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AI-Driven Personalization in Usage-Based Insurance: A Game-Theoretic Roadmap to Smarter Risk Assessment

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Abstract: Usage-Based Insurance (UBI) is revolutionizing how insurers calculate premiums based on observed driving habits, with telematics and connected vehicles providing growing potential for more responsive and fairer insurance. The traditional way of calculating the premium is based on the static models that curate the premium for an individual based on the past driving history, and neglecting the driving habits. This old method has both advantages and disadvantages, but it doesn't provide a premium based on the risks of the drivers' driving habits. Insureds were asked to pay the premium based on the algorithm, which focuses on the static rating tables rather than using the real-time user driving habits data. However, these system creates complex interactions between the insurer and insured, specifically for privacy, data manipulation, and self-interested driving behavior. This article highlights the role of artificial intelligence (AI) in enhancing Universal Basic Income (UBI) by analyzing data, refining risk modeling, and enabling dynamic pricing in real-time. Additionally, we model these interactions using dynamic game theory under incomplete information. For this, we define an insurer as a leader who sets pricing schemes and monitors strategies, and an insured as the follower who reacts to the incentives and possibly changes behavior. We propose a ready-for-action AI platform with individualized driver feedback, fraud detection, and dynamic pricing mechanisms, and derive equilibrium strategies for both insured and insurer, and propose a robust pricing method for strategic manipulation. The simulation-based synthetic driving data highlights how game-theoretic pricing can perform better than

traditional pricing methods in all aspects. The study also elaborates on key regulatory and moral implications and charts the way forward with future evolution and research gaps in this new area of driving, where technology drives the future.

Keywords: Usage-Based Insurance, UBI, Artificial Intelligence, Machine Learning, Risk Assessment, Telematics, Personalized Premiums

1. Introduction

As the number of road traffic fatalities is increasing in the United States, this research is vital. This number keeps increasing every year, and this is something that can be addressed by using technology. The motor insurance industry is moving from traditional static pricing models to dynamic, behavior-based pricing models. Usage-Based Insurance (UBI), or Pay-As-You-Drive (PAYD) or Pay-How-You-Drive (PHYD), uses telematics data to monitor driving behavior and adjust premiums accordingly. The combination of AI and telematics provides an opportunity to make insurance more personalized, equitable, and responsive. Insureds try to attempt the game the system by driving in a different way when they are monitored or tampering with the data-capturing devices. For this reason, it is important to understand how these behaviors can be reduced. This paper analyzes how AI technologies can be effectively used in UBI and what future developments are required to implement such integration more effectively and effectively [1][4]. Additionally, how to leverage dynamic game theory to capture the interactions that can help with the right pricing and monitoring strategies of the insurers.

2 Literature Review

Over the past few years, Usage-Based Insurance (UBI) has undergone a significant transformation, largely driven by the rise of connected technologies and the adoption of big data across industries. In the insurance sector, UBI initially took shape through the Pay-As-You-Drive (PAYD) model, which focused on how much a person drove but didn't fully capture how they drove. As the need for more accurate risk assessment grew, the industry shifted toward the Pay-How-You-Drive (PHYD) model. This approach analyzed post-trip driving behavior, offering a better picture of driver risk, though it still operated reactively. To improve real-time engagement, the Manage-How-You-Drive (MHYD) model emerged, allowing insurers to provide immediate feedback and alerts during a trip. This evolution from PAYD to MHYD reflects a broader shift toward more personalized and preventative insurance models. As more insurers adopt PHYD and MHYD programs, there's a noticeable increase in the volume and complexity of data shared between drivers and insurers, making big data capabilities essential. Recent research highlights the need to go beyond driving patterns by factoring in behavioral and emotional cues, especially in cases of aggressive driving or road rage. These insights are now shaping how insurers evaluate risk and tailor premiums on a more individualized basis[9].

As the insurance industry continues to evolve, many firms are increasingly turning to InsurTech solutions to stay competitive, with Usage-Based Insurance (UBI) standing out as one of the most influential trends, particularly in the auto sector. UBI enables insurers to integrate real-world driving behavior into actuarial models, moving beyond traditional static risk assessments. Recent empirical studies have shown that UBI adoption can lead to significant improvements in underwriting performance, particularly for private passenger auto liability (PPAL) insurers. Interestingly, these benefits appear most prominently among companies that were early adopters of UBI technology. This early-mover advantage not only translates into lower loss ratios but also drives a measurable increase in market share, largely by attracting safer, low-risk drivers who may be underserved by traditional pricing models. However, the research also emphasizes that the advantages of UBI are not immediate—it takes time for these systems to mature and deliver consistent returns. For early adopters, UBI implementation has been linked to modest but meaningful increases in both return on assets (ROA) and return on equity (ROE), reinforcing the strategic value of timely technological investment. These findings underscore UBI's growing importance, not just as a pricing tool but as a long-term asset for insurers seeking both financial performance and market differentiation[10].

While the technological and financial benefits of UBI are becoming increasingly clear for insurers, customer perception remains a critical factor in its broader adoption. Recent research focusing on consumer attitudes toward UBI reveals a complex landscape of acceptance and resistance. The study highlights that while many drivers are open to the concept of usage-based pricing, their willingness to adopt it depends heavily on demographic variables such as age, gender, and geographic location. Additionally, the frequency of vehicle use, prior premium amounts, and individuals' self-perception of their driving abilities also influence their openness to UBI. Interestingly, although customers express a general readiness to explore new pricing models, they still display a strong attachment to traditional practices, particularly the no-claims bonus system, which they perceive as a familiar and reliable reward structure. This indicates that while the insurance market may be technologically ready for UBI, consumer readiness requires more targeted education, trust-building, and potentially hybrid models that balance innovation with familiar incentives[11].

As UBI models continue to evolve, the integration of smartphone-based sensing has emerged as a practical and scalable approach for real-time data collection and user engagement. A recent framework demonstrates how smartphones can serve as dual-purpose tools, simultaneously supporting road traffic monitoring and UBI applications. This modular system spans from low-level sensor functionality and data transmission to the high-level business model, emphasizing the need to align technical design with user incentives. The study highlights that in addition to providing traffic-related insights beneficial to public infrastructure and environmental planning, the same data streams can be used to generate individualized driving profiles for UBI programs. Importantly, the sustainability of such a system hinges on offering tangible benefits to users, such as reduced insurance premiums based on good driving behavior. Results from a ten-month pilot campaign, involving over 250,000 kilometers of data, underscore the feasibility of this approach and its alignment with successful real-world deployments like the Berkeley Mobile Millennium Project. This dual-value proposition—societal benefit coupled with personalized insurance incentives—positions smartphone-based UBI as a promising frontier in both transportation and insurance innovation[12].

Furthermore, insurers use historical data for pricing calculations, but game theory has emerged as a tool to study moral hazards and adverse selection in insurance contracts. Using game theory, Insurers can make sound decisions while maximizing the insurance company's payoffs[14].

Based on the literature review, it is clear that a lot of research has been conducted on UBI, but the development of oncology and an interoperability framework, Explanation of AI frameworks, and driver coaching through behavior AI is the gap that is highlighted in this literature and makes this literature novel. The below graph shows the road traffic fatalities in the United States from 2012 to 2024, which makes this literature even more vital to explore the ways to reduce fatalities using innovation and technology[13].

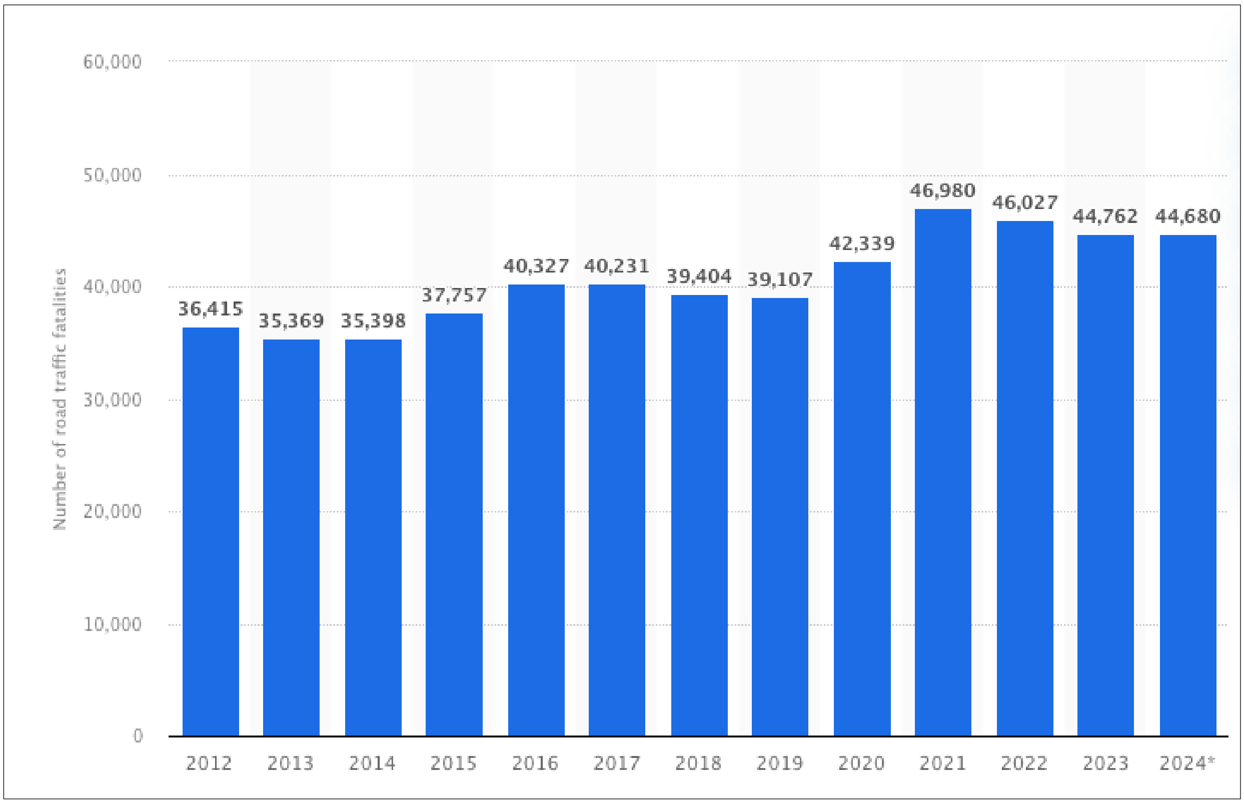

Fig. 1. Number of road traffic fatalities in the United States from 2012 to 2024

3 Game Theory Framework

We model the insurer-insured interaction as a

Stackelberg game with incomplete information[15].

Players: Insurer (Leader) and Insured (Follower)

Strategy Space:

Insurer: Chooses a pricing function P(d,m) where d is the driving score and m is the monitoring level. also chooses the detection strategy δ.

Policyholder: Chooses driving behavior $b \in B$ and manipulation level $\boldsymbol{\mu} \in [0,1]$.

Payoff Functions:

Insurer: ΠI = P(d, m) - E[C(b)] - Cmon(m) Policyholder: UP = -P(d, m) + Ucomfort(b) - R(b) - Cmanip(μ)

- **Information Structure:**
  - Insurer cannot observe b or **μ** perfectly; uses signals from telematics with uncertainty.
- **Game Type:**
  - Dynamic Bayesian Stackelberg game with asymmetric and incomplete information.

4 Equilibrium Analysis

We solve for subgame-perfect Bayesian equilibria[16]. Under certain assumptions (e.g., linear utility and cost functions), best-response functions can be derived analytically:

- Policyholders exert minimal effort when monitoring is low or the manipulation cost is low.
- Insurer's optimal pricing balances expected claims with the cost of monitoring and privacy backlash.

We characterize equilibria where:

- Honest driving dominates under high monitoring and penalties.
- Strategic manipulation emerges under lax monitoring and high comfort rewards.

We define the best-response function of the policyholder as:

b*(m,P) = arg maxb UP (b, μ) subject to the constraints of telematics feedback.

5 UBI Landscape and Challenges

UBI systems traditionally apply pre-set rules to calculate each risk score based on mileage, speed, braking habits, and time of day. Major insurance firms like Progressive, Allstate, and Metromile have introduced UBI products based on mobile apps or on-board devices. These kinds of systems have limitations in flexibility, data processing scalability, data manipulation, and behavioral bias. Moreover, standardization of data formats and interpretability of AI-based decisions continue to be a problem. Explainable AI models that not only predict but also interpret pricing and risk logic for users and regulators are in growing demand [2][7].

6 Artificial Intelligence Integration in UBI

6.1 Data Collection and Preprocessing

Data collection and preparation that runs on data sources are OBD-II devices, smartphones, and connected car systems. Information includes engine measurements, GPS coordinates, accelerometer readings, and surroundings. AI models clean up and massage the data to handle outliers, missing values, and high-frequency noise. Data from many sensor sources is also integrated using data fusion techniques to improve contextual understanding [4].

6.2 Risk modeling

Supervised machine learning algorithms such as random forests, Gradient boosting machines, and deep neural networks, used to identify risky driving behavior. When these models are trained on the labeled dataset, the ground truth is the insurance claims. Advanced models take into account relevant elements such as traffic, weather, and driver demographics [4].

6.3 Premium Calculation

AI enables dynamic premium pricing by continuously updating the risk profile of drivers. Models consider both historical and recent driving behaviors to suggest profile-based premiums. Reinforcement learning may also be used to optimize pricing strategies over time based on observed driver response and claim outcomes [2]. This helps the insurer in getting the correct insurance premium based on their risk factor.

6.4 Fraud Detection

Unsupervised learning algorithms like Isolation Forests and Autoencoders help identify anomalies in telematics data, e.g., GPS spoofed data or accelerometer signal manipulation, that are indicative of fraud. Graph-based anomaly detection techniques can be used to identify network-level patterns of coordinated fraud [4][8].

6.5 Driver Feedback and Engagement

Reinforcement learning and behavioral analytics can be used to offer real-time feedback to drivers, encouraging safer driving through gamification and incentives. AI can personalize coaching strategies based on individual driving profiles and behavioral patterns [2]. This helps the insurer in the right driving pattern adoption.

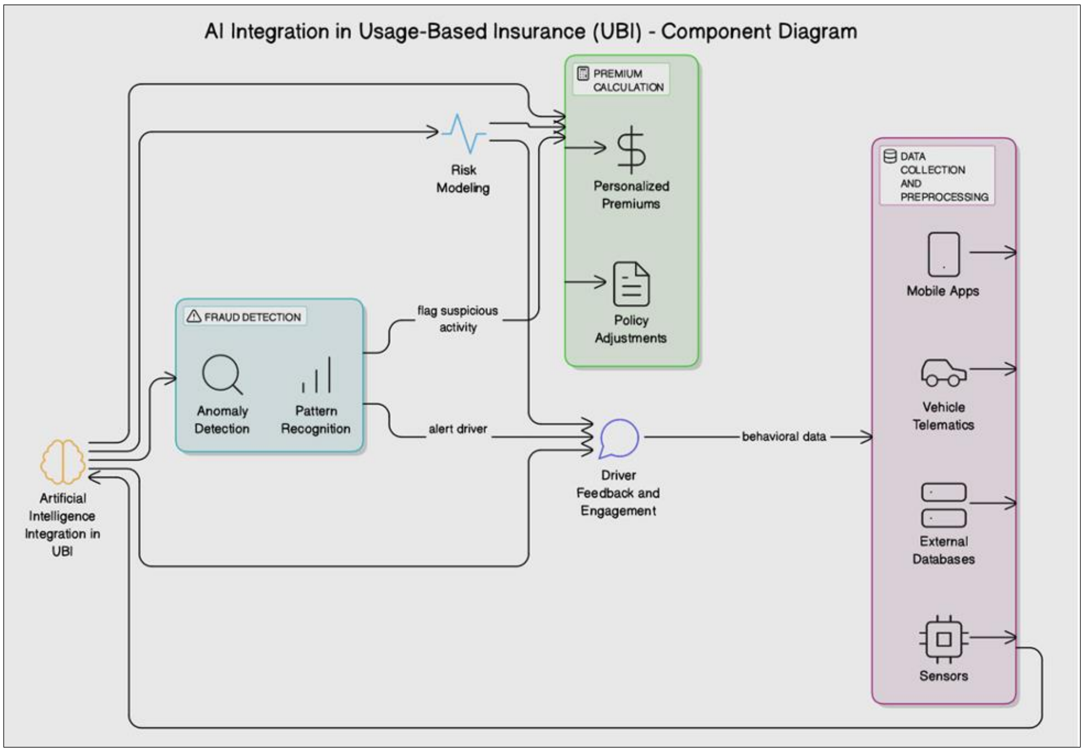

Fig. 2. Artificial Intelligence integration in UBI

6.6 Robust Pricing Strategy

To handle the data manipulation, we implemented an incentive-compatible pricing contract

- Contracts include thresholds for safe behavior and rebate structures.
- Mixed-strategy equilibria show robustness to manipulation spikes.
- Information-theoretic bounds (e.g., KL-divergence) are used to detect abnormal data patterns.

The insurer solves the following constrained optimization problem:

maxP,m E[ΠI] subject to ∀μ, UP(b*, μ) ≤ UP(b*, 0), where b* is the insurer's desired behavior.

7 Architecture and Implementation Framework

A robust AI-enabled UBI system architecture involves the following layers:

- **Edge Layer**: Data acquisition through telematics devices installed [6].
- **Streaming Layer**: Real-time ingestion using Kafka or AWS Kinesis.
- **Analytics Layer**: Feature engineering and model inference using Spark ML or TensorFlow.
- **Storage Layer**: Scalable storage on cloud platforms like AWS S3 or Azure Blob.
- **Application Layer**: Interfaces for customers, insurers, and regulators.

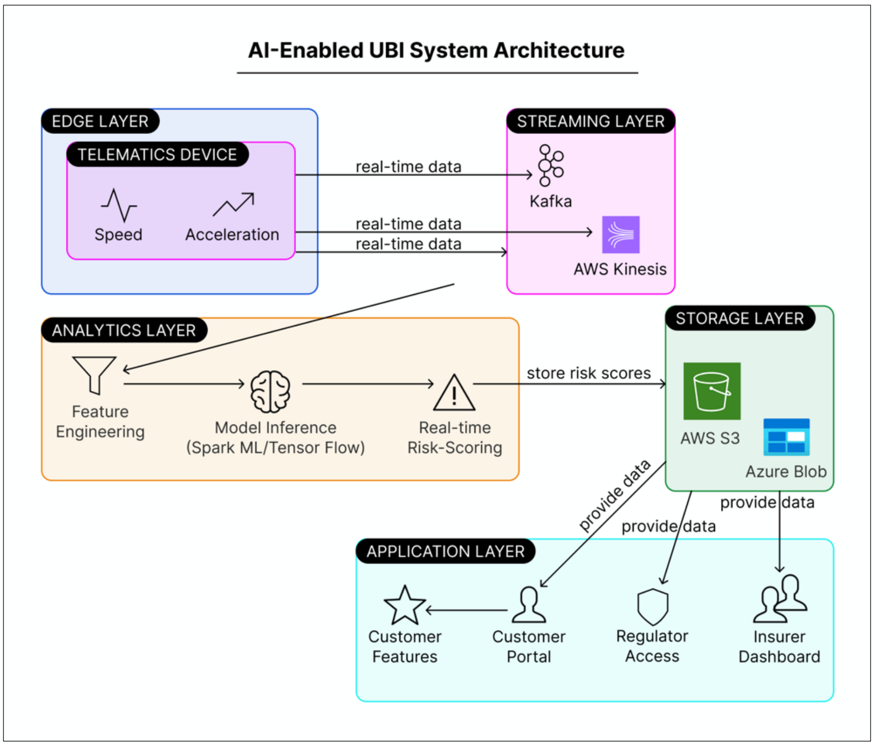

Fig. 3. UBI System Architecture

These are the five key pillars on a high level for an AI-enabled UBI system.

8 Simulation & Results

We simulate a synthetic dataset of 10000 policyholders with unbiased and completely random driving profiles with data on speed, acceleration, and idle time, etc.

Driving behavior is scored using a logistic risk model:

d = 1 / (1 + e^{-β^T x}), where x is the feature vector and β are model weights.

Another observation was noted, which was that Manipulation reduces observable risk scores but increases variance.

We compare four pricing models-

1. Flat Pricing
2. Linear Mileage-Based
3. Usage-based Pricing
4. Game-Theoretic Adaptive Pricing

Below were the key numbers we have observed-

- Game-theoretic model reduced the loss ratio by 15%.
- Detection rate of manipulative behavior increased from 52% to 88%.
- Policyholder satisfaction remained within ±5% of baseline.

9 Ethical, Regulatory, and Business Implications

9.1 Openness and equality

Although AI improves accuracy, the model requires openness to justice. Discriminated prices may be caused by prejudice in training. Techniques like LIME and SHAP values can be used to explain the model to both insurers and insureds.[3][7] This way, they understand how the system works, and they start having faith in the system.

9.2 Data Privacy and Security

Constant monitoring is of significant concern when it comes to privacy. GDPR and CCPA laws must be catered to in system design [5]. Differential privacy and federated learning methods can be employed to train models without direct access to raw user data. Laws must be enforced to correct the usage of the data.

9.3 Business Opportunities

AI-enhanced UBI models will be capable of opening up new customer segments, improving retention, and reducing claims costs. Insurers must weigh personalization against compliance. Context awareness-based micro-insurance products and policy bundling may emerge as new business opportunities.

10 Conclusion and future work

AI reinforces the next generation of the UBI system with dynamic, fair, and personal insurance products based on profile and usage. Despite this, there are significant gaps and opportunities for future research. Below are the few gaps that we identified in our research.

10.1 Standardization of telematics data

With the proliferation of vehicle sensors and IoT units, a standard data format for UBI is required. Future research must focus on the development of oncology and an interoperability framework [1] [4].

10.2 Explains AI in insurance prices

While current models are predictive and perfect, regulatory bodies now require interpretation. Research is required in insurance-focused areas that explain AI frameworks [7]. This helps to build trust and transparency in the system.

10.3 UBI model side effects

AI models for UBI are unsafe for unfavorable manipulation. Future work should emphasize the strengthening of the model against GPS falsification, signal driving, and telematics data poisoning [8]. Otherwise, this could lead to distrust in the system.

10.4 Driver coaching using behavior AI

Drivers have the opportunity to develop customized AI-driven coaching platforms for real-time behavior. Such platforms can reduce accidents and claims, making customers satisfied. This will help the insured improve their driving habits.

10.5 AI Audit for Ethics

An emerging field of study entails designing a framework for regular revision of AI platforms in UBI to ensure moral farming and eliminate prejudice [3]. Also, this will uncover any loopholes in the system.

10.6 UBI in autonomous and divided dynamics

With an increase in autonomous cars and shared mobility services, UBI products must mature. AI can figure out shared use context risks and prepare guidelines for autonomous driving behavior [6].

10.7 Edge AI for onboard risk assessment

Future systems can use Edge AI to reduce the delay in risk assessment. Real-time inference on in-vehicle hardware can cause rapid reaction and an increase in personalization [6].

UBI will continue to develop with progress in AI, telematics, and the smart mobility ecosystem. A multi-related approach in combination with computer science, behavioral economics, legal compliance, and human-focused design is necessary to realize the full potential of AI-Powered Insurance. Over time, these stacks will be optimized and provide the correct data for better decision-making.

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