Draft date: 11/15/2024

2024 Fall National Meeting
Denver, Colorado

SPECIAL (EX) COMMITTEE ON RACE AND INSURANCE
PROPERTY/CASUALTY (P/C) WORKSTREAM
Saturday, November 16, 2024
8:30 – 10:30 a.m.
Gaylord Rockies Hotel—Aurora Ballroom B—Level 2

ROLL CALL

Scott Kipper, Co-Chair	Nevada	Michael T. Caljouw	Massachusetts
Kevin Gaffney, Co-Chair	Vermont	Anita G. Fox	Michigan
Mark Fowler	Alabama	Andrew R. Stolfi	Oregon
Peni Itula Sapini Tea	American Samoa	Michael Humphreys	Pennsylvania
Barbara D. Richardson	Arizona	Cassie Brown	Texas
Timothy J. Temple	Louisiana	Mike Kreidler	Washington
Marie Grant	Maryland		

NAIC Support Staff: Aaron Brandenburg

AGENDA

1. Hear Opening Remarks and the Purpose of the Session
—*Commissioner Scott Kipper (NV) and Commissioner Kevin Gaffney (VT)*

2. Hear an Update from the District of Columbia Department of Insurance, Securities and Banking (DISB) on the Department's Initiative to Evaluate Unintentional Bias in Private Passenger Automobile (PPA) Insurance
—*Philip Barlow (DC)* — Attachment One

3. Hear a Presentation on the California Low-Cost Auto Program
—*Julia Juarez (CA)* — Attachment Two

4. Hear an Update on Casualty Actuarial Society (CAS) Research Papers Related to Race and Insurance—*Mallika Bender (CAS)* — Attachment Three

5. Hear a Presentation from Verisk on Testing of Models—*Steve Clarke (Verisk)* — Attachment Four

6. Discuss Any Other Matters Brought Before the Workstream
—*Commissioner Scott Kipper (NV) and Commissioner Kevin Gaffney (VT)*

7. Adjournment

Attachment One

EVALUATING UNINTENTIONAL BIAS IN PRIVATE PASSENGER AUTO INSURANCE REPORT

NAIC Special Committee on Race and Insurance
P&C Workstream

November 16, 2024

DISB

GOVERNMENT OF THE DISTRICT OF COLUMBIA
MURIEL BOWSER, MAYOR

UPDATE

- DISB provided an update to this group in June based on the draft report published on May 14.
- The draft report was exposed for two rounds of comments to ensure there was an opportunity for reactions to the initial comments.
- During the exposure period, DISB:
  - conducted outreach to stakeholders.
  - held a public meeting to address questions.
- The final report was modified to reflect the feedback received.

COMMENT SUMMARY

No changes were made to the analysis, though we did receive questions about:

- The use of linear regression
- Use of BIFSG
- Other technical questions

WHAT CHANGED?

Clarified the definition of harm—"that the use of rating factors correlated with race may result in members of a protected class paying higher premiums, particularly given the imperfection inherent in rating classification systems."

Removed all references to "causal factors" and "legitimate factors" and generally the wording around variables and factors.

Enhanced the executive summary to include issues that may explain the Black/White premium gap.

Tried to clarify what the report was and what it wasn't.

Identified next steps.

NEXT STEPS

- Create a balancing test to look at factors that are both correlated with losses and race.
- Conduct studies on the types and causes of claims by Black and Hispanic drivers.
- Study the impact of the differential in Black and Hispanic driving infractions.

NEXT STEPS

Conduct a review of telematics to identify appropriate consumer protections.

Analyze ways that wealth-related factors may contribute to the Black/white average premium gap.

Evaluate the reasons why quotes from agents were lower than direct online quotes and why Black drivers are less likely to get quotes from agents.

WHAT'S NEXT?

We are still finalizing our path forward, but our current thinking is described below:

- DISB will convene a working group to address the six items identified for future work.
- The working group will be made up of DISB staff and interested parties and will fall under our Insurance Advisory Committee.
- All actions from the working group will continue to be done in an open and transparent manner, with opportunities for public comment.
- We will continue to post relevant information on our website.

QUESTIONS

??

PREVIOUS PRESENTATION

The remainder of the slides are the previous presentation to the Special Committee on Race and Insurance P&C Workstream presented on June 20

BACKGROUND

- We determined this initiative will be deliberative and transparent to ensure the resultant data would address the issue of unintentional bias.
- We also decided to initially focus on private passenger automobile insurance as that is a line of insurance that affects many District consumers and has previously had questions raised about the use of non-driving rating characteristics.
- DISB engaged the services of O'Neil Risk Consulting and Algorithmic Auditing (ORCAA) to assist the Department and provide subject matter expertise.
- DISB held a public hearing, public meetings, produced exposures for public comment and engaged subject matter experts along the way

MOTIVATION

- To explore whether the use of certain information by auto insurers in the application and underwriting process may cause unintentional harm to those who are Black, indigenous, people of color, or belong to another protected class of Washington, DC consumers.
- To examine and look at rates using methodologies that have been developed more recently to evaluate potential bias in the use of algorithms.
- To determine the presence of unintentional bias.

APPROACH

DISB reviewed recent auto insurance applications from consumers in Washington, DC.

- All carriers writing private passenger auto policies in the District of Columbia submitted data from recent applications to DISB for testing.
- DISB is not looking to determine which pricing or rating criteria might be introducing unintentional bias into the rates, but rather could the differences in premiums be explained by looking at factors that are not considered reflective of unintentional bias.
- DISB did not require detailed information about carriers' underwriting or pricing models, such as a description of the models' structures, lists of variables used, and their weights. The focus was on the outcomes of these models.
- BIFSG methodology + outcome of models were used.

METHODOLOGY

Bayesian Improved First Name Surname Geocoding (BIFSG)

- A forerunner of this methodology, BISG, was developed to "help U.S. organizations produce accurate, cost-effective estimates of racial and ethnic disparities within datasets".
- U.S 2010 census data leveraged to guess an individual's self-reported race/ethnicity based on their name and address. The Census publishes tables on the demographics of census blocks and common surnames.
- The BIFSG methodology incorporates another piece of information — the individual's first name (i.e., "F" in "BIFSG") – and another application of Bayes' theorem to further refine the race/ethnicity inference.

2010 CENSUS DATA CATEGORIES USED

- Hispanic,
- non-Hispanic Black,
- non-Hispanic white,
- non-Hispanic Asian or Pacific Islander (“API”),
- non-Hispanic American Indian or Alaska Native,
- Multiracial,
- Other

The analysis used the largest four categories, the last three categories combined for less than 1% of the data.

OUTCOMES INVESTIGATED

Outcome Data	Consumer harm questions	Population
Quotes ($)	Are certain groups being quoted higher prices?	Interested potential customers
Underwriting decision (decline/ accept/ tier/class)	Are certain groups declined more often, or more likely to be placed in an expensive tier/company?	Applicants
Premium ($)	Are certain groups paying higher premiums?	Customers
Loss ratio (%)	Are certain groups charged more in premium, relative to the insurance losses they sustained?	Customers

OBSERVATION

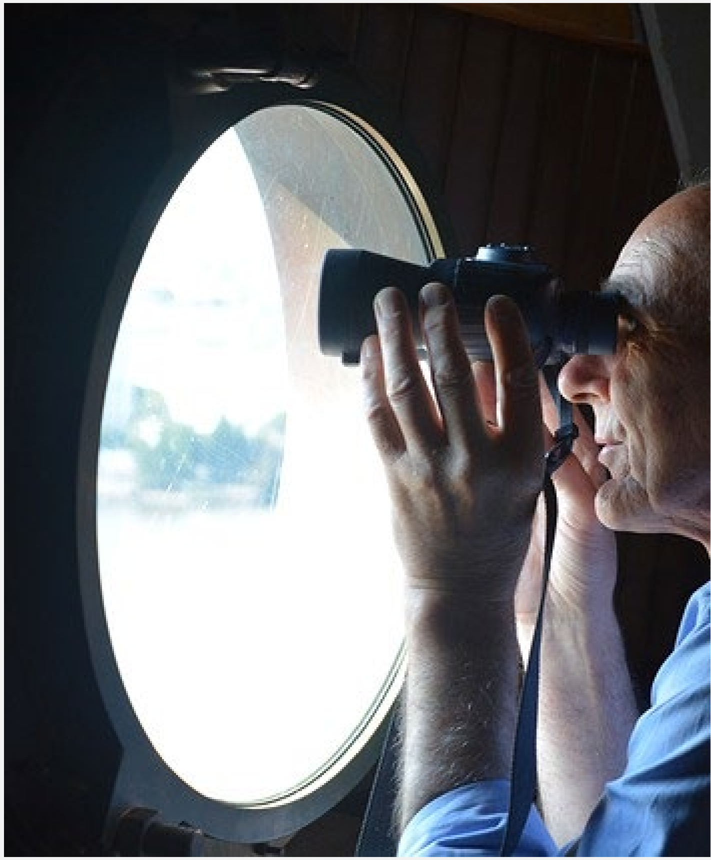
Quotes

"Are certain groups being quoted higher prices?"

Our review showed that quoted prices were consistent with premiums.

While we did not identify a bias issue with quote systems, there was information identified that might warrant a separate review:

- Quotes given by agents were lower on average than quotes given through other channels (e.g., online), and the race gap is smaller for quotes given by agents.
- Black consumers are less likely than others to get quotes through agents



OBSERVATION

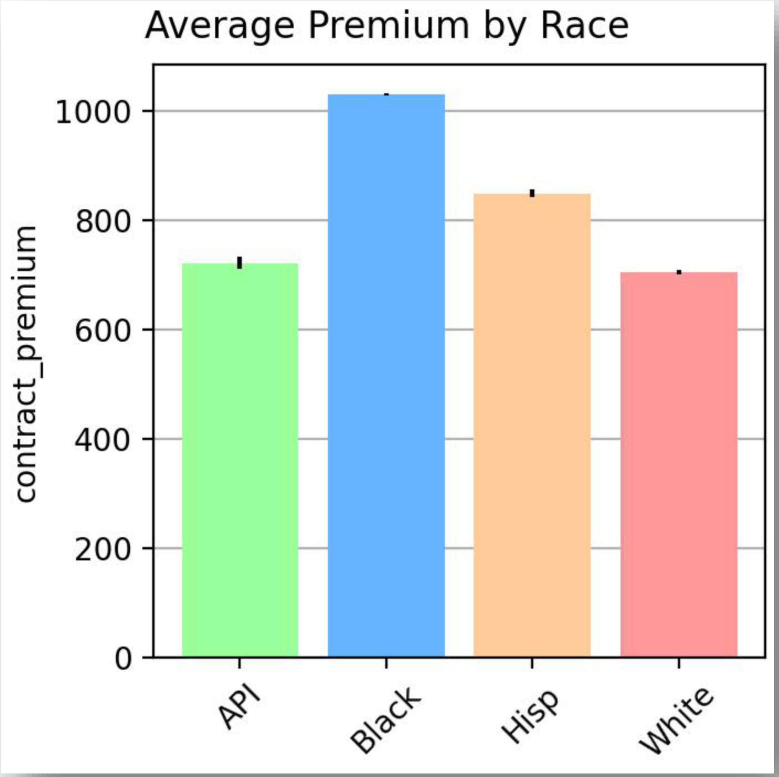
Underwriting Decision

"Are certain groups declined more often, or more likely to be placed in an expensive tier/company?"

- What we discovered with underwriting decisions is that there are very few actual declinations to offer coverage. Typically, a quote will be given for almost all risks – with higher premiums for drivers deemed riskier. We therefore did not pursue this outcome further.

PREMIUMS

Are certain groups paying higher premiums?



LOSS RATIO

Are certain groups charged more in premium, relative to the insurance losses they sustained?

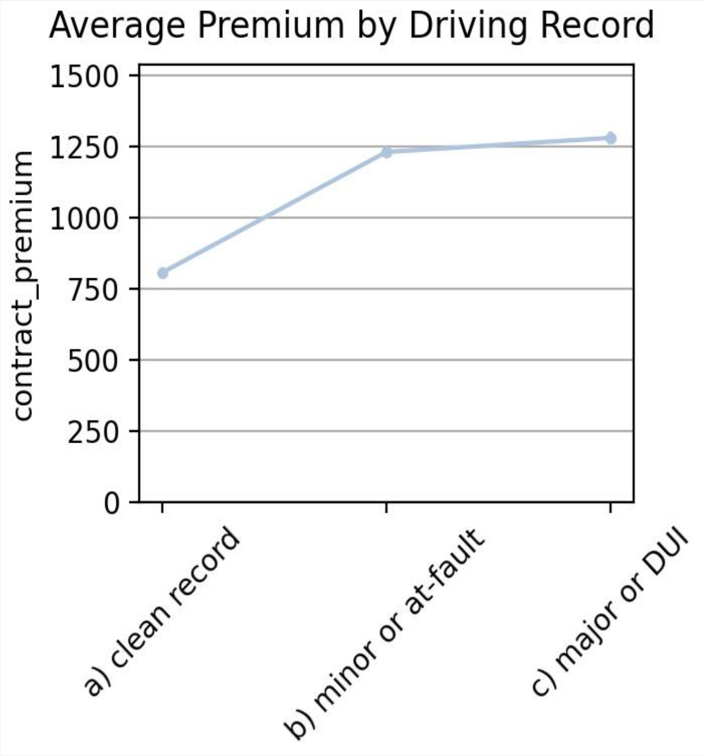
	Avg Premium ($)	Avg Loss ($)	Loss/Premium
inferred_race			
API	734.54	279.76	0.38
Black	1024.42	611.54	0.60
Hisp	858.82	370.32	0.43
White	709.96	256.49	0.36

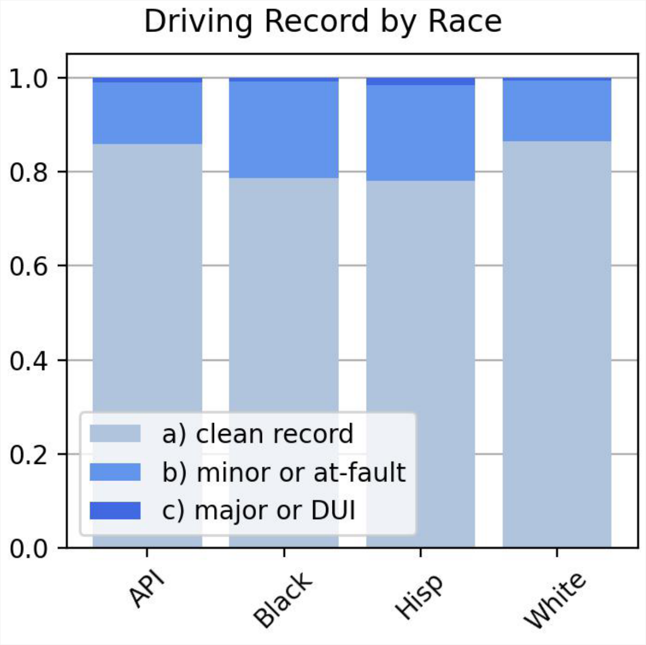
PREMIUMS AND LOSSES

- Black drivers pay higher premiums vs other drivers. However, losses for Black drivers are similarly higher than losses for other drivers.

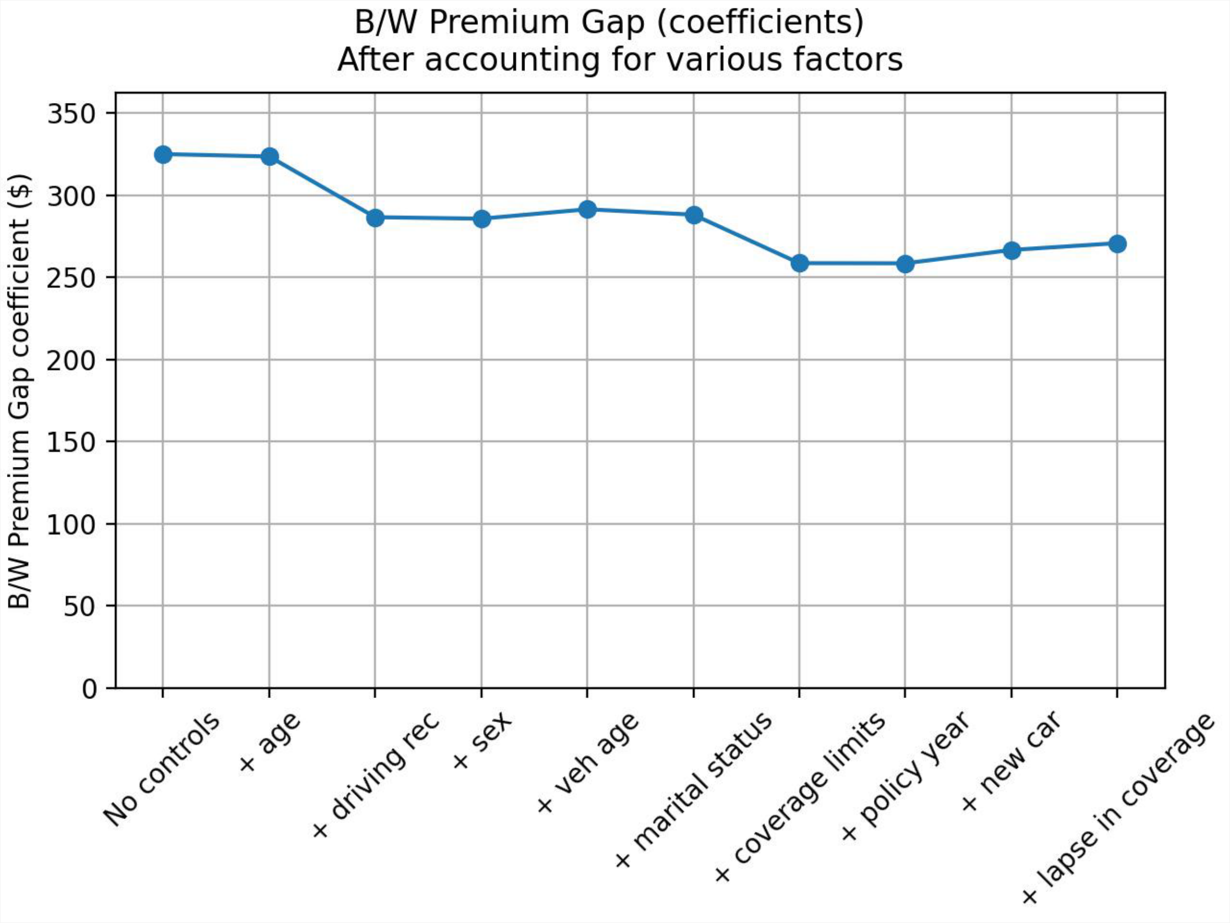
- This did not conclude our review to consider unintentional bias in premiums. We did further analysis to determine if factors more closely related to actual risk could explain the Black/white premium gap.

EXPLANATORY FACTORS





IMPACT OF VARIOUS FACTORS ON THE BLACK/WHITE PREMIUM GAP



WHAT EXPLAINS THE REST OF THE PREMIUM GAP?

- There are some risk-related rating characteristics that we did not have sufficient information to analyze.
  - (e.g., make and model of car).

- There are other rating characteristics that are commonly used by insurers which are likely responsible for the sizeable differences in premium rates.
  - They include credit-based insurance scores, education, occupation, etc. (proxy variables).

NEXT STEPS

- First, it is important to recognize that this is still a draft report. This is the first of its kind report and we are looking to receive productive stakeholder feedback that may result in changes to the report.
- There are elements for additional review identified in the report that could be undertaken.
- Other lines of business could be reviewed.
- We hope that other jurisdictions will take on some of these.

THANK YOU

DISB | WE ARE WASHINGTON DC GOVERNMENT OF THE DISTRICT OF COLUMBIA MURIEL BOWSER, MAYOR

Contact

Name: Philip Barlow

Title: Associate Commissioner for Insurance

Phone: (202) 442-7823

Email: philip.barlow@dc.gov

Attachment Two

California Low Cost Auto Insurance Program (CLCA)

Attachment Three

JULIA JUAREZ

November 2024

Program Overview

What is CLCA?

- CA Low Cost Auto Insurance Program **Established 1999**
- CLCA provides **affordable, low cost liability insurance**
- CLCA is a **state-sponsored program**
- **Goal:** to decrease the number of uninsured drivers

CLCA Statistics

- Program has nearly doubled in five years, from **19,931** policyholders in 2019 to **39,176** policyholders (as of 6/30/2024)
- In 2023, program had **21,157** new policy applications –an exponential jump from just **9,981** new policy applications in 2022

How do you qualify?

Valid CDL/AB60

Vehicle Value $25,000 or Less

Meet income guidelines

Be at least 16 years
Applicants under 18 must be legally emancipated

In addition, a clean driving record for the past 3 years is required.

History of CLCA

The road to get drivers insured in a cost-effective manner.

2000
Program launch

CALIFORNIA'S LOW COST AUTO INSURANCE

2006
Program expands into all 58 counties in California.

2015
Program expands the ability to join by changing eligibility qualifications.

- AB60 took effect allowing undocumented immigrants to obtain licenses and thus mandated to have insurance.
- Expanded vehicle value limits from $20,000 to $25,000.
- Began offering premium payment options to consumers.

AB60

2019
Program repeal date extended to January 1, 2025.

Eliminated gender distinction in rate surcharge, and allowed for students claimed as dependents.

2020
Applicants allowed to submit Certification of Income Eligibility form when proof of income is not available.

Premium credits authorized in response to Covid-19.

2021
Launched shorter eligibility questionnaire and simplified "Household" rule.

2022
Created a QR code analytic system to track effectiveness.

2023
Passed AB 917 to make the CLCA program permanent

AB917

2024
Implementation of the electronic payment vendor system

CALIFORNIA'S LOW COST AUTO INSURANCE

Attachment Two

Insurance Commissioner
Ricardo Lara

CDI
California Department of Insurance

CDI STAFF
- Julia Juarez
- Amy Nungaray
- Mike Riordan

CAARP
California Auto Assigned Risk Program

AIPSO OPERATIONS
- Administrative
- Policy Issuance
- Manages www.mylowcostauto.com

ADVISORY BOARD
- 4 Public Representatives
- 2 Producer Representatives
- 8 members representing subscribing insurers
- Commissioner/designee is final member

LAD CARRIERS
- Integon (All State)
- 21st Century (Bristol West)
- AISPO

Marketing Budget

Sequoia the Bear

The California Low Cost Auto Insurance Program is funded by a $.05 special purpose assessment on each vehicle insured in the state. Estimated funding for 2024 is up to $1.29 million.

The use of the funding is estimated as follows:

ESTIMATED BUDGET FOR 2024	
Marketing and Advertising Budget	$1,200,000.00
Materials Development and Production	$90,000.00
TOTAL BUDGET FOR 2024	$1,290,000.00

Thank you

CAS Research Paper Series on Race and Insurance Pricing

Phase 2 Research

November 16, 2024

Mallika Bender, FCAS, DE&I Staff Actuary
Casualty Actuarial Society

CAS Research Paper Series on Race and Insurance Pricing

Phase 1

casact.org/raceandinsuranceresearch

CAS Research Paper Series on Race and Insurance Pricing

Phase 2

New papers available!

Preparing for Tomorrow:

Regulatory insights and strategies for mitigating potential bias in insurance pricing

casact.org/raceandinsuranceresearch

Comparison of Regulatory Frameworks for Non-Discriminatory AI Usage in Insurance

Authors: David Schraub, FSA; Jing Lang, FSA; Zhibin Zhang, FSA; Mark Sayre, FSA

This report aims to provide a brief overview of recent and developing regulatory activity in China, U.S., Canada, and Europe as it relates to avoiding discriminatory use of artificial intelligence (AI) in the insurance industry

Published jointly by the CAS and Society of Actuaries

Actuarial Innovation and Technology

SOA Research INSTITUTE

CAS

Comparison of Regulatory Framework for Non-Discriminatory AI Usage in Insurance

August | 2024

AI Regulatory Frameworks - Approach

United States

Canada

Europe

China

- Context: Driving Philosophy behind insurance and regulation
- Responsibility: Who regulates Insurance and AI?
- Action: Current Developments in AI and Bias in Insurance regulation

AI Regulatory Frameworks - Key Takeaways

United States

- Decentralized
- Mostly industry-specific
- NAIC H-comm, states
- NAIC AI Bulletin

Canada

- Some Centralized
- Cross-industry
- NFRA
- MOST

Europe

- Centralized
- Cross-industry
- EIOPA
- DORA-GDPR, EU AI Act

China

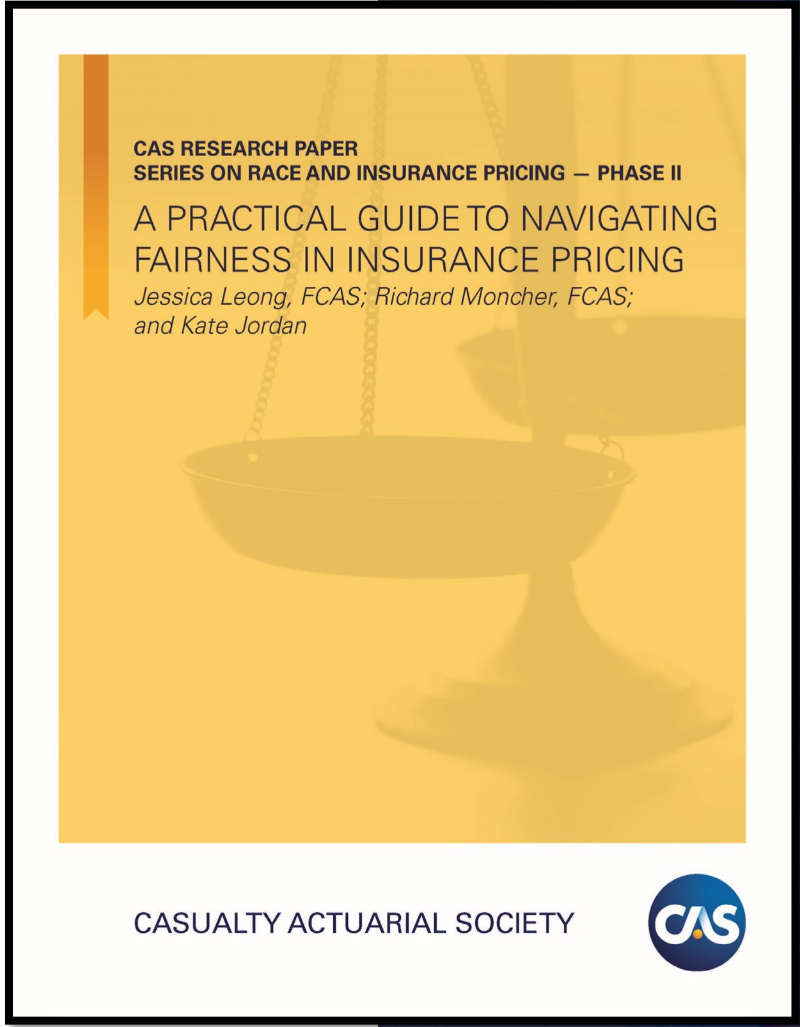
- Centralized
- Cross-industry
- OSFI, provinces
- AIDA

Attachment Three

A Practical Guide to Navigating Fairness in Insurance Pricing

Authors: Jessica Leong, FCAS; Richard Moncher, FCAS; and Kate Jordan

This report provides a framework to help insurers develop models that are more likely to comply with evolving regulations on unfair discrimination and bias.



Navigating Fairness: Approach

Overview of recent regulatory & legislative activities

- Insurance – US, Canada, Europe
- Non-Insurance – Lending, Housing, Hiring

Fairness Considerations for:

Project Planning → Data Prep & Exploration → Modeling → Implementation & Monitoring

Organization-Level Model Governance

Navigating Fairness: Model Governance

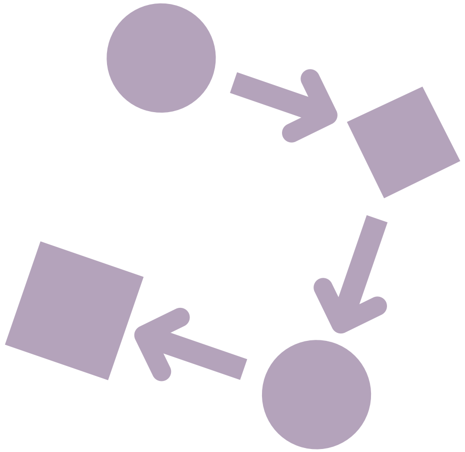
- Guiding Philosophy on Unfair Discrimination
  - Broad or specific compliance with regulations
  - What groups are in scope
  - What will you do and not do?

- Inventory of Models and Data Dictionaries

- Overall Approach to Measuring & Monitoring for Unfair Discrimination

Navigating Fairness: Modeling Process

- ✓Be mindful of how the business problem is **translated** into a modeling problem
- ✓Evaluate & improve **data credibility & quality**
- ✓**Test model results** for bias
- ✓**Monitor** model for **data drift**



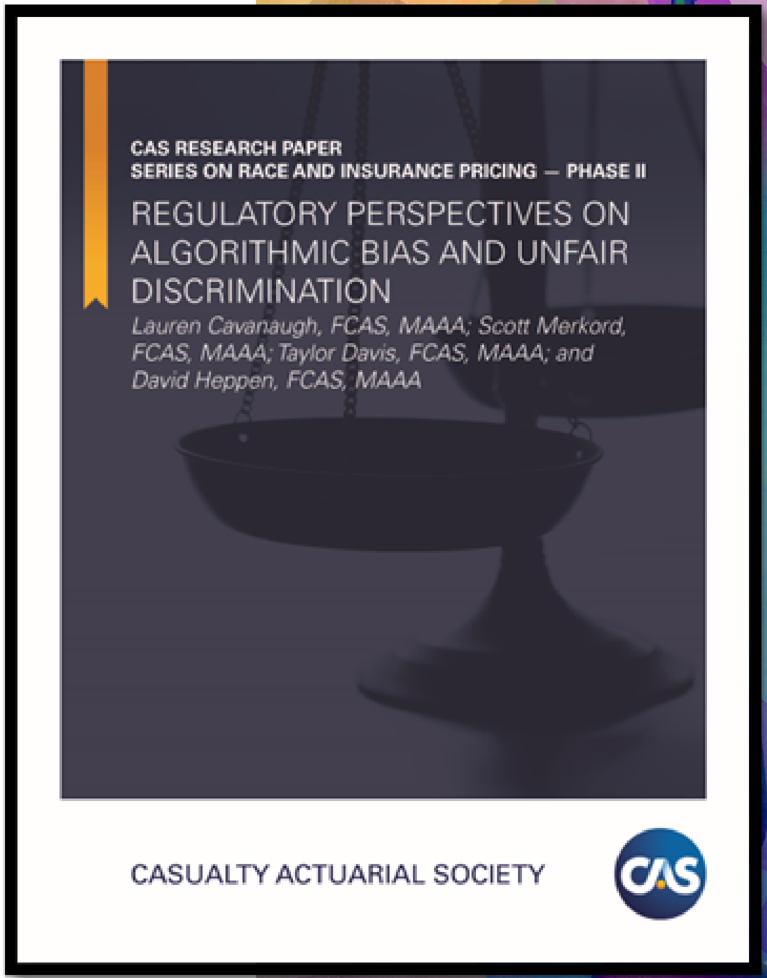
Attachment Three

Regulatory Perspectives on Algorithmic Bias and Unfair Discrimination

Authors: Lauren Cavanaugh, FCAS; Dave Heppen, FCAS; Scott Merkord, FCAS; and Taylor Davis, FCAS

Risk & Regulatory Consulting, LLC

This paper aims to explore regulatory perspectives on algorithmic bias, including U.S. state regulator concerns with current insurance pricing practices, perceptions of fairness testing approaches and plans for future activities.


CAS RESEARCH PAPER
SERIES ON RACE AND INSURANCE PRICING – PHASE II

REGULATORY PERSPECTIVES ON ALGORITHMIC BIAS AND UNFAIR DISCRIMINATION

Lauren Cavanaugh, FCAS, MAAA; Scott Merkord, FCAS, MAAA; Taylor Davis, FCAS, MAAA; and David Heppen, FCAS, MAAA

CASUALTY ACTUARIAL SOCIETY

Perspectives: Approach

Summary of Recent Regulatory Activity (U.S.)

Emphasis on collaborative efforts (e.g. NAIC)

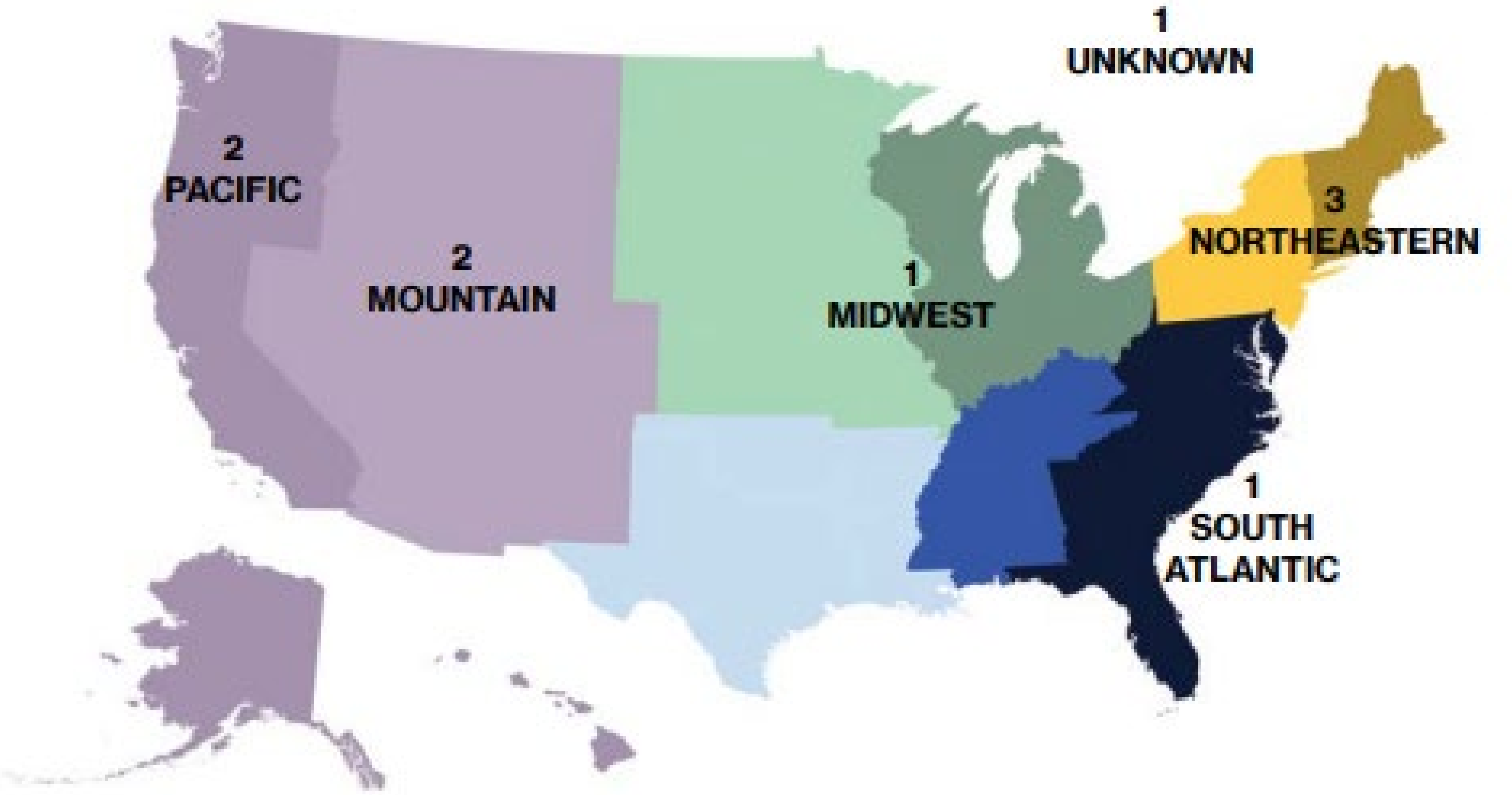
Survey of U.S. State Insurance Departments

Considerations for Actuaries Responding to Emerging Regulations

Definitions

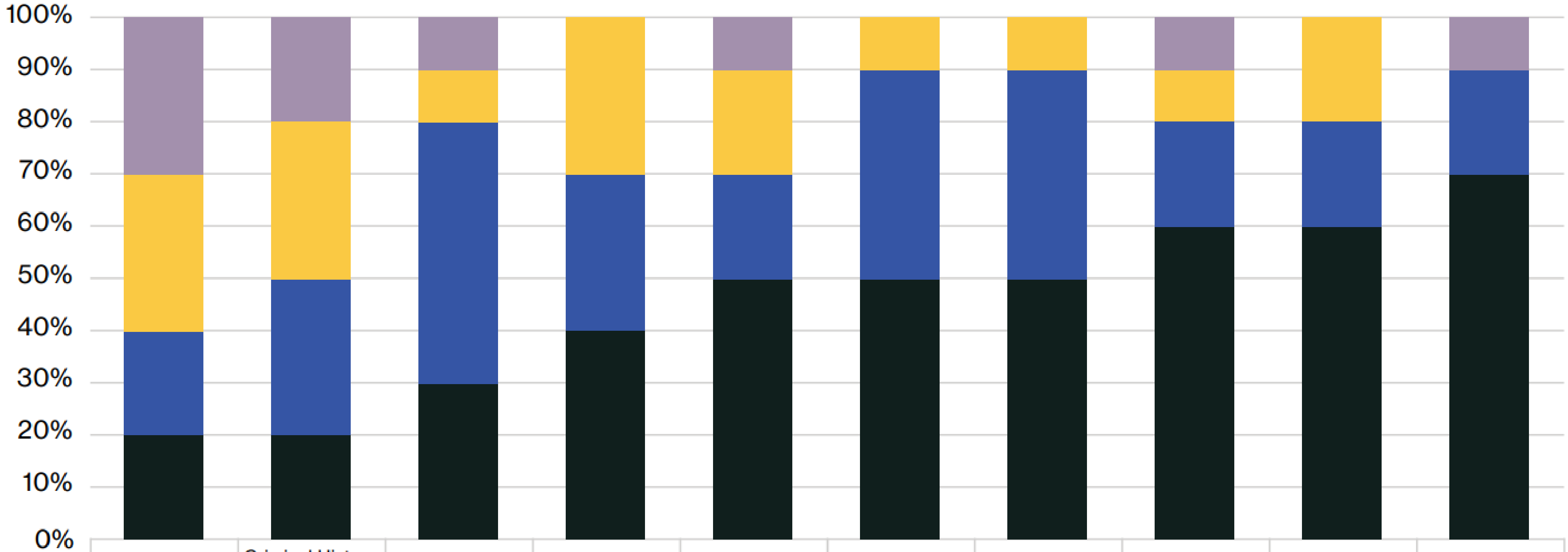
- **Artificial Intelligence (AI):** Refers to computer systems performing functions associated with human intelligence, such as reasoning, learning, and self-improvement.
- **Predictive Model:** Uses historical data and algorithms to identify patterns and predict outcomes for decision-making.
- **Machine Learning:** A subset of AI focused on computers learning from data without explicit programming.
- **Algorithmic Bias:** Includes systemic, human, and statistical biases, which can result from institutional practices, human thought errors, or non-representative data samples

Survey Respondents



Perspectives: Auto Rating Factors

Survey Results - Section III: Rate Elements Used in PPA Ratemaking



	Credit-based Insurance Score	Criminal History (besides that related to driving)	Occupation	Homeownership	Education Status	Geographic location variables	Gender	Motor Vehicle Records	Marital Status	Age
Prohibited/Restricted	3	2	1	0	1	0	0	1	0	1
Very concerning	3	3	1	3	2	1	1	1	2	0
Concerning	2	3	5	3	2	4	4	2	2	2
Not concerning	2	2	3	4	5	5	5	6	6	7

Perspectives: Plans & Perceptions

- Few are engaged in activities to address algorithmic bias
- Most agree multiple bias testing methodologies should be used
- Mixed views on use of race/ethnicity for bias testing
  - AND most disagree with using race/ethnicity inference approaches

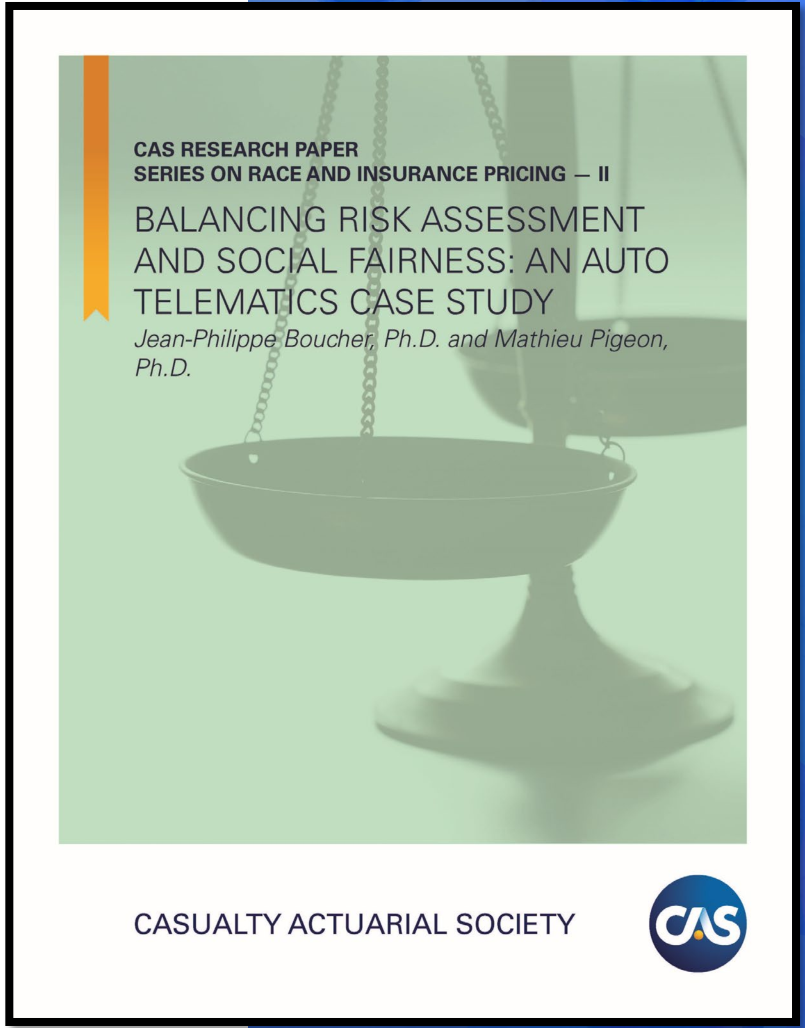
<u>Actuarial soundness does not satisfy discrimination concerns</u>

Attachment Three

Balancing Risk Assessment and Social Fairness: An Auto Telematics Case Study

Authors: Jean-Philippe Boucher, Ph.D. and Mathieu Pigeon, Ph.D

This analysis explores the potential for telematics or usage-based insurance rating variables to reduce insurers reliance on protected information, (e.g. sex, age), or sensitive information, (e.g. marital status, territory, credit).


CAS RESEARCH PAPER
SERIES ON RACE AND INSURANCE PRICING — II

BALANCING RISK ASSESSMENT AND SOCIAL FAIRNESS: AN AUTO TELEMATICS CASE STUDY

Jean-Philippe Boucher, Ph.D. and Mathieu Pigeon, Ph.D.

CASUALTY ACTUARIAL SOCIETY

Telematics: Approach

1. Develop Frequency & Severity Models
   a) Traditional Non-Sensitive & Sensitive Variables
   b) Traditional Non-Sensitive Variables & Telematics Variables

2. Evaluate potential for reduced reliance on Sensitive Variables

3. Test GLM vs Black Box models

4. Validate Results on Actual Insurer Data

Telematics Technology & Data

Collected via onboard diagnostics device or phone app

Informs Usage-Based Insurance products

<u>Benefits</u>

- Pricing Accuracy
- Personalization
- Encourage/incentivize safe driving

<u>Challenges</u>

- Implementation cost
- Consumer privacy
- Barriers to take-up:
  - lack of smart phone, old vehicles...

Existing Telematics Research

- Pricing Models perform better when one or more telematics variables are included.
  - Distance driven and driving habits significantly impact claims experience

- Use of one or more telematics elements can replace some sensitive variables such as sex or age.

Sensitive Covariates of Interest

- Age
- Sex

Sometimes considered "Protected Information"

- Marital Status
- Credit Score
- Territory of Residence

Can be correlated to protected info like race/ethnicity

Traditional Non-Sensitive Covariates:

- *Policy Duration*
- *Car Age*
- *Years Without Claim*
- *Region*
- *Car Use*
- *Annual Miles Driven*

Telematics Data Elements

- Distance Driven □ Avg Miles Driven Per Day
- Number of Days / Days of Week / Weekend
- Hard Acceleration
- Hard Braking
- Left/Right Turn Intensity
- Long vs Short trips
- Rush Hour Driving

*Can also include detailed GPS location (not used in this study)

Figure 3.12. Average Miles Driven per Day

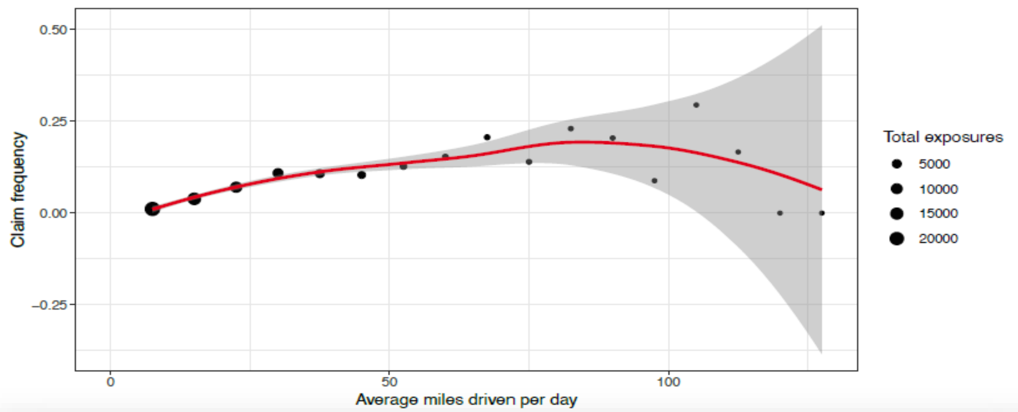
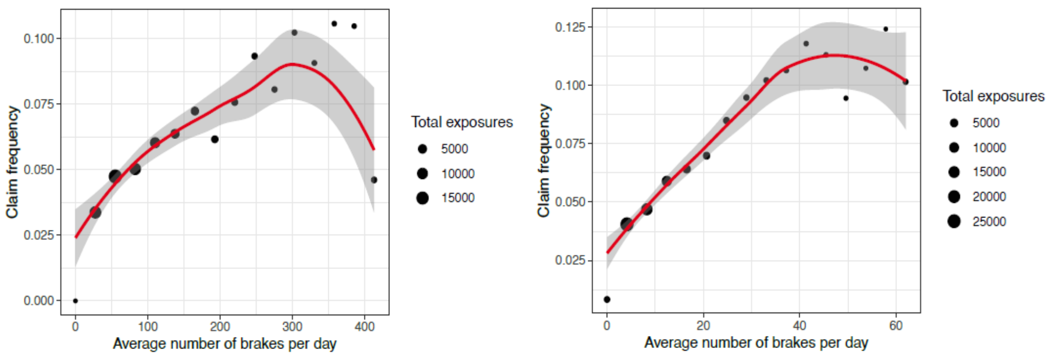


Figure 3.20. Claim Frequency vs. Average Number of Brakes

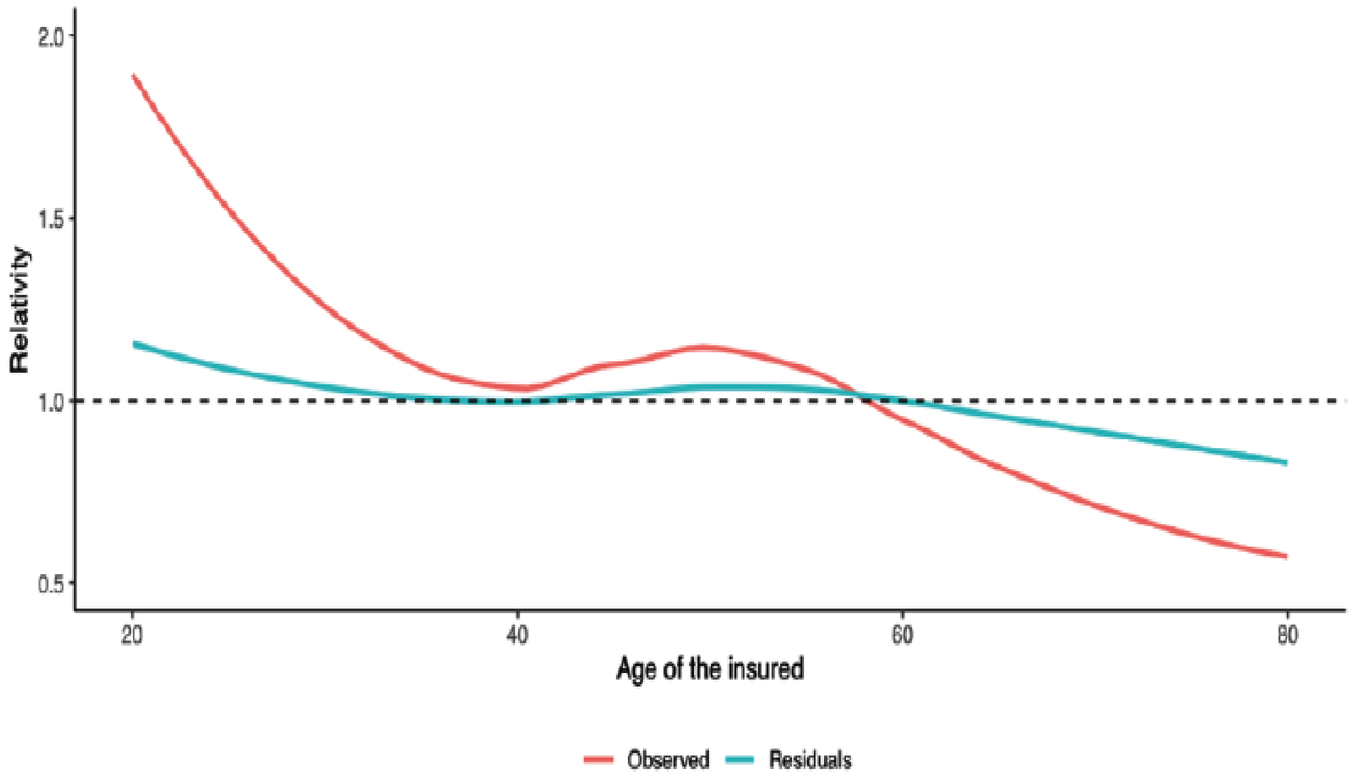


(a) Brakes of 6 mph

(b) Brakes of 8 mph

Results – Insured Age

Figure 2.2. Impact of Insured's Age Before (Red Line) and After (Blue Line) Adding Telematics Variables in an XGBoost Model

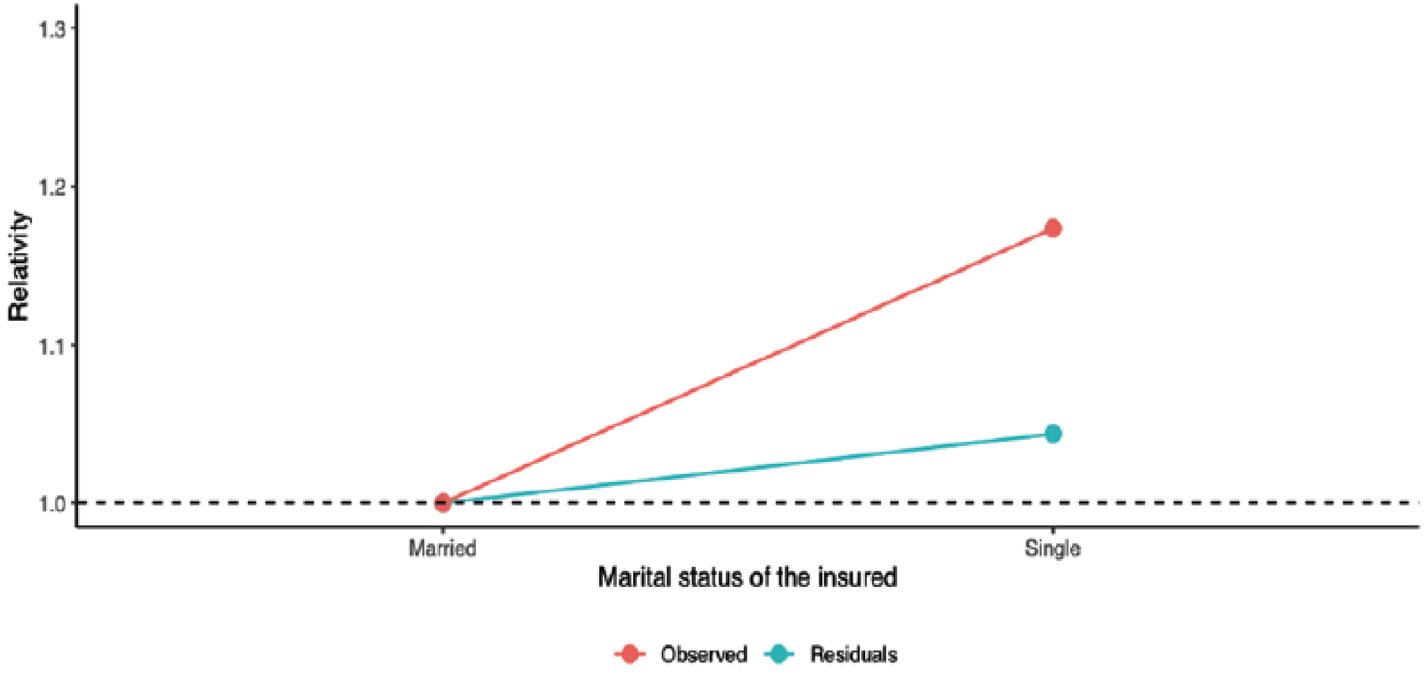


(a) Frequency

Similar results when tested on original insurer data

Results – Marital Status

Figure 2.4. Impact of Marital Status Before (Red Line) and After (Blue Line) Adding Telematics Variables in an XGBoost Model

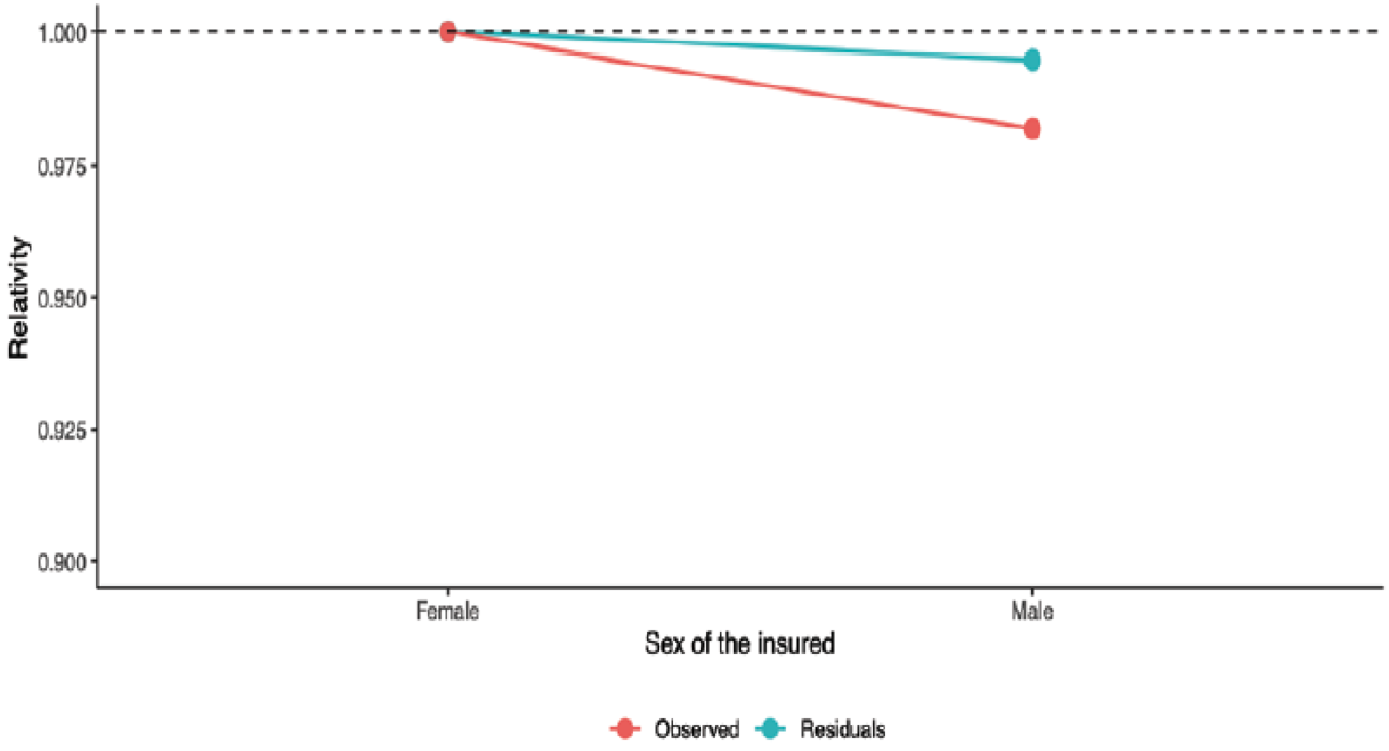


(a) Frequency

Similar results when tested on original insurer data

Results – Insured Sex

Figure 2.5. Impact of Insured's Sex Before (Red Line) and After (Blue Line) Adding Telematics Variables in an XGBoost Model



(a) Frequency

Similar results when tested on original insurer data

Results & Validation – Credit Score

Figure 2.6. Credit Score – Synthetic Data Set

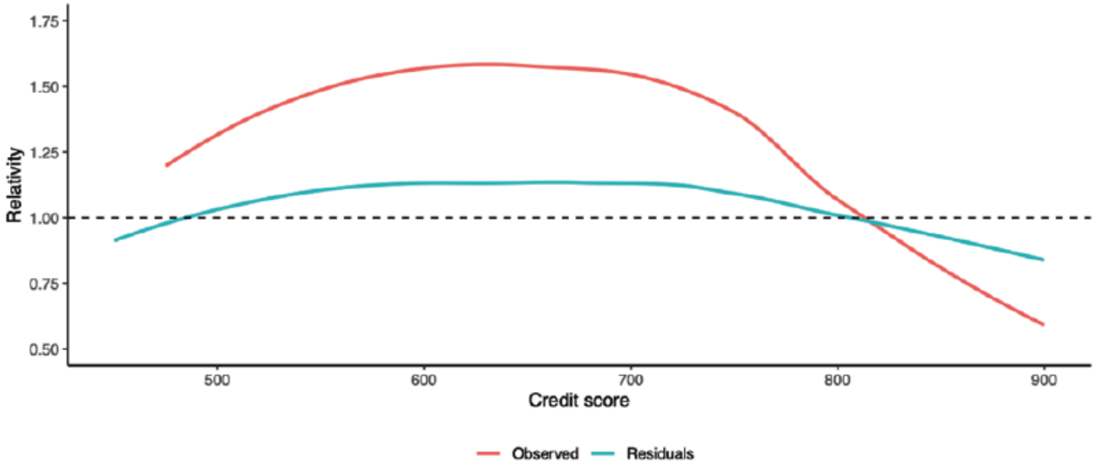
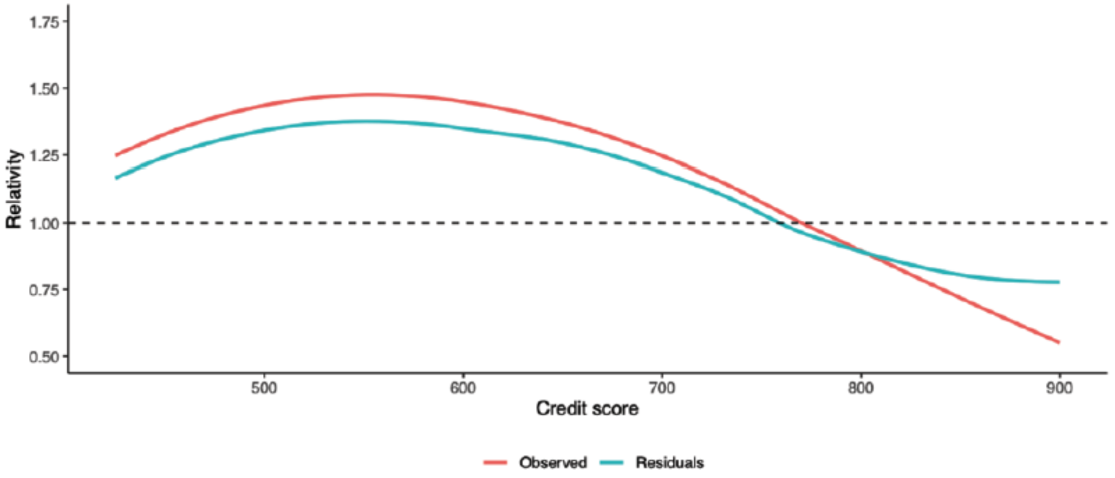


Figure 2.7. Credit Score – Original Data Set



Attachment Three

Insurer data <u>could not</u> confirm results

Attachment Three

Results & Validation – Territory

Figure 2.8. Territory – Synthetic Data Set

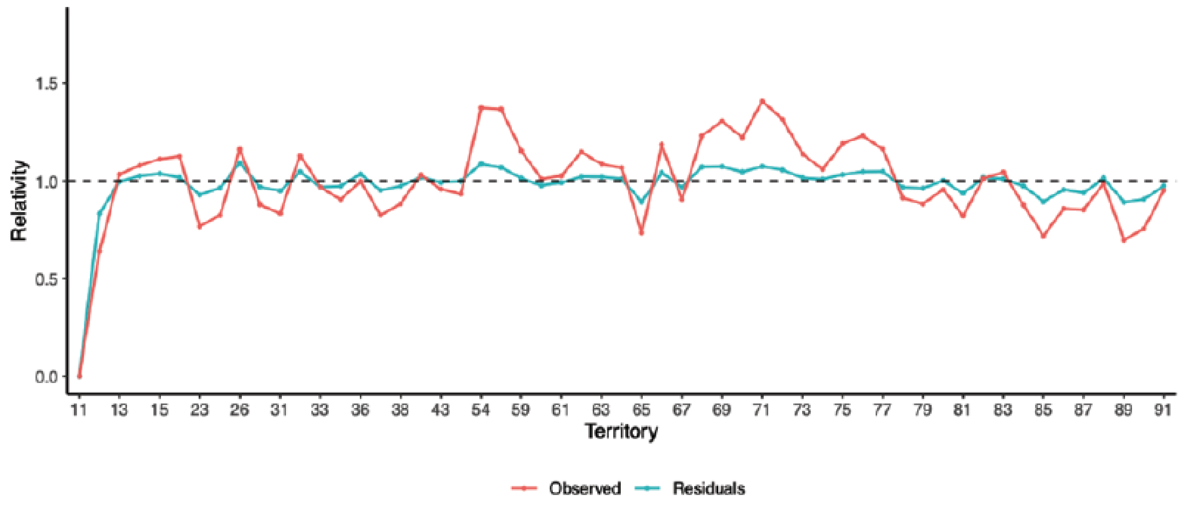
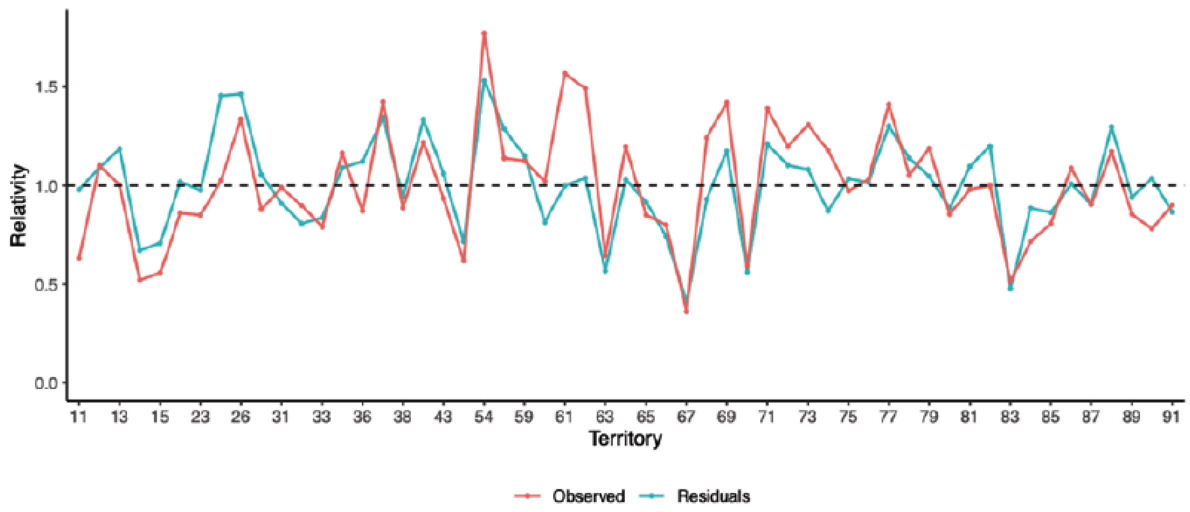


Figure 2.9. Territory – Original Data Set



Insurer data <u>could not</u> confirm results

Telematics: Caveats & Cautions

- Black Box Models (GBM) may unlock greater potential from telematics data
  - Pros: Flexibility, More Parameters, Interaction effects
  - Cons: Lacks transparency, Difficult to Implement/Explain

- Individual insurers may arrive at different conclusions
  - Unique policyholder mix
  - Varying definitions of rating factors
    - ex: credit score (CA) vs CBIS (US)

CAS Research Paper Series on Race and Insurance Pricing

New papers available!

casact.org/raceandinsuranceresearch

Q&A

Contact us: diversity@casact.org

casact.org/raceandinsuranceresearch

Verisk™

Attachment Four

Model Testing & Frameworks

November 16, 2024

National Association of Insurance Commissioners

Steve Clarke, Sr. Vice President, Government Relations

Verisk

Agenda

1. History
2. Risk Analyzer® Suite
3. BIFSG
4. Alternative methodologies
5. AI Governance Framework
6. Flexibility

Ratemaking Background

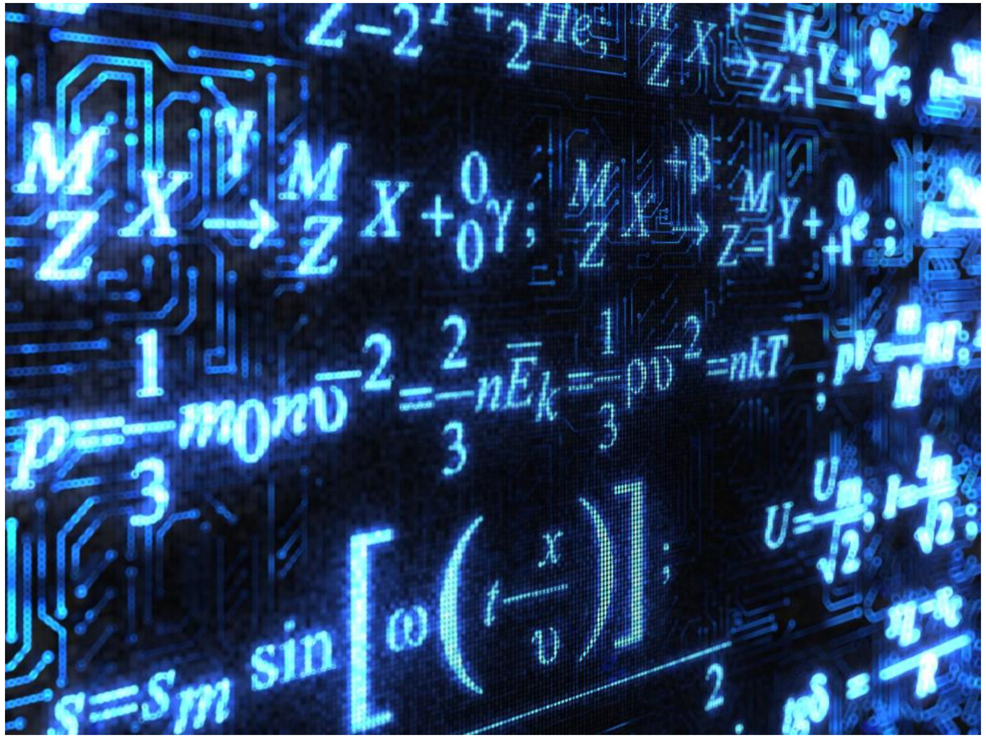
- Traditional ratemaking
  - Fair and adequate premiums
  - Observable characteristics
- Rates shall not be excessive, inadequate, or unfairly discriminatory
  - Actuarially sound estimate of the expected value of all future costs associated with an individual risk transfer
- Actuarial standards of practice
  - No. 12 Risk Classification
  - No. 56 Modeling
- Body of Case Law/Regulations
  - Insurance laws in every state prohibit “unfair discrimination” in rates
  - Safeguards against unfairly discriminatory outcomes

Risk Analyzer® Suite

- Analyzes loss environment in finer geographic detail.
- Variables associated with protected classes were explicitly not considered in modeling.
- Statistical methods used to remove potential contribution of protected class information on the final variables in the model.
- Extensively tested.
- Subjected to external peer review for both modeling methods and disparate impact.

Bayesian Improved Surname Geocoding (BIFSG)

- Widely known method for inferring race and ethnicity in data when this information is not available.
- Combines two commonly used methods to estimate race and ethnicity:
  - Geocoded address
  - First Name and Surname
- The ability to accurately classify individuals into racial or ethnic groups plays a crucial role in studying racial and ethnic disparities.
- Used by the Federal Reserve, Consumer Financial Protection Bureau, Medicare/Medicaid.



Life Insurance Solutions: Tobacco Usage Propensity Model

- Helps flag applicants for further review.
- Leverages audio analytics combined with several other data to estimate the likelihood that an individual uses tobacco.
- Model trained and validated on labeled data.
- The following items were tested in our study:
  - Age and gender (Self-reported)
  - Race/ethnicity, and religion (Imputed by BISG)
- Annual evaluation for model drift.

CO SB 169 (Unfair Discrimination)

- Applies broadly to insurers that use External Consumer Data and Information Sources (ECDIS)
- Requires insurers to test whether ECDIS, algorithms, and predictive models utilizing ECDIS result in unfairly discriminatory outcomes
- Establish and maintain risk management framework
- Life Insurance Underwriting draft regulation
  - Use BIFSG to estimate race and ethnicity
  - Application Approval Decision Testing
  - Premium Rate Testing
  - Variable Testing

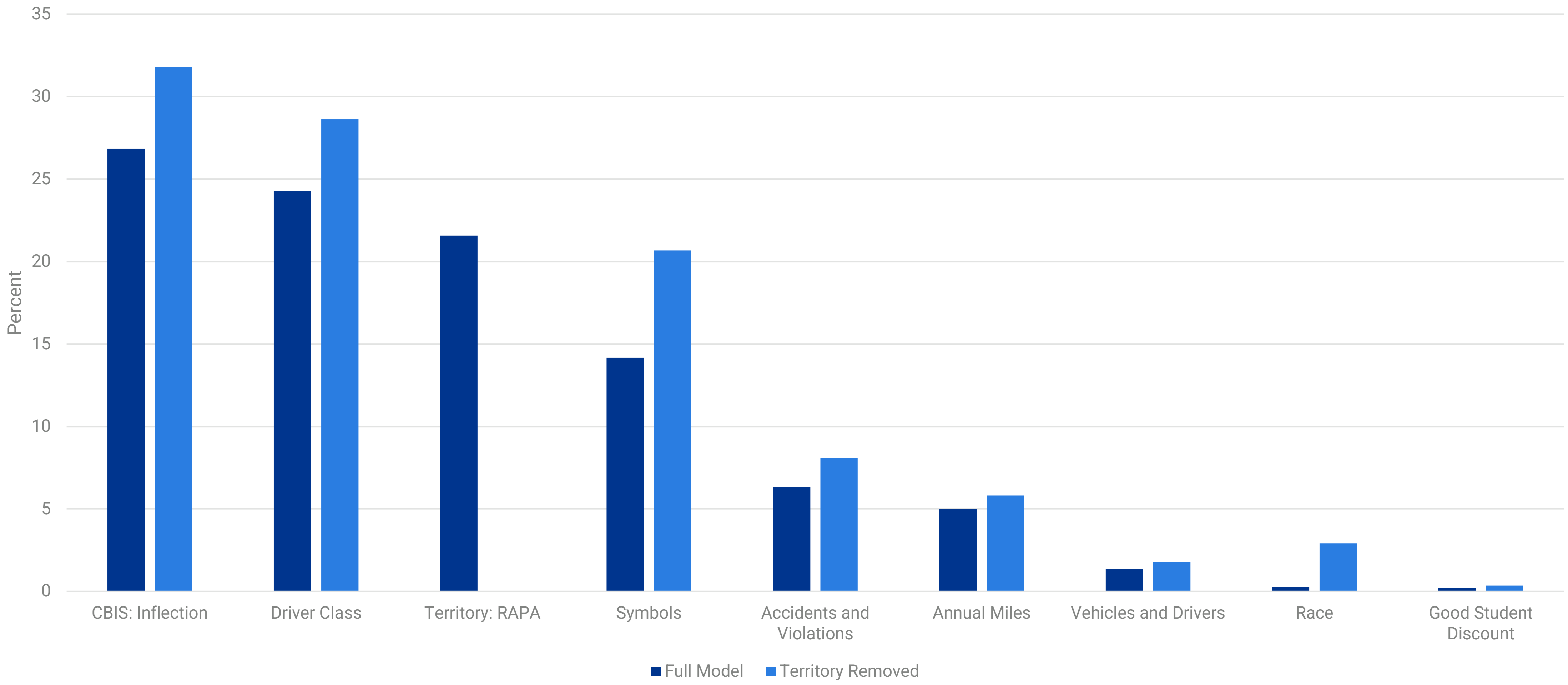
An Alternative Methodology at Work

Uncover insights at the national and state level without having to collect race information.

1. Compile data for personal auto rating plan
2. Impute race via appropriate methodology
   – Bayesian Geocode Imputation at the Zip level
3. Estimate GLMs for coverages using rating plan variables and imputed race information
4. Bootstrapping to properly assess the role of race in the models

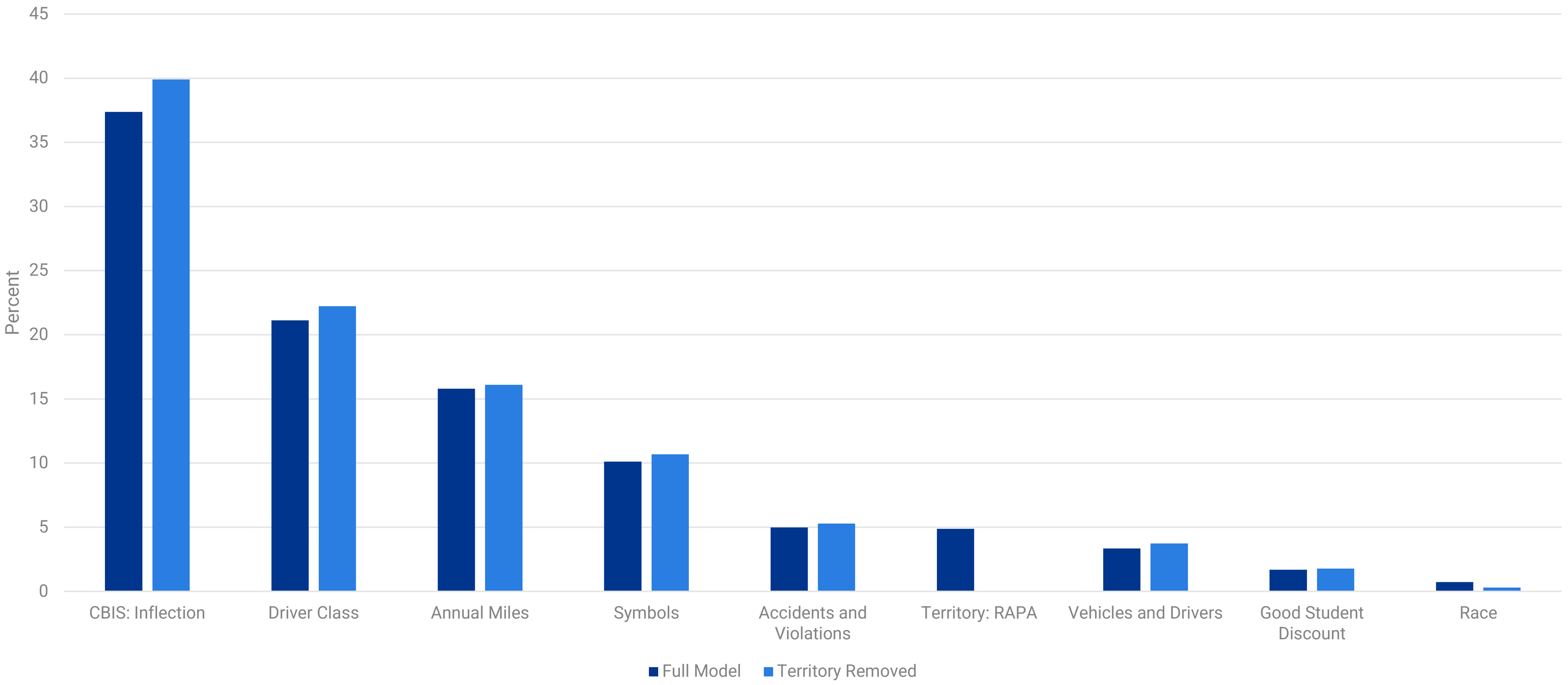
Collision Model Output with Race Imputation

Magnitude of contribution at the national level



Collision Model Output with Race Imputation

Magnitude of contribution at the state level



Loss Ratio Study

1. Loss ratios calculated, by ZIP Code, for all 50 states and DC
2. Loss ratio is generally higher in ZIP Codes with >=50% minority populations.
3. States with an unusually high or low percentage of minority population relative to the country wide average may show different results

2018-2019 Liability, PIP, and Physical Damage

		≥ 50% non-white (Predominant Minority)		
State	Indicator	# ZIPs	All Limits Loss Ratio	FR Limits Loss Ratio
AZ	No	255	69.80%	69.61%
	Yes	141	70.28%	71.48%
CO	No	459	83.72%	90.96%
	Yes	53	85.76%	88.41%
CT	No	243	66.13%	65.04%
	Yes	36	73.75%	73.31%
DC	No	17	56.16%	56.87%
	Yes	12	73.12%	75.11%
ID	No	270	66.95%	68.93%
	Yes	5	64.18%	75.14%
NV	No	116	66.37%	63.54%
	Yes	53	76.60%	72.91%
NJ	No	451	71.13%	67.74%
	Yes	141	82.20%	72.41%
NM	No	135	63.74%	62.14%
	Yes	225	68.77%	69.52%
NY	No	1542	71.16%	66.39%
	Yes	212	85.41%	78.88%
ND	No	365	62.08%	60.99%
	Yes	15	81.48%	89.65%
RI	No	71	69.59%	68.39%
	Yes	6	73.28%	71.66%
VA	No	740	68.56%	67.79%
	Yes	148	73.63%	71.78%
HI	No	10	74.38%	69.82%
	Yes	83	64.57%	61.68%

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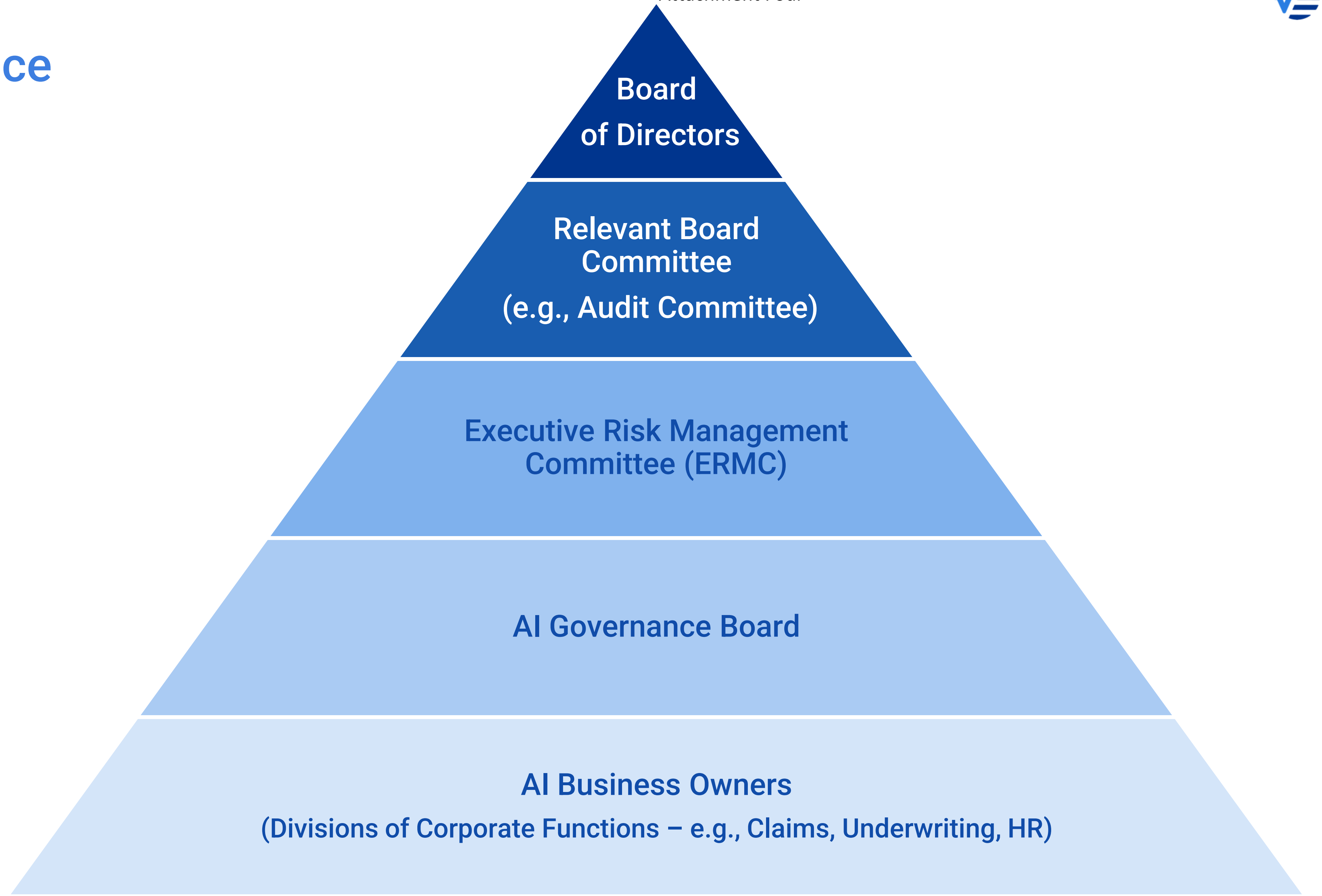
AI Governance

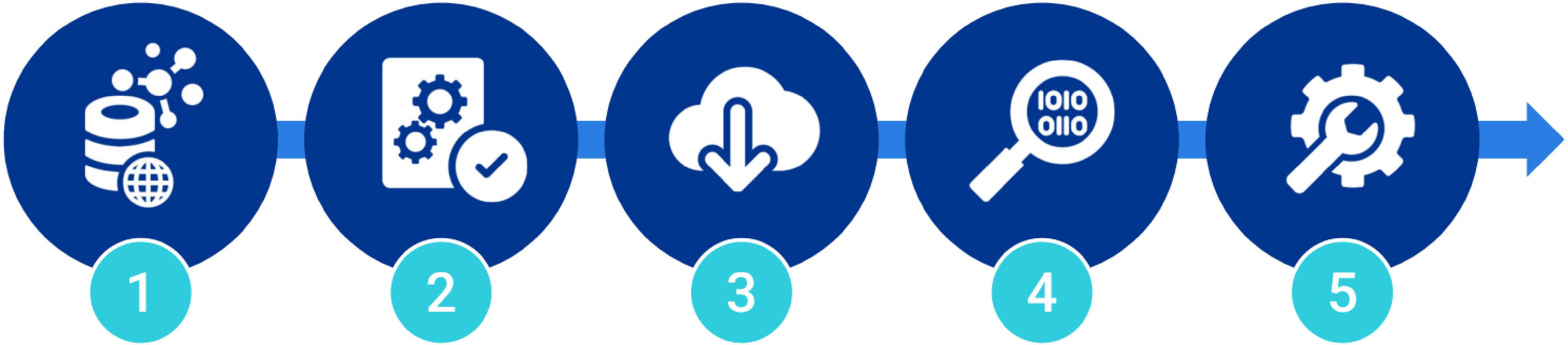


AI Governance

Ethical AI Principles (FAITH)

- Fairness
- Accountability
- Inclusivity
- Transparency
- Honoring Privacy

AI Governance Lifecycle



Inventory

Inventory AI systems including relevant data, function, and risk details.

Proposal and Review

AI business owners submit proposals for appropriate AI governance reviews.

Responsible Development and Deployment

Incorporate review guidance and FAITH ethical principles.

Monitoring

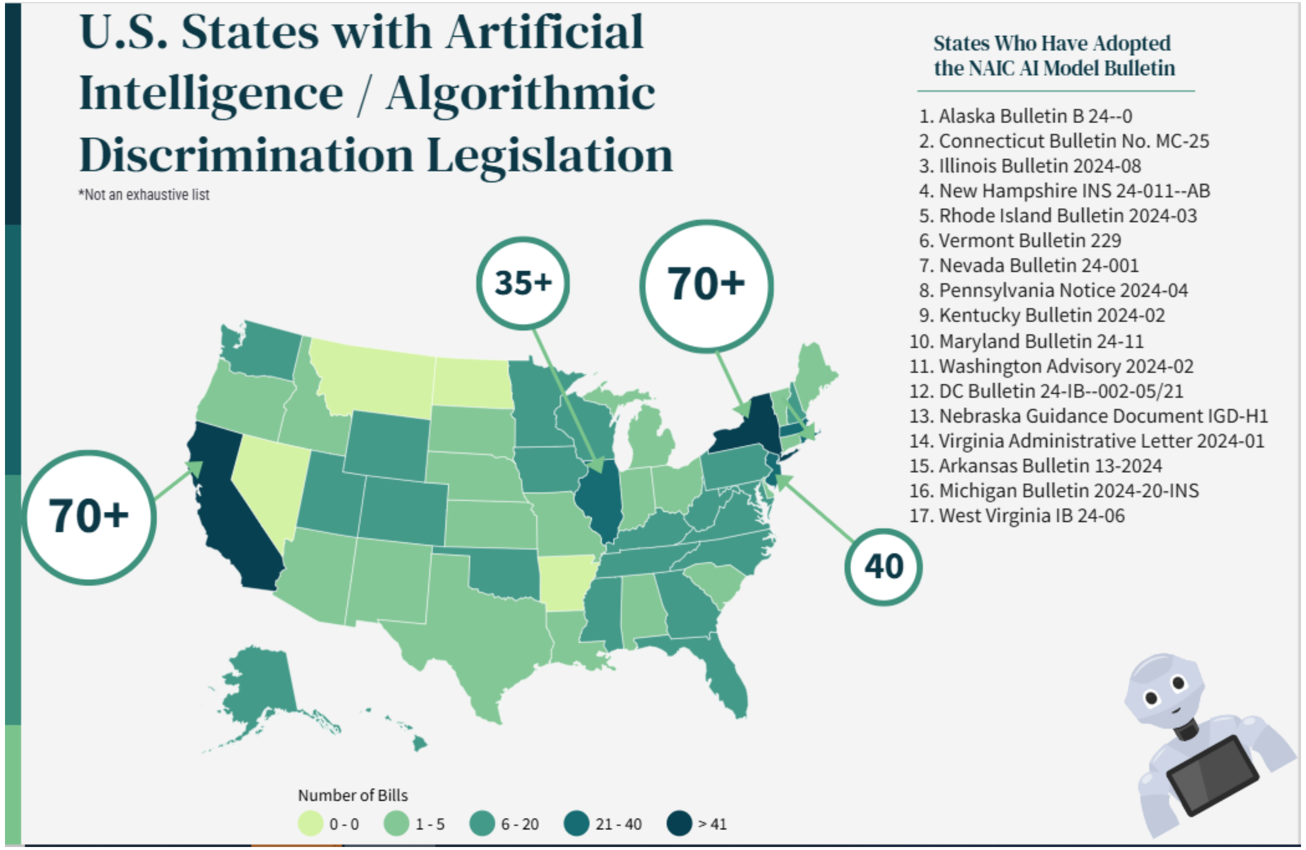
Monitor AI systems for continued adherence to the FAITH ethical principles throughout their lifecycle.

Maintenance

Implement ongoing adjustments to AI systems as needed, update inventory.

Flexibility

- Not all models need testing (i.e., Cat models, PPS, etc.,)
- Guidance vs mandates
- Filed vs non-filed models
- IP protections
- Flexibility
  - New Risk Analyzer® BOP approach
  - Modeling in presence of race
- What works
  - Set expectations
  - Standards
  - Peer review



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