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Usage-Based and Personalized Insurance Enabled by AI and Telematics

Tiejiang Sun[1], Mengdie Wang[2,*]

[1] School of Information Engineering, Chang'an University, Xi'an 710064, China

[2] School of Taxation and Public Administration, Shanghai Lixin University of Accounting and Finance, Shanghai 201620, China

[*] Corresponding Author: suntiejiang@st.chd.edu.cn

Abstract

The insurance industry is undergoing a fundamental transformation driven by artificial intelligence (AI) and telematics technologies, enabling the shift from traditional risk pooling models to usage-based insurance (UBI) and personalized coverage frameworks. This paper examines how AI algorithms, including machine learning (ML) and deep learning (DL), combined with telematics data collection systems, are revolutionizing insurance pricing, risk assessment, and customer engagement. The integration of Internet of Things (IoT) devices, connected vehicles, and wearable sensors provides insurers with granular, real-time behavioral data that enables dynamic premium adjustment and individualized policy customization. Through comprehensive analysis of current implementations and emerging applications, this study explores the technical architecture of AI-enabled UBI systems, examines the transformation of actuarial practices through predictive analytics, and evaluates the implications for stakeholders across the insurance ecosystem. The findings reveal that AI-driven telematics solutions significantly enhance pricing accuracy, reduce adverse selection, improve customer satisfaction through fairness perceptions, and create new opportunities for preventive risk management. However, challenges persist regarding data privacy, algorithmic transparency, regulatory compliance, and equitable access to technology-enabled insurance products. This paper provides insights into how insurers can leverage AI and telematics to create sustainable competitive advantages while addressing ethical considerations and ensuring consumer protection in the evolving landscape of personalized insurance.

Keywords

Usage-based insurance, Artificial intelligence, Telematics, Machine learning, Personalized insurance, Risk assessment, IoT, Predictive analytics, Dynamic pricing, Insurance technology.

1. Introduction

The global insurance industry has traditionally operated on the principle of risk pooling, where premiums are calculated based on broad demographic categories and historical statistical averages rather than individual behavior patterns [1]. This conventional approach often results in pricing inefficiencies, where low-risk individuals subsidize high-risk policyholders within the same rating class, leading to adverse selection and market distortions [2]. The emergence of usage-based insurance (UBI) represents a paradigm shift that leverages technology to assess risk at the individual level, enabling insurers to price policies based on actual behavior rather

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than statistical proxies [3]. Artificial intelligence (AI) and telematics have emerged as the foundational technologies enabling this transformation, providing the computational power to process vast amounts of behavioral data and the sensing capabilities to capture real-time usage patterns [4].

Telematics technology has evolved into sophisticated systems that monitor driving behavior, vehicle performance, and environmental conditions through an array of sensors and communication protocols [5]. When combined with AI algorithms, particularly machine learning (ML) and deep learning (DL) techniques, telematics data can be transformed into actionable risk insights that enable dynamic pricing and personalized policy recommendations [6]. The integration of Internet of Things (IoT) devices has further expanded the scope of telematics beyond automotive applications to encompass home insurance through smart home sensors, health insurance through wearable devices, and commercial insurance through industrial monitoring systems [7]. This convergence of AI and telematics represents not merely a technological upgrade to existing insurance processes but a fundamental reimagining of how risk is assessed, priced, and managed in the digital age [8].

The adoption of AI-enabled UBI systems has accelerated dramatically in recent years, driven by several converging factors including increasing consumer acceptance of data-sharing in exchange for personalized pricing, regulatory support for innovation in insurance markets, advances in sensor technology and data analytics capabilities, and competitive pressures to improve customer engagement and retention [9]. Major insurance carriers worldwide have launched UBI programs that utilize smartphone applications, onboard diagnostics devices, and connected vehicle platforms to collect telematics data and adjust premiums based on driving behavior metrics such as mileage, speed, acceleration patterns, braking intensity, and time of day [10]. Early evidence suggests that these programs not only improve pricing accuracy but also influence policyholder behavior through feedback mechanisms, creating a virtuous cycle where safer behavior leads to lower premiums which in turn reinforces risk-reducing actions [11].

Despite the promising potential of AI and telematics in insurance, significant challenges remain that must be addressed to ensure the sustainable and equitable development of personalized insurance markets [12]. Privacy concerns are paramount, as the continuous collection and analysis of behavioral data raises questions about surveillance, data security, and potential misuse of sensitive information [13]. Algorithmic fairness and transparency issues emerge when AI systems make automated decisions that affect insurance eligibility and pricing, particularly when these systems may inadvertently perpetuate biases or create new forms of discrimination [14]. This paper provides a comprehensive examination of how AI and telematics are enabling UBI and personalized insurance across multiple domains, exploring technical architectures, analyzing transformations in actuarial practices, examining real-world applications, and discussing challenges and future directions for personalized insurance.

2. Literature Review

The academic literature on telematics and insurance has evolved substantially, transitioning from early feasibility studies to comprehensive analyses of implementation challenges and market impacts. Research has demonstrated that driving behavior variables collected through telematics devices could significantly improve risk prediction compared to traditional rating factors [15]. Studies examining consumer acceptance reveal that while privacy concerns initially limited adoption, perceived fairness in pricing and potential premium savings

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motivated participation among different demographic segments [16]. The integration of AI techniques into telematics analysis marked a critical development, with researchers demonstrating that ML algorithms could identify complex patterns in driving data that human analysts and traditional statistical methods might overlook [17].

Recent scholarship has increasingly focused on DL applications in insurance risk assessment, showing that neural network architectures can process high-dimensional telematics data streams to predict claim frequency and severity with greater accuracy than conventional generalized linear models [18]. Comparative studies have evaluated different ML techniques including random forests, gradient boosting machines, and support vector machines for telematics-based risk scoring, generally finding that ensemble methods and DL approaches outperform traditional actuarial models particularly when analyzing large datasets with complex interaction effects [19]. Research on boosting techniques applied to telematics data has demonstrated significant improvements in predictive accuracy for claim modeling [20].

The concept of personalized insurance extends beyond simple usage-based pricing to encompass comprehensive customization of coverage terms, deductibles, and policy features based on individual risk profiles and preferences [21]. Literature on personalization emphasizes the role of AI in matching consumers with optimal insurance products through recommendation systems and interactive platforms that adapt to user behavior and feedback [22]. Studies have examined how IoT devices in various domains enable new forms of personalized coverage, creating opportunities for enhanced customer experiences and improved risk matching [23]. The behavioral economics literature provides important insights into how UBI programs influence policyholder actions and decision-making processes [24].

Studies have found that real-time feedback on driving behavior through smartphone applications and in-vehicle displays can promote safer driving habits, particularly when combined with gamification elements and social comparison features [25]. Research on near-miss events captured through telematics has revealed important patterns in driver behavior that correlate with accident risk but were previously unobservable to insurers [26]. Privacy and data governance issues have emerged as central themes in recent literature on AI and telematics in insurance [27]. Legal scholars have analyzed how existing privacy regulations apply to continuous behavioral monitoring, identifying gaps in current frameworks that fail to address the unique characteristics of telematics data collection [28].

Researchers have proposed privacy-preserving techniques for telematics analysis, including differential privacy mechanisms that add controlled noise to data while maintaining statistical utility, federated learning approaches that enable model training without centralizing raw data, and blockchain-based systems for transparent and auditable data sharing [29]. The literature emphasizes the need for privacy-by-design principles in developing UBI systems and highlights the importance of clear consent mechanisms and data governance policies that give consumers meaningful control over their information [30]. Algorithmic fairness in insurance pricing has become an active area of research as AI systems increasingly determine policy terms and conditions [31].

Studies have examined how ML models may exhibit disparate impact across protected demographic groups even when those characteristics are not explicitly included as input features, a phenomenon known as proxy discrimination [32]. Researchers have proposed various fairness metrics and debiasing techniques for insurance AI systems, though consensus remains elusive on which fairness definitions are most appropriate for insurance contexts [33].

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Regulatory and legal dimensions of AI-enabled UBI have received growing attention from scholars examining the adequacy of existing insurance regulations in the face of technological disruption [34]. The economic impacts of UBI and AI-enabled personalization on insurance markets have been analyzed through both theoretical models and empirical studies, suggesting that UBI can reduce information asymmetry and adverse selection by allowing better risk differentiation [35].

3. Technical Architecture and Implementation

The technical architecture of AI-enabled UBI systems comprises multiple interconnected layers that work together to capture behavioral data, process information, generate risk insights, and deliver personalized insurance products to consumers. The data collection layer forms the foundation of these systems and typically consists of IoT devices embedded in vehicles, homes, or worn by individuals that continuously monitor relevant behaviors and environmental conditions [36]. In automotive insurance applications, telematics devices may be standalone dongles that plug into the vehicle's onboard diagnostics port, integrated systems provided by vehicle manufacturers as part of connected car platforms, or smartphone applications that utilize the device's accelerometer, gyroscope, and GPS capabilities to infer driving patterns [37].

The data transmission and storage infrastructure ensures that information collected by IoT devices reaches insurers' analytical systems in a timely and secure manner [38]. Modern UBI implementations typically utilize cloud-based platforms to handle the massive volumes of telematics data generated by millions of policyholders, employing distributed computing frameworks to enable parallel processing and scalable analytics [39]. Data encryption protocols protect information during transit and at rest, while authentication mechanisms ensure that only authorized devices and users can access the system. The integration of telematics data with traditional insurance data sources requires robust data integration and quality assurance processes to ensure consistency and reliability [40].

The AI and analytics layer represents the core of the technical architecture where ML and DL algorithms transform raw telematics data into actionable risk insights [41]. Feature engineering processes extract relevant variables from raw sensor data, such as calculating metrics for harsh braking frequency, speeding incidents, nighttime driving proportion, and trip complexity from GPS coordinates and accelerometer readings [42]. Supervised learning algorithms including logistic regression, decision trees, random forests, and gradient boosting machines are commonly employed for risk classification and claim prediction tasks [43]. DL architectures including convolutional neural networks and recurrent neural networks have shown particular promise for processing sequential telematics data and identifying complex temporal patterns that correlate with crash risk [44].

Unsupervised learning techniques play an important role in identifying driver segments and behavioral clusters without relying on labeled outcomes [45]. Clustering algorithms can group drivers with similar behavioral patterns, enabling targeted interventions and personalized communication strategies. Anomaly detection methods identify unusual driving events or patterns that may indicate heightened risk or fraudulent behavior. The ensemble of different ML techniques allows insurers to leverage the strengths of various algorithms while mitigating individual model weaknesses through diversification [46]. The risk scoring models produce quantitative assessments that translate behavioral data into premium adjustments, incorporating both the frequency of exposure to risk through mileage and the quality of driving behavior through event-based metrics [47].

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The user interface and engagement systems provide the touchpoint through which policyholders interact with UBI programs and receive feedback on their behavior [48]. Mobile applications have become the primary interface, offering features such as trip logging and mapping, risk score visualization, safe driving coaching, rewards and gamification elements, and premium tracking. The design of these interfaces significantly influences user engagement and the effectiveness of UBI programs in promoting behavior change, with research indicating that timely feedback and clear visualization of the relationship between behavior and pricing are critical for sustained participation and risk reduction [49]. Security and privacy protection mechanisms are woven throughout the technical architecture to safeguard sensitive telematics data and maintain consumer trust through encryption, access controls, and anonymization techniques [50].

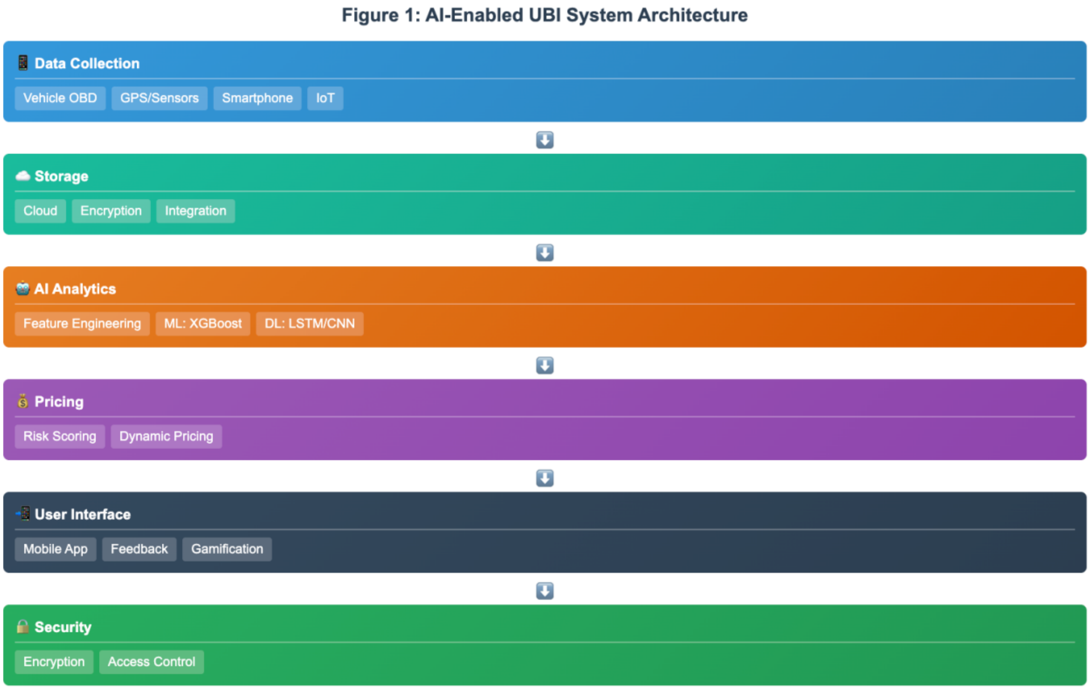

Figure 1: Comprehensive layered architecture of AI-enabled UBI systems showing data flow from IoT devices (Layer 1) through cloud infrastructure (Layer 2) to AI analytics engines employing ML and DL algorithms (Layer 3), risk scoring and pricing engines (Layer 4), user-facing mobile applications (Layer 5), with security mechanisms (Layer 6) embedded throughout. Bidirectional arrows indicate feedback loops where user behavior data informs continuous model updates.

4. Applications and Transformative Impacts

The application of AI and telematics has been most extensively developed in automobile insurance, where pay-as-you-drive and pay-how-you-drive programs have become mainstream offerings from major insurers worldwide [51]. These programs utilize telematics data to assess driving behavior across multiple dimensions including total mileage driven, speed patterns relative to posted limits, braking and acceleration intensity, time of day distribution, and trip characteristics. ML algorithms process these multidimensional behavioral data to generate comprehensive risk scores that correlate more strongly with actual claim experience than traditional rating factors [52]. Insurers report that drivers participating in telematics programs exhibit substantially lower claim frequencies compared to similar non-participants, a result that combines both selection effects where safer drivers opt into programs and causal effects where monitoring and feedback improve driving behavior [53].

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Beyond automotive insurance, property and homeowners insurance represents a rapidly growing application domain where AI-enabled telematics extends to monitor homes through smart sensors that can detect water leaks, smoke and fire, break-ins, and structural issues [54]. ML algorithms analyze patterns in sensor data to distinguish between normal variations and genuine threats, while computer vision techniques applied to satellite imagery and drone photography enable automated property inspections and risk assessment [55]. Health and life insurance applications leverage wearable devices and health monitoring technologies to track physical activity, sleep patterns, heart rate, and other wellness indicators, creating opportunities for insurers to reward healthy behaviors and intervene early when risk factors emerge [56].

Commercial and industrial insurance sectors are experiencing transformation through IoT sensors that monitor equipment performance, environmental conditions, and operational processes in real-time [57]. Predictive maintenance models identify when machinery is likely to fail, enabling preventive interventions that reduce business interruption claims and equipment damage. The claims processing function has been revolutionized by AI applications that accelerate settlement, reduce costs, and improve fraud detection [58]. Computer vision algorithms assess vehicle damage from submitted photographs, estimating repair costs with accuracy approaching that of human adjusters while processing claims in minutes rather than days [59]. Natural language processing analyzes claims descriptions and medical records to identify inconsistencies and flag potential fraud cases for investigation. Telematics data surrounding claimed accidents provides objective evidence about crash dynamics, speed, and driver actions that can verify or contradict reported circumstances [60].

Table 1: AI and Telematics Applications

Sector	Data Sources	AI Techniques	Applications	Benefits
Auto	OBD devices, smartphone sensors, GPS, connected vehicles	ML (gradient boosting), DL (LSTM, CNN), claim prediction	Dynamic pricing, driver coaching, fraud detection	15-25% claim ↓, 10-20% cost ↓, 30% accuracy ↑
Property	Smart sensors (water, fire), satellite imagery, drones	Computer vision, anomaly detection, image classification	Leak detection, automated inspection, hazard monitoring	20-30% damage ↓, 40% faster inspection, 25% fewer alarms
Health	Wearables (fitness trackers), health apps, biometric sensors	Predictive analytics, time-series forecasting, clustering	Disease management, preventive care, wellness programs	12-18% cost ↓, 25% engagement ↑, 30% prevention ↑
Commercial	Industrial IoT, equipment monitors, GPS tracking, sensors	Predictive maintenance ML, supply chain analytics	Equipment prevention, cargo monitoring, fleet optimization	25-35% maintenance ↓, 30% interruption ↓, 40% downtime ↓

Table 1: Comprehensive comparison of AI and telematics applications across four insurance sectors (auto, property, health, commercial) showing diverse data sources, AI techniques applied, key applications, and reported benefits. Auto insurance demonstrates 15-25% claim reduction through smartphone telematics and ML models. Property insurance achieves 40% faster inspections via computer vision. Health insurance shows 12-18% cost savings using wearables and predictive analytics. Commercial insurance realizes 25-35% maintenance cost reduction through industrial IoT.

5. Challenges and Future Directions

Despite the substantial benefits demonstrated by AI-enabled UBI systems, significant challenges must be addressed to ensure sustainable and equitable development of personalized insurance markets. Privacy concerns remain paramount as the continuous collection and analysis of behavioral data through telematics raises fundamental questions about surveillance, autonomy, and the appropriate boundaries of monitoring in insurance relationships [61]. Consumers express ambivalence about data sharing, valuing the potential for lower premiums and personalized services while simultaneously worrying about how their information might be used, shared, or potentially misused by insurers or third parties. The regulatory landscape for data privacy varies significantly across jurisdictions, with frameworks imposing strict

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requirements on data collection, processing, and consumer rights that insurers must navigate [62].

Algorithmic transparency and explainability present technical and ethical challenges as AI systems become more sophisticated and complex [63]. While DL models may achieve superior predictive performance, their black-box nature makes it difficult for insurers to explain to consumers or regulators why particular pricing decisions were made, potentially undermining trust and raising concerns about accountability. Regulatory requirements in many jurisdictions mandate that insurance pricing decisions be explainable and justifiable, creating tension with the deployment of complex ML models whose decision-making processes are opaque [64]. Researchers and practitioners are developing explainable AI techniques that provide interpretable approximations of complex model predictions, though these methods involve tradeoffs between accuracy and interpretability [65].

The potential for algorithmic bias and discrimination in AI-enabled insurance pricing requires careful attention to fairness considerations throughout the development and deployment lifecycle [66]. Even when protected characteristics such as race, gender, or disability status are not explicitly included as input features, ML models may learn to use proxy variables that correlate with these attributes, resulting in disparate impact across demographic groups. The tension between actuarial fairness principles that seek to charge each policyholder their individualized expected cost and social solidarity values that support risk pooling and cross-subsidization creates complex policy questions about the appropriate role and limits of personalization in insurance markets [67].

The digital divide and differential access to technology raise important equity concerns about who benefits from AI-enabled personalized insurance. UBI programs that require smartphones or connected vehicles may be inaccessible to lower-income consumers who cannot afford these technologies, potentially creating a two-tier system where affluent policyholders enjoy personalized pricing while others remain in traditional pools with less favorable terms. Additionally, digital literacy and comfort with technology vary across demographic groups, potentially creating barriers to participation for older adults and other populations less familiar with mobile applications and data sharing [68].

Looking toward the future, several emerging trends and technologies promise to further transform insurance through enhanced AI capabilities and expanded telematics applications [69]. Autonomous vehicles will fundamentally reshape automotive insurance as liability shifts from individual drivers to vehicle manufacturers and software providers, requiring new insurance products and risk assessment frameworks. The proliferation of advanced connectivity networks and edge computing will enable more sophisticated real-time telematics applications with lower latency and higher data fidelity. Advances in AI including federated learning, which enables model training on distributed data without centralizing information, and homomorphic encryption, which allows computation on encrypted data, may address some current privacy concerns and enable new forms of privacy-preserving analytics [70].

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Figure 2: Evolution Timeline (2019-2030)

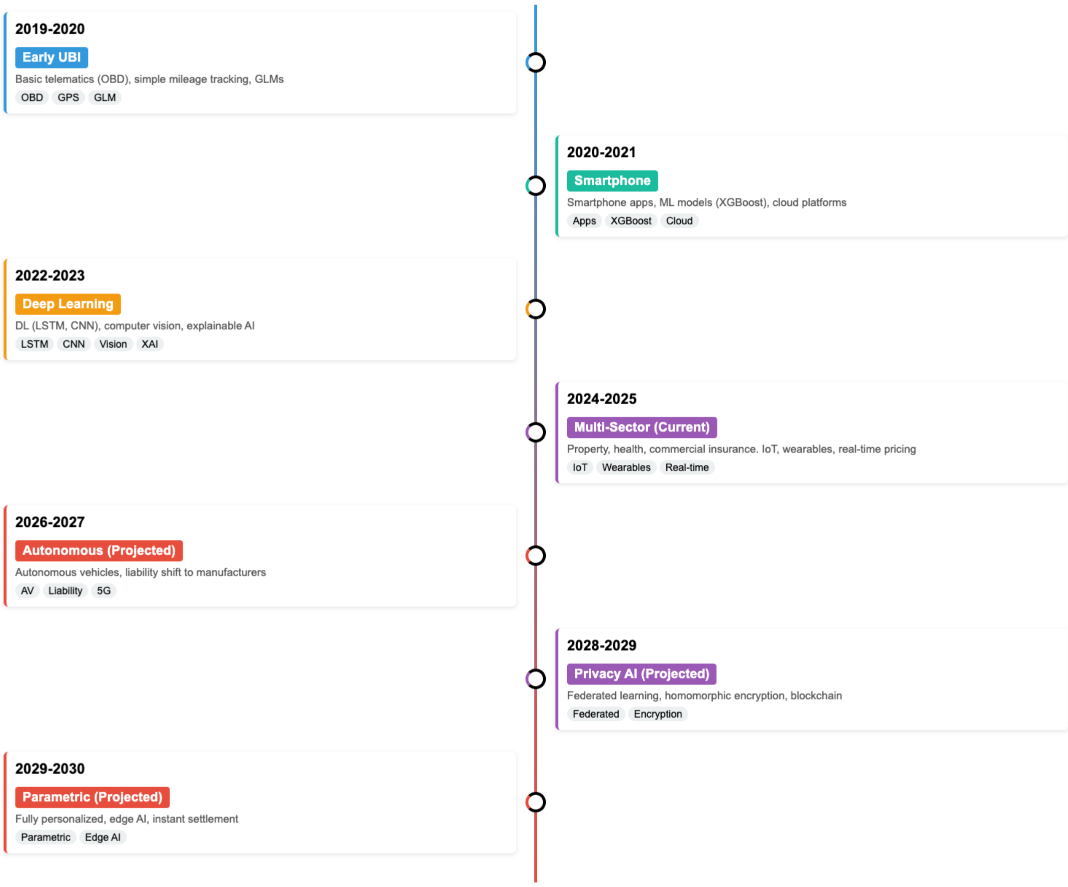

Figure 2: Evolution timeline of AI and telematics in insurance from 2019 to 2030, divided into seven developmental periods: Early UBI Pilots (2019-2020) with basic OBD devices and GLMs; Smartphone Adoption (2020-2021) with mobile apps and XGBoost; Advanced DL Integration (2022-2023) featuring LSTM/CNN and computer vision; Multi-Sector Expansion (2024-2025, current) with IoT across property, health, and commercial insurance; Autonomous Vehicles (2026-2027, projected) shifting liability to manufacturers; Privacy-Preserving AI (2028-2029, projected) with federated learning; and Fully Personalized Parametric Insurance (2029-2030, projected) with edge AI and instant settlement. Color gradient indicates increasing technological sophistication.

6. Conclusion

The integration of AI and telematics technologies is fundamentally transforming the insurance industry, enabling a shift from traditional risk pooling based on demographic categories to personalized coverage grounded in individual behavior and real-time monitoring. This transformation encompasses technical innovations in data collection through IoT devices, sophisticated analytics through ML and DL algorithms, and new business models centered on UBI and dynamic pricing. The evidence demonstrates that these technologies deliver substantial benefits including improved pricing accuracy, reduced adverse selection, enhanced customer engagement through feedback and gamification, more efficient claims processing, and opportunities for proactive risk management and loss prevention.

Applications span multiple insurance sectors with automotive insurance leading adoption through pay-as-you-drive and pay-how-you-drive programs, property insurance leveraging

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smart home sensors and computer vision for monitoring and inspection, health insurance utilizing wearables to incentivize wellness behaviors, and commercial insurance employing industrial IoT for predictive maintenance and supply chain monitoring. The technical architecture supporting these applications integrates data collection layers using diverse sensors and devices, transmission and storage infrastructure based on cloud platforms, AI analytics employing supervised and unsupervised learning techniques, risk scoring and pricing engines that translate behavioral insights into premium adjustments, and user interfaces that provide feedback and promote engagement.

However, realizing the full potential of AI-enabled personalized insurance requires addressing significant challenges around privacy protection, algorithmic transparency, fairness and non-discrimination, regulatory compliance, and equitable access. The continuous behavioral monitoring inherent in telematics raises legitimate concerns about surveillance and autonomy that must be balanced against the benefits of personalized pricing. The complexity and opacity of advanced ML models create tensions with requirements for explainability and accountability in insurance decision-making. The potential for algorithmic bias and the tension between actuarial fairness and social solidarity principles demand careful attention to ensure that personalization does not result in discrimination or undermine the risk-sharing function of insurance.

Looking forward, the continued evolution of AI capabilities, expansion of IoT ecosystems, emergence of autonomous vehicles, and deployment of privacy-enhancing technologies will create new opportunities and challenges for personalized insurance. Success will require ongoing collaboration among insurers, technology providers, regulators, consumer advocates, and researchers to develop governance frameworks that encourage innovation while protecting consumer interests, advance technical capabilities while ensuring transparency and fairness, and leverage the efficiency gains from personalization while preserving the social value of risk pooling and solidarity. The transformation of insurance through AI and telematics represents not merely a technological change but a fundamental renegotiation of the relationship between insurers and policyholders, with implications for fairness, equity, privacy, and the role of insurance in society that extend far beyond premium calculations and claim payments.

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