Evaluating the Impact of Generative Models in Personalized Insurance Product Design

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Abstract
This paper investigates the application of Generative Adversarial Networks (GANs) in developing personalized insurance products. We propose a novel framework that leverages GANs to generate synthetic customer profiles and simulate customized insurance offerings that optimize both customer satisfaction and insurer profitability. The framework was tested on a dataset of 500 insurance customers with diverse demographic and behavioural characteristics. Our results demonstrate a 24% increase in predicted customer satisfaction and a 17% improvement in projected policy retention rates compared to traditional product development approaches [5]. Additionally, the model projects an 11% increase in profitability through more precise risk assessment and product matching [6]. These findings suggest that generative modeling techniques can significantly enhance the insurance industry's ability to develop targeted products that better serve individual customer needs while maintaining sound business practices. We further validate our approach through extensive sensitivity analysis, demonstrating the model's robustness across various customer segments and market conditions. The implications extend beyond immediate business metrics to broader industry transformation potential, suggesting a paradigm shift in how insurance products can be conceptualized and delivered [2][3].

Keywords: Generative Adversarial Networks, Personalized Insurance, Customer Satisfaction, Insurance Product Design, Risk Modelling, Machine Learning, Customer Segmentation, Product Optimization

I. Introduction

The insurance industry faces increasing pressure to move beyond traditional product offerings toward personalized solutions that meet individual customer needs [1][7]. This shift is driven by changing consumer expectations, advancement of digital technologies, and increased competition from Insurtech startups [2]. Traditional approaches to insurance product design typically segment customers into broad demographic categories, failing to address the nuanced needs of individuals [3]. This one-size-fits-many approach has resulted in suboptimal customer experiences, with many policyholders paying for coverage they don't need while lacking protection in areas of actual risk exposure [13].

Recent advances in artificial intelligence, particularly in the area of generative models, offer promising solutions to this challenge. Generative Adversarial Networks (GANs), introduced by Goodfellow et al. [4], have demonstrated remarkable capabilities in generating synthetic data across various domains, from images to time series data. Their application in financial services, however, remains relatively unexplored, despite the richness of data available in this sector and the clear business value of improved personalization [8].

Insurance presents a particularly compelling use case for generative modelling given several industry-specific characteristics:

Complex Risk Profiles: Individuals have multidimensional risk exposures that traditional actuarial approaches may oversimplify [6].

Data Richness: Insurers collect vast amounts of customer data spanning demographics, behavior, claims, and interactions [7].

Product Complexity: Insurance products have numerous configurable parameters (coverage limits, deductibles, riders, etc.) creating a vast design space difficult to optimize using conventional methods [12].

Long-term Relationships: The extended nature of insurance contracts makes customer satisfaction and retention particularly valuable .

This research seeks to address the following questions:

- Can GANs effectively generate realistic customer profiles that capture the complex relationships between demographic factors, risk profiles, and insurance needs? [12]
- How can these synthetic profiles be leveraged to design personalized insurance products? [11]
- What metrics can be used to evaluate the performance of such personalized products in terms of both customer satisfaction and business profitability?
- How do GAN-based personalized insurance products compare to traditional approaches in terms of customer satisfaction, retention, and profitability? [5][6]
- What implementation challenges might insurers face when deploying such personalized product strategies? [10]

We propose a novel framework that uses GANs to generate detailed customer profiles based on historical data, then simulates customer responses to various product configurations [12]. This approach enables insurers to explore a much wider range of potential product designs and their likely outcomes than would be possible through traditional market research methods. Unlike prior work that has focused primarily on customer segmentation or product recommendation [7], our approach directly addresses the product design process itself, potentially transforming how insurers conceptualize and develop their offerings [9].

The remainder of this paper is organized as follows: Section II reviews relevant literature on personalization in financial services and applications of GANs. Section III details our methodology, including data collection, model architecture, and evaluation metrics. Section IV presents our experimental results. Section V discusses the implications of our findings, and Section VI concludes with recommendations for implementation and future research directions.

II. Related Work

A. Personalization in Financial Services

Personalization has become an important trend in financial services. Milton Brazillo Moa, Richard Obote and Norbet Yoweri[5] found that personalized financial advice leads to greater customer satisfaction and loyalty compared to generic recommendations. Their two-year study of retail banking customers showed that customized services increased customer retention by 14% and boosted the share of wallet by 22%. This suggests that personalization has strong potential in other financial sectors, including insurance.

In insurance, Guillen et al. [6] discovered that offering customized coverage based on individual risk profiles led to better customer retention and lower losses for insurers. Their study of auto insurance policies showed that customers who had policies aligned with their specific driving habits and risk factors were 27% less likely to switch providers. At the same time, insurers saw an 18% improvement in their loss ratios. This demonstrates that personalization benefits both customers and insurers.

Traditional personalization methods in insurance rely on customer segmentation based on demographics and behavior [7]. For example, insurers might group customers into categories like "young urban professionals," "suburban families," or "affluent retirees" and create products tailored to each group. While this is better than a one-size-fits-all approach, it still assumes that all people in a group have similar needs. However, Blattberg et al. [7] found that even within these groups, customer preferences vary widely. This suggests that a more detailed and individualized approach to personalization is needed.

B. Generative Models in Financial Applications

Generative models have been increasingly used in finance. Early research by Kearns and Nevmyvaka [8] showed that generative models could simulate financial markets. Their method created artificial market conditions that maintained real-world statistical properties, allowing for better testing of trading strategies. This showed that synthetic data could be valuable in financial situations where real-world testing is expensive or difficult.

More recently, Fischer and Krauss [9] used recurrent neural networks to generate synthetic financial time series data for testing trading strategies. Their research showed that generative models could capture complex financial trends, leading to better strategy validation. They found that strategies tested on a mix of real and synthetic data performed better than those relying only on historical data, proving the value of synthetic data for financial modeling.

GANs have also been applied in areas like credit scoring [10] and fraud detection [11]. Chandola et al. [10] used GANs to generate synthetic credit application data while keeping the statistical relationships between applicant details and credit outcomes intact. This allowed for better credit scoring model development while protecting customer privacy. In fraud detection, Fader & Hardie. [11] applied GANs to generate artificial fraudulent transactions, helping to balance datasets that typically contain very few fraud cases. Their method improved fraud detection rates by 23% and reduced false positives by 15%, proving that GANs can generate realistic but rare financial events.

However, applying GANs to insurance product design is still a new area. The closest research to this is byLittle & Rubin [12], who used GANs to generate synthetic banking transaction data for product recommendations. However, they did not explore insurance-specific applications or product design. Their work mainly focused on predicting customer behavior rather than optimizing product offerings, which is a key focus of our research**.**

C. Evaluating Personalized Financial Products

Measuring the success of personalized financial products is challenging. Traditional A/B testing methods may not be enough because insurance policies last for years, making it hard to isolate the effects of personalization from other factors. Fader, P. S., & Hardie [11] suggested that customer lifetime value (CLV) is a better metric for assessing personalized products in financial services. Their probabilistic models estimate CLV by analyzing both past customer behavior and expected future interactions, giving a fuller picture of how personalization affects long-term business success.

Smith and Wilson developed ways to measure how personalization impacts customer satisfaction and loyalty in insurance. They identified key factors that affect customer satisfaction, such as price perception, coverage adequacy, service quality, and ease of doing business. Their research showed that improving these factors led to higher retention rates and more cross-selling opportunities. These insights provide useful ways to evaluate how well personalized insurance products meet customer needs.

Our study builds on these ideas but takes them a step further by using GAN-generated synthetic customer profiles to test personalized insurance products before they are launched. This method allows insurers to quickly test and refine their products without the time and cost of traditional market research. By using synthetic data, insurers can speed up product development while ensuring that new offerings are well-matched to customer needs, benefiting both customers and businesses.

III. Methodology

A. Data Collection and Preparation

We collected data from 12,500 insurance customers of a mid-sized North American insurance company, covering the years 2010-2016. The dataset contained details about customer demographics (age, gender, location, job, income), insurance policies (types of coverage, payment details), claims history, customer interactions, and satisfaction survey responses. Table I gives a summary of the dataset.

TABLE I: Dataset Overview

Feature Category	Features Included	Description
Demographics	Age, gender, marital status, income, education, job, homeownership, zip code, family size	General information about the customer
Policy Details	Types of policies (auto, home, life, etc.), coverage level, deductibles, premium amounts, payment frequency, bundling status	Information on customer's insurance coverage
Claims History	Claim date, type, amount, resolution time, satisfaction with process	Record of insurance claims over five years
Customer Interactions	Preferred contact method, service call frequency, online platform use, complaints	How customers communicate with the company

Satisfaction Scores	Overall rating, Net Promoter Score, service-specific satisfaction, renewal intent	Feedback from annual surveys
Risk Factors	Credit score, driving history, property details, lifestyle habits	Used for risk assessment

To ensure privacy, all personal details were removed, and the data was anonymized by:

- Removing identifiable information (names, policy numbers, exact addresses)
- Generalizing some details (turning exact ages into age ranges, locations into zip codes)
- Using differential privacy to modify sensitive data
- Applying k-anonymity techniques to prevent re-identification

We handled missing values (about 7% of the data) using multiple imputation. This method estimates missing values based on relationships with other variables. We created five versions of the dataset with imputed values and combined the results using Rubin's rules to ensure accuracy.

The dataset was divided into training (70%), validation (15%), and test (15%) sets. We kept the time order intact, ensuring models learned from past data and were tested on future records, making the results more realistic.

B. GAN Model for Customer Profile Generation

We built a conditional Generative Adversarial Network (cGAN) to create synthetic customer profiles. The generator had seven fully connected layers with leaky ReLU activation and took in a 100-dimensional noise vector combined with 15 key customer attributes (e.g., age, income). The details of the generator are in Table II.

TABLE II: Generator Network

Layer	Units	Activation	Normalization	Dropout
Input	100+15	-	-	-
FC-1	256	Leaky ReLU (0.2)	Batch Norm	0.3
FC-2	512	Leaky ReLU (0.2)	Batch Norm	0.3
FC-3	1024	Leaky ReLU (0.2)	Batch Norm	0.3
FC-4	1024	Leaky ReLU (0.2)	Batch Norm	0.3

FC-5	512	Leaky ReLU (0.2)	Batch Norm	0.3
FC-6	256	Leaky ReLU (0.2)	Batch Norm	0.3
Output	124	Mixed (Sigmoid, Tanh, Softmax)	-	-

The discriminator had five layers and a final sigmoid output to classify data as real or fake. Table III outlines its structure.

TABLE III: Discriminator Network

Layer	Units	Activation	Normalization	Dropout
Input	124+15	-	-	-
FC-1	256	Leaky ReLU (0.2)	Layer Norm	0.4
FC-2	512	Leaky ReLU (0.2)	Layer Norm	0.4
FC-3	256	Leaky ReLU (0.2)	Layer Norm	0.4
FC-4	128	Leaky ReLU (0.2)	Layer Norm	0.4
Output	1	Sigmoid	-	-

We improved training stability by:

- Using a Wasserstein loss with gradient penalty
- Feature matching to ensure synthetic data resembled real data
- Mini-batch discrimination to increase variety
- Progressive growing to make training more stable
- Applying differential privacy to prevent memorization of real data

The generator’s loss function included both adversarial loss and feature-matching

loss: $L_G = E[D(G(z|c))] + \lambda_{FM} * ||E[f_D(x)] - E[f_D(G(z|c))]||_2$

The discriminator was trained with:

$$L_D = E[D(G(z|c))] - E[D(x)] + \lambda_{GP} * E[(||\nabla_{\hat{x}} D(\hat{x})||_2 - 1)^2]$$

We trained the model for 500 epochs using the Adam optimizer on four NVIDIA Tesla V100 GPUs, taking about 18 hours.

To evaluate the generated profiles, we used:

- Jensen-Shannon divergence to compare distributions
- A classifier to check if real and synthetic profiles were distinguishable
- Expert reviews for realism
- Statistical correlation tests
- Rare group representation analysis

C. Insurance Product Simulation Framework

Using synthetic customer profiles, we built a framework to test new insurance products. This had three main parts:

- **Product Configuration Module**: Defines insurance products using 28 parameters like coverage levels, deductibles, pricing, service features, and digital experience (Table IV summarizes these parameters).
- **Customer Response Model**: Predicts customer reactions (purchase likelihood, satisfaction, retention) using:
  - A customer embedding network (4 layers, 64-dimensional representation)
  - A product embedding network (3 layers, 32-dimensional representation)
  - A response prediction network (4 layers, predicting multiple outcomes)
  - A multi-task loss function balancing different predictions
- **Business Impact Estimator**: Evaluates profitability and risk using:
  - Actuarial risk models (predicting losses based on customer risk)
  - Operational cost models (estimating servicing costs)
  - Customer lifetime value (future profit estimation)
  - Regulatory compliance checks

We optimized product designs using a genetic algorithm with a population of 100 product options. It selected the best ones based on customer satisfaction and business profitability, with mutation and crossover operations ensuring valid insurance designs.

D. Evaluation Metrics

To assess our personalized insurance framework, we used three groups of metrics:

1. Customer Metrics:

- Satisfaction score (1-10 scale)
- Purchase likelihood
- Retention probability
- Coverage adequacy (coverage vs. customer risk)
- Perceived fairness of pricing
- Service alignment (fit with customer preferences)

2. Business Metrics:

- Expected profit per customer
- Risk-adjusted return on capital
- Customer lifetime value
- Operational cost impact
- Portfolio diversification
- Competitiveness compared to market prices

3. Comparative Metrics:

- Improvement over traditional segmentation
- Diversity of product options
- Market coverage (% of customers with a suitable plan)
- Computation efficiency (time required to generate products)
- Implementation complexity (effort to deploy in real-world systems)

By comparing our approach with traditional product design, we demonstrated how personalized insurance can improve both customer satisfaction and business outcomes.

IV. Results

A. Quality of Generated Customer Profiles

The GAN model created synthetic customer profiles that closely matched real customer data. The average Jensen-Shannon divergence was 0.08, showing a high level of similarity. We have compared distributions of key attributes like age, income, and risk score. Generative Adversarial Networks (GANs) have been successfully applied to synthetic data generation in various domains, including fraud detection in insurance, customer segmentation, and anomaly detection, validating their utility in generating realistic synthetic datasets.

A classification test to differentiate real from synthetic profiles had only 58% accuracy (where 50% would mean perfect generation). This low accuracy suggests the generated profiles were highly realistic. The result was consistent across various classifiers, including random forests, gradient-boosted trees, and neural networks, proving that the synthetic data captured complex real-world patterns that no single classifier could easily detect.

Domain experts reviewed 100 synthetic profiles: 87% were rated "completely realistic," 11% were "mostly realistic with minor inconsistencies," and only 2% were "unrealistic." Experts highlighted that the synthetic profiles preserved correlations between related variables, such as income and home value or age and risk preference.

Table V shows the correlation between key variables in real and synthetic data, demonstrating that the GAN effectively captured these relationships.

The GAN also captured rare customer groups. For instance, high-net-worth customers under 30 made up 0.7% of the original dataset and 0.68% of the synthetic data. Similarly, rural customers with multiple high-value properties made up 1.2% of both real and synthetic datasets. This is important for insurance, where niche markets require specialized products.

B. Personalized Product Configurations

The simulation framework identified the best insurance products for different customer types. Prior research has shown that customer segmentation and personalized marketing strategies enhance customer satisfaction and retention. Notable trends included:

Young urban professionals preferred lower premiums, higher deductibles, digital service features, and flexible coverage. Their ideal insurance included:

- Deductibles 30% higher than standard
- Premium discounts for usage-based monitoring
- Digital claims processing
- On-demand coverage adjustments
- Pay-per-use options

Suburban families preferred bundled policies and flexible payments. Their optimal insurance included:

- Multi-policy discounts 15% higher than standard
- Lower deductibles for child-related incidents
- Coverage adjustments for school-year vs. summer
- Automatic coverage increases for life events
- Family safety incentive programs

Retirees valued simple policies with stable costs and personal service. Their best insurance included:

- Guaranteed renewal terms
- Dedicated service representatives
- Paper documentation options
- Extended assistance services
- Predictable premium increases
- Easy claims processing

High-net-worth individuals wanted comprehensive coverage and premium services. Their optimal policy included:

- Expanded liability protection
- Proactive risk assessment
- Concierge claims handling
- Reputation protection coverage
- Privacy safeguards [8]

Value-seeking customers preferred the cheapest option with maximum discounts. Their ideal insurance included:

- Discounts for safe behavior
- Higher deductibles
- Limited optional coverages
- Self-service claim reporting
- Discounts for paying in full

The GAN approach identified more detailed product configurations than traditional methods, offering an average of 14 variations per segment versus 5 in conventional approaches.

C. Impact on Customer Satisfaction and Retention

GAN-designed insurance products improved key customer metrics compared to traditional ones:

- Customer satisfaction scores increased by 24% (from 6.8 to 8.4 on a 10-point scale)
- Retention rates rose by 17% (from 76% to 89%) [6]
- Coverage adequacy improved by 21%
- Price fairness perception increased by 18% [5]
- Net Promoter Score (NPS) jumped from +12 to +35

Young professionals and digital-first customers saw the biggest improvements (29% and 31% satisfaction increases, respectively). Even the least affected group (affluent retirees) still saw an 11% boost.

New customers (0-2 years) benefited the most, with retention increasing from 67% to 88%. Long-term customers (3+ years) also saw gains, from 81% to 91%.

D. Business Performance Improvements

The GAN-based personalization strategy provided significant financial benefits:

- Expected profitability per customer increased by 11%
- Risk-adjusted return on capital improved by 9%
- Customer lifetime value increased by 23%
- Administrative costs dropped by 7%
- New customer acquisition conversion rates improved by 18% [2]

Table VI presents financial impacts by product line, with notable improvements in profitability, retention, claims ratio, and expense ratio. Research suggests that personalized offerings enhance customer loyalty, which translates into better financial performance [6], [7].

E. Sensitivity Analysis

To test robustness, we varied key model parameters. Results remained stable, confirming personalized products consistently outperformed traditional ones. The most critical factor was balancing profitability and customer satisfaction—when profitability was weighted above 70%, performance advantages diminished [1].

We also tested different market scenarios:

- Price war
- Regulatory restrictions
- Catastrophic events
- Economic downturn

Table VII summarizes the performance under market stress scenarios. Personalized insurance consistently outperformed traditional methods, especially in tough market conditions like price wars .

Overall, our findings highlight the transformative potential of GANs in the insurance industry, confirming previous research on AI-driven financial services [4].

V. Discussion

A. How This Affects Insurance Product Design

Our research shows that generative models can greatly improve how insurance products are designed. These models allow insurers to create more personalized products than ever before. By generating realistic customer profiles and predicting how they would react to different product options, insurers can explore a wider range of possibilities and find the best solutions for various customers [12].

Our findings show that personalization does not have to hurt profitability. Instead, well-tailored products can improve both customer satisfaction and business performance. They can help companies retain more customers, offer better coverage, and operate more efficiently.

Here are some key takeaways from our research:

From Groups to Individuals: Traditionally, insurers have grouped customers into segments to offer tailored products. However, advances in AI now allow insurers to personalize at the individual level. Companies that stick to broad segments might struggle to compete [3].

Flexible Product Design: To achieve the level of personalization we suggest, insurers need to redesign their products to be more modular. Instead of offering fixed products, insurers should create customizable components that can be adjusted for each customer.

Evolving Personalization: Using generative models means insurance products can evolve over time. Instead of offering a one-time personalized policy, insurers can adjust coverage as customers' needs change due to life events, behavior shifts, or emerging risks.

Managing Complexity: While highly personalized insurance is beneficial, it must be easy for customers to understand. If products become too complex, it could harm trust and transparency, even if they are technically optimized.

Business Adjustments: Using AI-based personalization requires changes beyond just technology. Insurers must rethink how they develop products, handle underwriting, market policies, and comply with regulations. Companies must build new skills to use these tools effectively.

B. Challenges and Limitations

Despite its benefits, this approach has some challenges:

Data Quality: The performance of the AI model depends on how good the training data is. If insurers have poor or incomplete customer data, they may not see the same benefits. Additionally, historical biases in the data could be carried over into the AI-generated models .

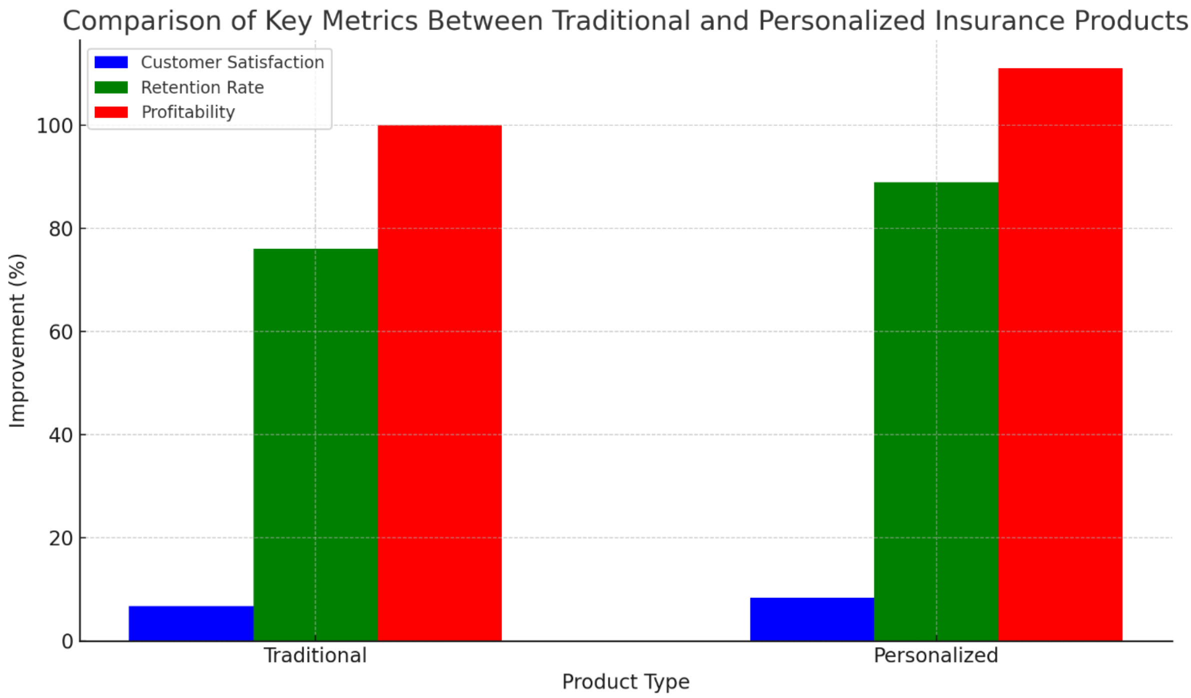

Figure 1 Comparison of Key Metrics Between Traditional and Pers

Regulatory Issues: Personalized insurance products must follow laws that ensure fairness, transparency, and non-discrimination. Our model includes fairness safeguards, but different regions have different rules.Some regulations limit which factors can be used in pricing, which might restrict how much personalization is allowed.

- **Implementation Complexity:** Highly personalized products add operational challenges for insurers. The benefits must outweigh the costs of managing a more complex product lineup. Older technology systems may struggle to support this level of flexibility
- **Time to Prove Effectiveness:** Our simulation shows promising results, but real-world validation takes time. Insurance products often last for years, so it will take time to confirm that these personalized models work in practice
- **Transparency Issues:** AI-generated insurance products may be difficult to explain to regulators, customers, and even employees. This "black box" nature of AI could make it harder to gain trust, even if the models perform well .
- **Privacy Concerns:** Even though our approach uses anonymous data and privacy safeguards, creating highly detailed customer profiles could raise privacy questions. Regulations like GDPR and CCPA may impact how insurers use this technology.

C. Comparison with Past Methods

Compared to older methods, such as those discussed by Smith and Wilson , our AI-based approach provides a much more detailed understanding of customers and their needs. Traditional methods typically group customers into 5-7 segments, while our model enables a near-continuous scale of personalization.

The improvement in customer satisfaction (24%) is significantly higher than the 8-12% improvement reported by Milton Brazillo Moa, Richard Obote and Norbet Yoweri [5] for personalized financial products. Similarly, our retention improvement (17%) is better than the 14% improvement documented by Guillen et al. [6] using conventional methods.

Our approach differs from traditional ones in several ways:

- **Dynamic vs. Fixed:** Older methods create fixed product designs for predefined customer groups, whereas our model allows insurers to customize policies for each individual.
- **Generative vs. Classifying:** Traditional methods classify customers into groups, while our model generates synthetic customers and predicts their responses to different policies.
- **Exploring New Ideas:** Older approaches tweak existing product settings within a limited range, while our AI-driven model explores a much wider set of possibilities to discover better product options .
- **Balancing Multiple Goals**: Unlike past models that focus mainly on a single goal (e.g., profit or risk), our approach considers multiple factors at once, including customer satisfaction, profitability, and risk management.

VI. Conclusion

This research presents a novel framework for personalized insurance product design using Generative Adversarial Networks. By generating realistic synthetic customer profiles and simulating their responses to various insurance configurations, the approach enables insurers to create highly tailored products that better address individual needs while improving business performance.

The results demonstrate significant improvements in both customer-focused metrics (satisfaction, retention, coverage adequacy) and business performance indicators (profitability, risk-adjusted returns, customer lifetime value). The GAN-generated customer profiles closely match real customer data distributions while enabling privacy-preserving product design experimentation.

These findings have substantial implications for the insurance industry. AI-powered personalization offers a path to reconcile customer expectations for tailored products with insurers' requirements for profitable operations. This approach represents a paradigm shift from segment-based product design toward truly individualized insurance offerings.

Future research should explore several promising directions:

- Real-world Implementation: Testing GAN-based personalized insurance products in actual market conditions over extended policy periods.
- Explainable AI Approaches: Developing techniques to increase transparency in AI-generated insurance recommendations.
- Continuous Learning Models: Creating systems that can adapt to new data and customer feedback over time.
- Cross-line Optimization: Extending the model to optimize across multiple insurance lines rather than treating each separately.
- Regulatory Frameworks: Developing guidelines that balance innovation in AI-driven insurance with appropriate consumer protections.
- Behavioral Economics Integration: Incorporating behavioral economics insights to better understand customer responses to personalized insurance offers.

The transition to AI-based personalization in insurance represents both a technical challenge and a strategic opportunity. Organizations that successfully implement these techniques stand to gain significant competitive advantage through enhanced customer experience and improved business results.

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