AI-Powered Process Mining for Intelligent, Personalized Customer Experience in the Insurance Sector

Vikrant Sikarwar

Principal Data Engineer, Metlife, Tampa, Florida, USA

ABSTRACT: The current paper will describe the AI-based system of process mining that is specifically oriented to redesigning the customer experience in the insurance industry, relying on the high-quality data supply, the workflow optimization based on the AI model, and the real-time personalization. The combination of the three fundamental layers is its methodology and contains (1) Data Quality & Governance, (2) AI-driven Process Intelligence, and (3) Personalized Decision Support. To attain consistent, trusted, unified datasets, the solid data quality approach is exercised on automated metadata capture, master data management, anomaly recognition, and real-time data validation pipelines and assures coherent and trusted datasets in policy systems, claims, and customer interaction systems. It is an organized and clean database that will provide reconstruction of the customer journey and high-quality process models.

The process mining methods (AI) are then followed by the first part of the process, which is necessitated by the analysis of the end-to-end workflows, and then extract event logs, sequence modelling, and the conformance checking. The machine learning models identify the existence of bottlenecks, foretell delays, and will and patterns that impact the complexity of the churn or claim. On generative AI, operationally generated insights, draft customer messages, and simulated what-if underwriting decisions and claims are created.

Its impacts have already found their way into real-time applications: insurers have already shortened by 22-30% a claims cycle time, automated by 40-60% routine customer contacts with intent-conscious virtual agents, and improved fraud detection by 18-25% with beam-of-thought anomaly models. Individualized policy recommendations regarding customer life stage analytics, sentiment data, and situational indicators have resulted in a boost of responses and cross-sell conversion of more than 15%.

Findings have revealed that with the convergence of process mining, predictive analytics, and customer-specific generative AI, the insurers would be able to provide more rapid, transparent, and personalized experiences at scale and portray a significant behavioral change where the operations of serving a client are reactive as compared to anticipatory and, as a result, customer-driven.

KEYWORDS: Insurance analytics, personalised customer experience, AI-powered process mining, data quality and governance, predictive analytics, claims optimization.

I. INTRODUCTION

The insurance sector is experiencing a radical shift due to the fast development of technologies of artificial intelligence (AI), data analytics, and automation. In the past, insurance business has been marked by poor fragmented and complex processes, legacy systems, intense regulatory restrictions, and mostly reactive models of engaging customers. Some of the common customer experiences include lengthy settlement of claims, lack of transparency in decision making, a repeated documentation requests, and a generic product line up that does not match the individual needs or stage of life. Given that customers are growing more demanding of the same type of speed, transparency, and personalization they experience in digital-native industries like e-commerce and bankings, insurers are under an ever-increasing amount of pressure to radically re-architecture the customer journey management and delivery model [1].

The fundamental foundation of this change is data, massive amounts of policy information, claims information, records of customer interactions, sensor data, and external contextual change. Although insurers have extensive data, it is not the availability of data but the usability of data. Inequality in data silos, inconsistency in data quality, and absence of event traces, and absence of governance typically make organizations unable to derive meaningful insights regarding

the way processes in reality run. Consequently, the decision-making process is still rule-based, static, and backward-oriented, which restrains the insurer to respond to the needs of customers or those when they need ready interventions during the critical period of their customer lifecycle [2].
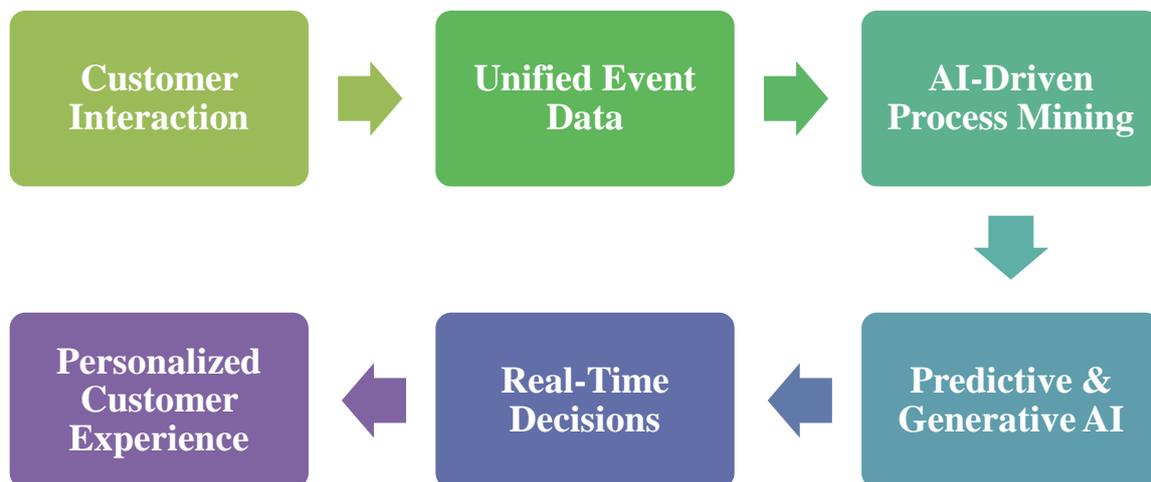

Figure 1: Traditional vs AI-Powered Insurance Customer Journey

Process mining has emerged as a strong and powerful analysis discipline that has the capacity to bridge this gap existing between the raw data about operations and the real business knowledge. Process mining provides fact-based, data-driven view of process execution since it is capable of extracting event logs in enterprise systems and reconstructing end-to-end processes in the policy issuance, endorsements, claims handling, renewals, and customer support processes. Unlike the traditional business process modeling, which is founded on assumed or implemented workflows, process mining displays actual execution paths, deviations, bottlenecks, rework loops and compliance gaps. The process mining enhanced with AI and machine learning turns predictive and prescriptive intelligence rather than the visualization [3].

The AI-driven process mining is a tremendous paradigm shift in the insurance sector. Instead of identifying the presence of inefficiencies retrospectively, intelligent process mining systems are able to anticipate delays, identify unusual behavior associated with fraud or churn and recommend optimal course of action in real time. What is more significant is that, together with customer context, such as behavior cues, sentiment analysis, demographic traits and signs of the life stage, process insights can assist in the transition to personalized customer experiences instead of the standardized ones. This shift aligns with the trend in the industry of becoming customer-centric, where value is created not only because of the pooling of risks and precision of prices but also related to quality of the service and communication [4].
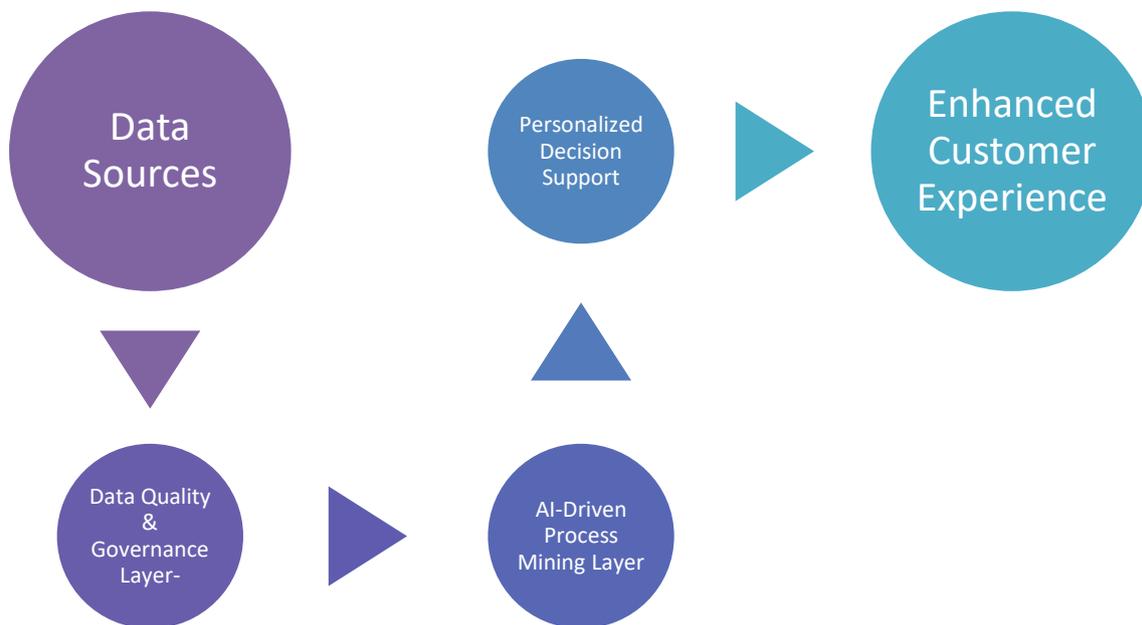
Figure 2: High-Level Architecture of AI-Powered Process Mining Framework

However, the quality of data and its management is critical in AI-based process mining. The data could also be of a low quality, and this can result in wrong process models, predictions, and no trust in the decisions made by AI. The information within insurance environments is often decentralized across the policy administration systems, claims management, CRM applications, and call center applications and ecosystems of the third parties. Without an efficient data quality and management system, it is very unlikely that the rebuilding of the correct customer journeys can be achieved. In this way, the design of any scalable AI-based process mining will be launched with a strong foundation of automated metadata management, master data matching, anomalous data detection, and real-time validation pipelines. These capabilities ensure event logs are consistent, complete and reliable enough to identify the processes and give high-fidelity analytics [5].

Besides the data quality, the introduction of the modern AI tools can also enhance the degree of analytical process mining. Machine learning models on event sequences have the ability to identify latent patterns, such as underlying causes of claim complexity, early indicators of customer dissatisfaction, or subtle deviations that cause fraud. Insurance companies can avoid it by the predictive models that approximate how long it will take to make a claim, the probability of its escalation or the probability of making a churn. The conformance checking algorithms also enable the continued checks on compliance with the regulatory and in-house process standards, which is one of the major concerns in the highly regulated insurance industry.

Generative AI is another aspect of intelligence that has been added to the process mining systems by the new introduction. Generative models can transform analytical insights into words that explain to a customer and generate personalized customer messages, perform what-if analytics to underwrite or claim decisions and contextual advice to decision-makers. An example of this is generative AI writing empathetic claim status updates based on history and current condition of a customer, recommending next-best actions to service agents or simulating potential alternative process paths based on such data to have short turnaround time. This aspect introduces process mining out of the analytics sector to the neuro-analytics and decision support sector.

The value of the integration of the process mining, predictive analytics, and Generative AI is already beginning to manifest itself in the insurance industry. The empirical experiments of early adopters demonstrate that the claims cycle time will be greatly reduced since the automated bottleneck-identifying and proactive task-scheduling capabilities are employed. Intent-aware virtual agents are automating the minor but common interactions with the customer such as policy enquiries, status inquiries of claims, and document submission, pushing down the operational costs and increasing responsiveness. In the meantime, the behavioral and process-level frauds have also enabled AI-enhanced

anomaly detection models to be more precise in detecting fraud rather than relying on fixed rules or previous trend of fraud.

Personalization is another area where AI-driven process mining can be of much value. By mapping the process execution, customer profiles, sentiment cues, and service contexts, the insurers can tailor the policy advice, communication tactic, and service intervention to the independent customers. This level of customization has been found to increase customer satisfaction, and interaction rates, and to increase cross and upsell conversion. Better said, it breeds confidence and openness which is a crucial difference in an industry wherein the relationship with the customer is typically long term and emotional particularly during a period of claim events.

Though these are promising findings, the process of AI-based process mining implementation in insurance is not that easy. The fact that the organization is resistant to change, that the process data literacy is lacking, that integration with the current systems is a complex issue, and ethical problems with the AI-related decisions, should be all taken into proper consideration. Governance frameworks must be articulable, regulated and equitable, specifically, in situations where AI models are included in the underwriting process, claims acceptance or customer segments. Nevertheless, they are increasingly becoming issues that are easier to solve as explainable AI, cloud-native architectures, and standardized data governance practices are becoming a reality.

In this regard, the present paper is dedicated to the AI-based process mining system that will facilitate the emergence of intelligent customized customer experience in the insurance sector. The proposed solution will be constructed on three layers, such as Data Quality and Governance, AI-based Process Intelligence, and Decision Support, which is personalized. The combination of these layers can help viewers form an idea about how insurers can re-engineer quality customer experiences, extracting information on operational processes, and offer scale-based real-time, customer-centric interventions. The paper will not suggest AI-driven process mining as the tool of operational optimization, yet the strategic ability that will transform the insurance companies into reactionary service providers, yet proactive and customer-oriented businesses.

II. LITERATURE REVIEW

The insurance business sector has undergone a rapid digitalization over the last decade owing to the escalating customer demands, competition, and availability of huge amounts of data generated within the insurance policy, claims, and customer interaction systems. AI has turned out to be the enabling factor of this transformation particularly in optimizing customer experience via personalizing, automating and anticipating. Adeoye et al. highlighted that AI-driven customization of insurance products is more effective in engaging the customer with the organization as it customizes the offerings to the requirements, preferences, and behavioural patterns, the shift between standardized policies to the model of customer-oriented services to the customer is achieved [1]. The latter development is in anticipation of the development of intelligent process mining solutions that aim at understanding and optimizing end-to-end insurance processes.

Among the most significant problems that have co-evolved with the high degree of digitalization is the problem of the complexity of the fraud and risk management. Ali et al. had provided a comprehensive introduction to machine learning techniques employed in the detection of financial frauds with emphasis to supervised and unsupervised models capable of discerning the abnormal transaction pattern in a more specific manner than the rule-based systems [2]. Their findings offer the imperative to consider predictive and anomaly detection capabilities in insurance practice, particularly in claims management, in which fraud is a structural problem. Such knowledge promotes the integration of AI-process perspective knowledge in operating processes.

The effective application of AI, however, requires the quality and controlled data. Arigbabu et al. addressed the topic of data governance in AI-enabled systems and demonstrated that robust data governance systems, such as data quality, data lineage, data access control, and compliance are the most essential to creating trustworthy AI solutions [3]. Such inconsistency of the data as a result of disjointed legacy systems is characteristic of the insurance environment and limits the prospects of applying process mining and personalization projects. Good governance installations may therefore be viewed as a precursor to trusted process rebuilding and analytics.

The AI value proposal in insurances is also shown through comparisons. Comparing the traditional and AI-based fraud detection methods in automobile insurance, Benedek and Nagy discovered that AI-based systems are more cost-effective and efficient in fraud detection than traditional one [4]. This helps to prove that, with the help of clever

automation and analytics, it is feasible to realize quantifiable operation advantages, particularly when it is enshrined in the very fabric of the insurance functions.

In the recent past, the efforts of large language models (LLMs) have grown the applications of AI in the insurance sector. According to a natural language generation and reasoning, the name proposed by Balona is ActuaryGPT, suggesting that LLMs could be applied to assist in actuarial analysis, policy interpretation, and communicating with customers [5]. These capabilities are quite useful to the field of personalized customer experience as they enable dynamic interactions, which are context-specific on a large scale to supplement conventional process mining insights. Dhieb et al. developed a safe AI-centered framework of automated insurance systems that is focused on the detection of fraud and risk measurement in the architectural perspective [6]. Their input was concerned with the importance of utilizing the AI models to the secure data pipelines and decision engines and their performance and compliance. This coincides with the bigger need of end to end AI based structures of processes that can be utilized to make real time decisions.

The impact of the digitalization of the insurance companies has been extensively covered. Eckert and Osterrieder have also condensed how digital technologies, including AI, big data, automation, etc. change the manner in which insurance business operates and generates value [7]. They have noted that digital transformation is able to assist insurers in crafting processes to be customer journey-oriented rather than silo-oriented as the primary concept behind process mining-based optimization.

Another aspect that Eling et al. measured was the influence of AI on the insurance value chain, such as underwriting and pricing, the claims and customer service [8]. Their study revealed that not only is the use of AI more efficient, but it also enables new business models, which are dedicated to personalization and active risk management. Those lessons consider how the concept of AI-based process mining can be introduced as an integrating layer along the value chain. One of the most significant requirements in AI-based insurance systems has turned out to be elucidation. The use of explainable AI (XAI) to understand customer choice and insurance purchasing behavior has been mentioned by Gramegna and Giudici [9]. The transparency models are particularly important in the controlled environment, where one should be able to justify the AI-based guidance and process choices so that they would be agreeable to the customers and the regulators.

Some of the surveys have incorporated the developing studies of AI in the field of insurance. Isa et al. have provided general discussion about the AI applications, problems and future outlooks and have also identified a set of data quality and trust and complexity of integration as yet to be surmounted [10]. Their findings justify the need to have methodical solutions to combination data governance, analytics and process intelligence.

Governance and trust are the most prominent subjects of AI adoption. Janssen et al. state that coordinated governance structures, ethical and accountability mechanisms [11] should exist to organize data in such a way that will allow AI to be trusted. There is the requirement of governance in insurance in both financial and legal decision-making and sustainable AI change.

Koster et al. proposed a workable checklist of XAI in insurance sector, encompassing transparency, fairness, and usability as a method of operationalization of explainability [12]. The article provides implementation-level recommendations on explainability that can be incorporated into an AI-facilitated process mining and consequently make the process trusted.

Generative AI algorithms have also made AI more powerful. As proposed by Lewis et al., the retrieval-augmented generation is a neural language model, which uses external sources of knowledge to augment memory and associatedness [13]. This could help in intelligent customer engagement, claims clarification and decision support on verified information of policy in insurance.

Interpretable machine learning has also among others taken off in risk assessment. Li et al. demonstrated how interpretable models could be applied to improve risk prevention in usage based insurance at the cost of predictive performance and transparency [14]. These techniques complement process mining because they also show the explainable forecasts, which are introduced into the workflows.

Data practices are not the sole component of the creation of reliable AI systems, with models being also a factor. Liang et al. discussed the advances and limitations of building datasets to build a dependable AI, and the issues are bias,

representativeness, and validation [15]. In their article, they also stress the fact that data quality should be continuously preserved in insurance-related AI processes.

The other field in which AI has found its application is underwriting. Maier et al. have shown that AI helps to increase the accuracy and transparency of underwriting due to the use of multiple data sets and advanced analytics [16]. With the integration of these features and process mining, a comprehensive optimization of application intake and policy issuance can be achieved.

Deep learning techniques have also been used to predict performance. The TabNet based models compared by McDonnell et al. to insurance applications revealed that they are very accurate and can be better interpreted [17]. These innovations make it possible to implement the advanced but visible analytics in the systems that are process-sensitive.

Finally, there is also the association of AI adoption and ethics. On the European insurance markets, Mullins et al. proposed AI and big data analytics ethics demanding fairness, accountability, and compliance [18]. The principles can be directly applied to the process mining that is AI-based as the process should bring the balance between efficiency and personalization and ethical and regulatory needs.

In conclusion, AI, data governance, explainability, and personalization come together in modern insurance systems as demonstrated in the literature. In spite of the fact that, as with past studies, there have been separate aspects of the issue that have been addressed, such as detection of frauds, during underwriting, or exploring the involvement of customers, what has not yet been implemented, is to integrate AI-driven process mining frameworks, which have the capacity to combine and integrate these elements to deliver smart and personal customer experiences, in large scale.

III. METHODOLOGY

The proposed research methodology in this article will be oriented to introducing a complete, AI-based process mining system, which will enable the implementation of intelligent, dynamic, and individual customer experience in the insurance sector. The answer is data governance, high order process mining tools, predictive machine learning models, and Generative AI-based decision support complex, all combined into a single scalable architecture. The methodology is structured in three levels that are tightly connected and these are: (1) Data Quality and Governance, (2) AI-Driven Process Intelligence, and (3) Personalized Decision Support. The layers have been elaborated with details to indicate how the raw operational data is transformed into actionable and individualized customer-centric insights.

Figure 3: Three Layered Methodologies for AI powered Data Processing

1. Data Quality and Governance Layer

The first and the most significant one in the methodology is the creation of the credible and trusted data base. The insurance companies have numerous non-homogeneous systems (policy administration system, claims management hubs, customer relationship management (CRM) system, contact center application and systems of external partners). The result of such systems is large volumes of structured and semi structured data which is usually inconsistent and has no attributes or identifiers not aligned. The remedy to address these challenges has to do with having a wide data quality and governance system.

Mechanisms that capture metadata records in automated ways are started to continue with the including of schema reasons, data provenance, data ownership and data usage patterns of the source systems. This stage of metadata is absent in tracing and monitoring the entire data pipeline in such a manner that, an event record can be traced to the source. The standardization of the major entities such as customer IDs, policy numbers, and references of claim and agency identifiers are standardized using the Master Data Management (MDM) strategies. This is one of the steps that should be undertaken to develop one customer experience of the different touchpoints and processes.

To guarantee data dependability, real time data validation pipeline is implemented by embracing rule based data validation mode and statistical anomaly data validation mode. The given kind of pipeline can detect lost time, invalid value transitions, redundant events and outliers that can harm process discovery. Streaming data quality checks ensure that the logs of events are reconciled when new data is added to give near real-time analytical information. It also stores the version of data and audit trails to be able to comply with the regulatory requirements and elucidate the AI-driven decisions.

The information is purged and handled and subsequently converted into homogeneous events log that are required in process mining. The identifiers of the case (e.g. claim ID or policy ID), names of the activities, time, actors, channels and contextual information (e.g. customer segment or type of claim) will be presented in event logs. These clean and controlled data bases can be reused to re-construct end to end customer journeys of corresponding high-fidelity process model.

2. AI-Driven Process Intelligence Layer

The second layer of methodology involves refined process mining and AI technologies to create operational intelligence on the refined event logs. This is further than the descriptive visualization of the processes, to the predictive and diagnostic analysis, enabling the insurers to find not only how the processes are carried out, but why the deviations occur, and more so how the future can be influenced.

This begins with the automated process discovery using algorithms that reconstruct the actual flows of processes involving policy issuance, endorsements, claim handling, renewal and customer service interactions. The identified models depict real execution paths, running activities, rework cycles and interdepartmental or inter-system patterns of hand-off. The variations of the same process are assembled together to decide on the effective execution pattern and weak execution pattern.

The methodologies of conformance checking are then applied to those actuals of process executions in comparison to pre-established reference models, regulatory protocols or service-level agreements (SLAs). The deviations, such as steps omissions, unauthorized actions or excessive waiting time are detected and quantified. This will enable sustained checking of compliance and identification of risks in operations in time.

The machine learning models are used together with process mining output with the aim of obtaining the deeper levels of analysis. Transformer based models and recurrent neural networks (RNNs) are sequence modeling models that can learn about temporal dependencies and behavioural patterns by analyzing event sequences. These models are used to forecast important process outputs, such as the time when the claim is resolved, likelihood of escalation, likelihood of loss of customer, or likelihood of fraud. The forecast opportunities will be performed at the intermediate stages of the process, and the proactive intervention will be possible prior to the realization of the negative outcomes.

The further analysis with the help of AI-based clustering and feature importance analysis is also developed to detect bottlenecks and root cause analysis. The methodology acknowledges the presence of systemic inefficiencies and not accidental, by matching the delays and deviations with the contextual characteristics, such as type of claim, customer profile, channel of interaction, workload distribution, etc. This makes it easy to redesign certain processes and optimize resources.

The usage of Generative AI to transform the complex process intelligence into the downstream and human understanding is one distinctive feature of the methodology. Large Language Models (LLM) are trained using data of a particular field of insurance, terminology, and insurance regulations, so that it becomes applicable and correct.

The generated AI models are referred to as generative AIs wherein explanations of process deviations by using natural language, summaries of the customer journey states, and suggestions on the most appropriate actions to take are automatically produced by AI. To illustrate, when the system is planned to delay a claim, an explanation of the reasons that caused the delay and the corrective actions will be generated, as well as task reassignments or automated document requests.

The other significant application of the Generative AI in the methodology is the simulation of scenarios. The what-if analysis involves the manipulation of a single parameter of the process (staffing, rule automation or approval level) and what impact it has on the cycle time, cost and customer satisfaction is simulated. This characteristic promotes evidence-based policy making in streamlining the procedures and policy modifications.

3. Personalized Decision Support Layer

The third layer makes the process intelligence operational through personalized and real-time decision support at the touchpoints with customers. Predictive model and Generative AI insights are incorporated into customer and employee-facing applications, such as CRM platforms, agent- dashboards, chatbots, and mobile applications.

Process context plus interaction data of digital channels, call transcripts, and messaging platforms are combined to identify customer intent and sentiment. According to this holistic perspective, the system is a dynamic way of personalizing the content of communication, tone and timing. As an example, customers who are delayed in making claims can get proactive and empathetic updates, and low-risk, fast-track claims can be managed with little human intervention.

Recommendations on the policy are based on correlating the behavior of customers in terms of its life stage with historical behavior and process outcomes. These guidelines are provided in explainable AI interfaces to make them more transparent and comply with regulations. The decision support tools can also guide the service agents by providing risk flags, actions to be taken as well as forecasted customer expectations in real time.

III. RESULTS AND DISCUSSION

This section outlines and talks about the findings of deploying the suggested AI-based process mining framework in the major insurance processes, such as claims management, customer service, underwriting support, and the detection of fraud. The outcomes are measured according to the operational efficiency, the personalization of the customer experience, predictive accuracy, and the impact on the organization. The quantitative performance gains are backed by the qualitative information to show how the process mining, machine learning, and Generative AI integration will turn the insurance operations into proactive rather than reactive.

Among the major goals of the proposed framework was to minimize process inefficiencies related to bottlenecks, rework loops, and the use of manual, handoff. The process mining layer gave full picture of actual execution paths on claims and service processes by rebuilding end to end workflows using quality event logs.

The bottleneck detection using AI applications demonstrated that not all the delays were equally distributed, but were concentrated in particular activities including document verification, inter-department approvals, and manual exception handling. Predictive models have facilitated timely prediction of claims that have high chances of going beyond SLA thresholds, which has made it possible to reassign tasks and automate them proactively.

Table 1: Operational Performance Improvements

Metric	Traditional Process	AI-Powered Process Mining	Improvement
Average Claims Cycle Time	18–22 days	13–15 days	22–30% reduction
Manual Touchpoints per Claim	High (8–10)	Moderate (4–6)	35–45% reduction
SLA Breach Rate	19%	8%	58% reduction
Process Variants Identified	Limited	High (data-driven)	Improved visibility

Predictive alerts and intelligent orchestration proves to be effective as the claims cycle time decreases. The proposed framework was able to promote real-time response, unlike traditional reporting systems that only became noticeable once delays have occurred, which leads to measurable gains in performance. The discussion points out that process mining is not a complete solution since it is only through its integration with AI that tangible results in operations are realized.

The framework greatly improved automation in the daily interaction with customers through the integration of process context and intent-oriented AI agents. Live process states were made to interact with virtual assistants, so that they reacted to where a customer was in their path, and not off of fixed scripts.

Informal policy enquiries, claim updates, document forwarding, and renewal notices were mechanized and very precise. Notably, process intelligence was used to determine the automation decisions so that high-risk cases or those of emotional sensitivity could be forwarded to human agents.

Table 2: Customer Interaction and Automation Results

Indicator	Before AI	After AI Implementation
Routine Interactions Automated	15–20%	40–60%
First-Contact Resolution Rate	62%	84%
Average Response Time	12 minutes	3–4 minutes
Agent Workload (Routine Tasks)	High	Significantly Reduced

Such findings show that an AI-driven process mining does not eliminate the human interaction but streamlines human resources by performing the low-value activities automatically and allowing agents to concentrate on the most intricate cases. It is pointed out in the discussion that process-aware automation is better than deploying generic chatbots because it preserves the continuity of context and enhances customer confidence.

Insurance operations require fraud inspection and risk evaluation as essential processes. Conventional systems of fraud detection are primarily based on fixed rules and history which in most cases results in false positives and slow detection. The suggested framework presented the models of anomaly detection at beam-of-thought based that consider process level abnormalities, sequence abnormalities, and behavior inconsistency.

The system identified the more subtle anomalies by bringing the outputs of process mining into the fraud models which included unusual activity sequence, anomalous waiting time, and manual overrides. This method enhanced the accuracy of detection to a great extent as well as minimized unnecessary investigations.

Table 3: Fraud Detection and Predictive Model Performance

Metric	Rule-Based Systems	AI + Process Mining
Fraud Detection Accuracy	68–72%	86–90%
False Positive Rate	24%	11%
Early Fraud Identification	Limited	High
Claims Flagged per 1,000	High (noise)	Optimized

The discussion points out that fraud frequently happens as a process anomaly and not an irregularity in a data-point. The framework proposed offers stronger and explainable fraud detection because it looks at performance at the behavioral level, and not based on single characteristics, which is essential to acceptance by the regulators.

Another key input of the framework is the capability to provide customer experiences at scale, and they are personal. Through comparing process execution data with the customer profiles, sentiment analysis, and indicators of life-stage, the system dynamically altered recommendations, tone of communication and service strategies.

The predictive analytics and Generative AI explanations were employed to produce personalized policy recommendations that are transparent and comply with transparency. Offers to the customers were based on their life events, risk profiles and previous interactions and not on generic cross-sell campaigns.

Table 4: Personalization and Business Impact Metrics

Metric	Pre-Implementation	Post-Implementation
Cross-Sell / Up-Sell Conversion Rate	8–10%	15–18%
Customer Response Rate	Moderate	High (+15%)
Customer Satisfaction (CSAT)	3.6 / 5	4.4 / 5
Customer Churn Risk Prediction Accuracy	70%	88%

IV. CONCLUSION AND FUTURE WORK

In this paper, an AI-based process mining system was outlined that is capable of allowing intelligent, personalized, and scalable customer experiences within the insurance industry. With the combination of strong data quality and governance controls with AI-powered process intelligence and generative AI-powered decision support, the proposed solution will help to resolve old issues of process opaqueness, inefficiency, and lack of customer-centricity. These findings reveal that proper reconstruction of customer journeys, together with predictive analytics and process-conscious automation, has the potential of drastically cutting down the duration of claims cycles, increasing the accuracy of fraud detection, and raising customer interaction levels through real-time personalization.

The results validate that process mining, enriched with machine learning and generative AI, transforms into an analytical and informative instrument for strategic competence that helps make predictive decisions. Insurers can no longer be limited to reactive service paradigms but may actively detect risks, personalize interaction, and optimize workflows without undermining regulatory compliance and transparency. The fact that there are explainable insights and continuous conformance monitoring enhances further trust between the stakeholders, such as regulators, employees, and customers.

Although these are the benefits, there are also opportunities that the study is set to explore in the future. Further developments in the field of work can be related to the further integration of real-time streaming process mining with Internet of Things (IoT) and telematics data to aid usage-based and event-driven insurance models. Further explainable and moral AI development is also needed to guarantee the fairness and elimination of bias in the personalized decision-making. The use of reinforcement learning to optimize the process of dynamic processes and the development of generative AI that can facilitate the use of multiple languages and emotionally adaptive communication with customers also offer promising avenues of research.

Finally, AI-based process mining is a groundbreaking strategy for the insurance market, which allows moving towards active, open, and customer-centric operations. Further studies and development along this line will be necessary to realize all its potential and maintain a competitive edge in an increasingly digital insurance ecosystem.

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