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AI-Enabled Underwriting Brings New
Challenges for Life Insurance: Policy and
Regulatory Considerations

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AI-Enabled Underwriting Brings New Challenges for Life Insurance: Policy and Regulatory Considerations

Azish Filabi, J.D., M.A. | Sophia Duffy, J.D., CPA

IMPORTANCE Life insurance companies are increasingly utilizing “big data” factors and automated systems, including artificial intelligence and machine learning, in their underwriting systems. These developments could elevate the risk of unfair discrimination against protected classes because some factors, such as criminal histories and credit scores, may be inaccurate or reflect historical and systemic biases, and because an automated system may substitute certain big data elements for prohibited characteristics. The majority of current regulatory approaches do not address this risk. A governance structure is needed that is based on industry-wide standards, including certification of AI-enabled underwriting systems, and periodic audits of the system’s output.

OBJECTIVES To describe the current regulatory infrastructure relating to unfair discrimination in insurance underwriting, particularly with respect to life insurance, and how it may become strained with the increasing use of “big data” and AI-enabled systems. To propose a governance infrastructure to address the novel data sources, systems, and related risks.

SUMMARY Insurers are increasingly using novel data sources and automated systems for risk classification and underwriting. Automation has improved operational efficiencies in the accuracy and speed of underwriting, but it also raises new considerations relating to unfair discrimination. In this paper, we review the current regulatory structures relating to unfair discrimination and suggest they are insufficient to police the myriad new big data sources available. Moreover, AI-enabled systems increase the risk of unfair discrimination if a facially neutral factor is utilized by an automated system as a proxy for a prohibited characteristic. Furthermore, many insurers rely on unregulated third-party algorithm developers, and therefore do not own and may not have access to the logic embedded in the system, which raises unique ethical implications, particularly with respect to accountability among AI actors.

To address these issues, we propose a framework that consists of three parts: (a) the establishment of national standards to serve as guardrails for acceptable design and behavior of AI-enabled systems; (b) a certification system that attests that an AI-enabled system was developed in accordance with those standards; and (c) periodic audits of the systems’ output to ensure it operated consistent with those standards. The framework rests on the existing state-based regulatory infrastructure and envisions a self-regulatory organization who can work with the NAIC to develop standards and oversee certification and audit processes. Regulatory enforcement remains with the states. Part I describes the use of technology in life insurance underwriting. Part II discusses the unfair discrimination that can occur due to factors that reflect societal biases, and the unfair discrimination that could occur in artificially intelligent systems if facially neutral factors are substituted by the system for prohibited factors. The current industry standards and regulatory scheme for unfair discrimination in underwriting is also discussed in Part II. Part III describes the ethical concerns regarding accountability when third-party data inputs and underwriting systems are utilized. In Part IV, we propose a governance approach and framework to address these concerns.

AI-Enabled Underwriting Brings New Challenges for Life Insurance: Policy and Regulatory Considerations

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Abstract

Insurers are increasingly using novel data sources and automated systems for risk classification and underwriting. Automation has improved operational efficiencies in the accuracy and speed of underwriting, but it also raises new considerations regarding unfair discrimination. In this paper, we review the current regulatory structures regarding unfair discrimination and suggest they are insufficient to police the myriad new big data sources available. Moreover, artificial intelligence (AI)-enabled systems increase the risk of proxy discrimination, which occurs when a facially neutral factor is utilized as a proxy for a prohibited characteristic. Furthermore, AI-enabled systems raise unique ethical implications, particularly regarding accountability among AI actors. Many insurers rely on

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unregulated third-party algorithm developers; therefore, they do not own and may not have access to the logic embedded in the system.

To address these issues, we propose a framework that consists of three parts: 1) the establishment of national standards to serve as guardrails for the acceptable design and behavior of AI-enabled systems; 2) a certification system that attests that an AI-enabled system was developed in accordance with those standards; and 3) periodic audits of the systems' output to ensure it operated consistent with those standards. The framework rests on the existing state-based regulatory infrastructure and envisions a self-regulatory organization that can work with the NAIC to develop standards and oversee certification and audit processes. Regulatory enforcement remains with the states.

Section 1. Underwriting Algorithms and AI Change the Landscape in Life Insurance Risk Classification and Underwriting

Life insurers are increasingly automating their processes. Automation is used to accelerate the underwriting process, make predictions about risk and classifications; and in time, artificially intelligent systems may even mimic human decision-making.¹ According to data collected by the Life Insurance Marketing Research Association (LIMRA) in 2017, nearly half of the life insurance sector develops their own underwriting algorithms in-house, while other insurers use algorithms provided by third-party software developers who specialize in algorithm design, or they rely on a reinsurer system.²

In many cases, the “big data” sources used as inputs into the algorithm are collected and provided by third parties.³ The categories of data elements are numerous. Typical health-related data sources include medical information such as prescription history, attending physician statements, or medical information bureau records. Non-medical information that could be relevant to mortality includes credit profiles, financial history, social media, and criminal history, among others. Increasingly, these data elements are becoming electronic and digitized, which eases integration into underwriting processes and provides opportunities for more sophisticated underwriting, such as artificially intelligent underwriting.

The New York State Department of Financial Services (NYDFS) reported in 2019 that the use of non-medical factors such as homeownership, education level, court records, and credit information by insurers for underwriting purposes is increasing.⁴ In addition, other “big data” sources such as social media postings, internet usage, and even publicly-available photographs were utilized in some predictive models,⁵ raising concerns about the appropriateness and integrity of the data sources used.

1. See Kerbeshian, J., & Matson, P. (2018, August). Emerging Underwriting Methodologies and their Impact on Mortality Experience Delphi Study. *Society of Actuaries*, 11. <https://www.soa.org/globalassets/assets/files/resources/research-report/2018/2018-delphi-study.pdf>.

2. See Sondergeld, E.T. *Use of Data for the Underwriting of Life Insurance Products*. https://content.naic.org/cipr_topics/topic_accelerated_underwriting.htm#:~:text=Underwriting%20in%20insurance%20is%20the,order%20to%20charge%20accurate%20premiums.

3. See Kerbeshian & Matson, 2018, p. 1.

4. See New York State Department of Financial Services. (2019, January 18). *RE: Use of External Consumer Data and Information Sources in Underwriting for Life Insurance*. Insurance Circular Letter No. 1 (2019). https://www.dfs.ny.gov/industry_guidance/circular_letters/cl2019_01. See Hamilton, L. R., Lakatos, A. C., & Webb, K. E. (2019, February 14). *An Unconventional Circular Letter: NYDFS Provides the Nation's First Directive on the Proper Use of Unconventional and Alternative Data*. Mayer Brown. <https://www.mayerbrown.com/en/perspectives-events/publications/2019/02/an-unconventional-circular-letter>.

5. See New York State Department of Financial Services, 2019. See Hamilton et al., 2019.

The current, and potential future, use of these and other data sources, as well as the terminology for the different algorithmic systems, varies broadly across the industry, as highlighted in a 2018 report by the Society of Actuaries (SOA).⁶

The terms “accelerated underwriting,” utilizing new data sources such as digital medical records to replace more invasive robust medical exams; “predictive analytics,” utilizing variables in a model to make predictions about risk and classifications; and “algorithmic underwriting,” utilizing a model to assess risk and/or flag an application for human review, are often used to describe related developments.⁷ The term “artificially intelligent underwriting” is also used to describe an underwriting model that mimics the existing human decision-making capabilities.⁸

To date, a fully “sentient” AI model that mimics and potentially supplants human decision-making has not been developed. Many insurers anticipate that by 2023 to 2028, they will review all applications to determine whether the applicant qualifies for “algorithmic underwriting.”⁹ When systems are designed to “learn” from data and adapt accordingly, further complexity arises from the fact that projected consumer outcomes will change over time. The survey results from the SOA report showed that the more advanced models that rely on these machine learning (ML) techniques are less-commonly used, but insurers reported that using such complex AI-enabled tools is a long-term goal.

Scholars and policymakers have noted numerous challenges and concerns regarding systems design and outcomes with the increasing use of AI. They often highlight the complexity and opacity of the systems’ decision-making processes. Those challenges are exacerbated when algorithms are designed by third-party vendors, whose intellectual property is often proprietary, such that even the primary user and client (e.g., an insurance company) may not be able to access the algorithm’s logic and decision-making processes. When multiple AI actors are involved, the data supply chain becomes complicated. For example, when insurers contract with third-party developers, those companies may be beyond the scope of the existing regulatory infrastructure.

The opacity issue relates to a concept referred to as the explainability challenge in AI.¹⁰ The systems are designed to find correlations between disparate datasets to identify patterns that would not otherwise be available based on traditional rules-based or linear analysis. When those decisions use complex ML, they are increasingly difficult to interpret by humans. In a 2017 report on *AI and Machine Learning in Financial Services*, the Financial Stability Board (FSB) recognized the lack of interpretability of automated systems as a potential macro-level supervisory

6. See Kerbeshian & Matson, 2018.

7. See Kerbeshian & Matson, 2018, p. 12.

8. See Kerbeshian & Matson, 2018, p. 11.

9. See Kerbeshian & Matson, 2018, p. 11, 18.

10. Burrell, J. (2016, January 6). How the machine ‘thinks’: Understanding opacity in machine learning systems. *Big Data & Society*. <https://doi.org/10.1177/2053951715622512>.

risk for the financial services sector, which could result in unintended consequences.¹¹

Professor Jenna Burrell has identified three categories of opacity that render algorithms potentially inscrutable to their users and, sometimes, to their designers as well.¹² While not all algorithms are “black box” systems, those that are more advanced rely on deep learning or ML techniques designed to process high volumes of input data and related outcomes—i.e., a “learning set”—to “train” the machine to recognize patterns to eventually generate its own pathway towards a desired result. These systems are opaque because they process high volumes of data and infer relationships between data points that surpass that which a human could reasonably compute within similar time constraints. The accuracy and predictive ability of the algorithm is a trade-off against its complexity. Such systems are the most automated, yet, as of this publication date, least likely to be used by industry.

Even for those linear algorithms that are less complex, if the algorithm was not designed to be transparent, the ability for stakeholders to understand which factors drive the outcome of an underwriting decision also raises consumer protection and ethics concerns.¹³ With such algorithms, opacity relates to two characteristics. The first is the designer’s assertion of proprietary rights over the system; therefore, the programming cannot be shared. The second characteristic of opacity is technical illiteracy, a term Burrell uses to acknowledge that computer science remains a specialized field that most of the population cannot decipher. This technical illiteracy extends to experts in functional fields who would need to cross interdisciplinary boundaries to understand, and then manage, the social implications of the algorithm design.

We refer in our analysis in this article to practices that encompass big data integration and the spectrum of practices up to and including fully artificially intelligent underwriting. We therefore use “AI-enabled” systems as a general term to capture both the novel big data sources available to insurers and artificially intelligent underwriting practices, which may become more common in the future. Furthermore, we recognize that the big data sources themselves, such as credit scores, are embedded with complex algorithms, adding further complexity to this challenge.¹⁴

Our focus is on the unfair discrimination risks that arise due to the complexity of AI-enabled underwriting and the utilization of data sources not historically used

11. While beyond the scope of this paper, some computer scientists conceptualize the explainability of an AI system in a range from black box systems that are inscrutable to interpretable models. See Gunning, D., Stefik, M., Choi, J., Miller, T., Stumpf, S., & Yang, G-Z. (2019). XAI-Explainable artificial intelligence. *Science Robotics*, 4(37). Others are developing techniques to render black box AI explainable. See Bussmann, N., Giudici, P., Marinelli, D., & Papenbrock, J. (2020, April 24). Explainable AI in Fintech Risk Management. *Frontiers in Artificial Intelligence*, 3(26).

12. See Kerbeshian & Matson, 2018, p. 11.

13. See Kerbeshian & Matson, 2018.

14. See Hurley, M., & Adebayo, J. (2016). Credit Scoring in the Era of Big Data. *Yale Journal of Law and Technology*, 18(1).

in underwriting models. Even for data sources traditionally used, such as credit scores, the scale of the potential impact a system would have as it applies to an entire applicant pool is far greater with AI-enabled underwriting compared to individual decisions from human actors. We then discuss the current regulations that address discrimination in underwriting, including new regulations that address some of the big data risks. Lastly, we propose a principles-based model for setting standards to address current deficiencies in the regulatory infrastructure, while recognizing that ML and AI tools are continually evolving and will need a dynamic oversight model.

While AI-enabled underwriting and bias in algorithm design has generated much public interest, there is presently limited public data regarding the market practices using these new technologies and their effect on business models in financial services. Our analyses and proposals rely on publicly available information, limiting our ability to engage in full empirical analysis of the topic. We aim to support further study by policymakers and industry regarding this challenge by offering frameworks for standard setting and market practice.

Section 2. Algorithms and AI Increase the Risk of Unfair Discrimination

Section 2.A. Unfair and Proxy Discrimination in Insurance

The potential for discrimination in insurance underwriting is clear when a prohibited characteristic, such as race, is used in the underwriting process. However, discrimination that may occur within an AI-enabled system is less obvious and more difficult to detect, particularly when a protected class characteristic, such as race, is not used directly. Namely, an AI-enabled system can operate in ways that result in unfair discrimination by utilizing data sources that reflect historical discrimination, such as credit scores or criminal records, as a proxy for race. These current insurance regulation schemes are not designed to address the potential for this type of unfair discrimination, called proxy discrimination.

The NAIC set forth model regulations regarding unfair discrimination that provide guidance at a national level.¹⁵ They defined unfair discrimination as “refusing to insure, or refusing to continue to insure, or limiting the amount, extent or kind of coverage available to an individual, or charging a different rate for the same coverage...except where the refusal, limitation or rate differential is based on sound actuarial principles or is related to actual or reasonably anticipated experience.” As discussed in Section 2.B, most state laws address this type of discrimination by listing specific factors, such as race, age, and sexual orientation, and limiting or prohibiting its use in the underwriting process. AI-enabled systems

15. See *Model Regulation of Unfair Discrimination in Life and Health Insurance on the Basis of Physical or Mental Impairment* (#887). (1979, June). NAIC. <https://content.naic.org/sites/default/files/inline-files/MDL-887.pdf>.

increase the possibility of proxy discrimination because a sophisticated machine can use facially neutral data to learn about behavioral characteristics that mimic the characteristics of protected classes. Factors derived from aggregated “big data” sources, such as credit scores, may therefore potentially stand-in for prohibited protected class characteristics.

According to Professor Daniel Schwarcz and Professor Anya E. R. Prince, proxy discrimination occurs when a “a facially neutral practice... disproportionately harms members of a protected class (and)... the usefulness to the discriminator of a facially neutral practice derives, at least in part, from the very fact that it produces a disparate impact.”¹⁶ However, there is not yet a standard definition of proxy discrimination within the context of insurance underwriting, nor a consensus on whether it is considered discriminatory intent or discriminatory impact. With respect to property/casualty (P/C) insurance, the National Council of Insurance Legislators (NCOIL) have proposed a model that defines proxy discrimination based on discriminatory intent. NCOIL defines proxy discrimination as “the intentional substitution of a neutral factor for a factor based on race, color, creed, national origin or sexual orientation for the purpose of discriminating against a consumer to prevent that consumer from obtaining insurance or obtaining a preferred or more advantageous rate due to that consumer’s race, color, creed, national origin, or sexual orientation.”¹⁷

Although the NCOIL definition attempts to address the public policy concerns of proxy discrimination in insurance by including “intent” in the model legislation, it leaves unaddressed the question of how AI-enabled systems could use facially neutral data to learn about patterns of behavior that stand in for prohibited characteristics, such as race. In such cases, an insurer may not have intended to discriminate based on protected class characteristics when it initially began using facially neutral factors, yet continued use of those factors without appropriate risk management frameworks could result in discriminatory outcomes, as if they had used prohibited characteristics.

Section 2.B. Regulatory Infrastructure for Unfair Discrimination and Related Gaps

The potential for AI-enabled underwriting to result in unfair discrimination has gained the attention of industry experts and organizations. In recent years, industry, related associations, and the NAIC have produced research and principles to study

16. See Prince, A. E. R., & Schwarcz, D. (2020). Proxy Discrimination in the Age of Artificial Intelligence and Big Data. *Iowa Law Review*, 105, 1257–1318.

17. See National Council of Insurance Legislators Property/Casualty Insurance Modernization Act amendments as adopted by the Special (EX) Committee on Race in Insurance Underwriting on March 5, 2021, and the Executive (EX) Committee on April 18, 2021. Available at <http://ncoil.org/wp-content/uploads/2021/04/PC-Modernization-Model-Adopted-4-18-21.pdf>.

the possibility of unfair discrimination that may emerge as big data and algorithms gain prominence.¹⁸

Life insurance is a state-regulated activity, and regulatory authority falls under each state's department of insurance (DOI) or similarly authorized agency. With regards to unfair discrimination, many states have taken a proscriptive, factor-by-factor approach. Each state has a unique regulatory and enforcement regime generally restricting certain discriminatory practices or more explicitly limiting or prohibiting the use of factors such as protected class characteristics (e.g., race) or other factors determined by law to be unfairly discriminatory for insurance risk classification (e.g., genetic information; zip codes) (see Table 1).¹⁹ Prohibitions and limitations only extend to underwriting products in that state.

Table 1

Life Insurance Underwriting Factor	State/Territory Restrictions
Race	24% prohibit
National Origin	24% prohibit
Religion	20% prohibit
Age	24% generally restrict; 76% expressly permit
Sexual Orientation	25% completely prohibit; 4% strongly limit; 73% generally restrict
Gender	2% prohibit; 98% expressly permit
Genetic Information	Approximately 30% expressly permit; 50% generally restrict; less than 20% specifically limit or prohibit
Credit Score	Approximately 25% expressly permit; 75% generally restrict; less than 10% specifically limit or prohibit
Zip Code	78% generally restrict; 16% have some limitations; 2% prohibit

This table describes the level of general restriction, limitation, or prohibition of various underwriting factors for the purposes of offering life insurance. The information is derived from Avraham et al., (2014) and was created by the authors in a self-published white paper. See Filabi, A., & Duffy, S. (2021, March). AI, Ethics and Life Insurance: Balancing Innovation With Access. *The American College of Financial Services*. <https://www.theamericancollege.edu/sites/default/files/ai-ethics-and-life-insurance-white-paper.pdf>.

When states provide factor-by-factor regulation, it gives clear guidance for insurers on the lawfulness of using the factor to issue, renew, and/or cancel the

18. See NAIC. (2020, August 20). *NAIC Unanimously Adopts Artificial Intelligence Guiding Principles*. https://content.naic.org/article/news_release_naic_unanimously_adopts_artificial_intelligence_guiding_principles.htm. See Kerbeshian & Matson, 2018. See Balasubramanian, R., Chester, A., & Milinkovich, N. (2020, July 31). *Rewriting the rules: Digital and AI-powered underwriting in life insurance*. McKinsey & Company. <https://www.mckinsey.com/industries/financial-services/our-insights/rewriting-the-rules-digital-and-ai-powered-underwriting-in-life-insurance>.

19. See Avraham, R., Logue, K. D., & Schwarcz, D. (2014). Understanding Insurance Anti-Discrimination Laws. *Southern California Law Review*, 87(2), 195–274, 199. <https://repository.law.umich.edu/articles/1734/>. Case law has not supported the imposition of the Civil Rights Act of 1964's prohibition on refusing service or denying customers the "full enjoyment" of the businesses' goods and services based on a protected class, such as race, gender, or religion, on the underwriting process for life insurance.

policy.²⁰ When states provide only “general restrictions” against unfair discrimination, the guidance is less clear. Based on current practice, the definition and identification of unfair discrimination relies on judgment by state insurance regulators and industry practitioners, such as actuaries, to determine the “unfairness” of variables and their impact on access to products. This state-based regulatory framework results in varying levels of consumer protections against unlawful discrimination across the nation. It is also at odds with the fact that many large insurers offer national coverage area and are therefore likely to develop one or a few underwriting systems that comply across the multiple states, rather than unique systems for each state. This scenario increases the regulatory reach of more restrictive states, likely marginalizing other states. In other words, if most insurers follow the rules of California, Colorado, and New York (discussed below), those states set the stage for a national regulatory standard.

With regards to proxy discrimination, a state’s factor-by-factor approach may be insufficient because a facially neutral variable used in risk classification or underwriting could stand in for a protected characteristic. Prince and Schwarz note that current laws regulating insurance discrimination are incapable of continuing to safeguard consumers when confronted with proxy discrimination by AI. Colorado and New York are the only states so far to enact regulations that directly address the specific risk posed by AI-enabled life insurance underwriting. California has narrowly addressed the issue for proprietary algorithms for P/C underwriting.

The NYSDFS issued a Circular Letter in January 2019 that highlighted concerns over negative consumer impact due to the use of “unconventional data” from unregulated sources for life insurance underwriting.²¹ The impetus for the New York Circular Letter was the NYSDFS’s concern that insurers lacked rationale for using “big data” for underwriting purposes that could be discriminatory (e.g., insurers may be using the data just because it is available), and the use of the data lacked transparency.²²

The Circular Letter expressly prohibits using criteria for underwriting purposes unless the insurer can establish that the approach is not unfairly discriminatory (pursuant to existing rules)²³ and requires the insurer to demonstrate such compliance.²⁴ In addition, the Circular Letter suggests that insurers are accountable for verifying that third-party algorithms used are not discriminatory. The Circular Letter explicitly states that insurers must take responsibility for AI-enabled systems, even if the insurer utilizes an algorithm developed by a third party.²⁵

In July 2021, Colorado enacted the Restrict Insurers’ Use of External Consumer Data Act,²⁶ which directly addresses the risk of the use of big data and AI-enabled

20. See Avraham et al., 2014, p. 195–274.

21. See New York State Department of Financial Services, 2019.

22. See Hamilton et al., 2019.

23. See New York State Department of Financial Services, 2019.

24. See New York State Department of Financial Services, 2019.

25. See New York State Department of Financial Services, 2019.

26. See Colorado General Assembly. (2021). *Restrict Insurers’ Use of External Consumer Data Act*. SB-21-169. <https://leg.colorado.gov/bills/sb21-169>.

insurance practices. The law prohibits insurers from unfair discrimination in insurance practices based on protected characteristics and prohibits the use of external data sources, such as social media or court records, that “unfairly discriminates against an individual” based on protected characteristics. The law broadly applies to all insurers and insurance practices, including life insurance; however, the Act notes that the specific rules determining when unfair discrimination has occurred will differ within each insurance line, determined by the appropriate insurance commissioner. As of the date of this publication, specific regulations have not been promulgated. The law also calls for transparency and justification of external data sources used in any practice by an insurer, the establishment of risk management controls over the insurance practices to avoid unfair discrimination, and an assessment of outputs to determine if discrimination has occurred.²⁷

In California, the DOI issued a Legal Division Opinion in August 2018 that addressed algorithmic underwriting related to P/C insurance. The Opinion requires that the algorithmic rules of “proprietary” systems used in underwriting be submitted to the insurance commissioner for review. California’s Insurance Code also requires that the underwriting rules be available for public inspection.²⁸

California, Colorado, and New York have made great strides in tackling the risks presented by novel data sources, but as of the date of publication, existing regulations are narrowly focused on only a few aspects of the emerging risks. The Colorado and New York approach is that the insurer self-evaluate their data and underwriting systems, including third-party data and systems, to establish compliance that implies that internal review is sufficient and insurers can effectively access and assess third-party systems. California’s regulatory guidance addresses the need for transparency of underwriting algorithms, but it does not yet address sources of potential discrimination and systems for review or audit. Neither state has established methods and standards for conducting self-evaluation.

The regulations described above address unlawful discrimination at the operational level and focus largely on the usage of potentially discriminatory factors in the risk classification and underwriting process. The California and New York approach either does not address or only lightly addresses other critical concerns that must be resolved to address AI-enabled underwriting. These regulatory gaps arise because: 1) there is not yet a clear definition for proxy discrimination; 2) current regulations do not address AI-specific risks, or are narrowly focused, lacking a comprehensive approach; and 3) with the exception of Colorado and New York, accountability for unfair discrimination in the context of novel data sources is not addressed by the states.

27. See Colorado General Assembly, 2021.

28. See State of California Department of Insurance. (2018, August). *Confidentiality of Underwriting Rules Filed with Rate Applications Pursuant to California Insurance Code section 186 1 .05(b)*. <http://www.insurance.ca.gov/0250-insurers/0300-insurers/0200-bulletins/bulletin-notices-commiss-opinion/upload/GCLetterOpinionUWGGuidelines.pdf>.

Section 2.C. Industry Approach to Addressing Unfair Discrimination

The *Model Regulation of Unfair Discrimination in Life and Health Insurance on the Basis of Physical or Mental Impairment* (#887) calls for insurers to base system design on sound actuarial principles. The Committee on Risk Classification of the American Academy of Actuaries (Academy) has set forth a “Risk Classification Statement of Principles” for insurers to consider when designing risk classification systems.²⁹ The Academy guidance includes statistical considerations, such as “causation” and “predictive stability,” while recognizing that ultimately, the actuary determines whether a variable is sufficiently predictive by using their professional judgment. The Principles also present other areas where the actuary must exercise judgement with respect to the influence of qualitative elements, such as “public acceptability” of a factor and the “availability of coverage.”

The NAIC definition of unfair discrimination and the Academy Principles demonstrate that an insurer’s risk classification system balances professional judgment with statistical accuracy as inputs into business models for pricing and access to insurance products. The Academy recognizes that the overall system design is subjective: “[t]he decision as to the relative weights (of the factors) to be applied will, in turn, be influenced by the nature of the risks, the management philosophy of the organization assuming the risk and the judgment of the designer of the system.” Therefore, while one actuarial principle requires that a statistical relationship exist between the factor and risk classification, actuarial judgment determines the weight of the factor in the system’s design in light of all of the actuarial principles.

Big data introduces new considerations regarding how to weigh a factor not directly related to the mortality and health of the applicant, such as criminal history or credit scores. Principles such as causation, public acceptability, and availability of coverage must be re-examined in the context of unfair discrimination. The role of causation has been a long-standing challenge for insurance regulation, particularly for underwriting life insurance. Some models may provide scientific clarity, such as whether a factor (e.g., smoking) is likely to cause a future outcome (e.g., early mortality) versus simply correlate with outcomes based on historical data.³⁰ Absent scientific clarity, or a legislature’s prohibition or limitation in the use of a factor (see Table 1), assessing unfair discrimination relies on judgment that the rates are based on factors related to the assessment of risk.³¹

A factor can therefore be utilized to differentiate, and thus discriminate fairly, among individuals as long as it is necessary for the insurers’ classification of risk.³²

29. See American Academy of Actuaries. (2014). Risk Classification Statement of Principles. <http://www.actuarialstandardsboard.org/wp-content/uploads/2014/07/riskclassificationSOP.pdf>.

30. See Avraham et. al., 2014.

31. See Avraham et al., 2014, p. 195–274, 233.

32. See Schwarcz, D. (2020). Towards A Civil Rights Approach To Insurance Anti-Discrimination Law. *DePaul Law Review*, 69(2), 659–697, 667. <https://via.library.depaul.edu/cgi/>

What is deemed “unfair” varies and relates to judgment of whether differences in rates reflect differences in expected losses with reasonable accuracy.³³ When balancing these principles, the weight of a factor directly related to health history, such as medical records, may be higher than a factor, like criminal history records, that is less directly related and may be problematic from a public acceptability standpoint.

While a factor with a statistically negligible correlation that demonstrates some predictive value could theoretically be included, best practice would suggest that the system weigh that factor less heavily than a more reliable factor or a factor that the insurer wants to consider more prominently.³⁴ For example, insurers who design a system with disparate impact in mind may place a heavier weight on public acceptance.

Section 3. Categories of Ethical Implications and the Appropriate Nexus of Responsibility

Who is the appropriate party responsible for the ethical implications resulting from an algorithm? Algorithms developed by third parties cloud the nexus of accountability. While insurers may be ultimately responsible for their products and related consumer protections deriving from the technology used, they are not, in many cases, necessarily the parties that are most knowledgeable about the technical details of the underwriting system. They are also often not the parties with the most influence over system design.

The NAIC Principles on AI, adopted in August 2020, recognize that in addition to insurance companies, there are numerous corporate entities involved in the life cycle of AI design and implementation, including data providers, rating agencies, and advisory firms, whom they refer to as “AI actors.” They articulate accountability as a core principle, and AI actors should be held accountable “consistent with the actors’ roles, within the appropriate context and evolving technologies.”³⁵

viewcontent.cgi?article=4128&context=law-review.

33. See McKenney, M. (2016, December). *What is Unfair Discrimination in General Insurance Rating? A Regulator’s Perspective*. Society of Actuaries General Insurance Insights. <https://www.soa.org/news-and-publications/newsletters/general-insurance/2016/december/gii-2016-iss3/what-is-unfair-discrimination-in-general-insurance-rating-a-regulators-perspective/>. (“...differences in rates must reflect differences in expected losses and expenses with reasonable accuracy. If they do not, the rates are unfairly discriminatory.”). See American Academy of Actuaries, 2014. (“Differences in prices among classes should reflect differences in expected costs with no intended redistribution or subsidy among the classes.”)

34. For a general discussion on unfair discrimination in insurance, see Shapo, N. (2020, November 11). Principles of State Insurance Unfair Discrimination Law: Thoughts Regarding NAIC and NCOIL Policymaking. https://content.naic.org/sites/default/files/call_materials/Unfair%20discrimination%20law%2C%20Nov.%2011%2C%202020.pdf.

35. See NAIC, 2020.

Categorizing an algorithm’s potential unethical and unlawful outcomes can help address these questions. Drawing from the work of the Professor Kirsten Martin, we highlight two areas of potential implication—category mistakes and process mistakes³⁶—and add a third category; i.e., social impact. Social impact relates to implications for access to financial services and long-term impacts of the allocation of social resources. The NAIC Principles also contemplate social impact as a category, establishing that AI actors should be held accountable for the “creation, implementation and *impacts* of any AI system, even if the impacts are unintended.”

Category mistakes are errors that result from the system incorrectly labelling or classifying data, thus creating either false positives or false negatives. For example, facial recognition software might falsely identify an individual as being a smoker when they do not smoke; i.e., false positive. Alternatively, in the context of a credit score, a system might conservatively group someone, or a group of people with certain behaviors, as unlikely to repay their mortgage; i.e., false negatives.³⁷

Process mistakes are undesirable outcomes that are built into the algorithm design or occur over time as the algorithm “learns” from the training data inputs. The mistake occurs in the norms of the decision-making processes coded into algorithm design. For instance, using data that is either irrelevant to the task (e.g., using marital status data in an employment decision) or using data that is unlawful or inappropriate (e.g., using race as a category for mortgage determination). These decisions are embedded with concerns regarding fairness, procedural justice, and due process.³⁸

With respect to social impact, there is overlap with the first two categories of mistakes, but the concerns raised are broader because it considers the impact of decisions made by an algorithm on an individual, as well as the long-term implications on the allocation of resources between communities, demographics, and inequality. These topics include public policy considerations about how to define societal fairness and systemic bias or discrimination.

This third category is imperative in the context of business ethics because it defines a locus of responsibility that is not inherently captured in the institutional frameworks of a corporation. In other words, addressing the needs of historically disadvantaged consumers may be in the blind spot of an insurer that relies on current market-based business models.

Section 3.A. A Proposed Framework for Determining Responsibility

A framework that addresses responsibility among AI actors should consider both regulatory liability—i.e., government interactions with the licensed insurance company—as well as contractual mechanisms among the various private sector actors.

36. See Martin, K. (2019, June). Designing Ethical Algorithms. *MIS Quarterly Executive*.

37. See Martin, June 2019.

38. See Martin, June 2019.

Regulatory authority is presently unlikely to reach the non-insurance actors in the chain; therefore, the locus of control is the insurance company. State insurance regulators license insurers to do business consistent with a regulatory infrastructure designed to protect consumers.³⁹ The Circular Letter issued by the NYSDFS also emphasizes this framework.

As between civil parties, contractual mechanisms can define and trigger loci of responsibility. Professor Martin asserts that developers should be held accountable for the algorithms they create because the systems they construct in the algorithm design allocates roles and responsibilities for actors further along in the supply and value chain.⁴⁰ The algorithm designers have most control over category mistakes and process mistakes, and they are best positioned to address them. Vendor contracts should clearly identify each category of mistake, as well as related audit rights, design standards, and certification requirements (further described below). This level of detail would proactively establish expectations regarding unfair discrimination and social impact.

The ideal outcome is to incentivize the party with the most control over the category of mistake to proactively identify and mitigate problems. Model contract clauses would enable industry-wide adoption of these practices and empower insurers to delineate their approach to unfair discrimination. They also help establish industry norms relating to the chain of AI actors and help prepare companies to explain compliance with regulations.⁴¹

The contractual mechanisms described above, combined with the audit and certification requirements described below, aligns the insurers' processes and approaches with that of the public interest.

Section 4. A Proposed Framework for Addressing Risks of Unfair Discrimination

Creating a measurable definition of proxy discrimination as it could arise from AI-enabled underwriting will be challenging, largely because insurers can use an underwriting factor as long as it is related to actual or reasonably anticipated experience, and standards do not presently define the threshold for effectiveness of the factor. Therefore, each insurer's justification for the usage of a factor will be unique. In addition, third-party developed algorithms may utilize factors in ways that the insurers cannot fully access.

39. See NAIC. (n.d.). *State Insurance Regulation: History, Purpose and Structure*. NAIC State Regulatory Brief. https://www.naic.org/documents/consumer_state_reg_brief.pdf.

40. See Martin, K. (2019, December). Ethical Implications and Accountability of Algorithms. *Journal of Business Ethics*, 160(4), 835–850.

41. Keeping regulatory accountability with the insurance company is consistent with the emerging views of the banking regulators on this topic. See *Implications of fintech developments for banks and bank supervisors*. (2017). Basel Committee on Banking Supervision. <https://www.bis.org/bcbs/publ/d415.htm>.

Innovation enabled by AI could produce many consumer benefits. Therefore, state insurance regulators should be mindful of balancing the need for consumer protection with enough flexibility to encourage industry modernization.

To address these issues in a flexible manner, we propose a certification and audit process based on nationally accepted standards that will guide insurers and state insurance regulators in the identification of unfair discrimination, including the use of facially neutral factors that proxy for protected classes and will harmonize regimes across the states. A uniform definition of proxy discrimination is not necessary to implement this model, which consists of three parts: 1) the establishment of nationally accepted standards for algorithm design; 2) certification by algorithm designers to demonstrate adherence to those standards; and 3) independent audit processes for back-end review. This process is not intended to create a definition for unfair discrimination within the underwriting system; rather, the audit process would create controls over the system and identify when the system's outputs should be further investigated to determine if discrimination has occurred.

Our proposal relies largely on industry-led self-regulation, with limited changes in law. The NAIC, which serves as the U.S. standard-setting body for insurance, should develop the standards in close collaboration with AI actors and industry. Legal mandates should require that all insurers use these standards.⁴² An independent self-regulatory body should oversee the certifications and audits, including the processes relating to those functions. The governing board of this entity should include members from a broad group of stakeholders; i.e., industry, state insurance regulators, and community representatives.

Section 4.A. Establishing Nationally Accepted Standards

While an exact definition of proxy discrimination in the context of AI-enabled systems may remain elusive, standards can be developed to ensure that algorithmic systems are developed with best practices in systems design and actuarial principles. In conjunction with certification and audit, the standards can help identify when outcomes fall outside standard norms and will flag when further investigation is warranted to determine if proxy discrimination may be occurring.

One of the major weaknesses in relying on AI systems is that the system is only as good as the data. For instance, while the data about criminal incarceration rates may be technically accurate, the socio-economic context from which the data is derived may result in biased results. In other words, assessing error rates among life insurance underwriting outcomes, such as percentage acceptance among product applications or assessment of a "fair" price, when using criminal history as a data

42. Our proposals do not rise to the level of requiring federal chartering of insurance or rate regulation. However, for our proposed new standards relating to AI-enabled systems to be most effective, a federal mandate would be expedient while we recognize the challenges in federal action on matters in insurance. See Harrington, S. (2006). *Federal Chartering of Insurance Companies*. Networks Financial Institute Policy Brief.

input does not necessarily control for either the socio-economic issue of high incarceration rates among Blacks or for the possibility that the algorithms containing such data have bias-driven errors.⁴³

While the insurance industry cannot undo these historical injustices and biases, the public acceptability in the use of these factors should be heavily considered in the current socio-economic environment. As we discussed in Section 2, determining unfair discrimination requires either: 1) a legislature's determination to prohibit or limit the use of a factor; or 2) reliance on a system and practice of judgment under principles of unfair discrimination. The standard-setting processes we suggest below enable industry to work within option 2 to determine the right "weight" for potentially biased factors in the systems design. The categories of standards to consider are: 1) the level of accuracy of the data (e.g., whether the input accurately reflects the actual behavior exhibited); 2) the level of actuarial significance expected from each category of input (e.g., how much the input contributes to the evaluation of risk); and 3) the target outcomes appropriate for algorithm calibration.⁴⁴ These proposals aim to address the gaps identified in Section 2 in the context of the existing regulatory regimes for unfair discrimination to help determine "publicly acceptable" factors per the Academy and what constitutes "actual or reasonably anticipated experience" per Model #887.

- 1) Accuracy: When insurers rely on big data sources, such as health data from fitness trackers or credit data, the data should be carefully evaluated for accuracy. Commercial health products like fitness trackers can be circumstantial, and the accuracy of the data is unclear. Some also criticize credit scores for its inaccuracy, particularly in the era of big data.⁴⁵ The standards should consider the likelihood for bias and mistakes in the data collection process, as balanced against the utility of that data for classifying risk.⁴⁶ For example, fitness trackers vary widely in calorie counts and heart rate monitoring.⁴⁷
- 2) Significance to Risk Classification: A basic framework to consider is to chart the relevance of the input as it relates to risk that the insurer is

43. See Završnik, A. (2020). Criminal justice, artificial intelligence systems, and human rights. *ERA Forum* 20, 567–583. <https://doi.org/10.1007/s12027-020-00602-0>.

44. The authors first raised these categories of standards in a self-published white paper but did not address the legal and regulatory rationales and support for these standards. See Filabi & Duffy, 2021.

45. See Hurley & Adebayo, 2016.

46. See Martin, June 2019, where Professor Martin defines two classes of mistakes algorithms can make—category mistakes and process mistakes—and proposes a model for determining when decision-making processes should reduce reliance on an algorithm when its outputs are pivotally important for society, such as critical financial decisions like credit decisions or buying a home.

47. Stanford researchers found that fitness tracker data is reasonably accurate for monitoring heart rate but varies widely for calorie count and energy expenditure. See Dusheck, J. (2017, May 24). *Fitness trackers accurately measure heart rate but not calories burned*. Stanford Medicine. <https://med.stanford.edu/news/all-news/2017/05/fitness-trackers-accurately-measure-heart-rate-but-not-calories-burned.html>.

evaluating. For instance, when the data input has a causal link to mortality (e.g., some health data), then the presumption could be that it is permissible; but where the causal link with mortality is more diffuse (like social media history or credit scores), then the presumption shifts towards excluding that data from the algorithm, unless it meets an agreed upon threshold of actuarial significance and there is consensus that the data inputs are reasonably accurate. This standard could enable innovation by allowing data inputs that some believe are more inherently biased, such as aggregated criminal history, to be used in an AI-enabled underwriting system based upon consensus on the appropriate level of significance to risk classification.

- 3) Target Outcomes: Standards should consider which outputs—i.e., offer rates, acceptance rates, etc.—among disparate demographic groups will be deemed an “effective” outcome.⁴⁸ In other words, the target could be set based on a firm’s target clientele or insurance rates prior to the use of AI-enabled underwriting, which is the status quo. Alternatively, the standard-setting process could drive a consensus view of the availability of insurance and payout rates, ideally a more inclusive future. This consensus view should be driven by the self-regulatory organization we propose because each insurer is generally incentivized to seek lower risk customers, therefore thwarting financial inclusion for historically disadvantaged consumers. Identifying the parameters of a national market for financial inclusion could lay the groundwork for new market entrants who seek to use technology to sustainably provide insurance products to those individuals.

These proposed categories of standards outline topics that need to be addressed to advance these challenges. Once the conversations begin on these topics, there will emerge a need for additional expertise and standards. Data scientists are increasingly developing statistical techniques to assess for fairness in algorithms and ML systems, which could benefit algorithms used for financial services.⁴⁹ For example, techniques to conduct “fairness tests” with respect to different user groups (e.g., Black and white populations) enable analysts to assess error rates among different user groups. However, those tests need to be conducted based on agreed upon standards, which we propose above.

48. See Martin, December 2019.

49. An analysis of “fairness” in the context of an economic system requires shared norms around the definition of “fairness” and “equality.” In the context of mortgage lending, writer David Weinberger describes the complexity of answering these questions, including whether the AI system should seek demographic parity, equal opportunity, or equal error rates. See Weinberger, D. (n.d.). *Playing with AI fairness*. What-If Tool. <https://pair-code.github.io/what-if-tool/ai-fairness.html>.

Section 4.B. Front-End Certification

We assert that both “front-end” certification and “back-end” audits are required to address the complexities of AI-enabled systems. Certification represents the algorithm developers’ compliance with standardized practices when creating an algorithm. Audits, to be conducted once the algorithm is operational, will review the system for adherence to those standards with respect to its outputs. This back-end review addresses the challenges faced with ML systems whose function is to innovate beyond human scale systems.

Certification is particularly relevant when an insurer is using technology from a third-party service provider. Moreover, developers can apply end-to-end reviews throughout the design process, while an audit is likely only able to assess the outputs of a system. This approach to certification is consistent with ideas developed by the Google AI team in collaboration with the Partnership on AI, who have proposed a detailed framework for ethical algorithm design, including procedures for governance, internal record keeping, and reporting.⁵⁰

Section 4.C. Independent and Periodic Audits

An independent self-regulatory entity should conduct the necessary audits; its work processes and audit reports should be available for inspection by state insurance regulators. Enforcement of the regulatory regime would remain within the purview of the states, as overturning the state-based regulatory framework governing insurance law is beyond the scope of this paper.

An audit would ideally be independent, to remove companies from the conflicted position of having to identify and report their own potentially discriminatory practices. This is particularly fitting for the life insurance sector, as companies no longer collect race-based data.⁵¹ Where protected attribute data, such as race, is unavailable or not collected by an insurer, computer scientists have developed nascent methods that can impute protected class data to an individual.⁵²

50. The Partnership on AI and Google AI team framework describes this process as an “audit.” We label it “certification” in the context of our proposal because it is an internal review process that adheres to procedures for record keeping and internal reports during the design process. An audit, in our terminology, is a backwards-looking assessment of a process. For the Google AI audit framework, see Raji, I. D., Smart, A., White, R. N., Mitchell, M., Gebru, T., Hutchinson, B., Smith-Loud, J., Theron, D., & Barnes, P. (2020, January 27–30). *Closing the AI accountability gap: defining an end-to-end framework for internal algorithmic auditing*. Conference on Fairness, Accountability, and Transparency (FAT* ’20), Barcelona, Spain. <https://dl.acm.org/doi/10.1145/3351095.3372873>.

51. See Paltrow, S. J., (2000, December 26). *Old Notion of Black Mortality May Have Influenced Insurers*. Wall Street Journal. <https://www.wsj.com/articles/SB977788852647718215>.

52. See Bogen, M., Rieke, R., & Ahmed, S. (2020, January 27–30). *Awareness in practice: tensions in access to sensitive attribute data for antidiscrimination*. Conference on Fairness, Accountability, and Transparency (FAT* ’20), Barcelona, Spain. <https://dl.acm.org/doi/10.1145/3351095.3372877>.

Those methods identify proxies for race by imputing race characteristics into the data.

Having a third-party self-regulatory body serve as a repository to collect this data, or its equivalent, protects the industry against any potential accusations of data misuse. As a matter of good governance, inferences about race should not be collected by a party that could use them for other purposes. The audits could be conducted on the systems' output so that even if the algorithm remains proprietary, the output of the systems could be evaluated to identify any outliers or deviations from identified standards.⁵³

In Section 1, we recognize that industry practice exists on a spectrum. Many insurers use stable algorithms, which may require less frequent audits, compared to complex ML algorithms, which may be the future of the industry. Auditing algorithms currently in practice will help develop technical literacy and data practices to address the algorithms of the future.

The proposed standards, certification, and audit systems are intended to flag when unfair or proxy discrimination may be occurring. We do not propose a new enforcement mechanism related to such findings; state insurance regulators shall continue to enforce unfair discrimination rules, consistent with their own practices, if such discrimination occurs. Moreover, an audit report issued by the self-regulatory body would generate detailed findings about practices that fell outside of the established standards, the volume and extent to which non-standard instances occurred, and remedies the insurer plans to institute to correct non-standard occurrences. Such findings should remain confidential in the context of the regulatory relationship. Each state should set parameters for the ultimate disposition of the report, taking into consideration volume or revenue thresholds. Moreover, state insurance regulators should establish requirements around timelines for remedial actions, safe harbors, and ultimately when penalties may be appropriate.

Section 5. Conclusion

AI-enabled risk classification and underwriting by life insurance companies are an accelerating trend. These developments are increasing access to new "big data" sources that can supplement traditional medical underwriting for life insurance. State insurance regulators, the NAIC, and industry groups have been studying big data and algorithmic underwriting practices to develop principles for ethical algorithm design and address risks of unfair discrimination.

We have identified several gaps in the unfair discrimination regulatory framework that will be strained by these technology developments. We also describe how AI-enabled underwriting raises new ethical questions and potential

53. For a discussion of how proprietary algorithms can nevertheless be audited through assessment of their outputs, see Hosanagar, K. (2019, November 4). *Why Audits Are the Way Forward for AI Governance*. Wharton School of the University of Pennsylvania. <https://knowledge.wharton.upenn.edu/article/audits-way-forward-ai-governance/>.

implications. To address these gaps and potential implications, we propose a governance framework that includes model contract clauses among AI actors, the creation of new standards for AI-enabled systems led by the NAIC, and a self-regulatory oversight body for certification and audit of algorithms designed in adherence to those standards. We identify the need for an independent self-regulatory organization to represent broad stakeholder perspectives, while recognizing that regulatory enforcement would remain with the state regulatory agencies.

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References to published literature should be inserted into the text using the “author, date” format. Examples are: (1) “Manders et al. (1994) have shown. . .” and (2) “Interstate compacts have been researched extensively (Manders et al., 1994).” Cited literature should be shown in a “References” section, containing an alphabetical list of authors as shown below.

Cummins, J. David and Richard A. Derrig, eds., 1989. *Financial Models of Insurance Solvency*, Norwell, Mass.: Kluwer Academic Publishers.

Manders, John M., Therese M. Vaughan and Robert H. Myers, Jr., 1994. “Insurance Regulation in the Public Interest: Where Do We Go from Here?” *Journal of Insurance Regulation*, 12: 285.

National Association of Insurance Commissioners, 1992. *An Update of the NAIC Solvency Agenda*, Jan. 7, Kansas City, Mo.: NAIC.

“Spreading Disaster Risk,” 1994. *Business Insurance*, Feb. 28, p. 1.

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