Auto Insurance Behavior-based Pricing Dashboard

Methodology & References

1. Dashboard Workflow Architecture

This dashboard implements a streamlined, end-to-end actuarial simulation framework that connects telematics-based risk segmentation with behavioral economics (price elasticity) to estimate revenue impact under alternative pricing strategies.
The workflow consists of the following components:

1. **Baseline: Traditional Pricin**g —An overview of the risk groups identified through telematics-based driving-behavior analysis.
2. **Strategy-Based Risk Pricing with Elasticity**— Simulate the actual revenue under realistic market conditions.
3. **Export Results**—Fit directly into an insurer's analytical ecosystem and actuarial workflow.

2. Scientific Basis: From Data to Risk Identification

Data Source & Features: Based on the POLIDriving dataset (Marcillo et al., 2024), using telemetry features (speed, rpm, acceleration, throttle_position), environmental variables (weather, visibility, precipitation), and physiological data (heart_rate).

Model Selection (GBM): A Gradient Boosting Machine classifier is used due to its superior accuracy (~95.6%) compared to MLP and Random Forest.

Risk Classification: The model outputs a probability score discretized into four ordinal levels: Low, Medium, High, Very High.

3. Key Modeling Assumptions

1. **Potential Market Pool:** Treated as a lead list, not an in-force book.
2. **Segment Homogeneity:** Each risk band shares the same base premium and elasticity.
3. **Independence:** Individuals are treated independently.
4. **Elasticity Rationale:** Customers "leave" when their price increases beyond their willingness to pay; customers "join" when lower prices make the policy attractive relative to alternatives.

   This is modeled through price elasticity:
   - High elasticity (e.g., Low-risk drivers) → more price-sensitive ($E \approx -1.5$)→ leave when price increases/ join when price decreases.
   - Low elasticity (e.g., High-risk drivers) → less sensitive($E \approx -0.2$)→tend to stay even under higher premiums.

   In the dashboard, these behavioral shifts are **represented through adjustments to the acceptance rate**, which determines the final number of acquired customers.

4. Actuarial Algorithms & Pricing Logic

A. Baseline Scenario — Traditional Pricing Benchmark

The baseline represents the insurer's current state under demographic-based premiums without any risk-based adjustments or elasticity effects.

A1. Baseline Volume (Market Penetration)

The uploaded dataset is treated as a potential market pool:

$$N_{pool}$$

Applying Initial Acceptance Rate yields the baseline customer volume:

$$N_{baseline} = \lfloor N_{pool} \times \text{Initial Acceptance Rate} \rfloor$$

A2. Baseline Revenue

Baseline revenue is computed using the insurer-defined demographic base premiums by tier:

$$\text{Rev}_{\text{baseline}} = \Sigma_r\, N_{\text{baseline, r}} \times P_{\text{base, r}}$$

This forms the "status quo" benchmark for measuring all improvements or losses under strategic pricing adjustments.

B. Dynamic Acquisition — Strategy-Based Pricing + Elasticity Response

This stage models actual market behavior, where customers react to price changes differently depending on their risk tier.

B1. Strategy-Adjusted Prices

Insurers configure risk-based loadings (discounts or surcharges) under their chosen strategy:

$$P_{\text{final, r}} = P_{\text{base, r}} \times (1 + \text{Loading}_{\text{r}})$$

Unlike static pricing approaches, the dashboard does not assume customer volume remains fixed; volume will be reevaluated using elasticity.

B2. Elasticity-Adjusted Acceptance Rates

Each risk tier has a insurer-defined price elasticity parameter E_r, capturing how acceptance changes with price.

Acceptance rate under new prices becomes:

$$\text{Rate}_{\text{new, r}} = \text{Rate}_{\text{initial, r}} \times (1 + E_{\text{r}} \times \text{Loading}_{\text{r}})$$

Where:

- $E_r < 0 \rightarrow$ higher sensitivity (acceptance drops when price rises)
- $\text{Loading}_{\text{r}}$ can be negative (discount) or positive (surcharge)

As required by actuarial feasibility:

$$\text{Rate}_{\text{new, r}} \in [0\%, 100\%]$$

B3. Acquired Customer Volume

Updated customer count:

$$N_{\text{actual, r}} = \lfloor N_{\text{pool, r}} \times \text{Clamp}(\text{Rate}_{\text{new, r}}) \rfloor$$

This directly captures real-world behavioral response to pricing.

B4. Final Dynamic Revenue

The final revenue under strategy + elasticity is:

$$\text{Rev}_{\text{dynamic}} = \Sigma_r\, N_{\text{actual, r}} \times P_{\text{final, r}}$$

B5. Revenue & Customer Uplift

Finally, uplift relative to baseline:

$$\Delta\text{Revenue} = \text{Rev}_{\text{dynamic}} - \text{Rev}_{\text{baseline}}$$

$$\Delta N = N_{\text{acquired}} - N_{\text{baseline}}$$

These outputs drive the dashboard's summary cards and charts.

C. Underwriting & Commercial Controls — Insurer-Defined Pricing Inputs

These variables represent **business levers**, not model parameters.
Insurers differ in their risk appetite, regulatory constraints, target market, and pricing strategy.

- **Base Premiums** depend on insurer's loss-cost models, expense loadings, and underwriting rules.
- **Strategy Loadings** reflect competitive positioning: aggressive margin-taking vs. conservative market-share growth.
- **Price Elasticity** varies by insurer, market maturity, and distribution channels.

For these reasons, the dashboard treats these inputs as **insurer choices** rather than fixed backend calculations. The purpose of the simulation is to show **how strategic choices interact with telematics risk segmentation** to drive volume and revenue.

5. Further Applications

The exported results can **be directly incorporated into an insurer's existing data and pricing infrastructure.** After download, the data may be loaded into internal data warehouses such as Snowflake, BigQuery, or Redshift, where it becomes part of the insurer's telematics or pricing feature stores. From there, the adjusted premiums, updated acceptance rates, and projected revenue outputs can be **fed into pricing engines or actuarial models** (including Earnix, Guidewire, or internal Python/R workflows) to evaluate how the proposed strategies would perform if deployed in production.

These results also **support underwriting and marketing decisions** by identifying segments that are price-sensitive, margin-accretive, or strategically important for acquisition. When combined with historical claims or retention data, the exported files can be used for **further studies such as elasticity calibration, lifetime value estimation, portfolio mix optimization, or regulatory fairness review.**

In short, the exported dataset serves as a practical bridge between the dashboard simulation and the insurer's real-world pricing, underwriting, and product development processes.

6. Academic References(Main)

- Marcillo, P., et al. (2024). POLIDriving Dataset. *Applied Sciences*.
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