2024 LIFE INSURANCE & ANNUITY CONFERENCE

Powering Growth

Avoiding Disparate Impact Through Enhanced Underwriting Models

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Agenda

DEFINITIONS

TESTING

REGULATORY OUTLOOK

Focus

CT S.2: Developers and Deployers of Artificial Intelligence Systems

NY Circular Letter 1 2024: Artificial Intelligence Systems and External Consumer Data Information Sources in Underwriting and Pricing

CO SB 21-169: External Consumer Data Information Sources and Models using External Consumer Data Information Sources in all Insurance Processes

NAIC Model Bulletin: Artificial Intelligence Systems

LA HB 673: External Consumer Data Information Sources, Algorithms and Predictive Models

Executive Order: Artificial Intelligence

NIST: Artificial Intelligence (AI Risk Management Framework)

Artificial Intelligence (AI)

CT: Artificial Intelligence means **any technology**, including, but not limited to, machine learning, that uses data to train an algorithm or predictive model for the purpose of enabling a computer system or service to autonomously perform any task, including, but not limited to, visual perception, language processing or speech recognition, that is normally associated with human intelligence or perception.

NY: Not called out

CO: Not called out

NAIC Model Bulletin: refers to a **branch of computer science** that uses data processing systems that perform functions normally associated with human intelligence, such as reasoning, learning, and self-improvement, or the capability of a device to perform functions that are normally associated with human intelligence such as reasoning, learning, and self-improvement. This definition considers machine learning to be a subset of artificial intelligence.

LA: Not called out (defines Algorithm and predictive model)

Executive Order: meaning set forth in 15 U.S.C. 9401(3): a **machine-based system** that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. Artificial intelligence systems use machine- and human-based inputs to perceive real and virtual environments; abstract such perceptions into models through analysis in an automated manner; and use model inference to formulate options for information or action.

NIST: Not called out

Webster: the capability of computer systems or algorithms to imitate intelligent human behavior; a **branch of computer science** dealing with the simulation of intelligent behavior in computers

Artificial Intelligence System (AIS)

CT: means any **machine-based system** that, for any explicit or implicit objective, infers from the inputs such system receives how to generate outputs, including, but not limited to, content, decisions, predictions or recommendations, that can influence physical or virtual environments

NY: means **any machine-based system** designed to perform functions normally associated with human intelligence, such as reasoning, learning, and self-improvement, that is used – in whole or in part – to supplement traditional medical, property or casualty underwriting or pricing, as a proxy for traditional medical, property or casualty underwriting or pricing, or to establish "lifestyle indicators" that may contribute to an underwriting or pricing assessment of an applicant for insurance coverage

CO: Not called out

NAIC Model Bulletin: is **a machine-based system** that can, for a given set of objectives, generate outputs such as predictions, recommendations, content (such as text, images, videos, or sounds), or other output influencing decisions made in real or virtual environments. AI Systems are designed to operate with varying levels of autonomy

LA: Not called out

Executive Order: means any **data system, software, hardware, application, tool, or utility** that operates in whole or in part using AI.

NIST: an **engineered or machine-based system** that can, for a given set of objectives, generate outputs such as predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy

External Consumer Data Information Sources (ECDIS)

CT: Not called out

NY: includes data or information used – in whole or in part – to supplement traditional medical, property or casualty underwriting or pricing, as a proxy for traditional medical, property or casualty underwriting or pricing, or to establish "lifestyle indicators" that may contribute to an underwriting or pricing assessment of an applicant for insurance coverage. For the purposes of this Circular Letter, ECDIS does not include an MIB Group, Inc. member information exchange service, a motor vehicle report, or a criminal history search. An insurer conducting a criminal history search for insurance underwriting and pricing purposes must comply with Executive Law § 296(16). See e.g., Insurance Circular Letter No. 13 (2022).

CO: Governance: means, for the purposes of this regulation, a data or an information source that is used by a life insurer to supplement or supplant traditional underwriting factors or other insurance practices or to establish lifestyle indicators that are used in insurance practices. This term includes credit scores, social media habits, locations, purchasing habits, home ownership, educational attainment, licensures, civil judgments, court records, occupation that does not have a direct relationship to mortality, morbidity or longevity risk, consumer-generated Internet of Things data, and any insurance risk scores derived by the insurer or third-party from the above listed or similar data and/or information source

CO: Proposed Testing: for the purposes of this regulation, a data source or an information source that is used by a life insurer to supplement or supplant traditional underwriting factors. This term includes credit scores, credit history, social media habits, purchasing habits, home ownership, educational attainment, licensures, civil judgments, court records, occupation that does not have a direct relationship to mortality, morbidity or longevity risk, consumer-generated Internet of Things data, biometric data, and any insurance risk scores derived by the insurer or third-party from the above listed or similar data and/or information source. ECDIS does not include traditional underwriting factors

LA: means a data or information source that is used by an insurer to supplement traditional underwriting or other insurance practices or to establish lifestyle indicators that are used in insurance practices. "External consumer data and information source" includes credit scores, social media habits, locations, purchasing habits, home ownership, educational attainment, occupation, licensures, civil judgments, and court records

NAIC Model Bulletin: Not called out

Executive Order: Not called out

Testing Requirements

CT: Developers disclose “measures used examine suitability of data sources, possible biases and appropriate mitigation” and “measures developer has taken to mitigate any known or reasonably foreseeable risk of algorithmic discrimination” (for high risk AIS); deployers “complete an impact assessment”

NY: quantitative assessment: encouraged to use multiple statistical metrics in evaluating data and model outputs; qualitative assessment: able to explain, at all times, how the insurer’s AIS operates and to articulate the intuitive logical relationship between ECDIS and other model variables with an insured or potential insured individual’s risk

CO: Proposed Testing: using BIFSG to estimate race/ethnicity, determine statistically significant difference in approval rates for each estimated race/ethnicity as indicated by p-value less than 0.05 [using logistic regression]; using BIFSG to estimate race/ethnicity, determine is there is a statistically significant different in premium rate per thousand of face amount for estimated race/ethnicity as indicated by p-value less than 0.05 [using linear regression]; [then move to variable testing if failed either of above tests]

LA: not defined

NAIC Model Bulletin: Validating, testing, and retesting as necessary to assess the generalization of AI System outputs upon implementation, including the suitability of the data used to develop, train, validate and audit the model. Validation can take the form of comparing model performance on unseen data available at the time of model development to the performance observed on data post-implementation, measuring performance against expert review, or other methods; Due diligence and the methods employed by the Insurer to assess the third party and its data or AI Systems acquired from the third-party to ensure that decisions made or supported from such AI Systems that could lead to Adverse Consumer Outcomes will meet the legal standards imposed on the Insurer itself

Executive Order: NIST AI risk management framework

What Are We Talking About When We Talk About Bias Testing

Example of bias testing in proposed NY Circ 1 2024

17. **Quantitative Assessment.** Insurers are encouraged to use multiple statistical metrics in evaluating data and model outputs to ensure a comprehensive understanding and assessment. Such metrics may include, among others:

    i. <u>Adverse Impact Ratio</u>: Analyzing the rates of favorable outcomes between protected classes and control groups to identify any disparities.

    ii. <u>Denials Odds Ratios</u>: Computing the odds of adverse decisions for protected classes compared to control groups.

    iii. <u>Marginal Effects</u>: Assessing the effect of a marginal change in a predictive variable on the likelihood of unfavorable outcomes, particularly for members of protected classes.

    iv. <u>Standardized Mean Differences</u>: Measuring the difference in average outcomes between protected classes and control groups.

    v. <u>Z-tests and T-tests</u>: Conducting statistical tests to ascertain whether differences in outcomes between protected classes and control groups are statistically significant.

    vi. <u>Drivers of Disparity</u>: Identifying variables in AIS that cause differences in outcomes for protected classes relative to control groups. These drivers can be quantitatively computed or estimated using various methods, such as sensitivity analysis, Shapley values, regression coefficients, or other suitable explanatory techniques.

Bias Testing Workflow

Evaluate Business Application Context
- What does “harm” mean in this system
- Identify the reference group

Consider metrics
- Model performance metric
- Bias metric & threshold

Test and adjust
- DO THE TESTING
- Investigate source of bias
- Identify and apply appropriate remedy

Deploy & Monitor

MLOps

Bias Testing Workflow

Evaluate Business Application Context → Consider metrics → Test and adjust → Deploy & Monitor

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Defining “Harm” Provides The Frame For Bias Testing

Biz Context

How could your model or system create “harm” for a potential user

In underwriting, there are several potential opportunities for harm:

- Acceleration rate
- Decline / Offer rates
- Price

Taking time at the start of your analysis to understand this concept of harm sets the foundation for the rest of the process

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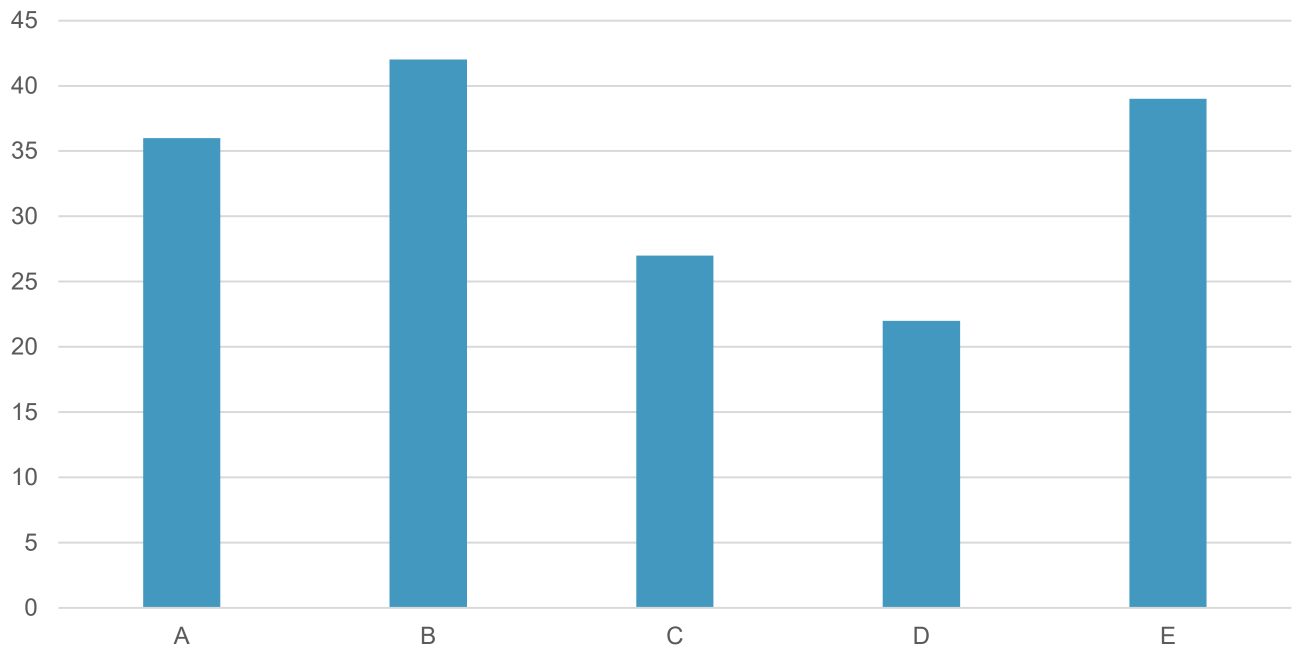
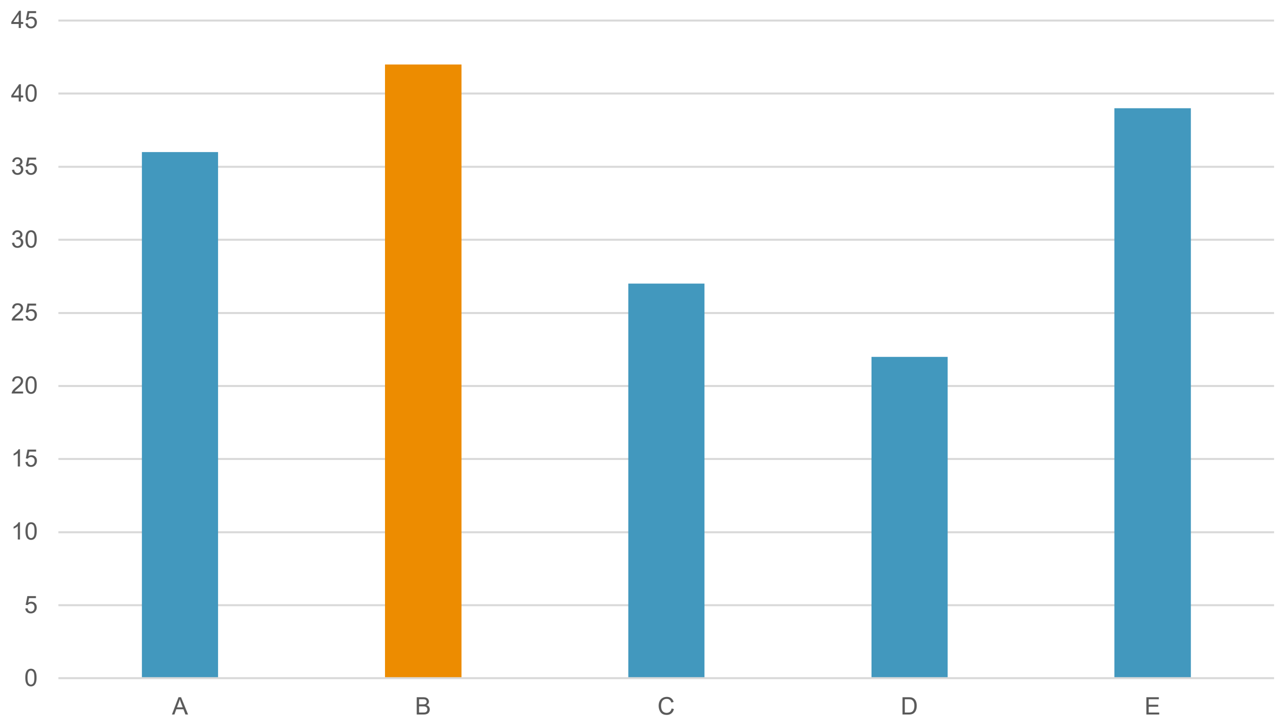
Testing For Bias Is A Comparison Between Groups

Biz Context

Version 1



Version 2



Before you can begin testing, you must identify a reference group that you will compare all other groups against

In testing for bias, we compare the “harm” experienced by a group to a baseline level—the reference group is how we get this baseline.

One approach is to use the largest group as the reference group – but you should consider the social and historical context in this selection.

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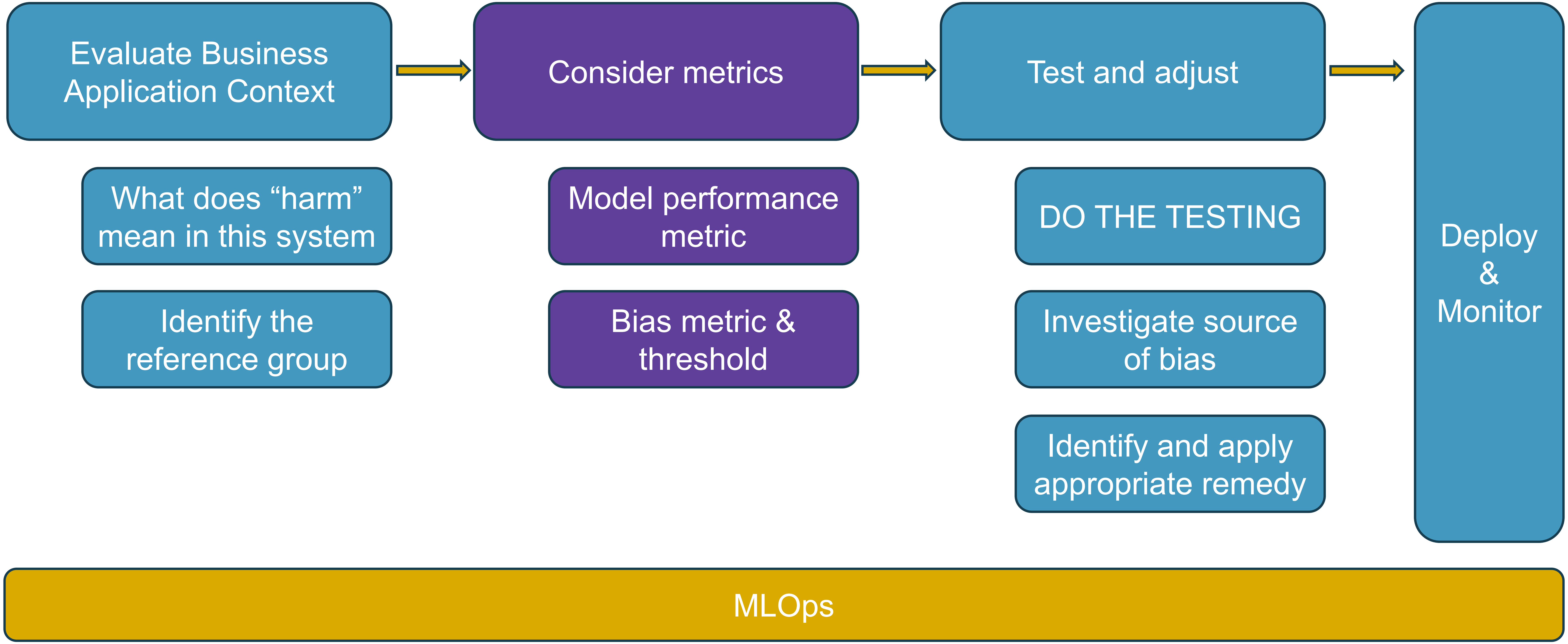
Bias Testing Workflow



Measuring Model Performance For Each Group

Metrics

You need to pick a metric that you are going to use to understand the performance of the model or system for each group

In selecting this metric, it is important to consider:

- How you have defined harm in your model/system
- The output / structure of the model(s), for example classification vs regression type models
- If you are testing an assistive model vs a punitive model

Examples of performance metrics include:

- Accuracy, Precision, Recall, AUC
- MSE, RMSE, R^2 , Adjusted R^2
- A/E, Decline Rate, Acceleration Rate

Selecting A Bias Metric And Threshold

Metrics

Fairness metrics are how we assess the relative performance of our models for each group – and ultimately determine if there is evidence of bias

The model performance metric will guide your selection of a fairness metric along with your interpretation of harm and your overarching bias testing philosophy

Sample of bias metrics:

Metric	Definition	Example
Disparate Impact (Statistical Parity Difference)	Difference in selection rates between groups of interest and the reference group	Offer Rate(protected group) - Offer Rate(reference group)
Disparate Impact Ratio	Ratio of selection rates between groups of interest and the reference group	Acceleration Rate(protected group)/ Acceleration Rate(reference group)
Predictive parity difference	Difference in true positive rates between groups of interest and the reference group	A/E(protected group) – A/E(reference group)

https://fairware.cs.umass.edu/papers/Verma.pdf

Bias Testing Workflow

Evaluate Business Application Context →
- What does “harm” mean in this system
- Identify the reference group

Consider metrics →
- Model performance metric
- Bias metric & threshold

Test and adjust →
- DO THE TESTING
- Investigate source of bias
- Identify and apply appropriate remedy

Deploy & Monitor

MLOps

Test And Review The Results

Testing

As you perform the testing, remember this is science - you need to set your hypothesis BEFORE you do the math!

What To Do When You Find Bias

Testing

You are not limited by the precedent of what has been done before – your goal is to ensure that the bias in the ultimate outcome is mitigated

1. Look at the nature of the bias you are seeing and trace back through the model and modeling process
2. Think about how your model functions in the broader context of the system
    1. Rules
    2. Population limits

At the end of the day, this is about problem-solving, and you get to decide how to solve the problem so that it works for your mission

Bias Testing Workflow

Evaluate Business Application Context

- What does “harm” mean in this system
- Identify the reference group

Consider metrics

- Model performance metric
- Bias metric & threshold

Test and adjust

- DO THE TESTING
- Investigate source of bias
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Deploy & Monitor

MLOps

Now What?

Deployment

MONITOR!

You have done all this work to mitigate bias, but those results are only valid if the population the system is operating on is the population you tested on

SHARE!

Propagate best practices and learnings – you are not the only person doing this kind of work at your company. Share what you found and what you did about it. Investing in our internal practices pays long-term dividends

Bias Testing Workflow – We Made It!

Evaluate Business Application Context → **Consider metrics** → **Test and adjust** → **Deploy & Monitor**

- Evaluate Business Application Context
  - What does “harm” mean in this system
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MLOps

Positive Practices and Trends in the Wild

1. Bias testing is becoming an increasingly common practice – and a practice that we are willing to talk about
2. Increasing emphasis on model transparency and accessibility on models, data, and applications
3. “Science-ification” of bias testing, for example, the prevalence of “standard candle” data sets
4. Maturing practice of MLOps

GenAI and Future Concerns

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Current Regulatory Landscape

CO – SB 21-169, Governance reg 10.1.1, Testing

NY – Circular Letter 1 and Letter on use of AIS and ECDIS in Insurance Underwriting and Pricing

CT Notice

Other States

NAIC

- Model Bulletin - Use of Artificial Intelligence Systems by Insurers
  - States implementing
- Market Conduct Exams

Executive Order 14110 on AI

- US AI Safety Institute Consortium, House Financial Services

Current Regulatory Landscape – Open Issues

Protected Class Data

- Collecting data/Third Party Data
- Inference methods

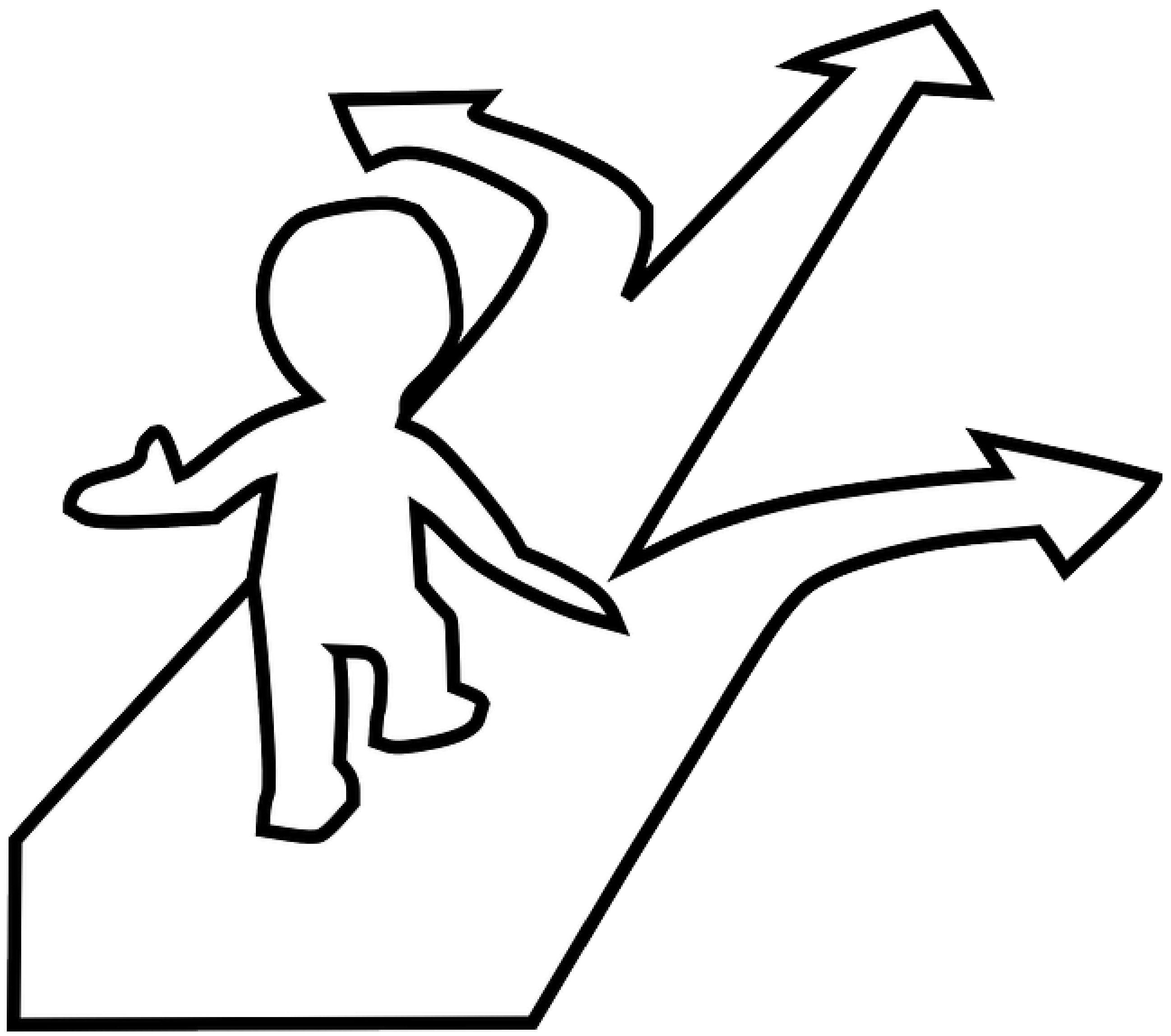
Testing

Differences in States

- Definitions
- Methods
- Prescriptive/Principal Based

Remediation

What is included?



Resources to Help You

Actuarial Standards of Practice	ASOP 12 Risk Classification
	ASOP 23 Data Quality
	ASOP 56 Modeling
Other sources	Actuarial Code of Professional Conduct
	NIST
Recent Issue Briefs and Actuarial Perspectives	*An Actuarial View of Data Bias: Definitions, Impacts and Considerations*; **July 2023**
	An Actuarial View of Correlation and Causation—From Interpretation to Practice to Implications; **July 2022**
	Issue Brief on Sourcing Protected Class Information in P&C Insurance; **June 2022**
	Big Data and Algorithms in Actuarial Modeling and Consumer Impacts; ***October 2022***
	Approaches to Identify and/or Mitigate Bias in Property and Casualty Insurance; **February 2023**
	Challenges and Opportunities with Rethinking Fairness Metrics for Life Insurance Processes: An Actuarial Perspective | SOA; **November 2023**

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Outstanding Questions

All different definitions - scope

Different types of testing

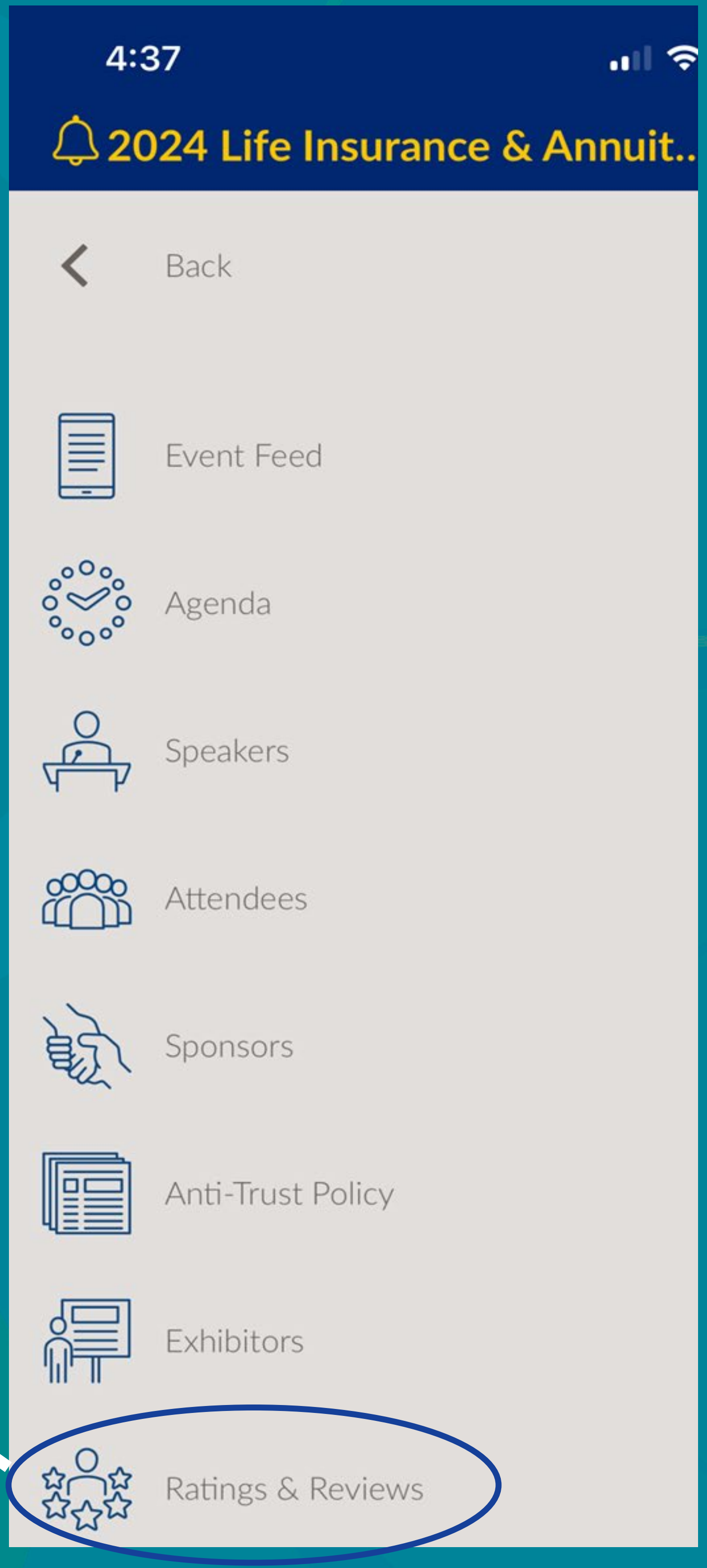
Are regs/tests meeting the goals

Rapid iteration – clear lines are hard, constant movement

Is ECDIS the real driver of problem

Please Provide Your Feedback on the Conference App

OPTION 1



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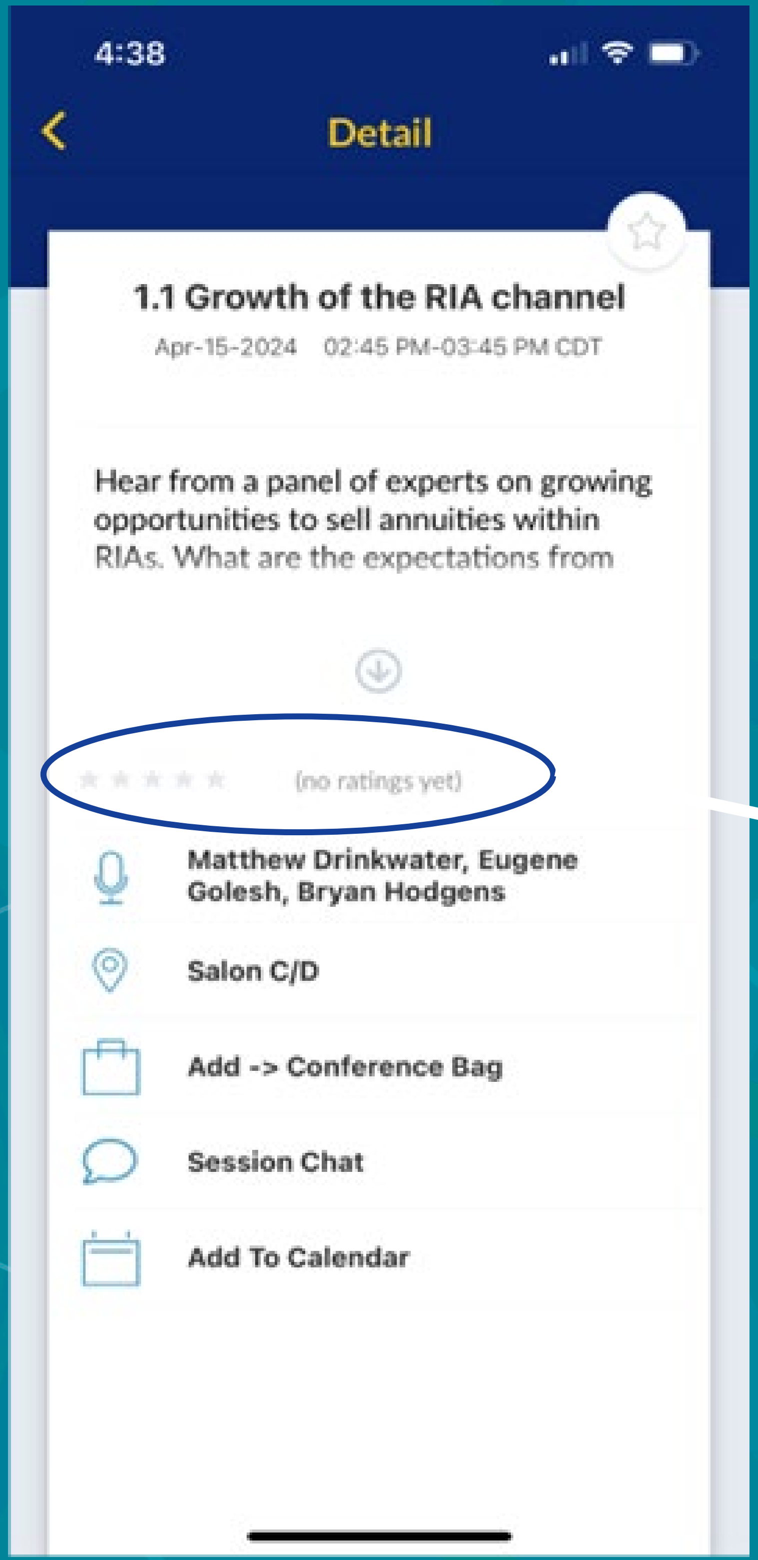

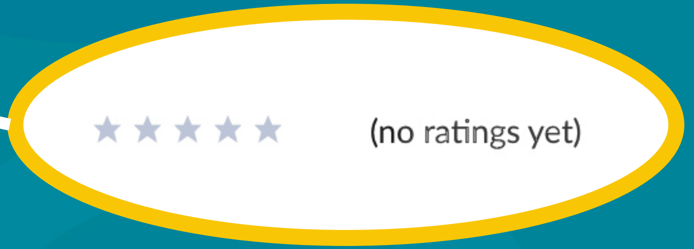

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Thank You

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