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(Review Article)

AI-powered life insurance claims adjudication using LLMs and RAG Architectures

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Abstract

The accurate assessment and adjudication of life insurance claims is a core competency of the insurance industry and the business of insurance, affecting financial stability and operational efficiency of the company and the relationship with the customer. The traditional methods of claims processing that heavily rely on rule-based systems and manual assessment have problems of inefficiencies, errors, and long time to resolution. However, as Artificial Intelligence (AI), Large Language Models (LLMs) and Retrieval Augmented Generation (RAG) architectures are becoming capable, they open the opportunity to revolutionize again claims adjudication, improving the accuracy, automating and also detecting fraud. Laying out the use of LLMs and RAG architectures in life insurance claims management, this paper illustrates the ability of these two architectures to automate decision-making, boost risk assessment, but also to optimize the operational workflow. Also, calls attention to the use of predictive modeling in addition to hosting robotic process automation (RPA) in the development of AI driven claims processing.

Keywords: Life Insurance; Insurance Claims; Large Language Model (LLM); Retrieval-Augmented Generation (RAG); Artificial Intelligence; Machine Learning; Natural Language Processing.

1. Introduction

The insurance industry is going through its biggest transformation in terms of AI and ML. Claims adjudication is a critical function in life insurance whereby policyholders submit claims to be validated and assessed. Actuarial models and manual review are standard ways of claims processing, but they are all inefficient, inconsistent and costly [1][2]. On account of the increasing volume and complexity of claims data, the ability to capture hidden patterns and deliver real-time insights is not sufficient using the conventional methods of analysis, and hence more sophisticated approaches to analyzing claims data are required.

Recent developments in NLP and deep learning have made it possible for LLMs to analyze vast volumes of textual material, extract pertinent information, and reach well-informed conclusions [3]. RAG brings further capability to this by allowing models to generate more contextually accurate and explainable outputs by integrating external knowledge retrieval mechanisms [4]. Automated document analysis and the detection of fraudulent activities are among the techniques provided by these AI-driven techniques that can help when it comes to claims adjudication and to make sure that as far as regulatory requirements go, they are being met.

In risk assessment, predictive modeling is essential because it uses past claims data to predict claim probabilities and spot possible fraud. Furthermore, repetitive administrative operations like data input and validation are streamlined by RPA, which lowers manual labor and operational inefficiencies [5]. The confluence of these technologies presents a prospective avenue for realizing AI-driven life insurance claims adjudication, which can aid the insurers in the realm of accuracy in decision-making, turnaround time of process and customer experience.

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The insurance sector is not an exception where the AI has become a fast revolution [6][7]. AI technologies have been integrated in such a way that the processes are stream lined, customer experiences are enhanced, and innovative products are delivered which are designed according to individual needs [8]. While the traditional insurance purchasing journey is where the consumers interact with the product relatively often, AI-driven solutions are bringing as consumers are increasingly interacting with digital platforms, providing personalized recommendations and real-time assistance.

1.1. Organization of paper

The paper organization is as follows: The Overview of AI in Insurance Claims Processing is provided in section II. Section III describes LLMs in Life Insurance Claims, section IV uses the RAG for Claims Adjudication, and Section V presents the literature review based on different research papers and research gaps. Finally, it provide the conclusion and future work of this work.

2. Overview of AI In Insurance Claims Processing

In order to ensure that insurance professionals get timely and proper compensation for their services, claim adjudication is essential, as seen in Figure 1. Insurance firms' long-term financial stability is significantly impacted by the efficiency and accuracy of claim processing [9]. In recent years, process automation and AI have transformed claim adjudication, leading to notable improvements in accuracy, efficiency, and overall financial performance.

2.1. Key Steps of Claims Adjudication Process

To comprehend how the insurance company decides whether to pay, reject, or deny claims, it is critical to understand the many procedures involved in claim adjudication [10].

Figure 1 Claim Adjudication Workflow

- **Eligibility verification:** In the initial process of claim review, the claims for simple errors and omissions, if left undetected, can lead to significant costs.
- **Verification of fraudulent/ duplicate claims:** When a claim is submitted to the Payer for reimbursement, it is checked whether the claim is duplicate or fraudulent and if it needs checking on a few parameters.
- **Coding, Bundling, and Diagnosis review:** Evaluation of pre-certification or authorization records to identify cases where there is an absent or invalid precertification issue
- **Detailed analysis of provider:** Cross-verification of the claims should be conducted to evaluate the claims' authenticity.
- **Benefit determination:** The process of comparing claims and benefit data to determine if the services provided are covered by the member's defined health benefits and whether the relevant benefit adjudication rules apply is known as benefit determination.
- **Appeals processing:** If your health insurance company denies a claim or cancels your coverage, you can challenge the decision and have a third party look it over.

2.2. Role of AI in Insurance Claims Processing

There are significant advantages for the insurance sector as a whole when AI is integrated. It not only helps us learn more about the newest marketing trends for drawing in more clients, but it also gets rid of a lot of the tiresome paperwork. AI delivers resources and answers open-ended queries to better meet the requirements and desires of customers [11]. AI and machine learning could improve insurance claims processing, customer service, and fraud detection. Data mining algorithms like J48, Naive Bayes, and Random Forest were used to investigate car insurance fraud and premium calculation [12].

Leveraging AWS AI services like Amazon Bedrock, Artificial Intelligence, Knowledge Bases, and Intelligent Agents in insurance claims processing brings numerous benefits.

- Enhances efficiency by reducing the time and effort required to process claims, improving accuracy, and minimizing error rates.
- Enhanced customer experiences because of quicker claims processing and personalized responses, boosting satisfaction and loyalty.
- Operational efficiency is further improved as automation allows less experienced handlers to manage claims more effectively.

Additionally, the system proactively ensures regulatory compliance by monitoring for legislative updates and suggesting necessary changes, thereby mitigating legal risks and maintaining customer trust [13].

2.3. AI Applications in Insurance

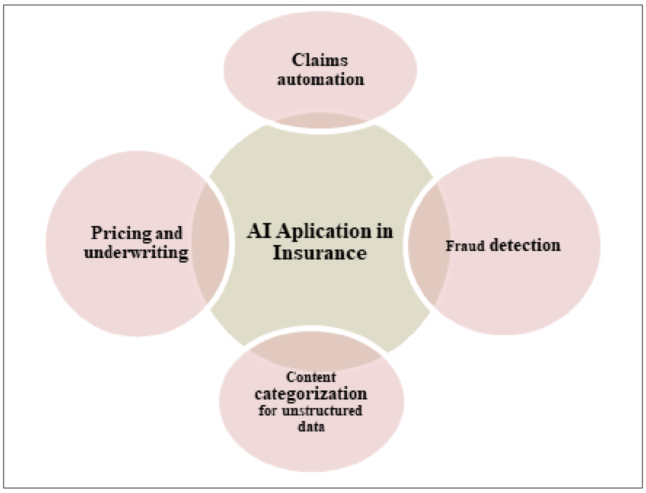

Figure 2 AI application in Insurance

The application of artificial intelligence by One of the most fundamental issues facing the insurance sector, asymmetric knowledge, may be lessened if insurance firms permit a more accurate estimation of loss possibilities [14]. It is shown in Figure 2.

- **Claims automation:** Customers' claims are settled more quickly when AI tools are used to handle claims because they increase processing efficiency.
- **Fraud detection:** Insurers may identify and flag odd trends that a person would overlook by using AI-driven fraud detection tools to examine vast volumes of data from various sources, potentially identifying fraudulent claims.
- **Content categorization for unstructured data:** This has to do with using AI technologies to read, analyze, and classify unstructured data in forms, emails, incoming letters, excel sheets, and other formats so that it may be transformed into machine-readable formats and processed further.
- **Pricing and underwriting:** AI offers insurers a plethora of options for product design and pricing. For instance, new risk factors can be created in conjunction with the related raw data to help provide more accurate insurance coverage [15].

3. Large Language Models (LLMs) In Life Insurance Claims

There are several points in the claims processing process where LLMs might be helpful. In Figure 3, the standard claims procedure is displayed. Note that the following examples and procedures are mostly tailored to non-life auto insurance claims [16]. This procedure was chosen since it is among the most crucial tasks that insurers do [17]. Additionally, a broad spectrum of actuarial and insurance audiences should find it easy to understand. The procedure itself includes a number of sections that call for different kinds of communication as well as the gathering of both structured and unstructured data. The claims management process is described below:

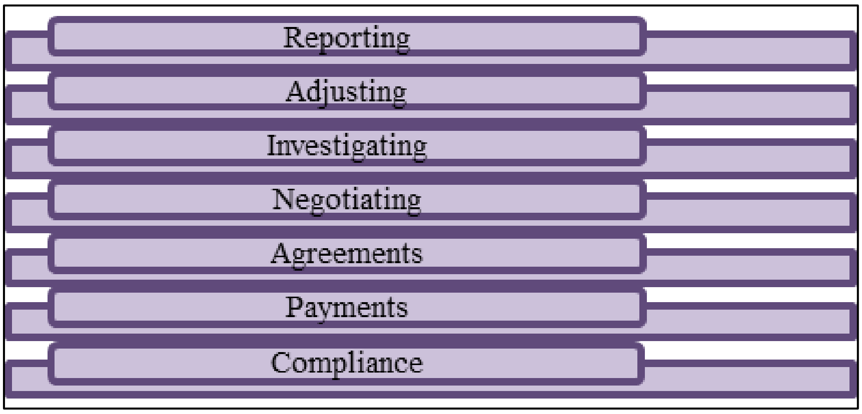

Figure 3 Claims management process

- **Reporting -** The policyholder notifies the insurer of a claim via phone, email, or an online portal.
- **Adjusting -** A claims adjuster is assigned by the insurer to look into the claim and compile pertinent data.
- **Investigating -** A claims adjuster looks into and gathers pertinent data, including police records, medical reports, witness accounts, claims descriptions, and other proof, in order to evaluate the veracity of the claim.
- **Negotiating -** An adjuster for claims engages in negotiations with the claimant and any other parties.
- **Agreements -** The claimant and the insurer come to an understanding.
- **Payments -** The claim is paid out by the insurer in installments or as a lump payment.
- **Compliance -** The insurer keeps thorough records of all acts done and guarantees adherence to legal and regulatory obligations.

3.1. Role of LLMs in Claims Processing

Integration of LLMs is helpful in claims processing. Some key roles defining claim processing are:

3.1.1. Automating Claims Assessment and Decision- Making:

The accuracy and efficiency of processing insurance claims have significantly increased with the use of intelligent automation, particularly machine learning models. It significantly reduces the manual intervention of concerned insurers and speeds up claim settlement times by automating some of the most crucial operations, such as data input, claim validation, and fraud detection [18]. Because automation requires less human participation, it increases efficiency and accuracy while cutting down on cycle time in the processing of claims.

NLP can be integrated with advanced technologies to process unstructured data and improve human- computer interaction, leading to meaningful outcomes that enhance decision-making and improve operational efficiency in various industries (Bahja, 2020). NLP can be integrated with advanced technologies to process unstructured data and improve human-computer interaction, leading to meaningful outcomes that enhance decision-making and improve operational efficiency in various industries (Bahja, 2020). NLP can be integrated with advanced technologies to process unstructured data and improve human-computer interaction, leading to meaningful outcomes that enhance decision-making and improve operational efficiency in various industries (Bahja, 2020).

3.1.2. Natural Language Understanding for Policy and Contract Analysis:

The potential for NLP to operate in tandem with modern technologies to provide significant results in decision-making and operational efficiency across a range of sectors is enormous when it comes to processing unstructured data. NLP technologies provide advanced contract analysis insight extraction features and, accelerate contract interpretation and automate time-consuming human tasks [19][20].

Large Language Models (LLMs) have emerged as a groundbreaking technology in the field of natural language processing (NLP) and artificial intelligence. These models, trained on vast amounts of textual data, have emonstrated remarkable capabilities in understanding and generating human-like text. The integration of LLMs into customer service chatbots represents a significant leap forward in automating and enhancing customer interactions Large Language Models (LLMs) have emerged as a groundbreaking technology in the field of natural language processing (NLP) and artificial intelligence. These models, trained on vast amounts of textual data, have demonstrated remarkable capabilities in understanding and generating human-like text. The integration of LLMs into customer service chatbots represents a significant leap forward in automating and enhancing customer interactions Large Language Models (LLMs) have emerged as a groundbreaking technology in the field of natural language processing (NLP) and artificial intelligence. These models, trained on vast amounts of textual data, have demonstrated remarkable capabilities in understanding and generating human-like text. The integration of LLMs into customer service chatbots represents a significant leap forward in automating and enhancing customer interactions Large Language Models (LLMs) have emerged as a groundbreaking technology in the field of natural language processing (NLP) and artificial intelligence. These models, trained on vast amounts of textual data, have demonstrated remarkable capabilities in understanding and generating human-like text. The integration of LLMs into customer service chatbots represents a significant leap forward in automating and enhancing customer interactions

3.1.3. Improving Customer Interaction and Support:

The incorporation of LLMs into chatbots has significantly expanded their potential for customer support applications. These models, trained on vast volumes of text, have demonstrated a remarkable ability to comprehend and generate genuine text that is human-like. LLMs have completely changed how computers interpret and produce natural language. Examples of these are Google's BERT and OpenAI's GPT-3 [21][22].

3.2. Architecture of LLM

The architecture of a LLM depends on several aspects, such as the goal of the particular model design, the computational resources available, and the type of language processing activities that the LLM is expected to do [23]. The overall architecture of LLM is depicted in Figure 4 and includes several levels, including feed-forward, embedding, and attention layers. Predictions are produced by a team working collaboratively on an embedded text [24].

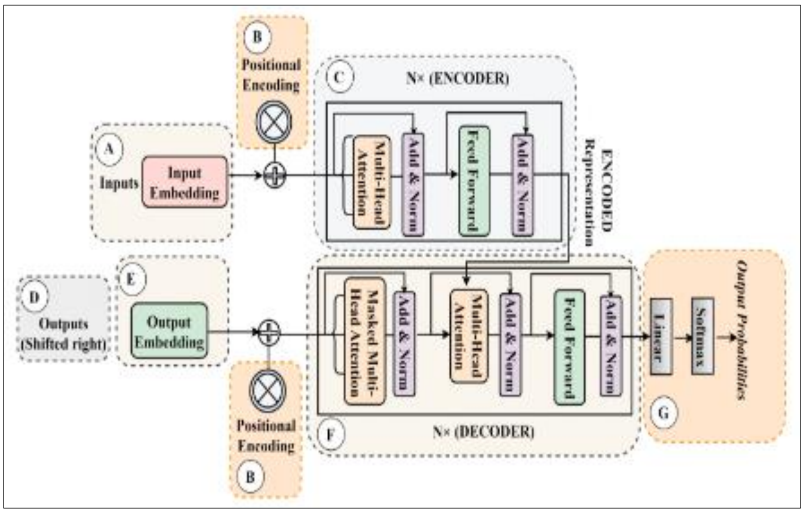

Figure 4 Architecture of Large Language Models (LLMs)

A summary of each language model—also known as Transformer-based language models—is given. These language models seek to anticipate future words in a text or words that are disguised throughout the training process by using a specific type of deep neural network architecture called the Transformer.

- **Inputs and Input Embeddings:** The training data for the machine learning models are tokens, which are textual units such as words or subwords. Nevertheless, these models handle numbers.
- **Positional Encoding:** Important semantic information is often conveyed by the word order of a sentence. When the same words are used in a different order, they have entirely distinct meanings.
- **Encoder:** The neural network that processes the incoming text includes an encoder, which is an essential component. Outputs (rightward shift). The transformer model's decoder learns to anticipate the following word in a sequence by examining the words that come before it during training.
- **Output Embeddings:** The model does not immediately recognize input embeddings that contain text. As a result, the output has to be transformed into a format called "output embedding."
- **Decoder:** The decoder handles input and output embeddings that are positionally encoded.
- **Linear Layer and Softmax:** The output embedding is converted into a higher-dimensional space by the linear layer, a fully connected neural network layer [25].

4. Retrieval-Augmented Generation (RAG) For Claims Adjudication

In the insurance sector, robotic process automation has been recognized as a game-changing technology for automating repetitive processes. The insurance industry faces growing pressure to optimize operations and enhance customer satisfaction due to increased competition and regulatory demands. Automation technologies, particularly RPA, have emerged as pivotal in transforming the industry's operational landscape. RPA has shown promise in automating repetitive, rule-based tasks such as basic claims processing, document verification, and data input. However, traditional RPA systems struggle with complex, non-standard cases that require contextual understanding and adaptive decision-making.

4.1. Retrieval-Augmented Generation (RAG) Architecture

The following is a basic Figure 5 workflow of a Retrieval Augmented Generation (RAG) system that illustrates how it essentially improves the capabilities of Large Language Models (LLMs) by establishing their outputs in pertinent, real-time data [26].

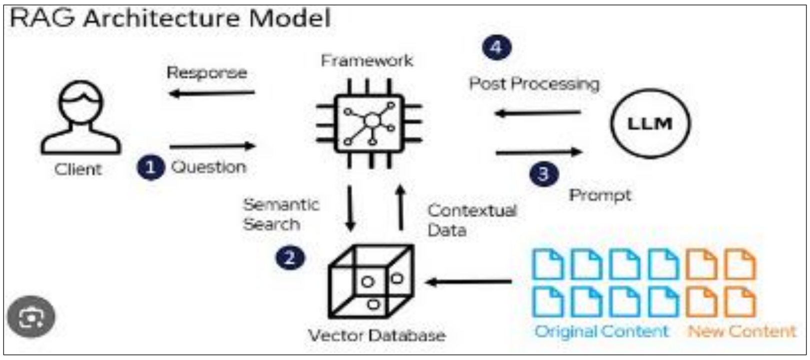

Figure 5 Architecture of Retrieval Augmented Generation (RAG) system

The architecture of Retrieval Augmented Generation (RAG) is defined below:

- **User query:** The user asks the LLM a question or sends a prompt. This question might be a factual investigation or a more general request.
- **Data retrieval:** The retrieval mechanism immediately examines all firm data after intercepting the prompt. Imagine it as an extremely powerful search engine that is particularly made to sort through all of the gathered, organized, and unstructured evidence. It finds the most important details pertaining to the user's inquiry.
- **Data-query fusion:** The RAG system carefully blends the user's initial inquiry with the data that was retrieved to produce a more targeted, thorough, current, and educational prompt for the LLM.
- **Contextual prompt delivery:** The LLM receives the freshly created prompt that has been enhanced with the user's inquiry and the data that was recovered.
- **Response generation:** The generating model LLM receives an enhanced prompt from the retrieval model, which adds extra contextual information to the user's initial prompt.
- **Output delivery:** The user receives the answer from the LLM [27].

4.2. Benefits of RAG Models

In a variety of fields where factual accuracy and contextual awareness are crucial, RAG models have been used [28].

- RAG increases accuracy by linking replies to outside information, minimizing hallucinations in language models, and improving the precision and dependability of produced responses.
- The most recent information may be found by using retrieval techniques. RAG preserves the promptness and precision of replies in contrast to conventional language models that just use training data.
- One benefit of RAG is transparency; citing sources allows users to confirm the veracity of the responses, boosting confidence in the model's results.
- RAG may be customized by indexing pertinent textual corpora; models can be made to fit various domains and offer knowledge assistance for certain disciplines.

- RAG can better regulate data usage in terms of security and privacy management thanks to its integrated roles and security controls in the database. On the other hand, refined models might not clearly control who has access to what data.
- The scalability of RAG is higher because it can handle big datasets without requiring training sets and parameter updates; it is more cost-effective.

4.3. Challenges in Insurance Claims Processing

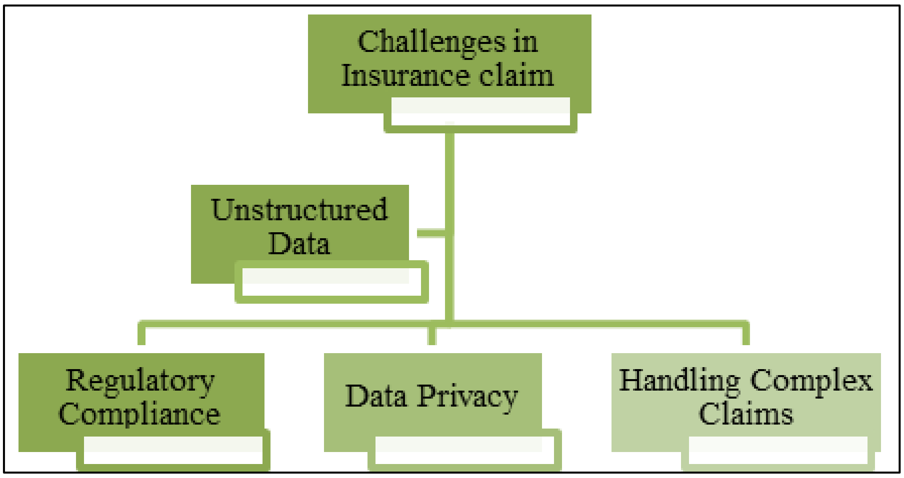

Figure 6 Challenges in insurance claims processing

Insurance claims processing is inherently complex, with claims often varying in nature, data formats, and levels of detail required [29]. Common challenges include and in Figure 6:

- **Unstructured Data:** Traditional RPA systems are primarily designed for structured data. However, claims processing involves unstructured inputs like PDFs, handwritten notes, and scanned documents, making automation more challenging.
- **Regulatory Compliance:** Insurance companies must adhere to strict regulatory requirements, which often evolve over time. These requirements increase the complexity of implementing AI-driven automation solutions.
- **Data Privacy:** Ensuring customer data privacy while using AI models for automation is crucial, particularly when generating synthetic datasets. Mishandling sensitive data could lead to compliance violations and reputational damage.
- **Handling Complex Claims:** Claims involving multiple parties, fraud detection, and special cases require contextual understanding and adaptive decision-making, capabilities that traditional RPA systems lack.

5. Literature Review

In Below Table 1 is an overview of some recent studies of research on integrating LLMs, RAG, and ML methodologies across different areas such as system configuration, information retrieval, security, and insurance claim adjudication.

Sawarkar, Mangal and Solanki (2024) suggest using hybrid query tactics in conjunction with semantic search techniques like sparse encoder and dense vector indexes to create the "Blended RAG" approach. For IR (Information Retrieval) datasets such as the NQ and TREC-COVID datasets, their work improves retrieval outcomes and establishes new standards. They also apply such a "Blended Retriever" to the RAG system, showing significantly better performance on generative Q&A datasets such as SQUAD, even outperforming fine-tuning [30].

Sharan et al. (2024) suggests a fraud-detecting approach based on machine literacy that is tailored for insurance claims in an Internet of Things environment. The suggested solution makes use of real-time data from IoT detectors and actual claim records, applying machine learning techniques like anomaly finding, bracketing, and clustering to spot suspicious trends and flag possibly fraudulent claims. The efficacy and efficiency of the suggested method are proven through a thorough examination utilizing deconstructed and real-world datasets, underscoring its possibility to reduce fraud hazards and improve the integrity of insurance operations in IoT environments [31].

Tural, Örpek and Destan (2024) it is emphasized that the integration of RAG architecture with information retrieval systems and LLMs provides more sensitive and accurate solutions in information-intensive tasks. This study emphasizes that the RAG architecture's ability to retrieve information by dynamically using the learnings obtained from large datasets of LLMs strengthens applications in the field of NLP [32].

Gummadi et al. (2024) outlines key strategies for securing RAG-based applications to mitigate these risks paper outlines key strategies for securing RAG-based applications to mitigate these risks. Ensuring data security through filtering, sanitization, and provenance tracking can prevent data poisoning and enhance the quality of external knowledge sources. Moreover, this study analyzes various use cases for LLMs enhanced by RAG, including personalized recommendations, customer support automation and content creation [33].

Van Nguyen et al. (2023) provides a thorough empirical assessment through comparison of various indicators and assessments from human underwriters. Lastly, the outcome shows that the binary relevance algorithm and decision tree classifier perform better than other currently used techniques for explainable exclusion, offering a more comprehensive picture of the risk profile of the client [34].

Vyas and Serasiya (2022) Among other things, technology may be used to develop a system that stops some forms of fraud in the fields of life, health, and auto insurance claims. This study will go over the many forms of fraud detection in insurance claim systems and how they are categorized using various machine learning techniques. Additionally, it provides guidance for the future of insurance claim system fraud detection [35].

Table 1 Related Work Summary on AI-Powered Life Insurance Claims Using LLMs and RAG

Reference	Methods	Key Findings	Challenges	Limitations & Future Work
Sawarkar, Mangal and Solanki (2024)	Blended RAG (Hybrid query techniques, sparse encoder indexes, and dense vector indexes)	Enhances Generative Q&A (SQUAD), outperforming fine-tuning performance, and produces improved retrieval outcomes on IR datasets (NQ, TREC-COVID)	Hybrid search tuning complexity	Further improvements needed in adapting hybrid search for different domains
Sharan et al. (2024)	Machine learning (anomaly detection, bracketing, clustering) applied to IoT-based insurance claims.	Real-time fraud detection leveraging IoT data enhances integrity of insurance claims process.	Scalability issues in large-scale IoT environments	Real-time data processing challenges for big data applications
Tural, Örpek and Destan (2024)	RAG architecture + LLMs in information retrieval	Strengthens NLP applications by dynamically retrieving information using LLM learnings	Retrieval efficiency concerns	Adaptation for domain-specific applications requires further improvements
Gummadi et al. (2024)	Security measures in RAG (filtering, sanitization, provenance tracking)	Prevents data poisoning; enhances security for LLM applications in recommendations, customer support, and content creation	Need for continuous updates to counter evolving threats	Long-term robustness of security mechanisms remains uncertain
Van Nguyen et al. (2023)	Binary Relevance Algorithm + Decision Tree Classifier	performs better than current techniques in customer risk profiling explainable exclusion	Limited evaluation on diverse risk scenarios	Needs testing in real-world applications for validation
Vyas and Serasiya (2022)	ML-based fraud detection in insurance claims (vehicle, healthcare, life)	Categories fraud detection methods and provides future research directions	Lack of empirical validation	Further work needed in integrating AI-driven fraud detection models

6. Conclusion And Future Work

The incorporation of AI into life insurance claim adjudication, efficiency, accuracy, and all-round decision-making of this thriving industry has been revolutionized. It is this paper that reviewed how AI-powered technologies such as LLMs and RAG could be leveraged to automate claims processing. By using LLMs, automated document analysis, fraud detection, and compliance verification, it achieves a significant reduction of manual work and improves the efficiency of operations. In addition, the RAG architectures also help to make AI-based decision-making more contextually accurate and explainable by capturing real-time knowledge retrieval. The pros of applying AI in which the main prospect of claims adjudication applications is the reduction of processing time, increase in fraud detection, improved regulatory compliance and superior customer service. Despite these challenges, AI-driven claims processing creates issues such as handling unstructured data, assuring the privacy of the data, regulatory compliance, and complex claims need of exhibitionist decision-making out of the blue.

Future research should be directed towards further improvement of AI techniques for optimizing insurance claims adjudication. It encompasses improving model transparency, reducing LLM hallucinations and making the decisions that LLMs make more interpretable. Another way of integrating AI and blockchain tech is to use it in order to add security and auditability aspects to the claims processing. Insurers need to strategically leverage AI technologies to incubate innovation, enhance efficiencies in businesses, as well as create an excellent experience for the customers.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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