

## Award Winner

# Reimagining Underwriting in Life and Annuity Insurance

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### ABSTRACT

While life and annuity insurance sectors have embraced technological modernization, underwriting practices often remain grounded in legacy systems that reflect potential historical and systemic bias. In this context, social equity refers to the fair and just distribution of resources, protections, and opportunities, ensuring that all individuals, regardless of background, have access to insurance benefits without unfair barriers. This essay explores how bias defined as unjust or prejudicial treatment stemming from data, systemic structures, or algorithms may manifest in underwriting and proposes strategies for moving from exclusionary models to inclusive ones. This essay suggests that underwriting can evolve into a tool for improving social equity and fostering public trust by integrating diverse data sources, transparent governance of artificial intelligence (AI) applications, and participatory design.

### INTRODUCTION

Insurance is designed to provide financial protection against unforeseen risks. However, if the mechanisms for assessing that risk, especially underwriting, reflect systemic bias, the promise of protection is unequally fulfilled. In this essay, bias is defined as the unjust distortion of decision-making outcomes caused by historical, structural, or algorithmic influences. In this essay, terms such as equity and fairness are used to distinguish between principles of justice: equity addresses structural differences and unequal starting points, while fairness concerns consistent and impartial treatment. While these concepts are interrelated, they are not interchangeable in all contexts.

Life and annuity insurance policies, meant to deliver financial security, may reinforce inequities when using outdated frameworks. To provide inclusive coverage in today's complex social and economic environments, underwriting models must be reimagined. This essay discusses how industry actors could adopt strategies to align underwriting practices with the ethical and operational goals of fairness, innovation, and accountability.

### UNDERSTANDING THE ROOTS OF BIAS IN UNDERWRITING

Bias in underwriting does not necessarily result from malicious intent. It may emerge from the ways systems are constructed and the data they rely on. Key contributors include:

1. **Historical Data Inequities:** Traditional underwriting relies on historical data to estimate future risk. However, these datasets may be embedded with past inequities. For example, communities historically denied access to healthcare, education, or stable employment may appear as higher-risk due to factors unrelated to actual

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individual behavior. Without adjustments, these models may inadvertently perpetuate systemic disadvantages. (Solon Barocas, 2019).

2. **Algorithmic Bias and Automation Risks:** As insurers turn to automated underwriting systems, machine learning models trained on biased data replicate and reinforce those biases. For example, while “ZIP code of birth” is not commonly used, location-based variables like current residential ZIP codes can serve as proxies for race or income, leading to discriminatory patterns. These models, left unchecked, may continue to produce exclusionary outcomes on a larger scale. (Prince, 2020).
3. **Proxy Variables and Redlining:** Neutral-seeming inputs like education level or employment history may correlate with demographic factors such as race, gender, or socioeconomic status. These inputs can unintentionally result in digital redlining, a term used to describe algorithmic exclusion of disadvantaged populations, even when explicit demographic data is not used. Identifying and recalibrating these inputs is essential for promoting equitable outcomes. (Binns, 2018)
4. **Opacity and Lack of Accountability:** Many underwriting systems provide limited transparency. Applicants often receive vague denials or high premiums without clear explanations. This lack of clarity prevents consumers from understanding decisions or contesting unfair outcomes, thereby reducing accountability and trust in the process.

Addressing bias in underwriting is both an ethical and strategic imperative. From my perspective on a moral standpoint, insurance should serve as a social safety net, not a barrier. Excluding vulnerable populations not only contradicts this mission but may also erode trust in the industry.

From a business perspective, inclusion can be a source of competitive advantage. A 2021 McKinsey & Company report, “Diversity Wins: How Inclusion Matters,” found that organizations prioritizing diversity and inclusion were more innovative and financially successful than their peers. Inclusive underwriting could open access to millions of underserved customers, expanding the market while enhancing an insurer’s reputation for social responsibility. (Diversity Wins: How Inclusion Matters., 2021).

## STRATEGIES FOR EQUITABLE UNDERWRITING

The following strategies are proposed as a framework to build underwriting systems that support fairness while addressing real-world market constraints:

1. **Incorporating Expansive Data**  
 Supplement socioeconomic datasets with data that better mirrors the realities of diverse communities. These supplemental datasets include:
  - Alternative credit datasets (e.g., utility and rent payment histories)
  - Community health indicators
  - Non-linear employment records (freelance and gig work)

Collaborations with public agencies and community-based organizations could help insurers gather more representative and context-rich data. (Raji, 2019).

2. **Algorithmic Fairness Audits**  
 As a part of continuous governance, periodically engage independent third parties to audit AI models for potential algorithmic bias, including:

- Assessing differential treatment of various demographic groups using group-specific metrics
- Incorporating Explainable Artificial Intelligence (XAI) to illuminate the pathways that lead to particular decisions

Employing fairness measures to ascertain and mitigate bias, such as equal opportunity or disparate impact ratios. This approach emphasizes continuous improvement over reactive compliance. (Binns, 2018).

### 3. Ongoing Bias Training for Underwriting Teams

Despite increasing automation, human underwriters still influence key decisions. Regular training on implicit bias, cultural awareness, and inclusive judgment can help underwriting teams make more thoughtful and equitable assessments. This training should be viewed as an evolving process rather than a static obligation.

### 4. Transparent, Applicant-Centric Communication

Building consumer trust requires transparency. Insurers might consider:

- Communicating underwriting criteria
- Providing detailed explanations for application decisions
- Offering applicants an opportunity to appeal or supply additional information

Such transparency empowers applicants to understand, challenge, and learn from underwriting decisions.

### 5. Feedback Loops and Participatory Design

A robust feedback system could help insurers identify and address unintended consequences of their policies. This may include:

- Collecting and analyzing applicant experiences and concerns
- Involving diverse stakeholders, including community representatives, in the underwriting model design

This participatory approach helps ensure that the systems reflect the needs and values of the populations they aim to serve.

## A VISION FOR THE FUTURE: EQUITABLE UNDERWRITING IN ACTION

A more inclusive underwriting framework might consider:

- Financial behavior over traditional employment status
- Current health outcomes instead of generalized mortality tables
- Decision letters that are explanatory and educational, rather than opaque and discouraging

This vision is not speculative. With responsible governance and a commitment to equity, insurers can evolve underwriting into a tool that supports financial inclusion rather than exclusion.

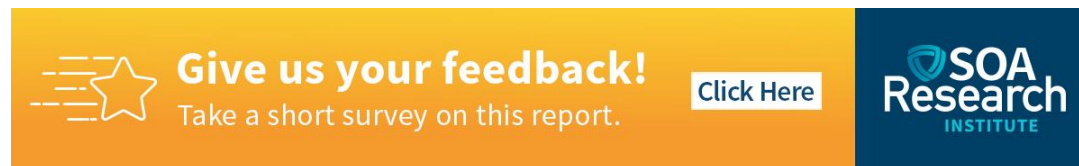
## CONCLUSION

Potential bias in underwriting is shaped by structural, data-driven, and algorithmic factors that can restrict access to insurance coverage for many individuals. Addressing this challenge involves the application of existing tools and approaches. These include the use of more representative and contextually appropriate data, the implementation of

fairness audits for AI systems, the provision of ongoing training for human decision-makers, increased transparency in communications with applicants, and greater involvement of diverse communities in system design.

As the insurance industry continues to evolve, it faces a clear opportunity to reassess long-standing practices. By moving toward underwriting models that prioritize inclusion, fairness, and accountability, insurers may enhance both the effectiveness and the social value of their services. The decision to modernize underwriting in line with contemporary ethical and technological standards may play a significant role in shaping the future of equitable risk protection.

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