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GENERATIVE AI IN INSURANCE: AUTOMATING CLAIMS DOCUMENTATION AND CUSTOMER COMMUNICATION

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***Abstract*—**Within risk management strategies, genuine losses incurred from perils in primary perils are routine but dispropor- tionate, resulting in claims that impact organizational effort and cost. Expanding business lines beyond simply on-lending deposits is key to returning the enterprise to profitability. Reducing annual customer complaints and retentions show institutions that priori- tize customer service and have proactive Mitigants on their watch list are invariably rewarded by lower claims. Current and recent developments in the finance, technology and insurance sectors have combined to allow possible associations between these areas. New services offered by local Insurers, Market Shortfalls with Private Equity funds and Corporate Private Banks, Increasing Consumer Demand and the introduction of Weather Money to address Private Pine interventions have highlighted a trend of increasing risk severity. Such increasing risk severity has the potential to develop a property risk and make allowance for a worsening of insurance coverage conditions.

KEYWORD: Generative artificial intelligence, automation, underwriting, claims handling, sentiment analysis, tone detection, evidence remarketing.

INTRODUCTION

The insurance industry supports the risk management foun- dation necessary for a working capitalist economy and enables individuals and organizations to thrive by mitigating the occur- rence and impact of adverse events. Nevertheless, the industry operates at high levels of inefficiency and incomprehensibility, resulting in unfulfilled opportunities for cost, service, and revenue improvement. The growing availability of generative artificial intelligence (AI) tools makes it feasible to create dedicated AI systems to improve productivity in the insurance industry. Generative AI has the potential to address these challenges in two specific areas: automating the generation of claims documentation and automating natural language communication with customers and potential customers in other roles. Both applications enable a strong positive business case through the creation of dedicated AI systems. The result is an increase in productivity for those teams supporting claims and customer communication.

BACKGROUND AND SIGNIFICANCE

In recent years, interest in generative AI has surged due to systems like OpenAI's ChatGPT and other transformative technologies. Accelerated advancements, powered by massive investments, computational progress, and vast data parameters, are now expanding generative AI's potential to numerous business domains and many discrete applications. In insurance,

Fig. 1. Generative AI in Insurance

large language models (LLMs) and text-generation AI tech- nologies can automate the labor-intensive tasks of documen- tation creation and customer drop-off—both key components of any claims operation—for many property-casualty carrier companies. These applications will not eliminate the role and strength of the human operator but instead amplify their nat- ural decision-making capabilities, reduce back-office overload during peaks in claim counts, and help align responses with the underwriting and people-risk portfolio assessment of the company. Global insurance and insurance tech stakeholders need to understand the capabilities and risks associated with these systems, the data required to operate them accurately and safely, and how they can best proceed to use generative AI's tools. Underlying technologies include LLMs capable of contextual understanding of data and texts during claims, adaptation models that allow policyholders to interact in their preferred way, formatting AIs that define the tone and vocab- ulary presented, and functionalities that ensure accessibility for all customers. The main risks include hallucinations that generate false content, biased interaction that can make a customer feel rejected during a distressing moment, and ill- timed responses that create a further burden for policyholders.

I. Foundations of Generative AI in Insurance

Generative AI automates document drafting and customer communication across insurance operations. Its core components, technologies, and data demands shape feasibility and practicality. Generative models built are adept in specialized domains—the technologies distil knowledge from textual data alone. Such narratives may be biased, overly verbose, and unfair to culturally, economically, or socially disadvantaged customers. 2.1 Core Technologies and Data

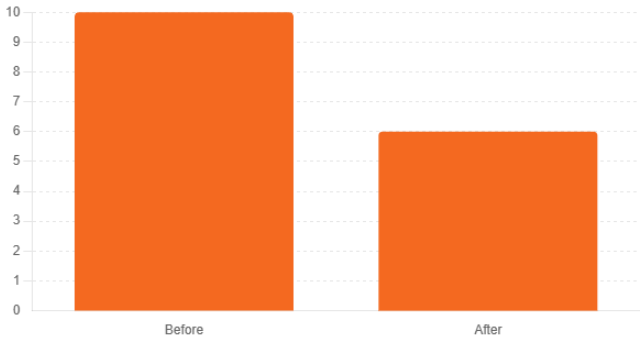

Fig. 2. Claims Handling Time: Before vs After

Requirements Document drafting hinges on Large Language Models (LLMs), trained Transformers on extensive text datasets with learning objectives that predict missing tokens and sequence order. LLMs equipped with web-scraping capability autonomously collate data from the World Wide Web. Foundation models focusing on specific domains achieve comparable performance levels without relying on prompt-tuning or instruction-fine-tuning techniques. Text-to- image-generation models (such as DALL·E 2) enable the automatic creation of non-visual evidence. Table-structured data can be converted into text using text-to-SQL models (e.g., ChatGPT) or other domain-tuned LLMs. Vision models like ChatGPT's vision component translate visual patterns into textual descriptions, enabling automatic generation of visual evidence descriptions from photos. Audio models designed to translate spoken words into text convert customer calls into textual dialogues. Risk-averse institutions adhere to qualitative models tested against data about observed events, while agribusiness increasingly embraces generative AI. Viewing core risks quantitatively permits the testing of any LLM with belt-driven simulations. Generative agents handle multiple concurrent conversations in the style of dialog-oriented LLMs. Automating core business applications ushers in reduced costs and errors, improved safety and governance, heightened workforce productivity, and accelerated innovations.

EQUATION 01: FLOW & BACKLOG: LITTLE'S LAW

Little's Law (stable system)

$$L = \lambda W \qquad (1)$$

L = average #claims in system (backlog)
λ = arrival rate (claims/time)
W = average time in system $W' = (1 - \alpha)W$
$L' = \lambda W' = \lambda(1 - \alpha)W = (1 - \alpha)L$

A. Core Technologies and Data Requirements

Four core technologies power generative AI: large language models (LLMs), generative

adversarial networks (GANs),

Parameter	Value
Monthly claim arrivals λ (claims/month)	1000
Baseline avg handling time W (days)	10
Automation cycle-time reduction ˆI±	0.4
Working days per month	22
Avg fully-loaded hourly wage w ($/hour)	45
Avg labor hours per claim (baseline)	3
One-time setup cost C0 ($)	250000
Monthly operating cost c ($/month)	35000
Baseline hallucination rate h	0.08

TABLE I

ASSUMPTIONS & PARAMETERS

deepfakes, and diffusion models. LLMs are the workhorses of large-scale text generation, designed to predict the next word in a body of training text, then fine-tuned or prompt-engineered for specific use cases. GANs comprise a ”gen- erative” network that creates increasingly realistic synthetic images and a ”discriminator” network that tries to distinguish real from fake—both improving iteratively until the genera- tor produces images seemingly indistinguishable from actual photographs. Deepfakes use GAN technology to convincingly transfer the lip movements or facial expressions of one person to another’s likeness, while diffusion models generate im- ages via complementary processes of adding controlled noise to existing pictures, then training an independent model to progressively remove that noise. Training these models is a data-hungry undertaking, often relying on massive, uncurated datasets drawn from the internet. Fraud detection is different: it seeks to classify novel cases as either real or fake, requires comparatively little training data, and can be performed using standard machine-learning classifiers. For these applications, pre-trained GANs can generate entirely new documents for testing. Risks include failing to detect novel forms of fraud, predicting real cases as attacking, and ”negative transfer” when the training dataset does not contain representative examples for the chosen classifier.

REGULATORY AND ETHICAL CONSIDERATIONS

Lack of accessible data has limited the application of generative AI in regulated industries, including insurance. These restrictions are gradually being relaxed. However, this has other implications, since the deployment of generative AI in highly regulated industries raises ethical considerations regarding the use of biased, uninformed, or non-inclusive de- ployments, and poses risks directly correlated with the volume and nature of the training data used. These considerations are paramount in the deployment of generative systems that engage in natural language interaction with policyholders, given the need for personalization, tone harmonization, and text adaptation, especially for customers with disabilities who require additional assistance. Generative AI enables new in- teraction and productivity paradigms that improve document production by individual companies and the overall industry. Policyholders must perceive value in document generation generated by insurers for their files rather than the other way around, especially for claims with

minimal losses. For

claims handling, harnessing generative AI enhances complex processes by enabling real-time claims narratives that auto- matically aggregate evidence from multiple sources, such as file notes, already collected material, and evidence still being gathered. When a complex claim is assigned to a dedicated handler, the narrative provides contextual information that improves understanding and facilitates the assessment of the data's reliability, as well as any potential biases associated with the resulting synthesis.

AUTOMATING CLAIMS DOCUMENTATION

Although generative AI is capable of automating large parts of the process of handling a claim, two applications are particularly promising in the short term: generating and stan- dardizing text for claims documents, and providing real-time narratives during video calls that explain the circumstances of the accident and summarize important evidence. The first application can enhance data quality by minimizing the vari- ation introduced by different humans writing these texts. The second application can alleviate some of the human bottleneck in the claim-handling process, requiring just a single person with expertise for a claim rather than two. Every insurance claim requires significant amounts of text to be written, both in word processing or PDF files and in smaller areas within web or mobile app interfaces. Generative-AI systems trained on appropriate data can automate much of this writing. Claims handlers typically write a narrative describing what happened in the accident, which is sometimes also presented as a voice phone call with the insured. An online video call between the insured and a claims handler can capture what happened in the accident and identify the important evidence—both visible in the video feed and audible in the conversation. Generative AI can generate a claims narrative and standardize the pre- sentation of supporting evidence. The result can therefore be much more consistent and of higher quality, containing more information and supporting evidence that the insurer requires for the claim to be approved. In parallel to claims radio calls with the insured, large language models (LLMs) can yet assist the claims handler taking the call. The conversation can be treated as combination of a video and an audio source, from which multimodal information extraction (MMIE) can detect salient events and objects for a claims narrative. The narrative is then recast into a coherent summary.

DOCUMENT GENERATION AND STANDARDIZATION

Natural language models can be used to transform inputs from claims-handling experts or external sources into full narratives. These narratives assist in documenting the claims journey and communicating it to all involved parties. Genera- tive models can also standardize claims narratives by pulling information from multiple systems and rerendering them in a common format, blocking out sensitive information and minimizing clarifications needed by claims teams. Doing so can make it easier to recognize fraudulent patterns. Using sophisticated generative models capable of image generation,

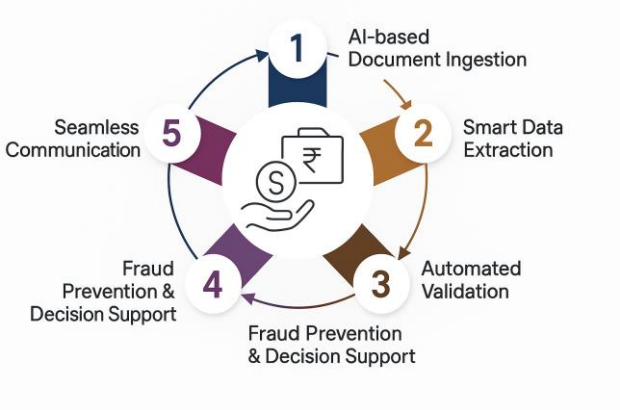

Fig. 3. Automating Claim Documents for 2X Processing Speed

insurers can automate the generation of damage assessment re- ports where those are used. With insurers increasingly allowed to settle non-complex claims without detailed visual evidence, synthetic examples can reduce solicited and unsolicited fraud. The entire process can be automated, with natural language prompts tailored to specific regions or classes of business, and the pre-fielding of key validation criteria so that the model responds accurately to a mix of business data and image inputs. Intelligent document-processing methods can also help extract information in structured form from additional claims-related documents generated by outside parties. The ability to use images from damage assessments has allowed for potentially catastrophic fraud claims to be soothed using generative mod- els that midway explain likely causes when images fail to clearly capture them. Assisting the claims-handler community, using documents such as case files from insurers' internal forensic departments at the correct quality and size, can be a major enabler for legal correspondence. Many handles dis- tilling case documents into final letters like language models also now understand legalese and their corresponding lawyers' styles.

REAL-TIME CLAIMS NARRATIVES AND EVIDENCE SYNTHESIS

In addition to synthesizing content for standardized docu- mentation, generative AI can assist insurance claim handlers by providing a real-time narrative of what took place and what may have become of the property involved. Such services can be helpful to complex commercial claims like those that frequently take months or even years to settle or to catastrophic claims that may overwhelm insurance companies' resources at a time of considerable anxiety for policyholders, adding to the difficulty of communication and the risk of error. Inbound communications can be monitored for key topics and, upon submission of the first such communication on a claim, a service can generate an initial narrative based on public news reports and social media. When enabled, claims adjusters can then be automatically kept abreast of developments in the local area by summarizing further correlated news items and social media posts, with the risk of hallucinations reduced

via factual verification. For claims against third parties where liability is disputed, the service can also summarize relevant and changing information from the claim submission, news, and social media that support or undermine a finding of liability.

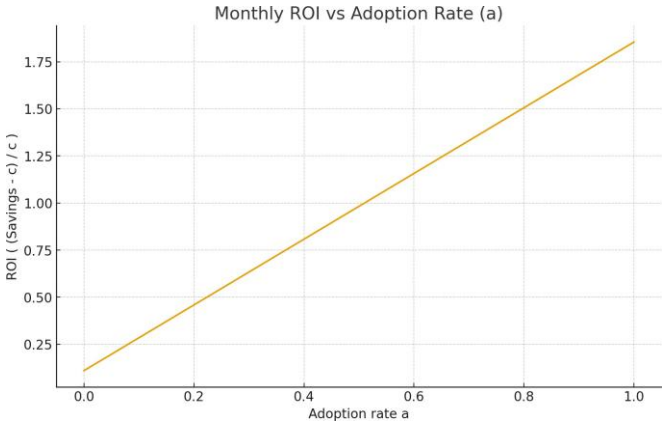

Fig. 4. Monthly ROI vs Adoption Rate (a)

To aid claims examiners reading the correspondence, prior discussions can be synthesized into a chronological, bullet- point narrative that addresses key matters.

II. Automating Customer Communication

Natural language processing and conversational AI facilitate dynamic, intuitive interactions with policyholders, improving accessibility and efficiency. By harnessing customer data and integrating external context—such as the insured's location and recent claims activity—solutions become more personalized and context-appropriate. Advanced tone management capabilities augment the deployment of voice assistants, better replicating the organization's brand attributes. Such capabilities open new possibilities for reaching previously underserved customer segments. Despite technological maturity, automating real-time, natural language interaction in conjunction with expressive tone selection presents challenges. To guarantee equitable service delivery, the use case must be directed toward enabling customer engagement and addressing high-volume inquiries. Generative AI should only be applied in a manner that's inclusive, such as simplifying communications for neurodiverse individuals, those with limited digital literacy, or non-native speakers.

Equation 02: Labor time and labor cost savings

Monthly labor hours before

$$H0 = Ih0\ h(a) = (1 - a)h0 + a(1 - a)h0 = h0(1 - aa)$$

$$H(a) = \lambda h(a) = \lambda h_0(1 - a\alpha)$$

$$\Delta H(a) = H_0 - H(a) = \lambda h_0 a\alpha\ Slabor(a) = wDH(a) = wlh0aa$$

	Handling time (days)	Backlog L (claims)
Before	10	454.545
After	6	272.727

TABLE II
KPIs BEFORE VS AFTER

NATURAL LANGUAGE INTERACTION WITH POLICYHOLDERS

Generative AI can be used to produce an Interactive Voice Response (IVR) system with an authentic voice, which pro- vides policyholders with a more interactive experience than current IVR systems. The IVR could provide localized services while allowing for real-time adaptation of response patterns. Generative AI and voice synthesis should also be employed to make automated agent solutions accessible to people with dis- abilities, elderly customers, and non-native speakers. Although voice-based solutions do not necessarily leverage generative AI, they can be integrated with natural language processing (NLP) to open new interaction paths with users. Generative AI enables personalized question-and-answer exchanges through chatbots and virtual assistants. Combining generative AI with Retrieval Augmented Generation (RAG) techniques (using external sources to generate and enhance responses) allows for contextualization of knowledge resources and contributes to answering specific customer queries more naturally. Such usage helps to retrieve existing information from multiple knowledge bases and improves the overall chat experience. Generative AI is useful for answering domain-specific cus- tomer FAQs when combined with RAG, and the usage of hyper-specialized external knowledge bases leads to additional performance improvements. Generative AI also allows for building a conversation flow in addition to question answer- ing in a virtual assistant. Integrating sentiment analysis into generative AI systems enables customization of the response tone for greater relevance, user engagement, and satisfaction.

PERSONALIZATION, TONE, AND ACCESSIBILITY

In addition to easing resource constraints by generating responses to standard inquiries, Generative AI can analyze unstructured elements of each policyholder's database for more personalized communications aligned with customer preferences. Such analyses can determine tone, diction level, word choices, and areas where relevant examples, metaphors, assets, or even humour can be woven in. Customers' social media interactions might additionally provide clues to the personalization cues that resonate with them, and sentiment analysis of past conversations with the insurer can identify which agents are successful at using the identified param- eters toward correspondence that policyholders perceive as reassuring. Automated tools could thus become skilled em- pathetic guides, communicating factors that policyholders find scary while providing comforting bolstering and explaining potential solutions. Language thought to be safe and attractive for a certain customer at one point in time could also be checked against previous support queries for indications of any change in tone preference. Generative AI can enhance communications by making them

more natural, nuanced, and informative. Tone and diction choices that are consistent with prior interactions can be employed, and inclusion of insights about prior communications or with non-insurance customer care could encourage better responses. Automated personalized messages conveying sympathy or understanding of challenges that affected a customer's area could help policyholders feel more that a company's culture supports its brand promise, while automatic reconnection to a customer adviser could make the conversation feel smoother and reduce the perceived business focus of an interaction. Communication could also draw on a company's knowledge graph to highlight products or services that an agent may have overlooked but that might bring additional value to the customer. The clarification questions posed could be in natural language, communicated in a preferred language, and sensitive to cultural factors. Consideration could also be given to disability and attention- deficit issues by providing greater clarity or concentration support for highlighted issues likely to be serious but less urgent.

Risk Management and Quality Assurance

A project's success hinges on delivering business value and justifying costs, yet the risks tied to inaccurate, biased, and phrased outputs merit careful consideration. Generative models may produce erroneous information, commonly known as "hallucinations." Although users may still find these outputs useful, recklessly deploying such content is extremely dan- gerous, especially when its veracity and verifiability are vital for the application and wider business context. Addressing this risk typically relies on a verification mechanism. The customer support agent automating models satellite instances, for instance, should be coupled with document sources that allow the response to be verified by a vectorized document retrieval (VDR) engine. A second area of risk concerns the encoded biases within the models. While these biases, often reflecting real-world prejudices and stereotypes, are usually harmless in general use, they may distort generated outputs when used by real people and have the potential to damage the company's brand. For this reason, companies should add an ex- tra layer of review when generating external communications. A final area to examine is the degree of inclusivity. Generative image models can produce visual content that appears out of place for non-dominant cultures or languages, especially those with low training dataset volumes. To prevent this problem, generative models must include the corresponding models for other languages and cultures when implemented in customer- facing channels.

ACCURACY, HALLUCINATIONS, AND VERIFICATION

Generative AI systems such as chatbots rely heavily on training datasets. Text generation performance hinges on the linguistic structure of prompts and the wording of desired outputs, but these aspects are frequently overlooked. The risk of hallucinations is inherent to transformer models; statistical data corroboration is essential to minimize the chances of

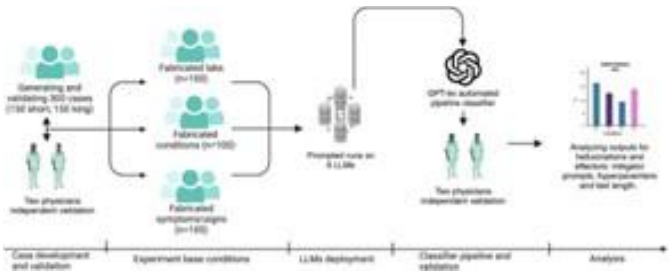

Fig. 5. Accuracy, Hallucinations, and Verification

presenting erroneous information. Crucial facts must be high-lighted and function as key anchors to the AI's accuracy. To ensure factual soundness and verification of process-relevant information (dates/timings, addresses, policy numbers, inci- dent locations, etc.) in generated documents, additional query engines should be integrated into the transformer's architec- ture, either by building document databases or enabling data access to third-party databases. Generative AI adoption in the insurance industry must include mechanisms or principles to counter biases and unfairness. Failed attempts to eliminate racism in AI models trained on biased social media data are illustrative of the difficulties involved. Examples include on- line notes and automated credit implementation and attribution tools that may reinforce both racial and gender biases. Secure systems should continuously polygraph user inputs during chat or image conversations to identify negative tendency patterns of customers. Diversity in voice and tone styles should also be adopted to counteract possible race bias in chatbots, audio responses, and insurance illustrations.

BIAS, FAIRNESS, AND INCLUSIVITY

Careful analysis of generative AI applications is necessary to avoid bias that can undermine customer trust and subse- quently damage businesses. Insurance policy language can be dense and technical, hampering understanding among less- expert audience members. Large language models seeking increased tone, tenor, and style accuracy can introduce scale- driven bias, expanding and repeating management, distribu- tion, underwriting, and customer service deficiencies. Develop- ers of systems based on large language models should utilize a dedicated development framework capable of measuring algo- rithm predictability and outcomes, while leveraging different outputs based on customer characteristics. Increasing focus on inclusivity among developers—in gender, race, culture, and religion—serves as an interesting direction to address bias naturally embedded in customer communications. Insurance companies seeking to personalize and tailor customer engage- ment should, naturally, remain sensitive to tone and tenor matching for a broad range of customer characteristics.

DEPLOYMENT STRATEGIES AND CASE STUDIES

Start small. Connect generative AI tools to existing systems incrementally, rather than waiting until they can be applied everywhere. Auto-claims documentation is a

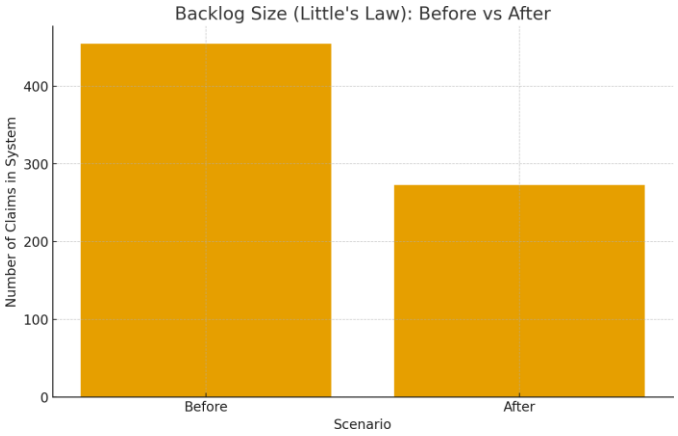

Fig. 6. Backlog Size (Little's Law): Before vs After

logical first step because it requires standardization and only partially relies on creativity. For policyholder engagement, start with FAQs—GPT can convincingly answer general informational queries before it can effectively answer specific questions about a customer's claim. Expect surprises. Create mechanisms for learning and iterating, and share failures as well as successes. The novelty of the technology will produce unexpected behaviours, some of which will be beneficial. Many insurers and reinsurers have already run pilots, and a few are scaling incrementally. Progressive has been experimenting since 2021 and deployed AI-assisted insurance agent responses this summer. H4 provides an API layer for insurers that want an immediate generative AI capability without in-house training and ingesting data and KYC. Chubb recently launched Chubb Chat, a generative AI application to handle standard insurance questions that gives written responses in a friendly tone of voice. Others are experimenting with the technology under the hood, using it to automate internal work like processing telephone speech transcripts and quickly summarising claim reports.

Equation 03: Customer comms → churn and LTV uplift

Let monthly churn be χ and ARPU margin M= ARPU × gross margin M=ARPU×gross margin

$LTV\,0 = qM(1-q)$new churn is $\chi' = \chi(1-\Delta)$ (2)

$$LTV\,1 = q'M(1-q')\ SLTV\,(a) = a(LTV\,1 - LTV\,0)12N \quad (3)$$

INCREMENTAL ADOPTION AND INTEGRATION

Building and integrating generative AI systems can feel daunting, often because of the worry that the technology may require a radical and complete change of the existing

operational model. However, there are many examples where organizations have successfully rolled out useful components that incrementally improve efficiency and customer satisfaction, support a crucial business case, and enhance a specific process, all while ensuring close integration with human ex- perts. This article outlines some illustrative examples, includ- ing evolving use cases from the insurance industry. Progress on foundational capabilities—especially the technologies nec- essary for creating and adapting large language models, dialogue management, and powering sophisticated multi-modal systems—has been so rapid and widely reported that most companies can expect many important pre-trained models to be available as simpler plug-ins from third-party providers. That simplifies early adoption considerably, allowing organizations to focus on the use case and user experience rather than the underlying technology. One insurance company, however, is developing LLMs that are unique to its business—predicting that the number of domains with useful off-the-shelf models will remain limited for some time.

INDUSTRY EXAMPLES AND LESSONS LEARNED

Lines of Aflac's new auto claims chatbot are powered by ChatGPT, an advanced chatbot that generates human-like text responses to user questions. Insurance customers can ask questions about the claims process and timelines, Aflac said in a statement. The bot's knowledge is limited to Aflac's auto claims process but will expand over time as the proprietary program becomes more sophisticated. At Travelers, generative AI is used to develop personalized communications for key moments throughout the lifecycle of a policy and claim. It's in production and in use by customers. "Using the technology, we have been able to optimize messages sent to customers that are getting quotes, purchasing policies, renewing or cancelling in- surance, and at claim time," said Zafer Younes, vice president of digital operations at Travelers. "We have also explored how generative AI can help customer service representatives when they chat with customers. The tool assists the representative by suggesting an answer based on ticket history and similar inquiries, enabling the representative to respond more quickly." Adopting such technology requires thoughtful execution and scaling. TBD's Girshick said it is wise to start small, with a key business challenge in mind. Generative AI "is not meant to take over everything; it is meant to be a helpful aid and take off the load." Organizations should pick clear use cases that will allow them to evaluate success and learn quickly. The technology should then be expanded to other areas based on lessons learned.

CONCLUSION

Generative AI is rapidly opening up new opportunities in insurance and, indeed, across the entire service econ- omy. By combining technologies for large language models and document generation with document management and recordkeeping workflows, insurers can automate processes that require significant investment in both time and expertise. Initially suited to backoffice operations, these capabilities are being more widely deployed in customer-facing applications. Large language models can be adapted to support interactive

communication, thereby reducing the burden on policyholders, improving turnaround time, and minimizing the risk of misun- derstandings. Many of these early customer-facing applications are addressing communications with policyholders on claims as these events require frequent interaction over an extended period. Using generative AI to draft documents for policy- holders helps alleviate their burden and the psychological stress often associated with a claim. Furthermore, the use of generative AI offers the potential to produce the documents early in the claims process, provide a clearly written summary with consistent terminology and personal tone, and ensure that the materials are accessible to those with diverse needs.

EMERGING TRENDS

The insurance industry is witnessing a paradigm shift in the way technology is leveraged to assist individuals and or- ganizations in safeguarding against, managing, and recovering from risk. Several promising trajectories with the potential to reshape core processes, augment human capabilities, and gen- erate new delivery models have emerged concurrently. Industry analysts have identified these emerging trends, labelled as the 5Rs: reassessment, renewal, reconciliation, restructuring, and reconfiguration. Their impact will likely be felt for years, if not decades, changing the ways in which insurers and customers alike perceive and use insurance. Responsible deployment and utilization of generative AI will enable insurers to deliver enhanced solutions and services in support of these trends, thereby enabling their customers to more effectively respond to a rapidly changing risk environment. Generative AI's nat- ural language capabilities can significantly reduce the effort involved in writing standard claims documentation, engaging with policyholders, and generating claim updates with appro- priate tone and degree of personalization for the audience. As innovative solutions evolve and become more widely adopted, generative AI will likely find new and unexpected applications in support of the insurance industry and its customers.

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