DeepScience
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Chapter 4: Generative AI in Insurance: Synthetic Data, Scenario Simulation, and Knowledge Generation

4.1. Introduction

Machine learning, in particular Generative AI (GenAI), represents the most transformative technology of our era. A practical application of AI has emerged in recent months with the advent of large-scale text- and image-generating systems, as well as the Interoperable Chatbots and for The technical breakthroughs underlying these applications have opened the opportunity for Generative AI to be extended to a much wider spectrum of further uses. In addition to Generating images or text, engineers can now deploy generative models to create auctions prices, design new drugs for Alzheimer, sport shoes and thousands of further applications. In insurance, these applications cover the largest set of use cases that the development of Generative systems implies: synthetic data creation, scenario simulation and even knowledge development. Empirical findings demonstrate that the latest term in the generation of data by machine learning constitutes a significant area with the greatest number of implementation applications over the major Generative-AI artificial intelligence groups.

Data lie at the centre of the insurance business model and the principal support of its strategic decision-making process. Data are used on the development of underwriting and pricing models to evaluate and accept risks, for portfolio selection of investment products, to understand customers' choices and preferences, to predict future claims, and in many other areas. However, insurance data are often highly confidential. Insurers are also facing the growing risk of privacy data breaches in machine-learning applications connected to personal data of their customers. The use of data-synthetic technology supports a wider and more innovative application of machine learning while addressing data privacy and confidentiality concerns. Data-synthetic technology is a solution to data shortage for risk modelling and actuarial applications in insurance. Stress testing and catastrophe modelling require the evaluation of these scenarios; however, it is often difficult to find a sufficient number of extreme, rare or tail observations in the data. Market and consumer behaviour or customer-contact scenarios also require the

generation of scenarios that make a strategic decision of a company face during a certain period.

4.1.1. Overview of Generative AI in Insurance

Business leaders and financial modelers in insurance often face significant obstacles developing and deploying analytical tools and domain-specific models. A dearth of appropriate data poses hurdles for steering decisions, validating models, building user interfaces, and improving training of advanced analytical systems. Generative artificial intelligence (AI)—a technology family that includes models such as chatGPT—helps address these difficulties through methods including synthetic data generation, intuitive data-querying in natural language, knowledge generation from written documentation, and simulated scenario modeling. The computational techniques employ large models pretrained on enormous volumes of data from diverse sources and serve broad classes of applications beyond insurance and risk. Tailoring generative AI systems to insurance and risk requires incorporation and fusion of other risk-analytical and financial-modeling techniques, knowledge, and expert experience.
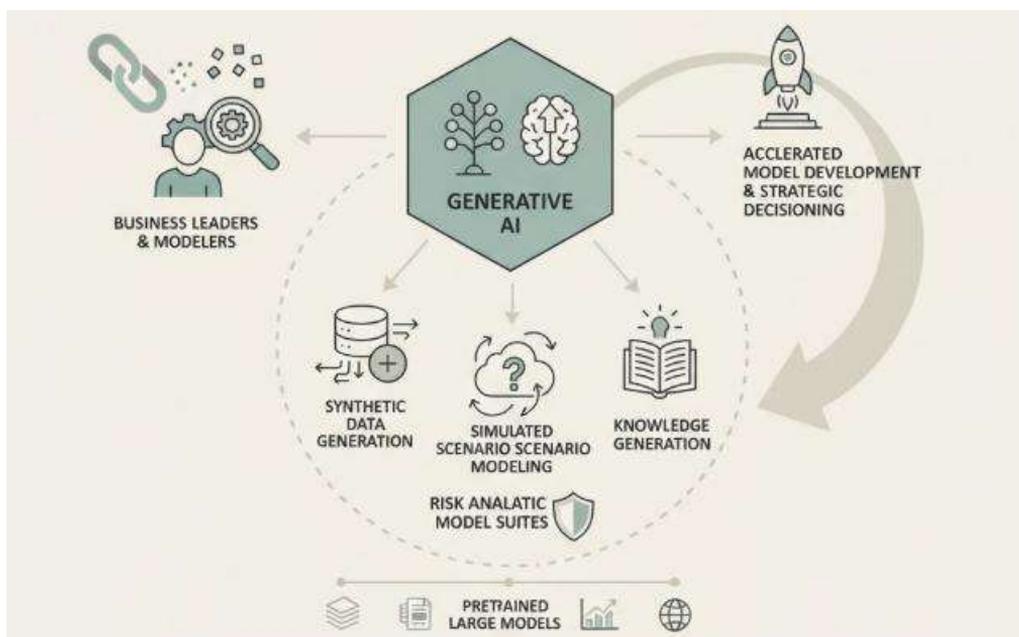

Fig 4.1: Generative AI for Risk Resilience: Bridging Data Gaps through Synthetic Augmentation and Simulated Scenario Modeling

Generative AI provisions three categories of capabilities useful to business leadership and financial modelers as they seek to strengthen the risk analytical tool suite of their organization: (i) generation of synthetic data, (ii) modeling of scenarios for risk

assessment and strategic decisioning, and (iii) generation of knowledge that supports downstream decisioning and actuation of business processes. When seamlessly integrated with appropriate risk-analytic model suites, these capabilities work together to overcome the data limitations that slow model development and constraint readiness assessment of strategic decisions.

4.2. Foundations of Generative AI for Insurance

Generative AI augments and extends existing data-driven AI technologies by predicting the future. Generative AI methods – Generative Adversarial Networks (GANs), Diffusion Models, and Auto-Regressive Models – learn the underlying data distributions and then generate new data consistent with those distributions. Though primarily driven by neural networks, Generative AI draws on a diverse internal toolbox. Importantly, Generative AI does not generate art and text at random. It has allowed machine vision systems to achieve human performance and surpass it on previously unsolvable language-based machine reasoning problems. Generative AI has not reached human capabilities in all these endeavors, and thus it cannot yet pass the Turing Test. Still, the models are poised to sharpen innovation cycles in most, if not all, industries, including insurance.

Most real-world data sets are not large enough. Synthetic data generation can thus augment data sets used for automating decisions with data-driven learning methods or enable privacy-preserving data sharing among different organizations in order to build models on larger, more comprehensive data sets while avoiding data leakage or infringing on customer privacy rights. For insurance risk models, data sets with gaps can also be filled by leveraging subject-matter expertise whenever possible, for example, to forecast variables or create historical records for unmodeled natural catastrophes. The consequences of adapting to such scenarios can then be assessed using extreme-value theory-based stress testing.

4.2.1. Core Concepts and Technologies

Generative AI combines deep learning methods with approaches from artificial intelligence research to create or extend data sources. By absorbing large amounts of information from existing data or documentation, generative AI models can generate plausible and predictive—or completely fictive—responses to particular tasks, challenges, questions, or situations. Generative AI impacts the first three of the six elements of a data and analytics strategy outlined at the 2023 Geneva Association conference on Artificial Intelligence and Data Analytics in Insurance.

A focus on technology rather than business processes, organizational structure, company culture, or technology adoption may seem misplaced. However, mainstream adoption of Generative AI will depend on the maturity and sophistication of each of these necessary precursors. Unlike earlier developments in artificial intelligence, which were deployed as specialized systems trained to address specific business challenges, commercial applications of Generative AI are often externally accessible tools incorporated directly into business operations. Accordingly, Generative AI has a profound impact on how companies conduct internal tasks and how they and their customers interact with those tasks.

4.2.2. Data Provenance and Governance

Authenticity, correctness, and appropriateness pervade the use of data to develop, train, and validate Generative AI methods and models. All user and used data remain subject to established privacy, security, and ethical rules throughout the life-cycle of the Generative AI model and its applications – from selection and collection to augmentation, validation, and operational employment. As the value and usefulness of conversions to the output domain depend on a reliable data return, consideration is also warranted for responsible development and application. The Digital Twin, and its representation in the output domain, is subject to the same risk factors as the physical system that the Digital Twin models – Data Quality is critical to Data Value.

In a data-limited environment, Generative AI offers opportunities for expanded, simulated, alternative, and adversarial-data creation to produce synthetic data with appropriate characteristics for any of the preceding Generative AI use cases – Data Augmentation, Data Privacy Protection, Predictive Risk Modeling, and Actuarial Statistical Applications. The Data Augmentation, Privacy, and Utility Trade-off in the creation and use of synthetic data, for risk modeling or any other area, are key to ensuring the faithful, accurate, and appropriately representative generation of synthetic data. Meaningful and warranted data synthesis requires careful consideration of these factors, both within the normal use of the process and within any generated scenario.

4.3. Synthetic Data for Insurance

Generative AI plays a critical role in supporting core technical tasks by enabling the generation of synthetic data, either alone or in combination with original data, for applications in data augmentation or privacy preservation. Actual risk models or even the solvency of an entire company depend heavily on the precision with which they characterize the physical world and the economy. For instances of low-dimensional spaces, examples drawn from available data may be sufficient to develop acceptable

models. However, financial and insurance data are often concentrated in very high-dimensional spaces.

Generative AI can also contribute directly to risk modeling and associated actuarial tasks, as the generation of an appropriate set of extreme year scenarios can offer very valuable information. Modeling is generally based on maximizing the likelihood of a series of observations leading to joint events and their consequences over the timescale of interest. In addition, the ability of generative AI tools to acquire knowledge from documentation, even if imprecise, may play an important role in the generation of scenario banks for the expected probability of crises with marked simulated value changes or extreme consequences.

4.3.1. Data Augmentation and Privacy Preservation

Synthetic data generation has become a popular tool in the machine learning community for data augmentation. Semantically consistent synthetic data, produced through generative adversarial networks, works well for downstream tasks, improving performance even in the presence of class imbalance. In oversampled domains, synthetic data not only improves model specification and reduces test error but also conveys a shift in the data distribution detected by rival classifiers. The use of generative models can also augment the development of intelligent systems in the area of finance, especially those grounded in data-driven algorithms. By generating dependency structures among financial time series with Granger-causality information, richer information could be injected into models such as Long Short-Term Memory and Gated Recurrent Units. LSTM and GRU models are thus augmented using quantile regression for predicting Value at Risk.

The provision of synthetic datasets instead of private data has emerged as a method to balance the need for data use and privacy concerns. With the mass adoption of AI and machine learning, many enterprises collect sensitive data from customers or partners, leading to the possible abuse of personal privacy. Banks, medical institutions, government agencies, and other organizations need to adhere to data privacy regulations, such as the Health Insurance Portability and Accountability Act and the General Data Protection Regulation. Privacy-preserving data mining methods mitigate the risk of data privacy leakage during data mining by adding perturbations into the data. Concerns about sensitive data leakage and the accessibility of sensitive data to authorized users trigger a demand for privacy-preserving synthetic data generation.
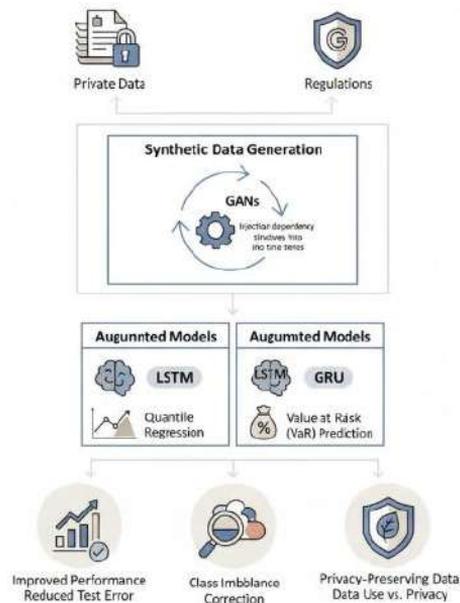
Fig 4.2: Privacy-Preserving Synthetic Data Augmentation: Enhancing Granger-Causal Financial Time Series Forecasting via Generative Adversarial Networks and Quantile-Augmented Recurrent Architectures

4.3.2. Risk Modeling and Actuarial Applications

Generative AI can assist actuarial modeling by generating synthetic surplus or simulated catastrophe loss experience. An early example, SynLif, produces correlated synthetic surplus data for life insurance companies. An interest that predates the recent generative AI boom is the use of synthetic data for catastrophe models, particularly hurricane models for the Gulf Coast. Generative AI can also assist pricing actuaries in developing exotic insurance products. For instance, during the 2007 financial crises, the Bank of England facilitated the design of insurance products covering various unexpected events, including insurance for limited money supply or epidemic effects not covered by traditional insurance markets.

Such exotic insurance products are useful not only for risk transfer but also for stress testing. The insurance industry requires accurate inflation models for pricing long-tail products such as annuities and pension products. Synthetic data generation enables actuaries to generate public market data and adjust interest rates based on synthetic inflation or future consumer behavior models during the training process.

4.4. Scenario Simulation and Decision Support

Scenario simulation is a class of generative AI applications that creates new data samples based on the distribution of existing data. Customers and market behavior can be modeled and simulated using existing data about customers and their contracts. Data samples consistent with plausible customer behavior can be generated to support the assessment of new markets. Stress testing of portfolios by simulating customer behavior in times of (perceived) distress can also be supported. Many scenario simulations support enterprise risk management applications, allowing levels of risk and loss in extreme conditions to be estimated more precisely than by applying simplistic assumptions about return periods. Such enterprise risk management applications are particularly important in actuarial functions.

Stress-testing scenarios provide a well-established decision-support use case for simulations that allow synthetic samples to be generated for service take-up, returns, loans, and other economic aspects of risk. Another major scenario-simulation use case uses Generative AI to model and simulate the joint occurrence of multiple extreme events aligned with enterprise risk management objectives. Such catastrophe scenarios typically either assume correspondingly low return periods (e.g., 1-in-200 years) or entail a high degree of uncertainty and rely on judgment (e.g., for 1-in-1000 events or combinations thereof). The number of possible events that can have meaningful occurrence relations grows exponentially with the number of events considered. As a result, the judgmental aspect of events following each other in quick succession is often ignored. The creation of realistic scenarios that allow such explosiveness to be reflected in realistic decision-support queries through generously sized sample sets is inherently subject to computer capacity limits. Market-place and customer-behavior scenarios explore plausible behaviors outside existing data. Service scenarios use past transaction data to explore what the uptake of a service would have been if it had existed.

4.4.1. Stress Testing and Catastrophe Modeling

Governments, supervisory authorities, and regulators in many countries produce and publish market scenarios. These include a broad range of variables that may be relevant for a financial institution to assess the impact of deterioration in the economic environment on the institution's risk profile and/or financial situation. Other recommended sources of market scenarios for stress testing come from banks, traders, and market-making institutions. Liquid markets often offer long-established instruments that can be used to create the curves required to stress-test portfolios across different sources of risk. Market makers in these instruments often offer stress-testing forecasts publicly or to selected clients. Market-implied measures of risk, such as implied volatility of equity and credit-swap prices, are also widely used in Example 2.

Recent literature proposes stress-testing scenarios that represent worst-scenario probability distributions for extreme but plausible market moves. Such scenarios may consist of several hundred inputs for a range of variables. These can be combined to generate a wide range of presentations, showing the impact of the stress scenario on P&L, capital adequacy, and other key variables. The sheer scale of these combinations and the need for bespoke solutions suggest that scenario generators are increasingly used to derive the maps between stress conditions and financial institution KPIs for regulatory and internal incentives.

Generative AI can assist catastrophe modelers on several fronts. Emergency managers want the best forecast to allocate scarce resources and capture the most lives. The public wants reliable information on the hazard and the impact on human life; scientists want better IPCC-quality forecasts of present climate variability and future climate trends; and also realistic scenarios of future events that lie outside the range of prior experience. Generative AI can offer solutions. Given an event, one should generate past events that could have led to the same consequences. This involves generating an Earth surface that has caused those consequences. Such a conditional generation is a new problem and requires a different model to supply the conditioning information.

Natural In-Language Models can also enable the production of landslide models conditioned on past events. In this case, the shape of the slides can be directly detected from satellite data, or approximated in roughening models from the slip surface. Past scenarios can then be indexed according to parameters and the model trained to generate landforms that are representative of the set (i.e. cluster centroids) conditioned on the input parameter.

4.4.2. Market and Customer Behavior Scenarios

Market and customer behavior scenarios can be developed for a broad range of contingencies. For example, models may be created to reveal how different stakeholders would respond to a designated event, such as a cyberattack or military conflict. Overly optimistic or pessimistic models may serve to doom a venture; Generative AI can be used to reveal possible dark scenarios through consideration of behaviors by different stakeholders in a joint decision process. Understanding these behaviors from a multi-agent perspective can lighten the load of crisis preparation.

The work of the MIT-IBM Watson AI Lab demonstrates the potential for such models for crisis scenarios, offering Generative AI scenarios of customer behavior as a cyber-attack unfolds.

A second area of behavior simulation concerns the interest of different categories of consumers in new product features. A multi-agent simulation framework is further

presented to predict how changes in customer preferences, risk perceptions, and socio-ecological systemic imitation impact the market demand of green products. This market demand is further investigated through a new hybrid consumer choice model (HCCM) that integrates the prevailing behavioral science models and Katz's theory of regional distribution of innovations across space.

4.5. Knowledge Generation with Generative AI

Instead of leveraging training data for prediction, Generative AI capabilities permit its use in knowledge generation. Designed primarily as large-language models, Generative AI systems produce coherent text, computer code, imagery, audio, and other content. Enabled by massive transformer neural networks, the training data corpus encompasses unstructured content across diverse domains. Such breadth and variety support a simple question-and-answer interface and the ability to achieve unexpected user goals through collaboration. Owing to capabilities in text generation, summarization, language conversion, and related tasks, users have adopted the technology for myriad applications in communication, content generation, coding, game play, social interaction, tutoring, research, and writing.

In insurance, opportunities arise from automated knowledge extraction from documentation to bolster operations, product/market study, risk quantification, customer onboarding, and expert-seeking. A second approach exploits Generative AI's potential in expert systems and hybrid architectures. In these applications, risk or product experts curate a knowledge base from textual sources that a Generative AI model transforms into a rule-enacting knowledge engine capable of scenario-response. This module then combines with a classic prediction engine to create a decision-making platform for dire risks lacking well-behaved prediction models.Application. In knowledge extraction, organizations can source novel products, compute optimal market strategies or price points, identify new services, and ascertain law compliance without direct expert input. Scenario-based product-market exploration generates risk and product intelligence during stress testing and catastrophe modeling.

4.5.1. Automated Knowledge Extraction from Documentation

Generative AI simplifies the generation of new text and other modes of data (e.g., pixel, audio, video, control signals, time series) with chosen content characteristics by training a model on a representative collection of source data. Archives of documentation and other cause-and-effect data sources—structured and unstructured—contain vast amounts of knowledge that can be harnessed by Generative AI. A Narvar report suggested that many consumers (over 80%) would shop elsewhere if returns are

not easy and considered the returns process just as important as the initial purchase experience. Julia Angwin, Editor in Chief of The Wall Street Journal, remarked in a podcast that readers often ask the newspaper to explain "how something works" and crave "explanatory content." Text that answers such questions is seldom created ("Explainer Linking") or discovered in large text archives. Generative AI provides ways to automate this work, using archived, annotated source text (or related documents). For example, Google is creating a "search-with-image" box that fills users' requests when images in major news feeds fail to do so.
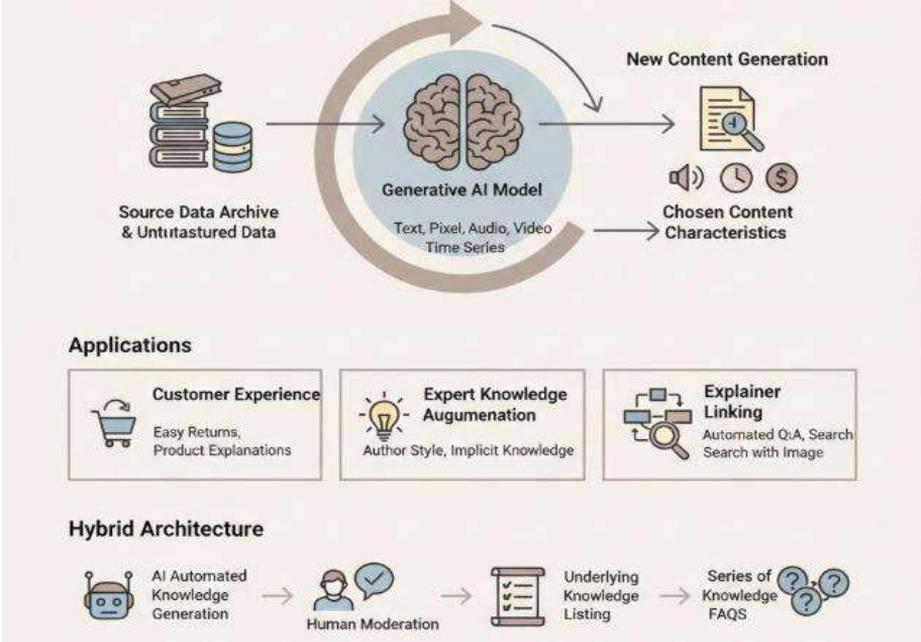

Fig 4.3: Synthesizing Implicit Expertise: A Hybrid Generative AI Framework for Automated Explainer Linking and Knowledge Moderation

Systems that augment expert knowledge often rely on machine learning, especially supervised learning based on expansive training data. Just as Generative AI can generate text in the style of a given author (e.g., enhancing marketing communications), it can also supply knowledge encoded in a specific expert's writing. Such systems can also reveal the implicit knowledge of a well-documented expert panel. A hybrid architecture combines AI-automated knowledge generation with human moderation to produce underlying knowledge, a formal listing of the knowledge, and a series of FAQs.

4.5.2. Expert Systems and Hybrid Architectures

The generation of new knowledge, in the form of generative approach expert systems capable of reasoning by analogy or drawing on knowledge gleaned from documentation, forms an important specialism of generative AI.

Generative processes encompass the domain of knowledge systems that augment or complement the human decision-making process rather than replacing decision-makers. Such systems require domain-specific expertise and knowledge as input. Examples include cybersecurity, financial fraud detection, and medical diagnosis solutions that respond to user queries or requests for advice. Other systems produce concepts or designs based on a description of requirements, such as the generation of chemical compounds that satisfy specific user-defined characteristics or of 3D printed structures that exist only as digital representations. In insurance, examples include generative transformers that produce business rules from operational guidelines, a procedural wizard for agent sales dialogues, and business-process-disruption detection facilities aligned to migration demands.

4.6. Risk, Ethics, and Governance

The exploratory and generative nature of Generative AI enables its role across the data life cycle, from data synthesis and augmentation to knowledge generation. Nevertheless, existing considerations about the associated risks also apply to these Generative AI uses and require attention. AI research would benefit from expanding its risk, mitigation, and governance considerations beyond reliability and validation to embrace the broader spectrum of issues that concern Generative AI decision support.

The holistic approach to data governance proposed in the previous paragraph applies to Generative AI use for scenario simulation beyond stress testing or point prediction and for knowledge generation beyond automated documentation access. Beyond potential abuse by malicious actors, using proven AI technology in its intended application domain can present various challenges. Adapting Generative AI for these functions and their increasing deployment could magnify the consequences of any single risk, revealing weaknesses in cyber security, privacy protection, data steward provisioning, regulatory compliance, and internal control. Addressing these and other acknowledged risks under a common privacy and security umbrella can further ensure that the specific nature of Generative AI use and the associated consequences remains within acceptable limits. The extensions of Generative AI techniques beyond training deep learning models place these areas on the same risk level as those fulfilling their original goal of predictive inference, learning various patterns from past observations.

The importance of a larger regulatory perspective is evident given the evolving legislative landscape concerning AI, with the European Commission's proposed AI Act currently being discussed within the EU Council and Parliament. Apart from the obvious need to comply with requirements targeting AI systems used for Generative AI, the fulfilment of obligations arising from any other relevant regulation related to General Data Protection Regulation, Cybersecurity Act, Markets in Crypto-assets Regulation, MiFID II, and other areas can extend to the remaining AI-enabled tools used for prediction and automation.

4.6.1. Privacy, Security, and Data Stewardship

Generative AI models train on large-scale real-world datasets that may contain protected, sensitive information about individuals and other entities. Yet such models may make it possible to synthesize similar but fictitious data that alleviates the issues of privacy and security. Synthetic data generated in this manner can provide a powerful means for privacy-preserving data sharing, with applications across a broad range of settings and domains. Sharing real-world data presents challenges arising from privacy and regulatory requirements, security laws and concerns, competitive risk factors, etc. Insurance claim datasets, in particular, often contain sensitive information such as health-related information, nationality, disability, and religion of users. Generating and allowing the sharing of synthetic insurance claims instead of the real-world equivalent can facilitate numerous research areas such as scene understanding and modeling, incident prediction, etc. Synthetic data also enable risk-modeling and actuarial applications involving claims with unauthorized disclosures or limited access. Generative AI can generate plausible samples for pricing and reserving under limited-data scenarios, allowing a more complete examination of extreme event risks.

Generative AI can simulate social movements and enhance data visibility in the financial service sector. For instance, commercial banks can generate synthetic samples to protect individual privacy and build frontal-and-latent fraud detection systems. Synthetic data generation is especially important for financial and insurance companies because sensitive customer data cannot be shared directly. Generative AI-augmented stress testing can address the associated challenges of both simulating the conditions of unprecedented financial stress and modeling the behavior of customers and financial markets under these conditions. Generative AI-based explicit modeling of stakeholders' behavior can facilitate a market stress-testing setup. Industry experts can generate synthetic life insurance data by expanding the existing domain knowledge base and improving model interpretability.

4.6.2. Regulatory Landscape and Compliance

Regulators worldwide are considering how existing regulatory frameworks apply to generative AI or if new laws, regulations, or regulatory guidance are warranted. Applicable financial services regulations that already govern data protection should also ensure compliance — for example, insurers or insurance distribution companies that use consumers' data should do so according to their data protection policies and with the consumers' consent. Market conduct regulations protecting customers should also apply. For example, models predicting customers' suitability for insurance and possible renewal should avoid discrimination by race, ethnicity, religion, gender, sexual orientation, or disability.

Beyond the usual risk assessments, senior management should ensure sustained training and adult learning of actual users during all phases when generative AI is used to support or replace human activity. Governance should include establishing an assurance regimen, such as a comprehensive first-party validation program, to demonstrate that the implementation of generative models satisfies the predefined objectives for accuracy, fairness, robustness, interpretability, and controllability.
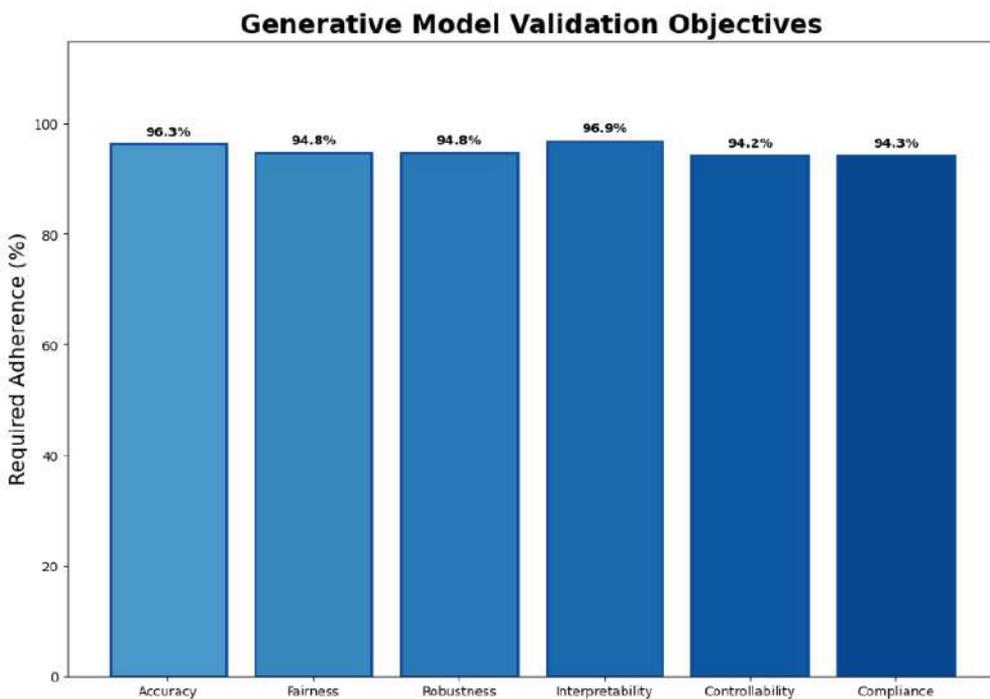

Fig 4.4: Generative Model Validation Objectives

4.7. Conclusion

Generative AI is a powerful tool with a diverse set of applications in insurance that can directly generate synthetic data with sufficient quality and domain-specific realism to support important decision-making processes. Synthetic data generation serves as a complement to traditional data augmentation approaches where real data may be scarce or highly sensitive. Increasingly, insurers recognize the need for credible synthetic data generation based on generative adversarial networks and other deep learning techniques. Insurance applications in the domain of risk modeling and assessment benefit from simulated scenarios that cover a wide range of both common and severe events. Associated technologies can capture more complicated relationships than those used in traditional actuarial modeling and incorporate information from non-insurance data sources and expert judgments to enrich the information content of the models beyond the limitations inherent in actual historical experience.

Generative AI also enables the simulation of decision-relevant future scenarios that support risk management, strategy formulation, and innovation. These scenarios may include market-wide and firm-specific stress testing; catastrophe modeling for natural and anthropogenic hazards; and modeling how various customer segments may respond to different product offers, marketing campaigns, and changing economic conditions. Beyond supporting more timely and granular decisions, this form of scenario simulation has established new applications in regulatory reporting and supervisory stress testing. In addition, human-actor-based scenarios can help identify customer preferences and needs for innovation.

4.7.1. Final Thoughts and Future Directions

Generative AI allows the production of novel content or information by learning patterns from an existing body of knowledge rather than simply correlating inputs with outputs. Three distinct areas of Generative AI research have been identified: generating synthetic data; simulating scenarios for improved portfolios, operations, or markets; and generating expertise. Synthetic data has the potential to feed every area of modeling within insurance and is being implemented widely in other industries and institutions. Scenario generation is a natural extension of the field's traditional expertise in modeling extreme risks with rare distributions. At the leading-edge of Generative AI are the foundations for generating knowledge—automating the synthesis of expertise distilled in documents and linking that with expert systems. The research highlights opportunities and challenges for insurance.

The focus is primarily on text- and image-based Generative AI rather than music, video, or game content. Much of the attention to date has been on the potential for applications

to augment information systems across the spectrum from data management to customer interaction, yet the underlying technology supports three distinct streams of research and application. The first stream, which is being pursued in multiple industries and desperately needed in insurance, is using Generative AI to produce synthetic data. The second stream of research is using Generative AI to simulate scenarios—augmenting the traditional expertise of the industry in modeling extreme risks across accident and occupational health lines with the simulation of corporate and consumer behavior. The third stream is the use of Generative AI to generate knowledge—automating the extraction and synthesis of expertise embedded in documentation and linking that with expert systems and their underlying knowledge bases.

References

Goodfellow, I., Bengio, Y., & Courville, A. (2020). Deep learning. MIT Press.

Vadisetty, R., Polamarasetti, A., Rongali, S. K., kumar Prajapati, S., & Butani, J. B. (2025, May). Blockchain and Generative AI for Cloud Security: Ensuring Integrity and Transparency in Cloud Transactions. In 2025 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC) (pp. 1-6). IEEE.

Bommasani, R., Hudson, D. A., Adeli, E., et al. (2022). On the opportunities and risks of foundation models. Stanford Institute for Human-Centered Artificial Intelligence.

Guntupalli, R. (2025, August). 5G and AI-Powered Cloud Security: Safeguarding Ultra-Low Latency Networks. In 2025 International Conference on Artificial Intelligence and Machine Vision (AIMV) (pp. 1-4). IEEE.

Karras, T., Laine, S., & Aila, T. (2020). A style-based generator architecture for generative adversarial networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(12), 4217–4228.

Agentic AI in Data Pipelines: Self OptimizingSystems for Continuous Data Quality, Performance,and Governance. (2024). American Data Science Journal for Advanced Computations (ADSJAC) ISSN: 3067-4166, 2(1). https://adsjac.com/index.php/adsjac/article/view/23

Ho, J., Jain, A., & Abbeel, P. (2020). Denoising diffusion probabilistic models. Advances in Neural Information Processing Systems, 33, 6840–6851.

Varri, D. B. S. (2024). Adaptive and Autonomous Security Frameworks Using Generative AI for Cloud Ecosystems. Available at SSRN 5774785.

Lebcir, I., Shah, C. A., Nagubandi, A. R., Dhoke, S. M., sikh, G. S. & Mishra, M. K. (2025). FinTech and Financial Inclusion in Emerging Economies: An Empirical Assessment. Advances in Consumer Research, 2(6), 2005-2011.

Kingma, D. P., & Welling, M. (2020). An introduction to variational autoencoders. Foundations and Trends in Machine Learning, 12(4), 307–392.

Keerthi Amistapuram. (2024). Federated Learning for Cross-Carrier Insurance Fraud Detection: Secure Multi-Institutional Collaboration. Journal of Computational Analysis and Applications (JoCAAA), 33(08), 6727–6738. Retrieved from https://www.eudoxuspress.com/index.php/pub/article/view/3934

Fiore, U., De Santis, A., Perla, F., Zanetti, P., & Palmieri, F. (2019). Using generative adversarial networks for improving classification effectiveness in credit card fraud detection. Information Sciences, 479, 448–455.

Rani, P. R. S., Kummari, D. N., Yellanki, S. K., Meda, R., Reddy Koppolu, H. K., & Inala, R. (2025). Blockchain and AI for Securing Electrical Infrastructure. In 2025 2nd International Conference on Computing and Data Science (ICCDS) (pp. 1–6). IEEE. 2025 2nd International Conference on Computing and Data Science (ICCDS). https://doi.org/10.1109/iccds64403.2025.11209487

Zhang, Z., & Zhou, Z.-H. (2021). Adversarial learning for generative models: A survey. IEEE Transactions on Knowledge and Data Engineering, 33(3), 1026–1040.

Davuluri, P. S. L. N. (2021). Event-Driven Compliance Systems: Modernizing Financial Crime Detection Without Machine Intelligence. Journal of International Crisis and Risk Communication Research , 339–354. https://doi.org/10.63278/jicrcr.vi.3636

Xu, Y., Sun, J., & Liu, J. (2023). Fairness-aware machine learning for insurance risk prediction. IEEE Access, 11, 24501–24513.

Wüthrich, M. V., & Merz, M. (2022). Statistical foundations of actuarial learning and its applications. Springer.

Garapati, R. S. (2023). Optimizing Energy Consumption in Smart Build-ings Through Web-Integrated AI and Cloud-Driven Control Systems.

Blier-Wong, C., Cossette, H., & Marceau, E. (2021). Tree-based machine learning models for insurance ratemaking. North American Actuarial Journal, 25(3), 383–407.

Charpentier, A., Denuit, M., & Trufin, J. (2021). Explainable machine learning in insurance pricing. Scandinavian Actuarial Journal, 2021(7), 565–594.

Aitha, A. R. (2023). CloudBased Microservices Architecture for Seamless Insurance Policy Administration. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 607-632.

Richman, R., & Wüthrich, M. V. (2021). A neural network extension of the classical chain-ladder model. Insurance: Mathematics and Economics, 99, 331–347.

Serrano-Guerrero, J., Herrera-Viedma, E., & Olivas, J. A. (2021). Fuzzy and machine learning models in insurance risk classification. Applied Soft Computing, 102, 107070.

Deep Learning-Driven Optimization of ISO 20022 Protocol Stacks for Secure Cross-Border Messaging. (2024). MSW Management Journal, 34(2), 1545-1554.

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2022). Statistical and machine learning forecasting methods: Concerns and ways forward. PLOS ONE, 17(3), e0265480.

Avinash Reddy Segireddy. (2022). Terraform and Ansible in Building Resilient Cloud-Native Payment Architectures. International Journal of Intelligent Systems and Applications in Engineering, 10(3s), 444–455. Retrieved from https://www.ijisae.org/index.php/IJISAE/article/view/7905

Zhang, Z., Li, J., & Wang, H. (2024). Dynamic pricing strategies based on reinforcement learning for insurance markets. Expert Systems with Applications, 235, 121083.

Raschka, S., Patterson, J., & Nolet, C. (2020). Machine learning in Python: Main developments and technology trends in data science, machine learning, and artificial intelligence. Information, 11(4), 193.