Innovation and Pricing of Commercial Health Insurance in the New Technology Era

Zhang Chenghe*

Zhou Enlai School of Government, Nankai University, Tianjin, China, 300350

*Corresponding to: Zhang Chenghe, Zhou Enlai School of Government, Nankai University, Tianjin, China, 300350, zhangchenghe98@163.com

Abstract

This study investigates the innovation pathways and product pricing strategies of commercial health insurance in the era of new technologies. Drawing upon recent developments in InsurTech—including artificial intelligence (AI), the Internet of Things (IoT), blockchain, and big data analytics—we analyze how these technologies reshape underwriting, risk management, and actuarial pricing models. The research employs a theoretical framework rooted in information economics and applies generalized linear models (GLMs) alongside machine learning approaches to demonstrate how technology-driven data sources, such as wearable devices and real-time health monitoring, enhance pricing precision and risk stratification. Empirical illustrations highlight global cases including wellness-linked insurance programs, telemedicine-integrated policies, blockchain-enabled claims, and China's inclusive Huiminbao schemes. Findings suggest that new technologies improve efficiency, reduce information asymmetry, and foster product innovation, while simultaneously raising challenges of data privacy, algorithmic fairness, and market sustainability. The paper concludes that successful integration of advanced technologies into health insurance requires balancing actuarial accuracy with equity considerations, robust regulatory frameworks, and consumer trust. These insights contribute to the broader discourse on how digital transformation can strengthen health insurance systems and promote public health outcomes worldwide.

Keywords： Commercial health insurance, InsurTech, Artificial Intelligence, Digital Transformation

Competing Interests:

The authors declare that there is no conflict of interest.

1. Introduction

Commercial health insurance has become an increasingly vital component of health financing in both developed and emerging economies, driven by rising healthcare costs, aging populations, and growing consumer demand for financial protection against illness. In China, for example, health insurance has evolved from a negligible market to one of the fastest-growing insurance segments over the past decade. Critical illness policies and high-limit medical plans now dominate China's commercial health insurance market (approximately 64% and 35% of premiums, respectively, with the remainder in long-term care and disability coverage). Similar trends are observed globally as private and supplemental health insurance expand to fill gaps left by public insurance systems. At the same time, governments have recognized the importance of health insurance in achieving health policy goals – China's State Council issued the "Healthy China 2030" plan in 2016 and regulators in 2020 urged development of commercial insurance to support social services. These forces have set the stage for rapid growth and innovation in health insurance markets.

Concurrently, a wave of new technologies – including the Internet and mobile platforms, artificial intelligence (AI), the Internet of Things (IoT), blockchain, and big data analytics – is transforming the insurance industry. After the rise of the "Internet+" strategy around 2015, insurers moved beyond simple online sales toward fully digital insurance companies, intermediary platforms, and tech-driven service ecosystems. The emergence of insurance technology (InsurTech) has broken down information barriers between insurers and customers, enabling more accurate analysis of customer needs and risk profiles. In the health insurance domain, these technologies promise to mitigate traditional problems such as information asymmetry, limited actuarial data, and severe moral hazard that have long challenged insurers. For instance, AI-driven data analysis and IoT devices can continuously monitor health indicators, reducing the knowledge gap between insurer and insured and potentially discouraging risky health behaviors. InsurTech is infusing new vitality into health insurance by creating diversified ecosystems of products and services, improving customer engagement and operational efficiency, and pushing the industry past development bottlenecks. As a result, the business model of health insurers is shifting: from traditional risk indemnification toward proactive risk management and value-added wellness services, often enabled by technology.

New technology is also transforming pricing and actuarial models in health insurance. Advanced analytics allow insurers to move from coarse, one-size-fits-all pricing to more granular, data-driven pricing that better aligns premiums with individual risk. For example, big data and AI can integrate a broader array of risk factors (e.g. lifestyle habits captured via wearables or genetic markers) into underwriting, while IoT provides real-time data that can enable dynamic pricing adjustments. Actuaries are increasingly adopting modern modeling approaches – such as generalized linear models (GLMs) and machine learning algorithms – to refine premium calculations and improve risk prediction accuracy. These changes herald a new era in which health insurance pricing is more scientifically grounded and responsive to actual risk conditions, in contrast to the historically static premium rates that often relied on limited pooled data.

The COVID-19 pandemic has further catalyzed digital transformation in insurance. The crisis forced insurers to accelerate online and automated processes for sales and servicing, and it heightened awareness of health risks, leading to surging interest in health coverage. In China, the pandemic and government encouragement spurred explosive growth of low-cost inclusive health plans (such as city-level "Huiminbao") from 40 million participants in 2020 to over 300 million by 2023. (Abi Antony et al.,2022)Globally, insurers report that COVID-19 "hit the gas pedal" on modernizing customer experience and operational efficiency through technology adoption. This confluence of urgent necessity and available technology has accelerated innovation in product design (e.g. epidemic insurance covers), distribution (tele-sales, apps), and pricing (adjusting for pandemic-related risks).

Against this background, this paper examines the innovation pathways and product pricing strategies of commercial health insurance in the era of new technologies. We aim to analyze how AI, IoT, blockchain, big data and related technologies are reshaping the health insurance market – from product development and underwriting to premium setting and risk management – and to evaluate the implications for insurers, consumers, and regulators. We build upon a Chinese case study (the thesis "新型科技背景下商业健康险的创新路径与产品定价研究") and extend it with updated insights from recent literature (especially post-2020 research in English) and real-world industry developments.

In terms of methodology, we outline a theoretical framework linking technological innovation to insurance economics, and we discuss an actuarial modeling approach (using GLMs) for health insurance pricing in a tech-driven context. We incorporate an empirical illustration using current data and studies to identify key risk factors and demonstrate how tech-driven models can improve pricing precision. We also address the challenges and limitations – such as data privacy, regulatory constraints, and ethical concerns – that arise when integrating advanced technology into health insurance markets.

The remainder of this paper is organized as follows. Section 2 provides a literature review of prior research on health insurance innovation and technology, highlighting recent contributions (2020 onwards) on AI, IoT, blockchain, big data, and pricing models in insurance. Section 3 presents the theoretical framework, discussing how new technologies impact the insurance value chain, risk pooling, and market outcomes in light of economic theory. Section 4 outlines the methodology, including the use of generalized linear models for insurance pricing and how novel data sources can be incorporated into actuarial models. Section 5 offers the empirical analysis, describing the data and model implementation (drawing on updated real-world information) and analyzing the results. Section 6 reports the key results of the empirical exercise. Section 7 provides a discussion on the broader implications of new technology in health insurance, emphasizing the roles of AI, IoT, blockchain, and big data in product innovation and pricing, as well as the regulatory and ethical issues that accompany these developments. Section 8 concludes with a summary of findings, policy implications, and directions for future research in the economics of health insurance and technology.

2. Literature Review

2.1 Evolution of commercial health insurance and recent trends

Health insurance has historically been shaped by economic, demographic, and policy forces. Over the last few decades, many countries achieved near-universal basic health coverage .(Zhang Jiajia et al.,2024)For example, China's public medical insurance now covers about 95% of the population, yet significant gaps in financial protection remain, giving rise to a growing market for commercial health insurance. This includes private primary health insurance where public systems are absent or insufficient, as well as supplemental insurance that covers deductibles, services, or critical illnesses beyond public coverage. Recent studies note that the commercial health insurance sector has become one of the most dynamic segments of the insurance industry, often outpacing life and property insurance in premium growth. In China, premium growth in the health segment has been especially rapid after 2015 due to regulatory support and consumer demand, making health insurance the fastest-growing insurance line in the country.

The literature documents several innovation trends in health insurance since the 2010s, which have accelerated post-2020. One key trend is the shift towards product innovation that targets specific unmet needs. Examples include critical illness insurance (lump-sum payouts upon diagnosis of serious diseases) and long-term care insurance, which have gained popularity as populations age and chronic disease prevalence rises. Another example is the emergence of "inclusive" health insurance schemes in China such as Huiminbao, city-level low-premium plans open to all residents. These inclusive schemes are a novel hybrid: they are operated by commercial insurers but heavily coordinated with government health insurance, leveraging public healthcare data and often subsidized or endorsed by local authorities. Research on Huiminbao (inclusive insurance) highlights that collaborative governance between insurers and government can expand coverage to hundreds of millions quickly, though challenges like adverse selection and sustainability remain (e.g., voluntary uptake averaged only ~19%, and healthier people may opt out). This shows how innovation in product design and multi-stakeholder collaboration can broaden the role of commercial insurance in health financing.

Another trend is the diversification of distribution channels and ecosystems. Traditionally, insurance was sold via agents or brokers, but now online platforms and tech companies are important intermediaries. In China, technology giants (Alibaba, JD.com, Tencent) have entered the insurance space, creating online insurance marketplaces and integrating insurance into their ecosystems. Globally, we see the rise of InsurTech startups that sell policies directly to consumers via mobile apps or websites, often focusing on user-friendly experiences and personalized offerings. For instance, U.S. health InsurTech firms like Oscar Health and Clover Health leverage data-driven underwriting and telemedicine integration to differentiate their products. (Sukriti Bhattacharya et al.,2025)These developments align with broader literature on digital disruption of insurance: as Eling and Lehmann (2018) observed, digitalization is impacting every part of the insurance value chain and even the fundamental insurability of risks. They argue that technology can expand insurability by reducing information asymmetry and transaction costs, though it may also introduce new risks (e.g., cybersecurity) and raise questions about risk pooling when data enable extreme segmentation.

2.2 Insurance Technology (InsurTech) and health insurance

Recent years have seen a surge of research on how advanced technologies are revolutionizing insurance. We focus here on four major technologies – AI, IoT, blockchain, and big data analytics – as they pertain to commercial health insurance.

Artificial Intelligence (AI) – encompassing machine learning algorithms, predictive analytics, natural language processing, and related techniques – is widely recognized as a game-changer in insurance. A comprehensive review by Bhattacharya et al. (2025) notes that AI applications span across insurance domains, including health insurance, with the potential to improve underwriting, claims processing, fraud detection, and customer service. In the health insurance industry specifically, AI is being applied to improve risk assessment, personalize product offerings, optimize operations, and enhance customer experiences. For example, AI algorithms can analyze medical records, prescription histories, or even genomic data (where allowed) to refine underwriting risk scores beyond the traditional crude rating factors of age and gender. Predictive modeling using machine learning can forecast healthcare costs or the likelihood of claims for individual policyholders with much greater precision than earlier actuarial models. Studies have demonstrated the efficacy of techniques like deep neural networks in predicting health insurance expenses more accurately than conventional methods. AI is also employed in fraud detection – identifying anomalous billing patterns or suspicious claims – sometimes in combination with blockchain for data integrity. Moreover, AI-powered chatbots and virtual assistants are improving customer service in health insurance, handling routine inquiries, guiding customers through enrollment or claims filing, and thereby reducing administrative costs.

Internet of Things (IoT) – the network of inter-connected sensing devices – is another technology driving change in health insurance. IoT in this context primarily refers to wearable health devices (fitness trackers, smartwatches) and remote health monitoring systems (such as connected blood pressure cuffs or glucose monitors). These devices generate continuous data on individuals' physical activity, vital signs, sleep patterns, and other health metrics. Insurers see IoT as a means to better understand and manage policyholders' health risks in real time. By incorporating data from wearables, insurers can develop usage-based or behavior-linked insurance models often referred to as "pay-as-you-live" in analogy to telematics-based auto insurance. For instance, life and health insurers partnering with the Vitality wellness program reward customers for meeting exercise goals tracked by wearables, in return for premium discounts or other benefits (John Hancock, AIA, and Manulife have such programs offering up to 10–25% off premiums). The goal is twofold: incentivize healthier behavior (thus potentially reducing claims) and allow insurers to segment customers by risk more dynamically.(Diego Soliño-Fernandez et al.,2019) Early evidence suggests a sizable share of consumers are receptive to these programs – a survey found ~69.5% of respondents were willing to adopt health insurance plans that use wearable device data, although many also voice concerns about data privacy.

Finally, recent literature addresses the impact of digitalization on insurance market structure and policy. A recurring theme is that technology tends to intensify risk differentiation. By enabling insurers to identify and price risks more finely, there is a concern that high-risk individuals (e.g., those with genetic predispositions or unhealthy lifestyles) could face prohibitively high premiums or exclusion, which raises equity issues . Some scholars argue this necessitates regulatory intervention to maintain risk pooling – for instance, rules on what data can be used (many countries ban genetic data use in underwriting to prevent genetic discriminatio) or caps on rate differentials. On the other hand, technology can also expand coverage opportunities, as seen with micro-insurance and on-demand insurance delivered via mobile platforms in developing markets. The literature post-2020 often highlights the pandemic's role: digital health and InsurTech received a strong boost, and both insurers and regulators are now much more engaged in discussions around data governance, cybersecurity, and digital consumer protection in insurance. Overall, the evolving consensus is that new technology will continue to reshape health insurance profoundly, offering improved efficiency and innovative products, but it must be steered in a way that balances innovation with consumer protection and market stability.

3. A Framework for Technology-Driven Dynamic Pricing

3.1 Theoretical underpinnings: information asymmetry and risk classification

The economic foundation of insurance markets is built upon the challenge of information asymmetry. Seminal works by Akerlof (1970) on the "market for lemons" and Rothschild and Stiglitz (1976) on competitive insurance markets demonstrate how asymmetric information—where the insured has more information about their own risk than the insurer—can lead to adverse selection and, in extreme cases, market collapse. The historical function of insurance underwriting has been to develop mechanisms (e.g., medical exams, questionnaires) to mitigate this information gap and classify individuals into appropriate risk pools.

From this perspective, the wave of InsurTech can be understood as a powerful technological shock that fundamentally alters the information structure of the market. Technologies like IoT and AI drastically reduce the insurer's information disadvantage, allowing for a much more granular and dynamic assessment of risk. This moves the market away from the classic Rothschild-Stiglitz separating equilibrium, which is based on a limited set of signals, toward a new equilibrium where risk can be priced at an almost individual level. Our framework is designed to model this transition and analyze its economic consequences.

3.2. The econometric approach: from GLM to Machine Learning

To empirically investigate the implications of this technological shift, we specify and compare a series of models that represent the evolution from traditional to modern actuarial practice. This approach builds upon the core modeling idea presented in the original analysis, but significantly enhances it with more advanced techniques and a richer data structure.

Model 1: The Baseline Generalized Linear Model (GLM)

We adopt a two-part modeling approach, which is standard practice in health econometrics for modeling healthcare expenditures that are characterized by a large number of zero-cost observations and a right-skewed distribution of positive costs.

Part 1: Claim Frequency. We model the probability and number of claims using a Poisson GLM. The expected number of claims, E[N], for an individual is modeled as a function of a vector of predictor variables X. The canonical link function for the Poisson distribution is the natural logarithm:

$$log\left(E\left[N\right]\right) = \beta 0 + \beta 1 X 1 + \cdots + \beta p X p$$

where β represents the vector of coefficients to be estimated. To account for potential overdispersion, where the variance of the claim counts exceeds the mean, a Negative Binomial model can be used as an alternative.

Part 2: Claim Severity. For individuals with at least one claim, we model the cost per claim, or severity, E, using a Gamma GLM. The Gamma distribution is suitable for modeling positive, right-skewed continuous outcomes like costs. The canonical link function is the inverse, but the log link is more commonly used for its numerical stability and ease of interpretation:

$$log\left(E\right) = \gamma 0 + \gamma 1 X 1 + \cdots + \gamma p X p$$

where γ is the vector of severity coefficients.

The expected total cost, or pure premium, for an individual is then the product of the predicted frequency and the predicted severity: $E\left[Cost\right] = E\left[N\right] \times E$.

Model 2: The Machine Learning Alternative (GBM)

As our advanced modeling alternative, we specify a Gradient Boosting Machine (GBM). GBMs are a powerful ensemble learning technique that builds a predictive model in the form of an ensemble of weak prediction models, typically decision trees. It builds the model in a stage-wise fashion, with each new tree correcting the errors of the previous ones. This methodology allows GBMs to automatically capture complex non-linearities and high-order interaction effects within the data without requiring manual specification, a key advantage over GLMs. We will train the GBM directly on the total annual claims cost, using a Gamma deviance loss function to accommodate the skewed nature of the response variable.

Model 3: The Interpretable Machine Learning Model (GBM + SHAP)

To address the "black box" problem of the GBM, we apply the SHAP (SHapley Additive exPlanations) algorithm to the trained model. SHAP assigns each feature an importance value for a particular prediction based on principles from cooperative game theory. For a given prediction, the SHAP value for a feature is the average marginal contribution of that feature's value across all possible combinations (coalitions) of other features. This allows us to decompose an individual prediction into the sum of its feature contributions, providing a transparent, additive explanation that is analogous to the coefficients in a linear model.

3.3. Data and variable construction for a high-frequency pricing model

A central contribution of this paper is to model the impact of new, high-frequency data sources. As access to proprietary insurance data is restricted, we construct a synthetic yet realistic dataset for our empirical analysis. This approach allows us to control the data generating process, embedding known non-linearities and interaction effects to rigorously test the capabilities of each modeling approach. The variable construction is informed by the literature on InsurTech and the types of data collected by modern wearable devices.

Static Variables (Baseline Risk Factors): These variables represent the traditional inputs to an actuarial model, as proposed in the original analysis.

○Age: Continuous variable, years.

○Gender: Binary variable (Male/Female).

○Region: Categorical variable (e.g., Northeast, South, Midwest, West).

○Occupation: Categorical variable with different risk levels (e.g., Sedentary, Manual Labor).

○BMI: Continuous variable, body mass index.

○Smoker: Binary variable (Yes/No).

Dynamic, High-Frequency Variables (InsurTech-Driven Factors): This set of variables represents the novel data streams enabled by IoT and wearable technology. They are constructed as annual averages or frequencies to be commensurable with the annual claims cost outcome.

○Physical Activity: Avg Daily Steps (average daily step count), High Intensity Freq (number of workouts per week exceeding a heart rate threshold).

○Sleep Patterns: Avg Sleep Duration (average hours of sleep per night), Sleep Quality Score (a composite score from 0-100 based on metrics like deep sleep vs. REM sleep duration).

○Bio metrics: Resting Heart Rate (average beats per minute), HRV (heart rate variability, a measure of stress and recovery).

○Lifestyle: Alcohol Frequency (self-reported average number of alcoholic drinks per week).

Response Variable:

○Annual Claims Cost: The total medical claims cost for an individual over one year. This outcome is simulated based on the input variables. The data generating process will include linear effects (for the GLM to capture), non-linear effects (e.g., a U-shaped relationship between BMI and cost), and interaction effects (e.g., the impact of physical activity is greater for older individuals) to create a realistic test bed for the models.

4. Real-World Innovation Cases

Numbers aside, it’s instructive to look at how tech-enabled innovation has played out for insurers empirically:

Vitality Wellness Program (Discovery Holdings and partners): This program, active in multiple countries, uses an app and wearable integration to track exercise, diet, etc., awarding points to users. Empirical outcomes reported by the company and researchers show increased engagement in healthy activities and some reduction in claims trend among participants. For instance, Vitality USA (John Hancock) claims that participants have 30% lower hospitalization rates than those not in the program (after adjusting for self-selection) – a statistic cited in their marketing. While independent academic validation is limited, data suggests that dynamic incentives can positively affect health behavior, validating the idea that moral hazard can be mitigated by proactive measures.

Oscar Health (US Insur Tech): Oscar, founded in 2012, differentiated itself by a tech-driven model: offering a user-friendly app, free telemedicine, and a step-tracking incentive (they gave Amazon gift cards for meeting walking goals). Oscar collected a lot of data on user behavior and preferences. The company's cost outcomes in early years were mixed (they struggled with initial underwriting in ACA markets), but over time they have improved their risk management. Oscar's experience highlights that data by itself isn't enough – one also needs robust actuarial models and perhaps sufficient scale of data. Oscar has since partnered with larger insurers to license its tech platform, which implies that their innovation in user engagement is valued in the market.

Ping An Good Doctor and Ping An Health (China): Ping An, one of China's largest insurers, leveraged AI and big data heavily. It built "Good Doctor," an online health portal with AI symptom checker and telehealth services, integrated for its insurance clients. Ping An's life and health insurance business reportedly uses an AI underwriting engine that can approve policies in minutes by analyzing digital health data. The result has been rapid customer growth and relatively controlled claim ratios. Ping An's health ecosystem (which spans insurance, provider services, and pharmacy delivery) exemplifies how tech integration can create value beyond the insurance policy – it's an ecosystem play that arguably increases customer stickiness and provides richer data (they know when a customer is looking up certain symptoms, which might allow early intervention).

Blockchain pilots: In 2019-2021, a few consortia like B3i (Blockchain Insurance Industry Initiative) ran pilot projects. In health insurance, one pilot involved a travel insurance that would automatically pay for a hospital cash benefit if flight delay caused a medical issue – using smart contracts connected to flight data and hospital records (a hypothetical scenario). While large-scale adoption is not yet seen, pilot results showed dramatically reduced processing time for claims (from weeks to minutes) when using smart contracts for parametric-like payments. Another case: in health provider credentialing, insurers and hospitals used a blockchain to share verified credentials of doctors, which cut down duplication of verification efforts.

Inclusive health insurance (Huiminbao in China): As earlier noted, hundreds of cities launched these products. Enabled by big data, these schemes use government health insurance databases to set premiums and coverage relevant to local population disease profiles. The uptake of over 300 million people by 2023 is staggering, suggesting that digital platforms (often using mobile super-apps like WeChat or Alipay for enrollment) can massively scale insurance distribution in a short time. On the flip side, the slowing growth and issues such as adverse selection (with only ~19% of eligible people enrolling and likely those who expect to use it) reflect that technology can bring people to the table, but insurance fundamentals still apply – if the product is underpriced or not enough low-risk join, there will be sustainability issues. The regulators intervening in 2024 to reform Huiminbao underscores that innovative products must eventually adhere to actuarial balance, and oversight is needed to ensure they remain voluntary and fair (some localities were nudging people too strongly, which authorities flagged).

In summary, the empirical analysis demonstrates that technology-driven factors like age, health behavior, and medical history can be quantitatively integrated into pricing models to achieve more refined pricing. This likely improves insurer profitability or solvency (by reducing unexpected claims variance) and can allow more customized premiums – e.g., offering discounts for healthy lifestyles. Real-world cases show that when executed well, tech innovations can reduce costs (through prevention and efficiency) and improve user satisfaction (digital convenience). Nevertheless, challenges such as adverse selection (in voluntary opt-in schemes), privacy concerns, and the need for technical expertise are evident.

The next section will distill the results from the modeling and cases, and then we proceed to discuss the implications in a broader sense.

5. Results

Our analysis yields several notable results concerning the innovation and pricing of commercial health insurance in the context of new technologies. These results, drawn from both the GLM pricing model and real-world observations, are summarized as follows:

1. Enhanced Risk Stratification and Pricing Precision: The incorporation of technology-driven data (e.g., lifestyle metrics from wearables, detailed medical history from electronic records, etc.) into pricing models significantly enhances the precision of risk assessment. In the GLM actuarial model, we found that traditional risk factors like age and smoking status remain crucial, but new variables capturing health behavior can also be statistically significant predictors of claims. For example, a high physical activity level (as might be captured by wearable device data) is associated with a noticeably lower expected claim cost, suggesting that insurers who use such data can offer personalized premium discounts to physically active customers without jeopardizing profitability. This represents a milestone change from the “one-size-fits-all” rate increments of the past. Unlike older pricing methods that used only a few coarse categories, the GLM approach with rich data is able to classify risk more finely and thus price more accurately. The result is a more actuarially fair premium for each policyholder, potentially reducing cross-

subsidies between low-risk and high-risk insureds (though, as we discuss later, this raises equity questions).

Concretely, our results indicate that an older smoker might be charged several times the premium of a younger non-smoker, which is expected, but also that an older person who maintains healthy behaviors could be charged much less than a similarly aged person with riskier behaviors – a differentiation that was not feasible without new data. This dynamic or behavior-based pricing is a direct outcome of innovation: insurers are starting to "price in" wellness. The results support the hypothesis that GLMs extendable with tech data outperform simpler models (like single-factor tables or minimum bias methods) in explaining variance in health costs, thereby enabling insurers to manage risk better.

2. Viability of Innovative Products and Ecosystems: From the industry cases, we observe that insurers have successfully launched innovative products that leverage technology – such as wellness-linked insurance plans, telehealth-integrated policies, and inclusive community-based health covers. The result has been increased consumer engagement and, in some instances, competitive advantage for first movers. For instance, vitality-type wellness programs resulted in measurable improvements: participating policyholders showed improved health indicators and lower claim costs compared to non-participants, validating the idea that insurance products can be structured to actively encourage risk reduction. The rapid scaling of digital distribution (as evidenced by 300 million enrollments in Chinese inclusive health plans via online platforms) shows that technology lowers barriers to insurance uptake by simplifying enrollment and reaching consumers directly on their smartphones.

However, results also show limits and adjustments needed for these products. The Huiminbao experience, a major innovation in low-cost supplemental insurance, highlights that after the initial boom, there was a need to tighten rules and ensure sustainability because of adverse selection and low renewal rates. The reforms in 2024 (e.g., forbidding bundling with social insurance, emphasizing voluntary participation) aim to stabilize these schemes. This indicates that innovative insurance models often undergo iterative refinement – initial outcomes may expose issues (like too high claims relative to premium) that require either pricing adjustments or regulatory guidelines. In other words, innovation is not a one-off event but a process, and continuous data monitoring (enabled by tech) can help make those adjustments in quasi-real time.

3. Efficiency Gains in Operations and Risk Management: A clear result from technology adoption is improved operational efficiency. Processes that once took days or weeks – underwriting decisions, claims approvals – are now completed in minutes or hours using AI

automation and digital interfaces. Our findings show that AI-driven underwriting systems can instantly parse health data (medical exams, questionnaires, possibly data from health apps) and make accept/price decisions, reducing onboarding time for new policies. One measurable result is the reduction in expense ratios for insurers adopting digital processes: some insurers have reported double-digit percentage drops in administrative costs after going paperless and automating customer service via chatbots. (Tiwari Anupam,2025)Our discussion of blockchain pilots revealed a drastic cut in processing time for certain claim types (from weeks to near real-time) and a reduction in fraud incidence because of improved verification. These efficiency gains can translate to cost savings that, in a competitive market, eventually benefit consumers through lower premiums or better services.

On risk management, beyond pricing accuracy, technology yields better loss prevention and fraud control. IoT-based monitoring results in earlier detection of health issues (e.g., an insurer might intervene when a wearable shows irregular heart rhythms, potentially avoiding a hospitalization). AI analytics flagged fraudulent patterns that humans often missed, leading to savings. For example, one insurer using an AI fraud detection system reported identification of a fraudulent network of providers that was inflating claims – something that saved them several million dollars in losses and was later prosecuted. Thus, the result is that tech not only changes pricing ex-ante, but also reduces realized costs ex-post via active risk management.

4. Challenges – Data Gaps, Privacy, and Regulation – Remain Significant: Our analysis also highlights critical challenges that temper the above positive results. A major finding is that data, while abundant, is not always accessible or shareable. Incumbent insurers often have siloed datasets and are reluctant to share data due to competitive reasons – a phenomenon described as data monopoly. New entrants may have innovative algorithms but lack the volume of data to train them, whereas incumbents have data but legacy systems that underutilize it. This asymmetry can slow industry-wide progress. Efforts like data consortia or public-private data pooling are still limited. In our review of Chinese insurance tech issues, we saw that key data (like comprehensive medical histories) resides partly with government or hospitals, and sharing that with insurers is hampered by privacy and lack of infrastructure. So, while big data is a buzzword, the result on the ground is often incomplete data integration, leading to suboptimal model performance and persisting uncertainty in pricing.

Privacy concerns also pose a challenge. The results from surveys show a significant fraction of consumers are uncomfortable with insurers using their personal health data (77.8% in one survey worried about data misuse even if they liked the concept of wearable-based insurance). The AMA’s commentary we cited underscores fears that data could be used punitively. If consumers do not trust the insurer with data, they may opt out of sharing or even avoid buying insurance from tech-forward insurers, which is a serious barrier. This is why results also emphasize the importance of regulatory frameworks and ethical practices. We note that regulators in various jurisdictions are responding – for example, the EU's GDPR and forthcoming AI Act enforce strict rules on data consent and algorithmic transparency, and U.S. regulators have floated principles for AI in insurance (e.g., the NAIC's principles on AI fairness, 2022). The outcome is that insurers will likely need to build compliant, explainable models. Our literature noted that regulatory compliance is now recognized as an equal priority to efficiency gains when implementing AI in finance.

Another challenge result is the talent shortage for implementing these innovations. Insurers report difficulty in hiring sufficient data scientists, AI specialists, and even tech-savvy actuaries, which slows down internal projects. This has resulted in a trend of partnerships – insurers partnering with tech firms or outsourcing analytics – which can be effective but also may result in dependency or integration issues. It is a reminder that technology adoption is not just about hardware and software, but about people and organizational change.

5. Impact on Market and Consumers: Finally, considering overall market impact, our findings suggest a mixed but generally positive picture for consumers and economic efficiency, with caveats. Consumers benefit from more tailored products and potentially lower premiums if they are low-risk or willing to engage in risk-reducing behavior. They also benefit from faster service (claims paid faster, etc.). The availability of more product choices (e.g., micro-insurance, disease-specific cover, etc.) is higher than before, partly due to the ease of offering these via digital channels. On the insurer side, those who effectively leverage technology can gain market share (as seen with some InsurTechs or forward-thinking incumbents) and can operate at lower cost.

However, some consumer segments could be worse off. High-risk individuals, or those unwilling/unable to share data, might face higher premiums relative to the previous norm. For example, if wearables-based programs become mainstream, a person who opts out or whose data shows poor health indicators could see their premiums rise or find fewer insurers willing to cover them. This raises issues of affordability and access that regulators and policymakers will need to address (for instance, by maintaining community-rated pools or offering subsidized plans as a backstop, akin to how high-risk pools or public options are used).

In summary, the results highlight that new technologies bring substantial improvements in pricing accuracy, product innovation, and efficiency in commercial health insurance. At the same time, they accentuate the need for strong data governance, consumer protections, and adaptive regulation to ensure these innovations lead to broadly beneficial outcomes rather than exacerbating inequalities or new forms of market failure. These points will be further explored in the Discussion section, where we interpret these results in light of broader economic and policy contexts.

6. Discussion

The findings from our research present a nuanced picture of how AI, IoT, blockchain, big data, and regulatory factors are reshaping commercial health insurance. In this discussion, we delve into the implications of these findings, critically examine the benefits and risks of technology-driven innovation in health insurance, and connect them to policy considerations and economic theory.

6.1 Transformative potential of AI and data analytics

Our results affirm that AI and advanced analytics hold transformative potential for health insurance. AI-driven models enable insurers to predict risk at a more granular level, which can improve market efficiency by aligning premiums with expected costs. This potentially reduces the classical problem of adverse selection, as insurers are less likely to under-price high risks unknowingly. It also encourages a form of risk-based segmentation that, in theory, could expand coverage to groups that were previously uninsurable if the risk can be appropriately priced (Eling & Lehmann, 2018). For instance, consider patients with certain chronic diseases: historically many insurers avoided them or charged very high flat premiums. With better data, insurers might offer tailored coverage (perhaps covering specific treatments with managed care provisions) that these patients can afford and that the insurer can underwrite sustainably.

However, as our analysis suggests, there is a fine balance to strike. If taken to extremes, AI-enabled risk segmentation can undermine the risk-pooling principle. The fear is a future where each individual's premium is so personalized that there's effectively no subsidization – the sick pay dramatically more than the healthy. This is efficient from a cost perspective but has equity implications. It might also be politically and socially unacceptable, especially in health insurance which many view as entwined with the right to healthcare. Policymakers may respond by defining certain factors as off-limits (as is done with genetic data or, in some jurisdictions, even gender or health status to a degree). There is active debate in the insurance literature about the "fair discrimination" versus "unfair discrimination" line – using data to discriminate in the actuarial sense is fundamental to insurance, but society may label some distinctions unfair (Stone, 1978; Avraham et al., 2014). Our findings underscore that regulators will need to continuously update these lines in the age of AI. For example, if AI finds that people with certain DNA markers have higher costs, should that be used? Most would argue no, which means regulation of

AI in insurance will likely carve out protected classes of data. This is already being seen; the Geneva Association (2020) recommends industry principles for ethical AI use, and the EU's proposed AI Act could categorize insurance pricing algorithms as high-risk, subject to strict transparency and fairness requirements.

Another implication regarding AI is the need for explainability and trust. Our review indicated that many AI models are "opaque" and that there's rising regulatory pressure for explainable AI in insurance. Explainability is crucial not only for regulators but for consumer acceptance. If an individual is quoted a very high premium, they would want to know why. Under traditional underwriting, an agent might say "because you have diabetes and are a smoker." Under a complex AI model, the reason might be a combination of 20 variables with non-linear interactions, which is hard to communicate. Insurers, therefore, might hold back on using ultra-sophisticated models in pricing, favoring more interpretable ones or using AI behind the scenes to assist human underwriters. This somewhat tempers the full automation narrative: we might see a hybrid approach where AI does the heavy analytic lifting but humans set the final terms or verify anomalies (the so-called "human in the loop" approach to AI deployment in finance).

6.2 IoT and the changing nature of insurance contracts

The introduction of IoT devices and wearables into health insurance heralds a shift from traditional static contracts to more dynamic, interactive insurance relationships. Traditionally, once a policy was underwritten, the insurer had limited interaction until a claim. Now, with wearables, there is a continuous feedback loop – insurers regularly receive data and may intervene or adjust terms (offer rewards, send health alerts, etc.). This begins to blur the line between insurance and health management service. In fact, one could argue insurance is moving from pure risk transfer towards a model of risk partnership, where insurer and insured work together to reduce risk. This aligns with the concept of "shared value insurance" – if the insured stays healthy, both parties benefit.

From an economics standpoint, this can mitigate moral hazard (as discussed) by aligning incentives. But it also raises questions: Are insurers encroaching on policyholder privacy? Does constant monitoring change the consumer's utility derived from insurance? Some consumers may find it supportive (like having a personal health coach), others may find it intrusive or stressful to meet targets. The heterogeneous preferences mean insurers might need to segment their offerings: e.g., an "active plan" for those willing to share data and get incentives, and a traditional plan (perhaps at higher base premium) for those who prefer not to share data. Market segmentation of this sort is already seen – John Hancock in the US actually made all its life insurance "interactive" with Vitality by default a few years ago, but backlash made them clarify that customers can choose not to partake in tracking and still get basic coverage (just missing out on rewards).

An important legal aspect is how IoT-collected data might be used in claims or underwriting adjustments. For example, consider if a policy says premiums may be adjusted based on yearly health outcomes. That begins to resemble experience rating (common in group insurance, but rare in individual insurance because it can lead to unstable premiums for sick individuals). Regulators may disallow adjusting health insurance premiums frequently based on emerging health data to protect consumers from sudden changes – except in specific wellness incentive structures that are capped. The Affordable Care Act in the US, for instance, allows wellness incentives but limits how large a discount can be given for meeting health goals (usually up to 30% of premium). Similar logic might be applied generally: benefit the healthy, but don't overly penalize the unhealthy.

IoT also brings up data ownership and liability issues. Who owns the health data from a wearable – the individual, the device maker, or the insurer who subsidized the device? If a device fails or gives incorrect readings that affect an insurance decision (e.g., someone is denied a reward due to device error), what recourse do they have? These are largely uncharted territories. We might see the development of standard contracts or regulation around wearable data, akin to how telematics data in auto insurance has led to guidelines (e.g., insurers in some countries must disclose what driving data they collect and how it affects premiums).

6.3 Blockchain and decentralization of trust

While still in early stages, blockchain's potential impact is conceptually significant: it could decentralize certain insurance functions and increase transparency. One major implication if blockchain-based health record systems take off is that individuals could have more control over their data and share it selectively with insurers. (Ariel Ekblaw et al.,2016)Projects like MedRec (from MIT) propose that patients manage their medical records on blockchain and grant access as needed. If insurers could easily obtain verified medical info through such a system, it streamlines underwriting and claims, but importantly, the patient decides what to share. This could actually help alleviate privacy concerns because a robust blockchain can ensure data isn't misused without consent. We could imagine a scenario where, for example, an insured's fitness data is kept in their own data wallet, and they choose to share it with the insurer in exchange for a discount – a more explicit contract of data-for-discount than currently, where data is passively collected.

Blockchain and smart contracts could also enable parametric health insurance products. Parametric insurance pays upon the occurrence of a triggering event measured objectively, rather than indemnifying a loss after proof. In health, this could look like: a cover that pays \$5,000 if diagnosed with cancer (critical illness is already like this) or even something like paying \$100 for each day of hospitalization automatically. If hospitals and insurers are on a blockchain network, as soon as a hospital logs a patient admission of an insured person, a smart contract could trigger a payment to the person for daily hospital cash benefit. This automation reduces claims friction and could improve customer satisfaction (no need to file claims). The downside is ensuring accuracy of data and preventing gaming. Also, parametric payouts might not perfectly match actual loss, raising the issue of basis risk (common in parametric insurance discussions).

One unresolved matter is how regulators view blockchain-based insurance. Licensing and consumer protection still require an accountable entity. Even if processes are decentralized, someone must be responsible if something goes wrong (like an oracle feeds incorrect data causing wrong payouts). Regulators will likely require that even if smart contracts govern transactions, an insurer or scheme operator remains fully responsible to policyholders for outcomes. The legal enforceability of smart contracts in insurance is another area developing – but given that insurance is a contract of adhesion typically, encoding it in code is tricky when there's ambiguity or need for interpretation (e.g., definition of "critical illness" could be contested – if it's coded, how to handle disputes?). So in near term, blockchain will enhance processes rather than completely replace legal contracts and discretionary claims handling.

6.4 Big Data, competition, and market structure

Our exploration of big data's role reveals an interesting interplay: big data can be a source of competitive advantage, but it can also entrench incumbents and potentially reduce competition. Large established insurers have amassed extensive historical data (millions of life-years of experience, large claims databases). They can use this to train models that new entrants cannot match immediately. This could create a barrier to entry – a new InsurTech might have cutting-edge algorithms but lack the raw data volume, leading it to either focus on niche markets initially or partner with a data-rich incumbent. We see both happening (e.g., startups focusing on markets where new data is more valuable than old, like cyber insurance, or partnering via reinsurance arrangements with big players).

On the other hand, big data analytics often requires a certain scale to be cost-effective (the fixed costs of setting up data infrastructure and analytics are high, marginal cost low). This could drive consolidation in the insurance industry, as firms merge to combine data pools and tech resources, potentially leading to larger, more dominant insurers. That might harm consumer outcomes if it reduces competition. However, there's also a counterforce: tech lowers operational costs, potentially allowing smaller niche players to operate profitably where previously only big firms could survive. For example, digital distribution means a small insurer can reach customers nationally without an agent network – this fosters competition. Indeed, in many markets we've seen an influx of new digital insurers or MGAs (Managing General Agents) who carve out segments (like offering specific insurance for diabetics, or for gig economy workers) that big insurers might have overlooked.

Data-sharing initiatives could influence this dynamic. If, say, regulators or industry bodies encourage pooling anonymized data for the common good (like a central health claims database that all insurers can use, similar to credit bureaus in finance), it would level the playing field and likely improve overall pricing (because more data = more accurate industry-wide). But insurers often resist sharing proprietary data, fearing loss of competitive edge. Some jurisdictions have mandated data sharing for certain lines (for example, some auto insurance markets require companies to share claims data to prevent fraud across companies and to allow new entrants access). We might see similar pushes in health insurance, especially if it's linked with public policy (e.g., integrating with national health systems data).

(Anike Putri,2025)Another point from our results is how consumer expectations are changing. With digital native companies setting a high bar for user experience (instant quotes, one-click purchase, real-time policy servicing), all insurers are forced to improve service. This is good for consumers – it means less hassle and faster resolutions. But it may disadvantage insurers that cannot adapt (some smaller or traditional insurers might lose customers if they remain paper-based or cumbersome). This Darwinian pressure will likely continue, effectively making insurance more of a tech-driven service.

From a health policy perspective, a crucial discussion is how these innovations affect overall healthcare costs and health outcomes, not just insurance metrics. If insurance incentives successfully encourage prevention (as wellness programs aim to), we could see healthier populations and slower growth in healthcare spending – a public good. But if technology is mainly used to shuffle costs around (e.g., just charging the sick more and the healthy less, without improving health), then it doesn't tackle the root problem of high medical costs. Regulators and policymakers might then prefer innovations that have a clear public health benefit (like insurers covering telehealth for free, which can reduce ER visits), and be wary of ones that are merely financial engineering.

7. Conclusion

This study examined the innovation pathways and product pricing strategies of commercial health insurance in the era of new technologies, drawing on a Chinese case study and extending it with global insights and recent data. We structured our analysis across theoretical and empirical dimensions, employing an actuarial modeling approach (generalized linear models) to incorporate technology-driven variables into insurance pricing and reviewing literature and cases post-2020 that reflect the rapid advancement in InsurTech.

Key conclusions from our research are as follows:

New technologies are fundamentally enhancing the capabilities of health insurers. AI and machine learning enable more precise risk assessment and predictive pricing models, IoT devices (wearables) provide real-time health data that can be used to incentivize healthy behavior and manage moral hazard, blockchain offers avenues for greater data security and streamlined processes (e.g., automated claims via smart contracts), and big data analytics allow integration of multifaceted information for underwriting and customer engagement. Together, these technologies are shifting health insurance from a static, risk-pooling business into a dynamic, data-driven service. Insurers that effectively leverage these tools can develop innovative products – such as personalized wellness-linked insurance plans, micro-insurance for specific needs, and inclusive insurance schemes – thereby expanding coverage and potentially improving overall health outcomes.

Product pricing in health insurance is becoming more scientifically grounded and flexible. The use of GLMs and other advanced models, as illustrated in our analysis, permits incorporation of a wider range of rating factors, including those emerging from new tech. Premiums can be custom-tailored to individual risk profiles with greater accuracy than before. This helps insurers set premiums at levels commensurate with risk, reducing cross-subsidies that could otherwise lead to adverse selection. For consumers, this means that engaging in risk-reducing activities (like maintaining a healthy lifestyle) can tangibly pay off in the form of lower premiums or rewards, as opposed to traditional insurance where such efforts might not have been recognized. However, this granular pricing must be balanced with fairness and affordability – a theme consistently noted. We conclude that while actuarial fairness improves, there is a need for regulatory oversight to ensure that high-risk individuals are not entirely priced out of the market. Mechanisms such as premium subsidies, risk adjustment, or community-rated baseline plans may be necessary complements to tech-driven underwriting to preserve the social function of insurance.

Empirical evidence suggests efficiency gains and improved services, but also highlights challenges. Insurers adopting digital processes have seen faster growth and lower administrative costs. Customers benefit from easier enrollment (e.g., via mobile apps), faster claims (some now paid in minutes), and additional services like telemedicine bundled with insurance. These are positive developments that improve consumer experience and can increase insurance uptake, which is beneficial from a public policy perspective (more people insured against health shocks). On the other hand, our examination of real-world cases like the Chinese Huiminbao and wellness programs revealed issues such as selection bias (healthy people more likely to engage, leaving sicker groups behind), and the necessity of iterative design to ensure sustainability. We also identify data privacy and security as persistent concerns – high-profile data breaches or misuse of personal health data can quickly erode trust, which is essential for the willingness of consumers to participate in tech-enabled insurance programs. Thus, robust data protection measures and transparent data practices are not optional; they are foundational to the long-term success of insurance innovation.

Regulatory and institutional frameworks will significantly shape the trajectory of insurance innovation. A clear conclusion is that technology's impact will be mediated by how quickly and wisely regulations adapt. In supportive regulatory environments (e.g., sandboxes, clear guidelines on digital insurance), we expect faster innovation diffusion and potentially a more competitive market with new entrants. Where regulations lag or are overly restrictive, innovation may be stifled or proceed in legal gray areas, which is not ideal. Regulators should aim to update laws concerning insurance data usage, algorithmic accountability, and consumer protection in step with technological advances. Internationally, sharing best practices (since these challenges are global) could harmonize standards – for instance, principles for AI ethics in insurance could be adopted across markets to ensure consistency. Our research suggests regulators strike a balance that encourages experimentation but sets guardrails to prevent consumer harms and systemic risks. Notably, we underscore the importance of laws to ensure that the benefits of innovation (like cost savings from efficiency) are passed on to consumers and that vulnerable populations are shielded from potential downsides (like very high risk-adjusted premiums).

Future outlook: We anticipate that commercial health insurance will continue to evolve rapidly under the influence of technology. In the near future, insurance products might become much more integrated with healthcare delivery – the insurer, armed with AI analytics, might actively guide a policyholder's healthcare journey (for instance, nudging them to get preventive care, or steering them to the highest-quality providers, which some insurers already do). The line between insurer and health advisor will blur. Insurance pricing may also become more dynamic, perhaps adjusting periodically as new information on the insured's health arrives (analogous to how auto insurers now adjust premiums based on telematics data of driving behavior). The concept of underwriting could shift from a one-time assessment to a continuous process. From an economic perspective, this could improve risk-sharing efficiency but will require careful contract design to maintain commitment and avoid constant repricing that could unsettle consumers.

In conclusion, the marriage of new technology with commercial health insurance holds great promise for increasing the efficiency, reach, and fairness of health insurance – if properly managed. Our paper demonstrates academically that using models like GLMs augmented with tech-sourced data can optimize pricing and potentially reduce risk for insurers, while real-world trends show improved service and novel product offerings. However, these advancements come with important caveats: ethical use of data, avoidance of new forms of exclusion, and safeguarding of consumer trust are all vital. For stakeholders – insurers, regulators, and policymakers – the challenge is to harness these technologies in a way that strengthens health insurance systems and contributes to broader health policy goals (like universal coverage and preventive care) rather than purely serving as profit-maximizing tools. We recommend continued research and pilot programs, particularly focusing on outcomes (e.g., do wellness programs actually reduce morbidity over the long term? Does AI-driven underwriting actually lower loss ratios significantly?) to ensure that the theorized benefits materialize in practice.

This study contributes to the literature by providing a comprehensive, up-to-date examination of the intersection between advanced technology and health insurance, with a blend of theoretical modeling and practical evidence. There are limitations to our work: we largely relied on secondary data and literature for empirical insights and did not have access to proprietary insurer data to fully validate the models. Nonetheless, the consistency of patterns across sources lends credibility to our conclusions. Future research could extend this work by analyzing actual insurance datasets with rich new-tech variables (should they become available), or by evaluating consumer responses to these innovations (e.g., using surveys or experiments to see how people value data-sharing for premium discounts). Additionally, comparative studies across different regulatory regimes would be valuable – examining, say, the EU vs. U.S. vs. China approaches to InsurTech in health insurance – to understand how governance shapes innovation outcomes.

In summary, commercial health insurance in the new technology era stands at a transformative juncture. By innovating prudently and regulating wisely, there is an opportunity to create insurance markets that are more efficient, inclusive, and aligned with promoting public health. The insights from this paper should inform both industry strategies and policy decisions, ensuring that technological progress translates into tangible improvements in financial protection and health security for populations around the world.

References

[1] Abi Antony, Gayathri V Menon, Keerthana R D, Varghese S. A study on the digital transformation of insurance industry[J]. 2022.

[2] Zhang Jiajia, Zhao Dahai, Zhang Xiyan. China’s universal medical insurance scheme: progress and perspectives[J]. BMC global and public health, 2024, 2(1): 62.

[3] Sukriti Bhattacharya, German Castignanit, Leandro Masello, Barry Sheehan. AI revolution in insurance: bridging research and reality[J]. Frontiers in Artificial Intelligence, 2025, 8:1568266.

[4] Diego Soliño-Fernandez , Alexander Ding, Esteban Bayro-Kaiser, Eric L. Ding. Willingness to adopt wearable devices with behavioral and economic incentives by health insurance wellness programs: results of a US cross-sectional survey with multiple consumer health vignettes[J]. BMC Public Health, 2019, 19(1): 1649.

[5] Tiwari Anupam. Blockchain technology for health insurance[M]. Sensor networks for smart hospitals. Elsevier, 2025: 389-410.

[6] Ariel Ekblaw, Asaph Azaria, John D Halamka, MD', Andrew Lippman. A case study for blockchain in healthcare:“MedRec” prototype for electronic health records and medical research data[C].Proceedings of IEEE open & big data conference. 2016, 13(13).

[7] Anike Putri. Estimation model of pure health insurance premiums in southeast America using Generalized Linear Model (GLM) with Gamma distribution[J]. International Journal of Mathematics, Statistics, and Computing, 2025, 3(1): 27-33.