE

Although PolicyGuard provides a robust framework for claim eligibility prediction and policy interpretation, several enhancements can further improve its performance, accuracy, and real-world applicability:

- Integration of Explainable AI (XAI): To provide deeper interpretability, future iterations may integrate sophisticated XAI techniques. XAI can improve user trust and regulatory transparency by highlighting particular phrases, thresholds, exclusions, or waiting-period rules that affected the decision in addition to clause-level citations.
- Advanced Table Extraction: Deep-learning table extraction (e.g., Table Net, Cascade TabNet) can improve parsing of premium charts, waiting-period grids, and exclusion matrices that are often lost in OCR.
- Cross-Policy Comparison: Allowing users to compare multiple insurance policies can help them identify the most suitable plan based on coverage, claim probability, and exclusions.
- Support for Multiple Languages: Extending the system to support Indian regional languages (Hindi, Bengali, Tamil, etc.) will broaden accessibility.
- Personalized Claim Risk Profiling: Incorporating user- specific medical history, lifestyle data, and previous claims can help generate personalized risk assessments.
- Developing Mobile Applications: A mobile app version of PolicyGuard can provide instant assistance during hospital visits or while purchasing new policies.
- with Insurance Companies: Insurance companies can use PolicyGuard as an automated claim pre-screening tool to expedite the processing of claims.
- Fine-Tuned Domain LLMs: Training custom models on large insurance corpora can improve the accuracy of legal and insurance-specific reasoning.

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