2025 LIFE INSURANCE AND ANNUITY CONFERENCE

Reimagine Tomorrow

Ensuring Fairness in Life Insurance Underwriting

Presentation disclaimer

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Model bias in underwriting models

What is model bias?

i. **Systematic behaviors** in a model that cause certain groups, patterns, or predictions to be **unfairly skewed**

- That is, unlike random errors, that fluctuate unpredictably, systematic bias causes certain groupings or patterns to be consistently advantaged or disadvantaged
- This is the “classic” definition of model bias. In world of AI/GenAI models change with every prompt, and insurers must build safeguards into these models to protect against biased results

ii. Sources of bias could include biased training **data**, flawed **algorithms** or **human** prejudices

Examples of bias in Underwriting

i. **Selection Bias** – training data for a predictive model is primarily collected from urban populations, this data may not represent the health profiles or risk factors of individuals living in rural areas

ii. **Algorithmic Bias** – algorithm disproportionately weighs certain attributes, such as age, and might inherently favor younger applicants with lower premiums, despite older applicants potentially having comparable health statuses

iii. **Label Bias** – labels used for training (e.g., high risk vs. low risk) or risk scores are assigned based on the outcomes of past underwriting decisions, which themselves may have been subjective or inconsistent

iv. **Implicit Bias** – training data may reflect past societal inequalities (using income level or zip code as variables), such as less access to healthcare or higher mortality rates in certain demographic groups and therefore perpetuate those inequalities

v. **Confirmation Bias** – belief that certain lifestyle choices (like exercise frequency) are strong predictors of long-term health outcomes could cause model owners to overlook or undervalue other significant predictors such as genetic predispositions or environmental factors

Panel (and audience!) discussion

Audience Question

What made you choose to attend this session?

A. I am actively involved in model bias testing for my organization’s underwriting models
B. My organization is considering model bias testing and I wanted to learn more and get industry perspectives
C. I am curious about / interested in the topic of model bias
D. Just wandered in

Underwriting perspective

How have Underwriters traditionally monitored and managed potential bias in the UW process (i.e., prior to the advent of predictive models)?

Distribution perspective

From a distribution standpoint, have you seen evidence that underwriting biases impact the accessibility of life insurance for certain demographics?

Insuretech and data science perspective

How do innovative distributors leverage 3rd party data, ML, AI to enhance customer experience? What's the associated risk, and what approach do they take to ensure the decision is sound and equitable?

Audience Question

Has your organization been carrying out model bias testing for underwriting models?

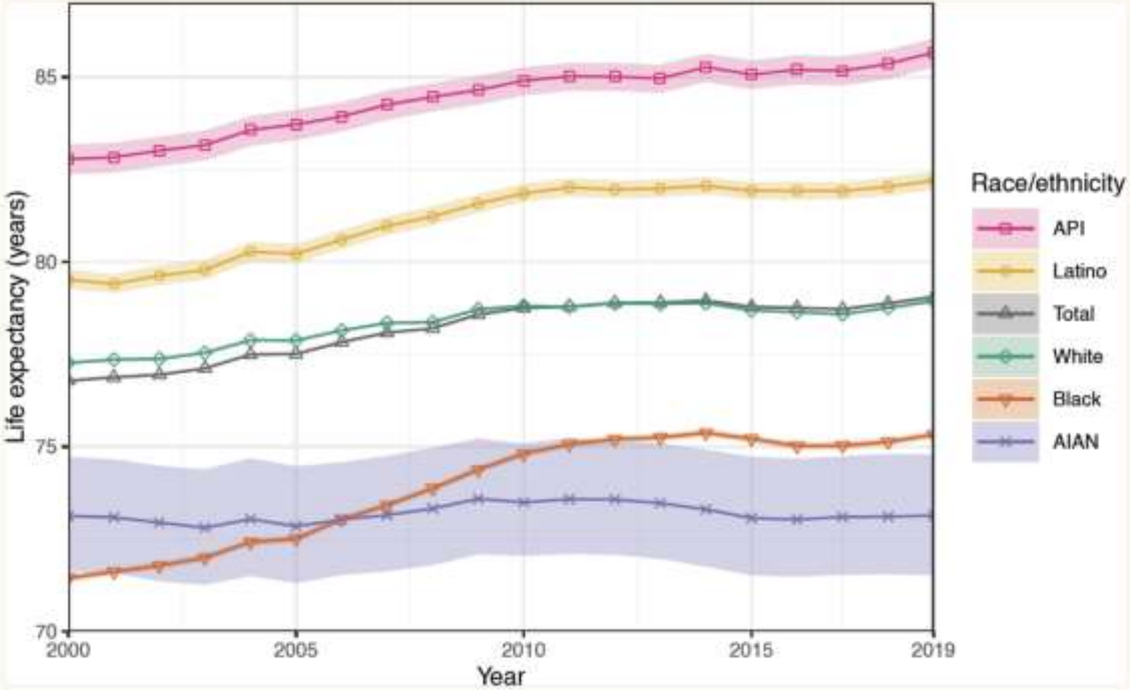
A. My organization carries out model bias testing routinely for all underwriting models
B. My organization carried out several model bias tests for some of our underwriting models
C. My organization is planning to carry out model bias testing for some/all underwriting models
D. My organization has no plans to carry out model bias testing

Underwriting perspective

What role do medical underwriting and health data play in perpetuating bias, and how can insurers mitigate this?

US Life Expectancy by Race and Ethnicity

Figure 1: National life expectancy by racial/ethnic group, 2000–2019.



Source: National Center for Biotechnology Information

Distribution perspective

How can life insurance distributors ensure that potential bias in underwriting doesn’t translate into discriminatory sales practices?

Insuretech and data science perspective

What data sources are most problematic when it comes to potential bias for Insuretech distributors, and what are the approaches to mitigate such risks?

Audience Question

In your opinion, are predictive models beneficial to your underwriting process?

A. Yes - they speed up decisions and allow our underwriters focus on the complex cases
B. Yes - we have noticed a significant increase in new business since we implemented predictive models in underwriting
C. A + B
D. It depends…
E. No - these models just added confusion and reduced transparency in underwriting decisions

Underwriting perspective

How has the emergence of predictive models and new data sources impacted the day to day life of undewriters?

Distribution perspective

What challenges do agents and brokers face when trying to explain underwriting decisions to customers affected by potential bias?

Insuretech and data science perspective

How can insurers collaborate with distributors to reduce potential data or modeling bias?

Appendix: US regulatory developments around model bias

State regulations focused on model bias

The past few years have seen significant transformations in U.S. model bias regulations. As advancements in big data, modeling techniques, and artificial intelligence continue to evolve, state regulators are progressively shifting the onus onto corporations to safeguard fairness and equity in their models. We at KPMG are actively tracking the continual evolution and development of State-specific model bias regulatory requirements, a subset of these laws and regulations is outlined below.

California

California Consumer Privacy Act (CCPA)

CCPA provides consumers with rights to access, delete, and opt-out of the sale of their personal data, which impacts how life insurers use personal data in models. Algorithms used by insurers must comply with these privacy regulations, which indirectly influence model bias.

Proposed Algorithmic Accountability Regulations

California is considering regulations that may require insurers to demonstrate that their models do not lead to unfair discrimination based on race, gender, and other protected classes.

New York

New York Department of Financial Services

NYDFS Circular Letter No.1 requires life insurers to avoid using external data sources and models in underwriting unless they can demonstrate that the models do not disproportionately impact protected groups. Insurers must provide transparency and ensure fairness when using algorithms.

Annual Reporting Requirements

NYDFS requires insurers to report how they use external consumer data and algorithms, promoting accountability and minimizing the risk of biased outcomes.

Illinois

Illinois Biometric Information Privacy Act

BIPA regulates the use of biometric data, such as facial recognition and fingerprinting, which some life insurers use in underwriting. Insurers must ensure that the use of this data does not result in biased decisions against any individual or group.

Anti-Discrimination Laws

Illinois prohibits discrimination based on protected categories, such as race, gender, and national origin, ensuring that algorithms used by life insurers do not reinforce these biases.

Colorado

Insurance Fairness Laws

Colorado prohibits life insurers from discriminating based on protected classes, similar to other states. This extends to the use of data-driven models in pricing and underwriting

Consumer Protection in Interaction with AI Bill

A bill that prohibits algorithmic discrimination against individuals based on their actual or perceived age, skin color, disability, ethnicity, genetic information, sex and other classifications.

Data Privacy Law (CPA)

Colorado’s data privacy law impacts life insurance companies by requiring that personal data be handled responsibly. This law indirectly influences how insurers design and monitor algorithms for fairness, since biased models could violate privacy laws.

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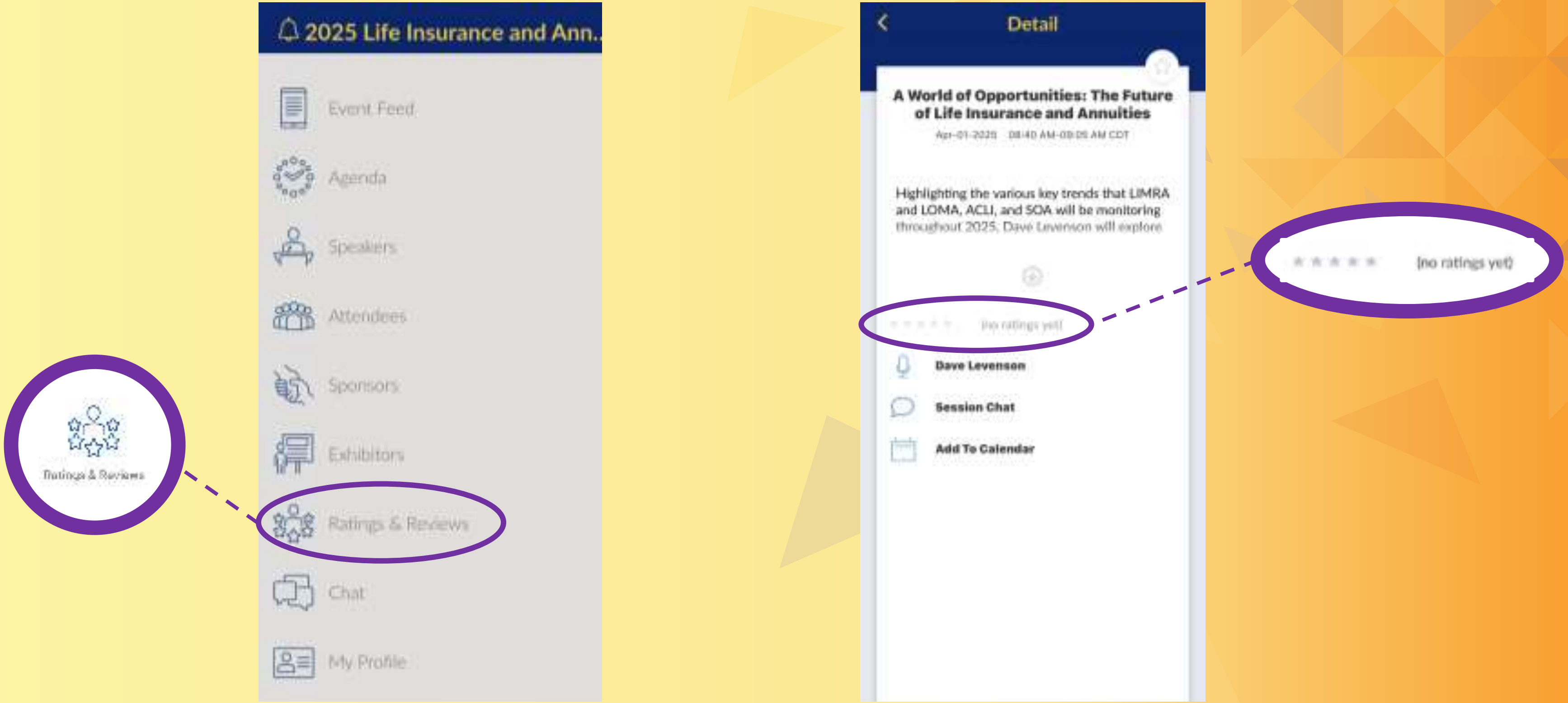

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