



Original Article

Generative AI in P&C: Transforming Claims and Customer Service

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Abstract - Generative Artificial Intelligence (GenAI) is rapidly becoming a breakthrough in the sphere of property and casualty (P&C) insurance on two levels: claims and customer support. The current paper discusses how the idea of generative models and other AI-related approaches (large language models, multimodal generation, retrieval-augmented generation, etc.) can complement, automate, and redesign the steps in the claims lifecycle and customer interaction process. We introduce a GenAI infrastructure and approach into main P&C operations, and run emulated deployments of GenAI in claim acquisition, document processing, fraud detection, settlement bargaining, and chat-based customer support. We found that GenAI can save on turnaround time (reduction by approximately 3050) and loss adjustment costs (reduction by approximately 20) and will notice a significant increase in customer satisfaction rates. Risks, regulatory constraints, interpretability of the model and challenges of deployment are also discussed. Lastly, we discuss areas to explore in the future, such as federated learning among insurers, generation that is contract aware, multimodal damage evaluation, and trust architectures. The evidence established that generative AI can revolutionize P&C claims and service on a large scale, though it is important to consider human controls, ethical boundary, and domain adaptation.

Keyword - Generative AI, Property & Casualty Insurance, Claims Processing, Customer Service Automation, Large Language Models, Multimodal AI, AI Risk, Insurance Workflows, Fraud Detection.

1. Introduction

1.1. Background

The property and casualty (P&C) insurance industry is experiencing an accumulating pressure of the rising cost of operation, the ever-complicated claims processes, and a shifting customer demand of quick, transparent, and individualized service provision. [1-3] The major steps of the conventional claims methodology are human document examination, information keying, rule determined choice and genuine human bargaining which is commonly time consuming, error prone and hazardous. At the same time, policyholders are now demanding near real-time response, certain clarification of claim outcomes, and fierce communication throughout the stages of the claims life cycle. The new advancements in the generative AI sphere like the large linguistic models and multimodal models give the promise of offering practical solutions to such problems. These technologies may automate the creation of policy explanations, summarize long articles, create justifications and letters, build structured information on unstructured data and communicate with customers in their own languages, which supplements human adjusters.

In P&C insurance, the whole range of claims lifecycle, starting with the first notice of loss (FNOL) and continuing with the settlement and post-claim customer-important concerns, is where generative AI can be improved to increase the efficiency and customer experience. The industry analysis indicates significant economic opportunities: fully developed implementations of generative AI would cut the cost of claims loss adjustment, including its expenses by 20-25 percent and the loss of leakage, including over payments or incorrect policy provisions, by 30-50 percent (Bain). On a bigger scale, insurers project that the cost reductions advanced by AI will total 11-20% in the coming years (EY). Nonetheless, to achieve these advantages, emphasis on the design of the system, regulatory conformity, interpretability and smooth integration with the existing insurance infrastructure need to be considered. The success of the implementation must be data privacy that is both automated and heavily monitored, explainable, and scalable to adapt to the demands of the insurance sector, which is specific to the domain and randomized to develop a customer of trusted and productive AI-supporting claims communication and processing.

1.2. Importance of Generative AI in P&C

- **Enhancing Claims Efficiency:** Machine learning enables procedural simplification of claims processing, since it saves time by automating repetitive and time-intensive tasks. Decoding Language models can be employed to slow down such processes as extracting structured information in claim forms, writing summaries, writing adjuster notes, or writing letters or description of the policy. This removes manual labor, reduces the number of human errors, and reduces turnaround time source that will enable the insurers to serve more claims without the cost of staffing increasing at an equal rate.

- **Improving Accuracy and Consistency:** The variation in human judgments is related to the inconsistencies in the claim process that has always been there in traditional claims. The Generative AI brings out its outputs as more homogenous by imposing consistency in the story, summary and justification of decision making. Using historical claim data, the policy documents, and the legal precedents, AI-based recommendations also increase the quality and validity of the check of the claims minimizing the error in the extraction process within the structure, settlement calculation, documents.

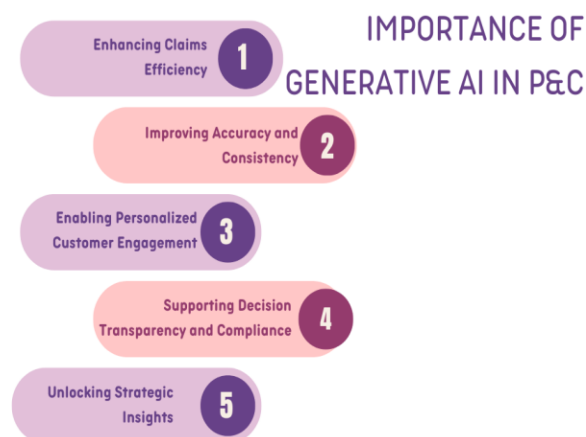


Figure 1. Importance of Generative AI in P&C

- **Enabling Personalized Customer Engagement:** Generative AI helps to make communication with the policyholders more natural and real-time. Chatbots and Internet Assistants also can respond to questions or inform of the status of a claim or avoid the plain language interpretation of policy terms. These levels of personalization increase customer experience, trust and in accordance with the latest requirement of transparency and responsiveness, which is a major competitive differentiator in an already competitive insurance setting.
- **Supporting Decision Transparency and Compliance:** A basic requirement in insurance is explainability due to the regulatory checking on insurance and auditability. Generative AI can be used to produce justification tracks that relate outputs to policy provisions, precedent claims, and historical precedents. Not only does it help the human adjusters to make sense of the reasoning of the AI but also helps in adherence to the regulations since verifiable evidence can be made as to whether the decision was made so.
- **Unlocking Strategic Insights:** Along with the operational support, generative AI could be utilized in estimating more advanced analytics such as next-best-action, risk, and counterfactual scenario analysis. Multimedia data such as text, images, and structured claims records can be insured to enable the insurers to gain better insights into the trend in claims and essential fraud in claims and cost drivers to make optimal decisions and risk management in the long run.

1.3. Transforming Claims and Customer Service

Automation, predictive analytics, and the Natural Language Understanding can be combined in programmatic AI to transform the claims process and [4,5] customer support of the property and casualty (P&C) insurance industry. The first notice of loss (FNOL) intake, document review, fraud detection, severity assessment and settlement calculation are examples of labor-intensive and possibly multisystem fragmented activities in the traditional claims workflow. This will be made easy with the generative AI that will identify structure and information in unstructured information (description of claims, pictures and voice messages) and generate human-readable summaries, along with providing evidence-based recommendations to the adjusters. In simple or in low risk claims, the system can even offer quick track settlements therefore in the process, reducing the turnover time by a significant margin, yet keeping in consideration that it still takes human decision-making on issues that require critical decision making. In line with this, the customer facing applications which are AI based conversational agents will provide real time updated information, answer questions related to the policies, and explain the claim result in plain language.

Such interactions bolster the standard of transparency, responsiveness as well as customer satisfaction rates to address a growing need of digital-first, personalized customer interaction. Moreover, with the help of generative AI, the decision making process becomes more transparent as it can generate reasons and provenance by linking suggestions with provisions in the policy, former claims, or regulation. It does not only help human adjusters make regular and consistent decisions yet increases auditability and compatibility with several regulations. The inclusion of multimodal characteristics additionally allows getting pictures, documents, and text data together and allows AI-based systems to perform their evaluations and examine the claims and generate unified narratives, which fit operational and legal needs. Cumulative, the advances allow the insurers to handle higher volumes of claims with minimal effort and reduced operation costs and inaccuracies or leakages. Instead of substituting

human competence with artificial intelligence, generative AI develops the hybrid workflow that enhances precision, promptness, and consumer satisfaction, imposes the basis of more assertive decision-making, risk evaluation, and proactive interaction in the lifecycle of claims.

2. Literature Survey

2.1. AI in Insurance and Claims

The use of AI and machine learning in the field of insurance has grown to underwriting, risk prediction, pricing, and fraud detection. [6-9] Research shows that conventional ML models, including logistic regression, decision trees, gradient boosting and neural networks can make predictions regarding risk and identify an anomalous pattern that would be indicative of fraud. ML has been used in claims processing, namely in the estimation of auto damage, fraud scoring, severity prediction, and claims triage. In a systematic review, Bhattacharya et al. note that, although predictive insurance modeling is a well-established method in the automotive, property, and health aspects, the knowledge of generative AI application is little sparse. Such exploration of existing ML models is a limitation because most of them are optimized to do classification/regression, and generate numeric/categorical data of the task, but not to produce human-understandable explanations, summaries or advice. This creates a void in the available tools that can convert the structured domain knowledge into actionable narratives or communications and this becomes essential in claims adjudication and customer interaction.

2.2. Generative AI & Insurance Use Cases

Generative AI is another variant of AI with a potential future insurance application. The initial studies and reports by the industry suggest that generative models can help insurance specialists with writing letters, summarizing case history, formulating recommendations about the further steps and even with automated customer care. Indicatively, McKinsey notes that insurers that are applicable to adopt generative AI tend to have sophisticated data infrastructure and highly dynamic operating models and rigorous governance frameworks. According to IBM, there are three dimensions that it focuses on, including domain specificity, trust, and risk mitigation, and that generative AI is to be used as a supplement to human decisions, not to substitute them. The Bain estimates that the full-scale adoption of generative AI would save claims adjustment costs by 20-25% and leakage by up to 50%, so the introduction of AI is already felt by the company in reality. Latest efforts at to create a next-best-action-generation method illustrate how generative AI can suggest fast a decision to a simple claim and decrease the processing times and bottlenecks in operations. Moreover, multimodal generative AI models like GPT-4V(ision) are capable of integrating text and image reasoning, which allows analyzing images of claims (like sounding vehicle) and at the same time continuous generation of the stories of internal or customer documentation. This convergence principle between the structured predictive and the generative layer is an idea of convergence that symbolizes the novel hybrid approach of harnessing the accuracy given out by data and readable output by the human eye.

2.3. Challenges, Risks, and Governance

Despite that a promising prospect, the usage of the generative AI in insurance processes is associated with enormous challenges. One of the most crucial problems is adversarial vulnerabilities; models may be guided by pertinent small input perturbations into successful predictions or deceiving outputs. The AI research adversarial on insurance is based on the detection and mitigation actions. The other necessary criterion is explainability since the domain specialists and regulators must understand why a model proposes a particular settlement or has a concern with potential fraud. This is with a regulatory provision in the area of data privacy and insurance provisions and operational transparency that in most instances require audit trails and human controls. Organizations such as IEEE have suggested that responsible generation AI utilisation should be directed, e.g. disclosure practices or risk categories, and standards, such as IEEE P3396, that are based on a distinction between process risk and outcome risk. In addition, insurers also need to grapple with model drift, domain adaptation and data quality, in order to make performance predictable over time. The way, through the provision of governance structures, of proper human bearings, of surveillance systems and controls to escalation, this is secured, therefore, is of importance to maintain once the functions of the insurance industry are generative artificial intelligent control.

3. Methodology

3.1. System Architecture

An intelligent claims processing architecture that combines the generative [10-12] AI with the traditional AI/ML models is suggested by us with three layers.

- **Data Layer:** The system has its base as the data layer which takes many different structured and unstructured inputs. This consists of claim forms, pictures of damaged property or vehicle, written policy documents, past claims information and any external information source of relevance like weather reports or traffic logs. This layer is meant to arbitrate and normalize data in the solution in order to be fully used by the downstream models, such as completeness, consistency, and relevance to be correctly processed.
- **Core Modules / Logic Layer:** Core modules layer is the layer of system analytical and reasoning. The system is given the capacity to retrieve domain documents, policies, and past claims to give out contextually correct outputs through retrieval and indexing components. The use of targeted tasks like detection of fraud, severity estimation, and triage of claims using structured AI/ML models is based on predictive modeling to identify and raise risks and

prioritize the cases. Large language models (LLMs) and multimodal models are examples of generative AI designed to supplement structured AI by generating human readable summaries, textual narratives or combining both visual and textual reasoning, filling the gap between predictive results and direct insight into action.

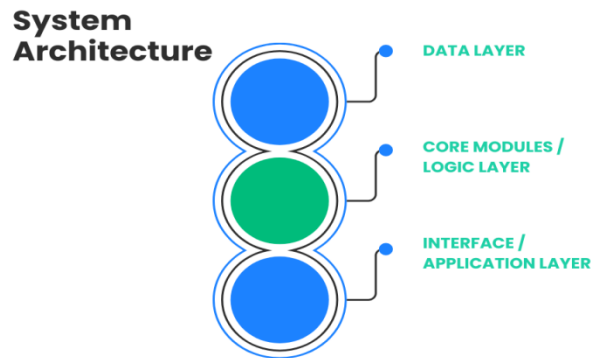


Figure 2. System Architecture

- **Interface / Application Layer:** The interface layer converts the system intelligence to the garnering of applications to the user. FNOL assistant takes claimants through loss reporting procedures, where the information is accurate and complete. Claim narrative generators convert structured information and model results to readable summaries to be reviewed internally or to be communicated to a customer. Conversational interfaces help the real-time engagement with the policyholders answering their questions and granting updates. Lastly, the decision explanation and audit module will provide transparency, which provides a way of understanding the computation of automated decisions, keep compliance and enable policy to support regulatory reporting.

3.2. Module Descriptions

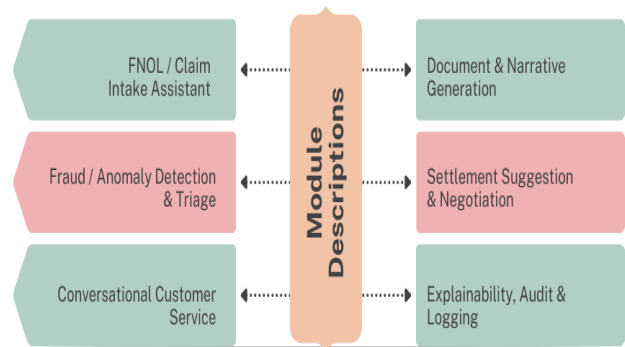


Figure 3. Module Descriptions

- **FNOL / Claim Intake Assistant:** FNOL assistant is the initial point of contact to interact with policyholders, they receive either free-text or voice statements regarding the incident. It receives the input by using large language models (LLMs) and prompt engineering to process the input and extract structured fields, such as date, location, and damage type. In case images are provided, a multimodal model authenticates the situation and suggests a preliminary classification of damage. Any unclear or dubious areas are marked accordingly to be reviewed by the human team and make sure to be efficient, accurate and maintain the monitoring of complicated or unusual cases.
- **Document & Narrative Generation:** The module takes advantage of domain-adapted LLMs to produce human-readable text outputs such as summary of claims, adjuster notes, letters to insured, and recommendations. It is also capable of generating a justification trace, tracing the generated text to the policy clauses, previous claims, or historical precedents that it is relevant to. This ensures that stories are well understood and can be taken to action with and in this case can be audited to contribute towards transparency and concerning regulation.
- **Fraud / Anomaly Detection & Triage:** Classical machine learning e.g. gradient boosting machines and neural networks test claims and estimate the risk of claims being potentially fraudulent or abnormal. The scores are then transformed into natural language descriptions by generative AI, e.g., The prediction is noted as questionable because the ruins of the damages are out of the chronology of geolocation. These understandings enable the Triage logic to offer an effective path of claims; low risk claims are quickly processed, medium risk claims are handled by an

adjuster, and high risk claims are met through a thorough investigation, which is far more efficient in the resource allocation and eliminating risk.

- **Settlement Suggestion & Negotiation:** In the simplest claims, the generative component can provide to settle claims based on past patterns of claim, reserves and policy limits. Interpretation In case it may require negotiation to be taken, the conversational agent will be talking to the claimant on fixed guardrails, referring to the policy terms, past claim and conventional pricing regulations. This module is well balanced and it helps to facilitate automation and resistance to the compliance objective and enhance customer experience through contextual and timely settlement offers.
- **Conversational Customer Service:** Chatbot interface will enable the clients to ask questions regarding their claims, e.g. where is my claim, why has this been offered etc. The LLM will respond with claim and policy information that are contextualized which provides clear, specific clarifications. In the event that the questions fall out of the system knowledge or should fall under human judgment, the module will automatically be handled by a live agent in order to guarantee responsiveness and quality of services.
- **Explainability, Audit & Logging:** All outputs of generative AI and structured models are also given with a history of the prompts that generated them (where available, e.g. attention weights) and provenance references (e.g. specific policy clauses). Any system decision and resulting output is audited, versioned and stored to allow audit examination, to guarantee regulatory compliance and to allow post-hoc analysis. This aspect builds trust because it gives a clear insight into why automated decisions and actions are made in such a way.

3.3. Algorithms and Formalism

The intelligent claims processing system proposed unites machine learning models that are structured and generative AI, which are used together to combine predictive analytics, [13-15] multimodal perception, and natural language generation. The structured ML modules, including fraud detection, severity prediction, and triage are provided at the core to be formulated as supervised learning tasks. Indicatively, considering the input historical claims data $(X) = [x_1, x_2, x_3, \dots, x_n]$ and the labels $(Y) = [y_1, y_2, y_3, \dots, y_n]$, a sequence of models are trained to risk a loss function $(L(y, f(x; \theta)))$, and θ is a symbol of the model parameters. Classifiers (e.g. fraud vs. non-fraud) or regression models (e.g. severity score) use gradient based optimization to learn θ . Simultaneously, the components of generative AI are addressed as the problems of conditional sequence modeling. When given an input context c (structured fields, textual description or images) the generative model G produces output sequence y such that the conditional likelihood $P(y|c)$ is optimized. In the case of multimodal inputs, text, image and tabular modalities are jointly embedded into a state $h = \phi(\text{text, image, structured data})$ which is used as conditioning context during generation.

A mixture of threshold based heuristics and reinforcement learning policies are used to carry out triage and routing decisions. Structured model $S(x)$ fraud/anomaly scores are converted to natural language rationales R using the generative model, which is interpretable. Settlement Suggestion Model and negotiation are based on a utility maximization, i.e. U_c versus U_r , and an offer O is chosen to maximize expected utility $E[U_c + U_r]$ subject to policy constraints. Formalization of logging, audit, and explainability Logging: provenance mapping functions $\pi(\text{output})$ in means of responses are ensure that any decision can be tracked. Overall, it is a hybridized system a product of probabilistic, deterministic and generative components which interrelate with one another through distinctly identified interface, allowing predictive precision and comprehended consequence and control. Formalism provides it a backdrop to maximize the performance of the models, accountability, and multimodal integration of information in the claims processing processes.

3.4. Training, Fine-Tuning, and Domain Adaptation

The success of the suggested insurance claims system means the specialized training, fine-tuning, and domain adaptation of the pre-trained large language models (LLMs) and multimodal AI elements. First, general-purpose LLMs are fine-tuned on domain corpora, such as policy texts, histories of claims, texts of regulations, and legal judgments. This mechanism will make sure that the model is conversant with insurance terms, policy terms, claim patterns, and domain reasoning. Fine-tuning The strategy of fine-tuning is normally annotated set learning based on a comparison between the model output and human-generated references, with the error defined by its difference. Retrieval-Augmented Generation (RAG) methods are used in order to achieve better retrieval and factual grounding. RAG relates the LLM with indexed policy documents, historical claims, and external knowledge, and by doing so, the model can access the relevant information at inference time and respond based on authoritative sources instead of using knowledge acquired in pretraining.

It is necessary to apply multimodal fine-tuning to connect a visual and textual information. Photographs, diagrams, or scanned documents that have been damaged are coupled with textual accounts to educate models that can match visual proofs with a textual account. This can help in automated operations such as assessment of the damage, creation of a claim narrative and a verbal assurance between incidents covered and evidence provided. The consistency of models in the human-in-the-loop (HITL) mechanisms is also ensured because the field experts can view the output, correct the malfunction, and provide feedback. Such corrections are refuted in the loop of training and this will prove helpful in reducing early defects or mistakes made by the veteran. Tracking model drift and retraining on more recent claim information periodically are also areas of

domain adaptation because the model must be applicable to the existing policies, trends of fraud and cases of new kind of claims. RAG integration, fine-tuning and multimodal alignment with HITL feedback are integrated to generate a robust adaptive system, capable of processing complex insurance data to generate context-sensitive correct discourses and making reliable and transparent claims workflow decisions.

3.5. Evaluation Metrics

The intelligent claims processing system performance measurement will be necessary to be multi-dimensional likened to its capacity to reflect the technical performance as well as the user-based outcomes. [16-18] The first axis is speed and efficiency and it is measured based on the turnaround time of action on a claim submitted by the customer. This is not only in order to ensure a quick claims processing; it reduces the operation bottlenecks of the system that makes the operation process more efficient. Seized data, that is associated with a date, place, or the nature of damage, is required to be precise and accurate. The measurement of the incidence of the erroneous elements gathered or incorrectly amalgamated is termed as the field extraction error rate that is utilized to record the credibility of the structured ML structures and generative parsing modules. The other dimension that is highly important is the offer quality that is said to be tested against the amount a given settlement should have historically with use of past information, policy conditions and actuarial provisions. This is the measure which is the one that quantifies the concept of being near that the suggested may be supposed to provide and will be treated in a somewhat fair and consistent way.

Customer experience is captured by conducting surveys such as Customer Satisfaction (CSAT) scores that provide the first hand account on how the claimants perceive the system, in regards to their clarity, responsiveness and helpfulness of the system. Explainability is also a prominent one; the human experts will also prioritize on the quality of generated rationale and explanation tracks; the reasonability of the model will be evaluated by the human expert, and whether the models make sense, and are understandable and receptive as well. This renders its outputs to its adjusters, regulators and customers as dependable. Finally, risk and safety are measured on a basis of the number of hallucinated or false material in generative works. The fact that the number of incorrect or fabricated statements is observed interests the reputational, legal and financial risks of insurers and lets one know changes in the retraining or fine-tuning of models. The combination of these evaluation axes will be a comprehensive methodology, in which the priority is assigned to speed, accuracy, customer satisfaction, interpretability and security to provide practical information that is expected to keep on improving and is guaranteed that AI-aided claims processing is also likely to meet the operational and regulatory needs. Having both quantitative and qualitative measurements of the system, that can be optimized by the application of the experts, the system in its turn is able to improve, so that it becomes even better and will produce maximum performance, trust and customer outcomes in different circumstances of claims.

4. Results and Discussion

4.1. Pilot Setup

In order to test the suggested AI-assisted claims processing system, we organized a pilot implementation with one mid sized property and casualty (P&C) insurer with the help of a pilot set of 1,000 anonymized claims across auto and property lines. The main goal of the pilot was to determine the practical usefulness of the system, its functionality and compatibility with the current workflows and retain the human control over the key choices. The control or the baseline involved the normal workflow of the insurer where the claims are processed manually with the use of conventional tools and procedures by the adjusters to review and process the claims. The GenAI-assisted modules, such as the FNOL assistant, document and narrative generation, fraud/anomaly detection, and settlement suggestion, were concurrently run on par with human adjusters in the pilot. Although the AI modules created automatic structured extractions, predefined summaries and proposed further steps, the ultimate approval and settlement of claims was specifically limited to human adjusters. This design made sure that automated decision did not have a direct influence on claimants, as they were kept in compliance and safe and were capable of collecting comparative performance data.

All AI generated outputs were stored and compared to those made by the human beings so that the quality and efficiency of offers, as well as the explainability, could be analyzed in a more detailed manner. Moreover, human adjusters were proposed to provide feedback on the ease of use, clarity and credibility of AI suggestions, which created a human-in the loop feedback mechanism of over and overrefinements. The conditions of operation offered by the running of such a system in a kind of controlled but realistic environment would enable to estimate on the effectiveness of the system on the matters of claim processing speed, data extraction and reduction of human work frailty, not subjecting the insurer or the policy holder to unwarranted risk. This pilot was also used to identify domain-specific problems such as dealing with ambiguous inputs, multimodal data combination, and interpretability preservation which were used to further fine-tune the model, train and build a workflow. In general, the arrangement enabled a safe, quantifiable, and implementable assessment of the incorporation of generative AI into insurance claims activities.

4.2. Quantitative Results

Table 1. Quantitative Results

Metric	Improvement (%)
Avg turnaround time	45.8%
Structured extraction error	63.5%
Settlement deviation (MAE)	34.6%
Fraction of claims fast-tracked	133.3%
CSAT score	12%

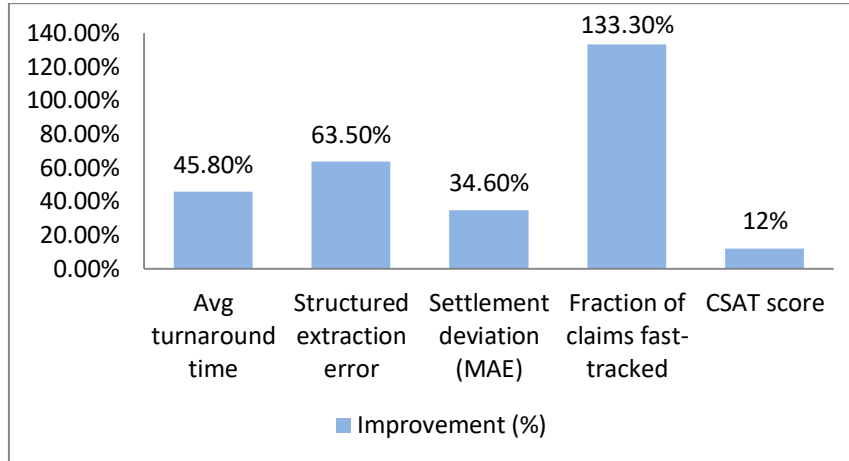


Figure 4. L Graph representing Quantitative Results

- **Average Turnaround Time (45.8% improvement):** The time used in terms of processing of the claims is less because the workflow with GenAI realized less turnaround time which was only around 26 hours compared to the 48 hours in the baseline workflow. This gain shows what efficiencies can be obtained based on structured extraction, preliminary triage and narrative generator to enable human adjusters assess other higher value activities and shift responses to policyholders faster.
- **Structured Extraction Error (63.5% improvement):** Field extraction was made much more precise when the given models were supplemented with LLMs and multimodals. The accuracy was decreased by half (8.5% in the manual baseline against 3.1% in the GenAI-assisted workflow). This decrease is a good sign that the analysis of free-text descriptions, voice inputs and images with the aid of AI can be used with certainty to generate structured data to further analyze, thus minimizing the number of corrections made by humans and enhancing consistency.
- **Settlement Deviation (MAE, 34.6% improvement):** Settlement recommendations produced by the AI were within the proximity of benchmark or expected funds than the baseline. The average error arrived at as reduced as compared to the previous one of 1,300 to the present cost of 850 as a result of the system allowing it to use historical claims information, policy guidelines, and predictive modeling to make reasonable and correct settlement approves without breaching the policy parameters.
- **Fraction of Claims Fast-Tracked (133.3% improvement):** The rate of claims that can be fast-tracked increased more than twice, namely 12% to 28%. The system allows faster process of simple cases, where the automated identification of low-risk claims and the generation of justifications, facilitates faster processing of simple cases, therefore allocating adjusters focus on complex or high-risk claims.
- **Customer Satisfaction (CSAT, 12% improvement):** Satisfaction was reported at 4.3 out of 5 which is a 12-percent growth when compared to the 3.7 index reported in the previous year. It is indicative of improved communication, enhanced responsiveness, and improved explanations produced by the AI modules, which proved that intelligent automation does not only help increase the efficiency of operations, but it also allows improving the general claimant experience.

4.3. Qualitative Observations

Qualitative observation performed during the pilot deployment was instrumental to provide a decent notion of the performance in the real-life setting, usability, and limitations of the GenAI-assisted claims processing system. The adjusters claimed that a large part of the generated explanations were highly useful in regards to documentation and justification of claims, and this helped these adjusters to write coherent stories and explanations to be examined internally or to defend the customers. Such AI created evidences were often valuable indicative policy provisions, past assertions, or situational information that would allow the adjusters to be more efficient in justification of said evidence. In certain cases, however, the generative offer propositions were prohibitively conservative as compared to historical settlement or what the claimant

expected. This involved human intervention and this portrays that despite the fact that AI can help in the decision making process, there should be human consideration in making final settlements and subtle settlements during the process of negotiations. There were also few hallucinations in which the system stated some policy words or the claims of the past which were nonexistent.

In the case, the explainability and audit module could detect these inaccuracies demonstrating that sound logging, and human-in-the-loop can be used to avoid any possible failures due to incorrect or biased results of claims. In addition, there was an indication of model drift during the pilot. Structured extraction was more likely to be erroneous, more so in claims that had unusual pattern of accidents, unusual property layout or unusual pattern of accident. The results of the observations made allowed concluding that the constant monitoring, periodic retraining, and domain adaptation, which would make the model correct and reliable in the long term would be required. Overall, the qualitative experience helped me to concentrate on the values of the importance of the system regarding making the claims processing more efficient, consistent, and transparent and necessitates human control, audit facilities, and sustained maintenance of the model in order to address the cases of edges, eliminate hallucinations, and spare trust. This knowledge may be utilized to automate processes, improve training information, and keep on synchronizing the generative AI output with the goals of the adjusters and the policyholders.

4.4. Discussion & Tradeoffs

- **Risk vs. Automation:** Even though most automation can lead to considerable efficiency increase, it is also associated with the danger that it should be approached cautiously. High-value claims with complexities and ambiguities are expensive to go unnoticed and result in beneficial financial and reputational risks thus requiring a full human-in-the-loop outlook within this scenario. A hybrid deployment pattern is the realistic tradeoff between safety and operational efficiency which in any condition of high-risk, expressly automates the low-risk that we have and delegates the high-risk cases to the management of humans. This will ensure that automation will not reduce the speed at which the normal process is to be executed but still it provides accuracy and accountability.
- **Explainability and Trust:** It is also factual that when there is clear thinking among the users, the confidence in the AI process of making decisions grows exponentially among the users. Presentation of provenance on model suggestions (explaining about a specific policy clause or historical assertion e.g., Clause 12.4, precedent in 2021 claim #X) also predisposed model suggestions more to have a preferential effect on the adjusters. Those roots will help a human being to understand the logic behind the recommendations, and, therefore, avoid the potential errors. Nevertheless, large language models do not have a clear internal rationale, and additional studies are required to facilitate the improvement of transparency and interpretability (particularly, to regulators and auditors).
- **Data, Privacy, and Governance:** The privacy policies, such as GDPR, and the anonymization practice standards must be followed when handling sensitive insurance claim data. The issue of the generative models is that as well they are capable of memorizing or recreating any private information unknowingly. The mitigation of such risks should be avoided by making sure that good governance is used, access controls and comprehensive audit logs are in place. These are useful in ensuring that there is compliance, protecting data of policyholders and provide traceability of any output of the AI to maintain legal and ethical standards of production deployments.
- **Model Robustness & Adversarial Safety:** Insurance processes based on generative and predictive models are prone to adversarial manipulation where the genuine but minute perturbation can be used to mislead a prediction or story generation. The way out of it is to execute adversarial testing, input sanitisation and verification of robustness in pipelines. Adversarial AI in insurance has resulted in having the most prevalent attack vectors and defense schemes, on which defensive measures can be developed. Malicious inputs in models are prevented by providing model robustness and the system reliability is ensured particularly in high stakes claims processing systems.

5. Conclusion

The paper has summarized a design that introduces the generative AI in property and casualty (P&C) insurance claims and customer service processes in a systematic architecture, module design, training plan and fine-tuning, and pilot check. Our proposed three-layer architecture will consist of a data layer through which we will ingest both structured and unstructured inputs then a core logic layer which will be composed of traditional AI/ML and generative AI models and finally an interface layer comprising of applications that the user can utilize, this will include FNOL assistants, narrative generation, settlement suggestions and explainability modules. The pilot study consisting of 1,000 anonymized claims demonstrated huge improvements in the GenAI-supported system compared to the base workflows including increased turnaround rate, higher structured fields extraction accuracy, reduced settlement variance, increased fast-track claims, and rated higher on customer service. Such results signify useful operational benefits, including potential specifications on costs, including reduced cost of adjustment and leakage and augmented clarity and enhancing human choices.

Nevertheless, some disadvantages also should be considered. First of all, the pilot results can be considered exemplary and not fully applicable to insurers with variable wage of claims, claims types, or associated with the peculiarities of the field. Secondary, the AI models need the capability to experience hallucinations and malfunctions e.g. to make a wrong reference to the policy provisions or not to understand the particularities of the claim, which is the rationale as to why the integration of

human control and audit flows remains necessary. Third, it is not fully explainable, provenance trace and rationale summaries increase trust, but the overall clarity of what the inner workings of LLM do is not a reality. These also be a variance in legal and regulatory limitations in various jurisdictions and it means that the deployment plans should be appropriately coordinated with the local compliance. Finally, the automated decision business and human judgement border is thin; artificially intelligent middleground processes must be highly adjusted to favour efficiency or risk avoidance.

Its future direction includes federation or collaborative GenAI approaches every time, where training of models conscious of contractual commitments and regulatory constraints, the dissemination of model improvements made anonymously with no transmission of sensitive data to the insurers. The advanced administration of multimodals would be applied where satellites photographs, drone shots and structural scan with textual description would be used to enhance the assessment of claims. The causal modeling and counterfactual generation idea could also allow the insurers to estimate the outcome of the so-called what-if-type problems (added cost, etc.) to make decisions and measure the risk. In addition, the reliability and accountability are going to be improved by combining trust and governance schemes, such as IEEE P3396-like risk assessment, and monitoring, the identification of model drift and reinforcement learning basing on human corrections. In conclusion, although it is a radical perspective on P&C insurance, with increased efficiency, accuracy, and customer experiences, safe and successful implementation should be well-considered according to detailed system architecture, active human-level supervision, domain customization, and governance that emphasize the existence of trust, compliance, and operational resilience.

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