



Date: 12/3/21

*Virtual Meeting
(in lieu of meeting at the 2021 Fall National Meeting)*

Accelerated Underwriting (A) Working Group

Monday, December 6, 2021

12:30 – 1:30 p.m. ET / 11:30 a.m. – 12:30 p.m. CT / 10:30 – 11:30 a.m. MT / 9:30 a.m. – 10:30 p.m. PT

ROLL CALL

Mark Afable, Chair	Wisconsin	Laura Arp	Nebraska
Grace Arnold, Vice Chair	Minnesota	Ross Hartley/Chris Aufenthie	North Dakota
Peg Brown	Colorado	Lori Barron	Ohio
Russ Gibson	Iowa	Elizabeth Kelleher Dwyer	Rhode Island
Rich Piazza	Louisiana	Lichiou Lee	Washington
Cynthia Amann	Missouri		

NAIC Support Staff: Jennifer R. Cook

AGENDA

1. Discuss latest draft of accelerated underwriting educational report and any comments received
– Grace Arnold (MN)
2. Any Other Matters
3. Adjournment

Comments should be sent to jcook@naic.org by close of business Dec. 3, 2021

Accelerated Underwriting (A) Working Group
Ad Hoc Drafting Subgroup

TABLE OF CONTENTS

- I. Introduction
- II. Procedural background of the Working Group and its Charge – Address presentations we received about current accelerated underwriting practices in life insurance.
- III. What is accelerated underwriting and put it in context of traditional underwriting
 - A. What is accelerated underwriting
 - 1. What is a predictive model
 - 2. What is a machine learning algorithm
 - B. What is traditional underwriting
 - C. What is simplified underwriting
 - D. How is accelerated underwriting similar and different from traditional underwriting and simplified underwriting
 - E. How prevalent is accelerated underwriting
 - F. Trends for the future
 - G. Recommendations
- IV. Discussion of issues and recommendations
 - A. Input data
 - 1. Traditional data
 - 2. Fair Credit Reporting Data (FCRA) data
 - 3. Nontraditional data
 - 4. Discussion of bias in input data
 - 5. Recommendations
 - B. Data Privacy

Conclusion

Appendices

Appendix A: Additional Procedural Background

Appendix B: Machine Learning/ Artificial Intelligence Definition in 6/24/21 Draft Big Data and Artificial Intelligence (EX) Working Group Survey on private passenger automobile (PPA) insurers' use and governance of big data.

Resources

New York Circular No. 1

Abbreviated Summary of Presentations

National Association of Insurance Commissioners (NAIC) Principles on Artificial Intelligence (AI)

Casualty Actuarial and Statistical (C) Task Force Regulatory Review of Predictive Models White Paper

Comments should be sent to jcook@naic.org by close of business Dec. 3, 2021

Introduction

In 2019, the National Association of Insurance Commissioners (NAIC) established the Accelerated Underwriting (A) Working Group to consider the use of external data and data analytics in accelerated life insurance underwriting, including consideration of the ongoing work of the Life Actuarial (A) Task Force on the issue and, if appropriate, draft guidance for the states. In addition, the 2021 charges of the Special Committee on Race and Insurance direct the working group to include an assessment of and recommendations, as necessary, regarding the impact of accelerated underwriting on minority populations. A more detailed procedural background can be found in the appendix. This paper is the output of over a year's work by regulators to understand the current state of the industry and its use of accelerated underwriting. It summarizes what the Working Group has learned over the past year, contextualizes that learning and the topic of accelerated underwriting within other NAIC work and standard regulatory product evaluation processes, and makes recommendations for regulators and insurers when evaluating accelerated underwriting.

Accelerated underwriting in life insurance may provide potential benefits to both consumers and insurers, if applied in a fair and non-discriminatory manner. In order to fairly deliver the benefits of more convenient and cost-effective processes, regulators and insurers should be guided by current law related to fair trade practices and unfair discrimination. Much of the discussion in this paper is framed in these general terms. The Working Group believes the charge to specifically address the impact on minority populations is included in these terms, and we have provided examples to illustrate the impact on minority populations. Future work products of the Working Group may address the charge from the Special Committee on Race and Insurance in more detail.

What is Accelerated Underwriting?

Throughout this paper, we use the term accelerated underwriting in life insurance. We propose the following as a definition:

Accelerated underwriting in life insurance is a process to replace traditional underwriting and allow some applications to have certain medical requirements, e.g., paramedical exams and fluid collection, waived. The process generally uses predictive models or machine learning algorithms to analyze data pertaining to the applicant, which includes both traditional and non-traditional underwriting data provided by the applicant directly, as well as data obtained through external sources.

Predictive models examine data sets for patterns to predict and assign the risk category, e.g., a model developer enters data points (potentially hundreds of thousands), and the model finds patterns and identifies future predictions of risk and assigns an insured to a risk category.¹ Machine learning algorithms are a process or set of rules executed to solve an equation², e.g., a life insurance underwriter uses a set of rules to place an individual

¹ For a more detailed discussion of predictive models in property and casualty insurance, see the Casualty Actuarial and Statistical (C) Task Force Regulatory Review of Predictive Models White Paper, Adopted by the Property and Casualty Insurance (C) Committee on Dec. 8, 2020.

² The Big Data and Artificial Intelligence (EX) Working Group developed a survey to conduct analysis on private passenger automobile (PPA) insurers' use and governance of big data, as used in an artificial intelligence (AI) and machine learning

Comments should be sent to jcook@naic.org by close of business Dec. 3, 2021

insured in a particular risk category. The ‘learning’ part of machine learning means that those programs change how they process data over time, much as humans change how they process data by learning. Machine learning often falls into two groups: supervised or unsupervised. The difference between the two is whether the program is directed to analyze patterns or is self-automated.

Predictive models or machine learning trains a system to make judgments when exposed to data that is unfamiliar to serve as a substitute for human-centric decision making. These are both subcategories of artificial intelligence, which should not be confused with a static rule-based algorithm.

Life insurance underwriting is the process of determining eligibility and classifying applicants into risk categories to determine the appropriate rate to charge for transferring the financial risk associated with insuring the applicant. Traditional life insurance underwriting involves assessing the applicant’s physical health, then determining whether an applicant is eligible for coverage and the risk class to which that individual belongs. Accelerated underwriting relies on predictive models or machine learning algorithms to perform some of the tasks of an underwriter. The exact parameters of the application of accelerated underwriting vary by insurer.

Presentations made to the Working Group indicated that life insurers use accelerated underwriting in primarily two ways: 1) Accelerated underwriting is used to triage applicants, where unsuccessful applicants are re-routed to traditional underwriting, and successful ones continue through the accelerated underwriting process; or 2) Accelerated underwriting is used to rate applicants based on risk categories.

Most predictive or machine learning algorithms used in life insurance underwriting are in their second or third generation. The COVID-19 pandemic sped up the adoption of accelerated underwriting in the industry as both consumers and insurers looked for options to purchase and write policies that relied more on technology and involved less in-person contact. This has highlighted the need for ongoing monitoring of the machine learning algorithms—both their development and their uses in the marketplace.

Presentations made to the Working Group indicated that adverse underwriting decisions are sometimes reviewed by human underwriters. Companies presenting to the Working Group stated that the accelerated underwriting process is less cumbersome, costs less than traditional underwriting, improves the underwriting experience for consumers, shortens issue times, and increases policy acceptance rates.³

General Discussion of Issues and Recommendations

Increasing automation of life insurance underwriting presents new regulatory challenges. Regulators must ensure that the process is **fair, transparent, and secure**. With regard to accelerated underwriting in life insurance, this concern pertains to input data, the predictive model or machine learning algorithm, and the

(ML) system. The survey is being conducted under the examination authority of Connecticut, Illinois, Iowa, Louisiana, Nevada, North Dakota, Pennsylvania, Rhode Island, and Wisconsin. This analysis will help inform the Working Group in completing its long-term goals of developing guidance and recommendations to update the existing regulatory framework for the use of big data and AI, including how to monitor and oversee the industry’s compliance with the NAIC’s AI principles. The survey work may be expanded to other lines of insurance as needed, such as life insurance and homeowners insurance. For the purposes of the survey only, AI/ML is defined as, “an automated process in which a system begins recognizing patterns without being specifically programmed to achieve a pre-determined result.” This is different from a standard algorithm that consists of a process or set of rules executed to solve an equation or problem in a pre-determined fashion, and evolving algorithms are considered a subset of AI/ML.

³ Presentations to Accelerated Underwriting (A) Working Group between Dec. 8, 2018, and Sept. 24, 2020.

Comments should be sent to jcook@naic.org by close of business Dec. 3, 2021

results of the process. One particular challenge is the potential for **unfair discrimination**. Due to the fact accelerated underwriting relies on predictive models or machine learning algorithms, it may lead to unexpected or unfairly discriminatory outcomes even though the input data may not be overtly discriminatory. It is critical to test the conclusions up front, on the back end, as well as, randomly, to ensure the machine learning algorithm does not produce unfairly discriminatory ratings. Testing can also be important in determining if a machine learning algorithm is accurate across demographic categories.

Such scrutiny is especially important when behavioral data is utilized. Behavioral data may include gym membership, one's profession, marital status, family size, grocery shopping habits, wearable technology, and credit attributes. Although medical data has a scientific linkage with mortality, behavioral data may lead to questionable conclusions as correlation may be confused with causation.

Recommendations

Consistent with the artificial intelligence principles approved by the NAIC in 2020⁴, the use of accelerated underwriting in life insurance should be fair and transparent. Companies should be accountable for operating in compliance with applicable laws, and the process and data used needs to be secure. To accomplish these objectives, regulators should dialogue with life insurers and third-party vendors to determine if consumer data is being used in problematic or unfair ways or generating unfair outcomes.

Insurers and other parties involved in accelerated underwriting in life insurance should:

- Take steps to ensure data inputs are transparent, accurate, reliable, and the data itself does not have any unfair bias.
- Ensure that the external data sources, algorithms or predictive models are based on sound actuarial principles with a valid explanation or rationale for any claimed correlation or causal connection.
- Ensure that the predictive models or machine learning algorithm within accelerated underwriting has an intended outcome and that outcome is being achieved.
- Ensure that the predictive models or machine learning algorithm achieve an outcome that is not unfairly discriminatory.
- Be able to provide the reason(s) for an adverse underwriting decision to the consumer and all information upon which the insurer based its adverse underwriting decision.
- Take steps to protect consumer privacy and ensure consumer data is secure.
- Have a mechanism in place to correct mistakes if found.
- Produce information upon request as part of regular rate and policy reviews or market conduct examinations.

Input data

⁴ See National Association of Insurance Commissioners (NAIC) Principles on Artificial Intelligence (AI) – Fair and Ethical a. AI actors should respect the rule of law throughout the AI life cycle. This includes, but is not limited to, insurance laws and regulations, such as those relating to trade practices, unfair discrimination, access to insurance, underwriting, privacy, consumer protection and eligibility practices, rate making standards, advertising decisions, claims practices, and solvency. b. Consistent with the risk-based foundation of insurance, AI actors should proactively engage in responsible stewardship of trustworthy AI in pursuit of beneficial outcomes for consumers and to avoid proxy discrimination against protected classes. AI systems should not be designed to harm or deceive people and should be implemented in a manner that avoids harmful or unintended consequences and corrects and remediates for such consequences when they occur.

Comments should be sent to jcook@naic.org by close of business Dec. 3, 2021

Predictive models or machine learning algorithms within the accelerated underwriting process rely heavily on data and multiple variables. Examples of the variables used by some accelerated underwriting models include customer disclosures, prescription history, digital health records, credit attributes, medical information bureau data, public records, motor vehicle reports, smartphone apps, consumer activity wearables, claim acceleration tools, individual consumer risk development systems, purchasing history, behavior learned through cell phone usage, and social media because accelerated underwriting relies on predictive models or machine learning algorithms, it may lead to unexpected or unfairly discriminatory outcomes, even though the input data may be facially neutral.

Traditional Data

Traditional data used in life insurance underwriting includes data collected through a traditional underwriting process. This data may include the following:

- Application data, e.g., medical records, prescription questions, vocation questions, financial profile
- Tele-interview
- Medical records
- Data from the Medical Information Bureau (MIB) ⁵
- Data from Motor Vehicle Records
- Prescription drug history
- Public records, e.g., criminal records, bankruptcy records, civil litigation, etc.
- Paramedical or medical exam, including EKG's in some instances
- Fluids, e.g., blood, urine, swab/saliva test to determine tobacco usage
- Financial and tax information

Considerations for use of Traditional Data

- Traditional data has a long and established history in the life insurance industry. Carriers, producers, and consumers are generally familiar with the process.
- Traditional data has a history of usage by insurance carriers. Trained underwriters and producers have years of experience and often understand the process well.
- The relationship of the traditional data elements to the risk is well established and consumers understand how the elements impact their risk classification or premium charged.
- State statutes and case laws were developed based on the use of traditional data containing consumer protections created under the assumption that this was the type of data collected or reviewed during an underwriting process.
- Presentations made to the Working Group represented that time and costs associated with obtaining and reviewing traditional data are significant.

FCRA Data

Data is subject to the federal Fair Credit Reporting Act (FCRA), which means applicants:

- (1) Should have a right to be told if this information is used to deny insurance, and
- (2) Have the ability to request the data a consumer reporting agency is providing to an insurer.

Considerations for use of FCRA Data

⁵ This data is subject to the Fair Credit Reporting Act (FCRA).

Comments should be sent to jcook@naic.org by close of business Dec. 3, 2021

- FCRA data is readily available.
- FCRA data is updated regularly.
- FCRA data is already used in property/casualty lines of business.
- There is existing regulation and oversight by the Federal Trade Commission (FTC) and Consumer Financial Protection Bureau (CFPB).
- Not all FCRA data is useful/ relevant to life insurance underwriting.
- If there is a dispute about findings, a consumer will have to obtain additional information and formally dispute these findings.
- FCRA data is extensive and accessing such data may result in access to non-usable credit attributes. In other words, significantly more data may be collected than is needed to determine risk.
- As additional rating factors are introduced via insurance scores or with specific data elements, unfair discrimination, including disparate impact, may be introduced or amplified.
- FCRA data may be used to predict mortality, but there may not be a reasonable explanation for that correlation.⁶

Nontraditional Data

Nontraditional data used in life insurance underwriting may include the following:

- Public records, e.g., assessor data, genealogy records, criminal records, court filings, voter information
- Property/casualty data from adjacent carrier(s)
- Marketing and social data, e.g., shopping habits, mortgage amount/lender, occupation and education, and social media, etc.
- Professional licenses
- Voice recognition used to determine smoking status
- Facial recognition
- Wearable devices

Considerations for use of Nontraditional Data

- Nontraditional data may be used to predict mortality, but there may not be a reasonable explanation for that correlation.
- As additional rating factors are introduced via insurance scores or with specific data elements, disparate impact across and between demographic groups may be introduced or amplified.
- Nontraditional data does not have the same consumer protections as FCRA and traditional data. For example:
 - There may not be a clear path for consumers to know how data affected their application and how inaccurate data may be corrected.
 - The type and purpose of data accessed are not required to be disclosed to the consumer.
 - There may be privacy concerns about the extent of the use of nontraditional data.

Recommendations

Existing regulations apply to accelerated underwriting programs in the same way as traditional underwriting programs. State Departments of Insurance (DOIs) have broad regulatory authority to make inquiries into the processes and procedures of life insurers in order to investigate potential unfair trade practices. Complaints

⁶ See Actuarial Standards of Practice (ASOP) No. 12

Comments should be sent to jcook@naic.org by close of business Dec. 3, 2021

about underwriting practices are opportunities for DOIs to review a life insurer's use of accelerated underwriting and data collection methods. Additional DOI actions may include market conduct and on-site examinations as appropriate under existing authority.

Specifically, examiners may:

- Review the life insurer's underwriting practices and underwriting guidelines during an examination or upon initial submission of the policy rates and forms and confirm the proper use of the data elements.
- Request that explanation provided to the consumer for any negative action taken by the life insurer adequately informs the consumer as to why a particular action was taken without the consumer having to make additional inquiries.
- Request information about source data regardless of whether the data or score is provided by a third party.

Form and rate reviewers may:

- Request that the life insurer provides information about how a predictive model or machine learning algorithm will be used.
- Consider requiring the filing of models used to analyze data.
- Consider questioning the extent to which data elements correlate to applicant risk.
- Request information about source data regardless of whether the data or score is provided by a third party.

Life insurers have a responsibility to understand the data they are using. To accomplish this, life insurers should conduct post-issue audits and data analysis. For example, analyses such as evaluating claims and lapse rates may be helpful. Life insurers and third-party vendors should ensure data inputs are accurate and reliable.

Life insurers and third-party vendors should ensure that the external data sources, algorithms, or predictive models are developed with sufficient internal controls and oversight and based on sound actuarial principles with a valid explanation or rationale for any claimed correlation and causal connection.

Data Privacy

Data privacy—a consumer's ability to retain control over what data can be shared about them and with whom—is not a concern unique to accelerated underwriting in life insurance. Protecting consumer privacy is an issue across all lines of insurance and is the subject of the NAIC Privacy Protections (D) Working Group, formed in 2019 under the parent committee of Market Regulation and Consumer Affairs (D) Committee.

The Working Group's charge is to review the state insurance privacy protections regarding the collection, use, and disclosure of information gathered in connection with insurance transactions, and make recommended changes, as needed, to certain NAIC models and other existing federal or state statutes.⁷

⁷ The Working Group has focused its reviews on the Insurance Information and Privacy Protection Model Act #670, and the Privacy of Consumer Financial and Health Information Regulation Model Act #672 – both drafted in response to the enactment of GLBA, and #668 – the Insurance Data Security Model Act, enacted in 2019/20. With a great deal of research assistance from NAIC Legal Staff, the Working Group prepared a gap analysis – upon which it continues to work. The Working Group is also reviewing the consumer data privacy protections other than those already in these models, such as the numerous provisions contained in federal acts such as the Fair Credit Reporting Act {FCRA}, the Gramm-Leach Bliley Act

Comments should be sent to jcook@naic.org by close of business Dec. 3, 2021

The primary focus of the Working Group is on the six consumer data privacy rights or types of consumer data privacy protections identified in the NAIC's Member adopted *Strategy for Consumer Data Privacy Protections* policy statement. The secondary focus is on issues such as notice requirements and standards, disclosure of information collected, disclosure of shared information, requirements to disclose sources of information, requirements to disclose business purposes, and a requirement to disclose third party involvement. The current assignments for the Working Group are intended to create a framework for the policy statement: defining the parameters of these consumer rights by offering suggested definitions, examples of consumer risks, and what may not be protected in federal laws or not covered under NAIC Model laws.

The Privacy Protections Working Group's policy statement will address the following consumer privacy rights:⁸

- 1) Right to opt-out of data sharing
- 2) Right to opt-in of data sharing
- 3) Right to correct information
- 4) Right to delete information
- 5) Right to data portability
- 6) Right to restrict the use of data⁹

The Accelerated Underwriting (A) Working Group will continue to watch the work of this group. If at any point issues unique to accelerated underwriting arise, we will endeavor to address them in a future work product.

{GLBA}, the Health Insurance Portability and Affordability Act {HIPAA}, Electronic Health Records {EHR}, etc. The Working Group is also analyzing the various provisions of recently enacted legislation, such as California's Consumer Privacy Act {CCPA} and its Consumer Data Privacy Regulation {CCPR}, Virginia's and Colorado's recently enacted Consumer Privacy Protection laws, certain provisions of the European General Data Protection Regulation {GDPR}, the NAIC's Record Retention Model Regulation and the NAIC's Unfair Claims Practice Model Act {UCPA}. There are a lot of jurisdictional issues that remain to be sorted through.

⁸ For purposes of the Working Group's paper, the use of the term "right" should be read as a basic protection, or, denoting access to making a request and not as a guarantee of having the requested right acted upon in the manner as the consumer requests.

⁹ for purposes of the Working Group's paper there is a distinction between an individual's data and information that results from the use of this data, e.g., the insurance score that results from the use of an algorithm.

Comments should be sent to jcook@naic.org by close of business Dec. 3, 2021

Appendix A: Additional Procedural Background

At the 2019 NAIC Summer National Meeting, the Life Insurance and Annuities (A) Committee discussed a referral it had received from the Big Data (EX) Working Group. The Big Data Working Group had discussed the use of predictive models in accelerated underwriting in life insurance, instead of medical examinations and the collection of fluids. The Big Data Working Group agreed that the issue would be most appropriately addressed by the life insurance subject matter experts and voted to refer the issue of the use of external data and data analytics in accelerated underwriting in life insurance to the Life Insurance and Annuities (A) Committee (Committee).¹⁰

The Committee discussed the referral and acknowledged that there are a multitude of issues surrounding insurers' use of data models and data analytics; issues that extend into many areas of insurance and overlap with the work of several groups at the NAIC. In addition to the Big Data (EX) Working Group, there is the Innovation and Technology (EX) Task Force, the Artificial Intelligence (EX) Working Group, the Casualty Actuarial and Statistical (C) Task Force, and the Privacy Protections (D) Working Group. The Life Actuarial Task Force was also looking at the use of accelerated underwriting in life insurance from an actuarial perspective, including looking at any potential impact on insurer solvency.

The Committee agreed that an effort to delve into accelerated underwriting in life insurance would need to be narrowly focused while taking into account the work of these other NAIC groups touching on the same topic.

Robert Muriel (IL) chaired the Working Group and Grace Arnold (MN) was the vice-chair. The following were Working Group members: Jason Lapham (CO); Russ Gibson (IA); Rich Piazza (LA); Cynthia Amann (MO); Rhonda Ahrens and Laura Arp (NE); Ross Hartley and Chris Aufenthie (ND); Lori Barron (OH); Elizabeth Kelleher Dwyer (RI); Lichiou Lee (WA); Mark Afable (WI). In January 2021, Commissioner Afable became chair of the Working Group and the rest of the membership remained the same.

The Working Group met for the first time on Oct 2, 2019, and developed a work plan to accomplish its charge. The work plan contemplated the Accelerated Underwriting (A) Working Group progressing through three phases with the goal of completing its charge by the 2020 Fall National Meeting. The first phase was focused on information-gathering. The second phase focused on identifying the issues and deciding on a work product, with the final phase devoted to drafting.

During the information gathering phase, the Working Group heard 15 presentations from varying stakeholders, including an academic (Professor Patrick Brockett¹¹), insurance companies, consulting firms (Deloitte and Milliman), a consumer advocate (Birny Birnbaum—CEJ), the American Academy of Actuaries, lawyers from 2 Illinois law firms (Foley & Lardner and Edelson), a machine learning assurance company (Monitaur), and a data analytics company (Verisk). Several of the presentations were held in regulator-only meetings when requested by presenters in order to share proprietary and confidential company-specific information.

Regulators from the Working Group volunteered to participate in two ad hoc groups to tackle the second and third phases of its work plan: There was an ad hoc NAIC liaison group to ensure awareness of and coordination with any work, including guidelines or protocols, developed by other NAIC groups, past and present, that related

¹⁰ See NAIC Proceedings – Spring 2019, Innovation and Technology (EX) Task Force, Attachment Two.

¹¹ Gus Wortham Chair in Risk Management and Insurance at the University of Texas at Austin and Editor, North American Actuarial Journal.

Comments should be sent to jcook@naic.org by close of business Dec. 3, 2021

to the Working Group. There was also an ad hoc drafting group that agreed to take the information gathered, identify issues, recommend and draft a work product for review and approval by the Working Group.

In November 2020, the ad hoc drafting group shared with the Accelerated Underwriting (A) Working Group a proposed draft outline for an educational report exploring accelerated underwriting in life insurance to provide guidance to regulators, industry, and consumer advocates, and other stakeholders. In February 2021, the ad hoc groups merged.

Appendix B: Machine Learning/ Artificial Intelligence Definition in 6/24/21 Draft Big Data and Artificial Intelligence (EX) Working Group Survey on private passenger automobile (PPA) insurers' use and governance of big data.

Artificial Intelligence/Machine Learning (AI/ML)

AI/ML describes an automated process in which a system begins recognizing patterns without being specifically programmed to achieve a pre-determined result. This is different from a standard algorithm in that an algorithm is a process or set of rules executed to solve an equation or problem in a pre-determined fashion. Evolving algorithms are considered a subset of AI/ML.

Artificial Intelligence / Machine Learning Systems include:

- Systems that adapt and adjust to new data and experience without manual human intervention.
- Systems that arrive at results for which the outcomes and the stepwise approach toward the outcomes were not configured in advance by a human programmer.
- Systems that dynamically respond to conditions in the external environment without the specific nature of such responses being known in advance to the designers of the systems.
- Systems that utilize neural networks and/or deep-learning algorithms, such as supervised, semi-supervised, and unsupervised learning algorithms.
- Systems that engage in automatic speech recognition, facial recognition, image recognition, text recognition, natural language processing, generation of customer-specific recommendations, automated customer communications (e.g., chatbots with non-preprogrammed prompts), autonomous or semi-autonomous vehicle operation or data gathering, or any other approach that does not require either preprogramming or a manual human intervention in every instance of an action or decision.
- Systems that automatically generate adaptive responses based on interactions with a consumer or third party.
- Systems that determine which data elements to rely upon, in a non-preprogrammed fashion, among a variety of possible alternatives.

Artificial Intelligence / Machine Learning Systems are not:

- Static “scorecards” that deterministically map consumer or other risk characteristics to treatments or decisions. (However, an AI/ML system may use the output of such static “scorecards” as input data for the AI/ML system to consider.)
- Systems with solely preprogrammed decision rules (e.g., “If A, then B” applied invariably in all situations).
- Tables of point or factor assignments in rating plans.
- Static rate making and/or predictive modeling methodologies, including linear regression, generalized linear modeling (GLM), or generalized additive modeling (GAM). Purely informational static databases, such as databases used to obtain reference amounts for claim settlements, or static databases pertaining to consumer characteristics or experience, regardless of the

Comments should be sent to jcook@naic.org by close of business Dec. 3, 2021

amount of information in the database. However, if AI/ML is used to create a static predictive model, that AI/ML system is considered within the scope of this survey.

- Deterministic “phone trees” that navigate consumers through pre-recorded voice prompts.
- Any approach that an insurer could have realistically utilized in the year 2000 or prior.

AI/ML Use Descriptions and/or Explanations

- **Underwriting: AI/ML Uses**
 - Automated Approval: Approving an application without human intervention on that particular application.
 - Automated Denial: Denying an application without human intervention on that particular application.
 - Underwriting Tier Determination: Decisions regarding the criteria to use to establish specific named or numbered categories (called tiers) which utilize combinations of attributes that affect an insurer’s underwriting decision.
 - Company Placement: Decisions regarding which of several affiliated companies within an insurance group will accept an individual risk.
 - Input into Non-Automated Approval Decision: Providing data, analysis, or recommendations regarding a decision to approve an application in a situation where a human decision-maker still has the ability and responsibility to affirmatively consider this information and make a decision independently of the AI/ML system. In this situation, the AI/ML system cannot automatically approve the application, and protocols exist that ensure that each recommendation from the AI/ML system is actively reviewed and not adopted by default.
 - Input into Non-Automated Denial Decision: Providing data, analysis, or recommendations regarding a decision to deny an application in a situation where a human decision-maker still has the ability and responsibility to affirmatively consider this information and make a decision independently of the AI/ML system. In this situation, the AI/ML system cannot automatically deny the application, and protocols exist that ensure that each recommendation from the AI/ML system is actively reviewed and not adopted by default.
 - Automate Processing Thru the Agency Channel: Enabling agencies to receive certain information about applicants automatically without specifically requesting that information and/or to provide quotes to the applicants and/or recommend a decision regarding the application to the agent without being based on preprogrammed decision rules.



Comments of the Center or Economic Justice

To NAIC Accelerated Underwriting Working Group

December 3, 2021

The Center for Economic Justice offers the following comments on the November 8, 2021 exposure draft of the working group's paper.

The paper continues to miss the key distinction between traditional underwriting and so-called accelerated underwriting – namely, the use of non-traditional, non-medical data. Insurers can accelerate the underwriting process in a number of ways that don't use non-traditional, non-medical data. Suppose that insurers were able to obtain traditional medical information in a faster, easier manner. Instead of asking consumers to provide a history of their prescription medicines or instead of obtaining and reviewing medical records from many providers, suppose an insurer could obtain that information electronically from a single source, like a prescription database. Although the insurer is still using the same traditional medical data, the insurer has accelerated the underwriting process.

If all insurers were doing was speeding up traditional underwriting methods, this group would not have been created. Just as property/casualty insurers speeded up auto and home underwriting by using all-claims databases and motor vehicle record databases instead of relying upon the consumer to provide that information, life insurers acceleration of access to and analysis of traditional medical information did not raise concerns among regulators.

It is not the use of predictive models or machine learning that distinguishes traditional underwriting from AUW – insurers have been applying such techniques to traditional underwriting data for years by more intensely analyzing traditional medical and other traditional data sources. The factor that most distinguishes AUW from traditional life insurance underwriting is the acquisition and use of non-traditional, non-medical data. This is evidenced by the fact that AUW models don't predict mortality – they can't because there is insufficient mortality data to develop a predictive model based on only a few years of data relating non-traditional, non-medical data to mortality. Rather, as the actuaries have stated, AUW is used to predict the same outcomes that would have occurred with traditional underwriting.

The problem with the current proposed definition of AUW is that, by lacking focus on the key differentiator of AUW from traditional underwriting, it obscures the new regulatory oversight steps needed to protect consumers from unfair discrimination and racial bias.

As we have urged in the past, the relevant definition for purposes of examining the adequacy of regulatory oversight and educating regulators and the public about AUW is:

Accelerated underwriting is life insurers' application of big data, artificial intelligence and machine learning to life insurance underwriting. What distinguishes AUW from traditional life insurance underwriting is the use of non-traditional, non-medical data using predictive models and machine learning.

The above definition focuses on the key differentiator between traditional underwriting and AUW and better sets the path for examining whether current regulatory structures require updating to protect consumers.

The error in the definition is reflected in the incorrect description of the differences between traditional and accelerated underwriting in the third paragraph on page 2.

Traditional life insurance underwriting involves assessing the applicant's physical health, then determining whether an applicant is eligible for coverage and the risk class to which that individual belongs. Accelerated underwriting relies on predictive models or machine learning algorithms to perform some of the tasks of an underwriter.

Traditional underwriting has always examined more than an applicant's health, including an applicant's financial situation (are they in bankruptcy?) and activities (are they a sky-diver?) as well as proxies for physical health (family history). Speeding up or more intensively analyzing these traditional data sources is not the reason why AUW is an issue of regulatory and consumer concern. It is the use of non-traditional, non-medical sources of data used with predictive models and machine learning that distinguishes AUW from traditional underwriting.

The fourth paragraph on page 2 continues to blur the needed understanding of AUW. The paper states that insurers use AUW to triage applicants and place applicants in different risk categories. Traditional underwriting has always done the same things. What distinguishes AUW from traditional underwriting is how the insurer does these two things – and for AUW that is the use of non-traditional, non-medical data sources in data-mined algorithms to accomplish these things.

At the bottom of page 2, the paper states that “increasing automation” of life insurance underwriting presents new regulatory challenges. Again, increased automation by itself is not the issue of concern. Automation can simply speed up manual processes using the same rules used by the formerly-manual process. And if all insurers were doing was speeding up traditional

underwriting by automating the acquisition and categorization of traditional medical information, there wouldn't be an AUW working group. Recall the origins of the NAIC's efforts on AUW at the Life Actuarial Task Force over five years ago – it was LATF's concern about the use of non-traditional, non-medical data used to predict traditional underwriting results as opposed to the use of traditional mortality tables.

The paper states that “the process” – referring to increasing automation – must be fair, transparent and secure, but offers no reference to the source or definition of these terms. As the text moves on to page three, the paper states a particular challenge is unfair discrimination, but offers no reference or definition of what is meant by unfair discrimination. As we have noted in several presentations, there are currently two types of unfair discrimination in insurance – discrimination not supported by actuarial analysis and discrimination based on protected class characteristics. The paper should explain why AUW raises new concerns about unfair discrimination.

We suggest that the paper discuss the history of life insurers' use of racial proxies for long periods of time as an example of the protected class unfair discrimination and life insurers' use of travel history as an example of unfair discrimination without actuarial basis (using Florida's actions to restrict such unfair discrimination).

We suggest that the first paragraphs on page 4 more clearly discuss the type of unfair discrimination at issue and how particular AUW data sources and applications raise concern for each of the two types of unfair discrimination. For example, this section of the paper discusses a concern about spurious correlations – where there may be a correlation between a particular data source and the insurer's outcome variable, but that correlation does not support the use of that data source as a reasonable or reliable predictor of that outcome variable.

Further, this section of the paper discusses testing, but is vague on the types of testing needed. The development of predictive models generally relies upon testing. The historical data is broken into two groups – one for development of the model and one for testing the model. The first group of data is data mined to develop the data elements and model specifications – the predictive model describes the relationship between the historical data and the outcome variable. The model is now run with the set-aside data to test whether model is reliable. We don't think this is the type of testing the paper is envisioning. The discussion of testing should reference testing for actuarial soundness on one hand and testing for protected class discrimination on the other hand.

In the recommendation section, the paper states AUW should be fair and transparent, but doesn't state to whom AUW should be transparent. AUW should be transparent to regulators, consumers and policymakers. The paper then states insurers should be accountable for operating in compliance with applicable laws. It is unclear why the word “should” is used or why this

statement is included. Insurers must operate in compliance with applicable laws. The question is whether existing laws are adequate to ensure that AUW is fair (which we expect to mean not unfairly discriminatory under current statutory standards) and transparent. Clearly, current regulatory requirements for life insurers need to be modernized for these consumer protections to be achieved. Yet, the paper makes no recommendation for or recognition of the needed improvements.

In the recommendations section on page 4, the paper sets out a list of “shoulds” for insurers and other parties involved in AUW. There is nothing in this list that distinguishes AUW from traditional underwriting – all of these “shoulds” apply to traditional underwriting data and methods.

This section fails to recommend specific testing for racial bias or algorithmic auditing to identify spurious correlations. This section fails to identify the needed requirement that insurers disclose to consumers the types and sources of data used – to actually implement the goal of transparency. The section fails to recommend requiring insurers to file AUW models with regulators – particularly credit-based AUW models. The section fails to recommend that life insurers using consumer credit information be held to the same standards as auto and home insurers. The section fails to discuss how the use of consumer credit, criminal history or consumer lifetime value information raises concern about algorithms reflecting and perpetuating historical racial bias. This section fails to recommend the development of regulatory guidance for what is needed to effectively implement the list of “shoulds” in a manner that complies with statutory standards.

In the section on traditional data, we suggest some authorities or sources be cited for the various assertions. For example, what is the source of the statement that “consumers understand how the elements impact their risk classification or premium charged?” What source does the paper rely upon to assert that consumers understand how MVRs and financial and tax information impact their premium charge or risk classification?

This section also claims that presentations to the working group represented significant time and costs associated with obtaining and reviewing traditional data. We suggest this is too generic a statement. While some sources of information remain costly and time-consuming to obtain – fluid and medical examinations – other sources of information have become readily and inexpensively available in digital formats – medical records, MVRs, MIB data, public records, prescriptions.

More importantly, the paper distinguishes traditional data from other types of data used in AUW, while largely dismissing any concerns with insurers' use of traditional data. We suggest that the paper's treatment of traditional data demonstrates and validates our points above about what distinguishes traditional underwriting from AUW – the use of non-traditional, non-medical data in predictive models and machine learning.

The next section of the paper discusses FCRA-compliant data. It is unclear why FCRA-compliant data is distinguished from traditional and non-traditional data. FCRA-compliant data are found in both the traditional and non-traditional data buckets. For purposes of defining AUW, whether data is FCRA compliant or not is not a distinguishing feature. For purposes of regulatory guidance and consumer protection, the FCRA provides a baseline of regulatory requirements for users of data and consumer protections. But, since FCRA-compliant data are found in both the traditional and non-traditional data buckets, it is not a third category of data. The FCRA serves as a guide for some of the regulatory changes and new consumer protections needed for AUW.

Further, the FCRA section is significantly incomplete. It is more accurate to describe data as FCRA-compliant or subject to the FCRA. The FCRA defines a consumer reporting agency and a consumer report and sets out a number of requirements for both consumer reporting agencies who collect and disseminate consumer reports and for companies using consumer reports provided by a consumer reporting agency. The list of consumer protections is far greater than those listed, including consent by the consumer for the use of the data, a notice of any adverse action, the ability to request a consumer report, the ability to correct erroneous data in a consumer report and the ability to request a reconsideration of the adverse action with corrected data. The FCRA also provides for oversight of the practices of consumer reporting agencies.

We suggest the working group review some documents regarding the FCRA.¹ For example the Consumer Financial Protection Bureau publishes a list of consumer reporting companies.² Some sources of traditional life insurance underwriting information are subject to the FCRA including data from the MIB, prescription drug histories and personal insurance claims information.

¹ https://files.consumerfinance.gov/f/201504_cfpb_summary_your-rights-under-fcra.pdf

² https://files.consumerfinance.gov/f/documents/cfpb_consumer-reporting-companies-list_2021-06.pdf

The paper then discusses non-traditional data sources. In the list of data sources, we suggest a broad grouping of biometric information, including facial, voice and other analytics based on personal biometric information. We suggest reference to the Illinois Biometric Information Privacy Act would be useful both to help describe biometric information and to identify needed new consumer protections. We also suggest more detailed descriptions of the sources of data and the uses and algorithms associated with those data. For example, how is specific biometric information used and for what purposes (e.g., to determine truth telling, biological age, body mass index)?

In the considerations section for non-traditional data, we see again a statement that such data may be used to predict mortality. We suggest a clear distinction between predicting the outcomes of the traditional underwriting process versus predicting mortality. It is unclear if insurers have sufficient historical data to associate non-traditional data sources with actual mortality.

The first consideration states that while non-traditional data may be used to predict mortality, there may not be a reasonable explanation for that correlation. This statement is problematic because it seems to assume that correlation is the same as actuarial soundness – it isn't. Further, it is unclear what a reasonable explanation means and how an insurer or regulator would interpret that term.

While we agree with the general thrust of the second bullet about racial bias, we suggest that the impacts of structural racism affect both traditional and non-traditional data sources. Further, we suggest the use of the term proxy discrimination as well as disparate impact. Proxy discrimination is the term used in the NAIC's principles for AI and is distinguishable from disparate impact. CEJ has presented the following definitions to the NAIC on several occasions:

Disparate Impact: Use of a non-prohibited factor that causes disproportionate outcomes on the basis of prohibited class membership and that such disproportionate outcomes cannot be eliminated or reduced without compromising the risk-based framework of insurance.

Proxy Discrimination: Use of a non-prohibited factor that, due in whole or in part to a significant correlation with a prohibited class characteristic, causes unnecessary, disproportionate outcomes on the basis of prohibited class membership.

Or

Proxy Discrimination: Use of an external consumer data and information source, algorithm, or predictive model whose predictive capability is derived in substantial part from its correlation with membership in one or more of such protected classes.

We attach a recent presentation to the NAIC to help the working group better understand these issues.

On the third bullet, we discussed above that some – even many – sources of non-traditional data used in AUW are FCRA-compliant data. This is not only important to better clarify the data categories used in the paper, but to demonstrate that many vendors of non-traditional AUW data sources and algorithms are the same consumer reporting agencies who provide data and algorithms auto and home insurers **and who currently file these algorithms with regulators**. A key consideration – and related recommendation – should be that life insurers (or third-party providers of AUW algorithms) file their models with regulators under the same types of regulatory requirements that exist for insurers filing credit-scoring models or catastrophe models for auto and home insurance. There is no rationale for treating auto and home insurers' use of credit and other non-traditional information differently from life insurers' use of the same data.

The recommendation in this section are significantly inadequate. The recommendations suggest that market conduct examinations are sufficient to ensure that AUW algorithms meet all the stated regulatory goals. We strongly disagree. First, market conduct examinations are infrequent and are typically triggered by some identified problem. Consequently, market conduct examinations cannot meaningfully address the activities of many insurers in a timely fashion. Nor are there existing metrics or data sources available to market analysts to trigger the types of concerns raised in the paper regarding racial bias or problems with data or algorithms. Second, there are no standards for market conduct examiners for most of the issues / considerations raised by the paper. Third, market conduct examinations are after-the-fact and not timely. Significant consumer harm – some irreparable -- will have occurred in the time it takes to start and complete a market conduct exam. Fourth, market conduct examinations are not the appropriate tool to establish the new guidance needed for insurers' use of big data and AI. You can't simply give market conduct examiners the NAIC principles for AI and expect enforcement or compliance or expect all insurers to discern regulatory guidance from the market conduct examination outcomes for one insurer.

The recommendations regarding form and rate are particularly puzzling since there is no rate regulation of life insurance and no current filing of life insurance rates. The only routine filing by life insurers is policy forms and applications. While a review of an application may indicate the use of a particular non-traditional data source, it's more likely that non-traditional data sources are not revealed in the application – so there would be nothing to trigger a form reviewer's question.

The first, third and fourth bullets under “form and rate reviewers” all assume some form of filing for a reviewer to analyze. There is a need for up-front filing and review of data sources and pricing models used by life insurers. Consumer protection demands that regulators stop the use of biased and unreliable data sources prior to use by insurers in the same way that regulators now stop the use of unfair, deceptive and prohibited policy form provisions prior to use by insurers.

Finally, we don't understand the last two paragraphs of this section telling life insurers they "should" engage in certain practices. How does the working group expect life insurers to respond to these "should" statements and what should regulators or consumers do if the insurers don't follow these exhortations?

The paper largely repeats the guidance for insurers set out in the NAIC principles for artificial intelligence. The purpose of the NAIC AI principles was to serve as the foundation for working groups to develop the application-specific regulatory guidance needed to operationalize those principles. ***We see no purpose served by only repeating those principles in a paper discussing a specific application of AI. The paper should be making recommendations for specific regulatory actions – new uses of existing regulatory authorities and tools and new regulatory authorities – needed to ensure that the AI principles are implemented for AUW.*** But, the paper offers no recommendations for how regulators and insurers should implement the AI Principles for life insurers' use of AUW.

Toward that end, the paper should be recommending specific statutory and regulatory changes, including:

1. Require life insurers to routinely file a list of the types, sources and uses of non-medical data for life insurance marketing, underwriting, claim settlement and anti-fraud. Regulatory attention to data and sources used for marketing is particularly important in the context of AUW because new data sources permit the micro-targeting of highly granular marketing to consumers, which effectively serves as pre-underwriting of life insurance. Regulators should pro-actively identify the types, sources and uses of data used by life insurers to timely stop the use of data that is biased, unfair or counter to public policy – instead of only learning about such data and data uses in a market conduct exam or through a media report. Further, regulators should not only collect this information, but publish summary reports to inform the public and policymakers about life insurers' data use.
2. Require life insurers to routinely file and regulators to routinely review algorithms used for marketing, underwriting, claims settlement and anti-fraud in the same manner that auto and home insurers are required to file credit-based insurance scoring models.
3. Require that all data sources used by insurers meet the consumer protection requirements of the FCRA, including consent, disclosure, challenge and correction.
4. Develop specific guidance and requirements for insurer testing of data sources and algorithms for actuarial soundness and protected class bias. It makes no sense to suggest that racial bias is a concern with AUW or other life insurer algorithms and then do nothing to prompt insurers to test for such bias and provide guidance for what sort of testing is reasonable and necessary. Why doesn't the paper recommend that all states – and the IIPRC – take the approach used by the New York Department of Financial Services in the cited Circular 1?

5. Recommend the development of guidance for life insurer collection and treatment of applicant data on race, ethnicity and other demographic characteristics to assist insurers and regulators in assessing proxy discrimination and disparate impact based on protected class characteristics. Again, if the potential for racial bias with AUW is a concern, then the relevant data must be collected to test and measure for such bias. The work of the health work stream of the Committee on race is relevant and instructional on this issue.
6. Develop / update guidance for third parties providing pricing algorithms to insurers. A third party vendors that collects information from insurers, combines that information with other data sources and then provides insurers with an algorithm for underwriting or pricing or claims settlement is engaged in collective decision-making with the insurers. Absent oversight of vendors providing these collective-pricing or collective-claims settlement algorithms, the third party algorithm provider may be engaging in prohibited antitrust and anti-competitive activities. This is vividly illustrated by comparing the regulatory oversight over mortality tables – review and approval by regulators of the raw material used by insurers for pricing and reserving life insurance – with the lack of oversight of non-traditional data sources and algorithms that are used for the same purpose.
7. Request that the Market Regulation D Committee direct the Market Conduct Annual Statement (MCAS) Blanks Working Group to complete its work on the AUW revisions to the Life Insurance MCAS line independently of the work of the AUW WG. The MCAS Blanks WG efforts on adding AUW reporting to the Life MCAS was stopped earlier this year to wait for a definition of AUW adopted by this working group for its educational paper. That directive was justified by an argument for coordination and consistency of terms among working groups. While “coordination and consistency” are generally reasonable considerations, this rationale was never logical or applicable in this context.

The MCAS effort is directed at data collection for specific market analysis purposes, so a precise definition is necessary to ensure the right data goes into the right data buckets. The AUW WG effort is directed at a different audience for a different purpose and, to date, has produced a vague and imprecise definition of AUW. It could never be used to generate reliable MCAS data reporting. We suggest that the AUW WG would benefit from review of the last version of the definition of AUW considered by the MCAS Blanks AUW subject matter expert group in which regulators and consumer stakeholders found agreement. AUW WG members will see a sharp focus on non-medical data obtained from other than the applicant (which would help inform this AUW WG’s definition) and the sharp difference in purposes of MCAS reporting and the charge of the AUW WG.

Text to accompany CEJ Presentation to Committee on Race, 12/1/2021

Slide 4

For those of you who don't know me, I'm Birny Birnbaum from the Center for Economic Justice.

The first few slides in the deck, which are available for download, provide background on me, my training as an economist at MIT, my service as an insurance regulator, my 30 years of work on racial justice in insurance. I'm speaking for both the Center for Economic Justice and the Consumer Federation of America and the nearly 300 state and national consumer organizations that are members of CFA.

Jump to Slide 5

To lay some groundwork, let's start by reviewing what fair and unfair discrimination in insurance means.

Unfair discrimination is generally defined in two ways. The first is actuarial – there must be an actuarial basis for different treatment of different groups of consumers. That is the “not unfairly discriminatory” portion of the statutory rate standards – not excessive, not inadequate and not unfairly discriminatory.

The second type of unfair discrimination is protected class discrimination – statutes that prohibit distinctions among groups defined by certain characteristics – race, religion, national origin. This type of discrimination is prohibited regardless of actuarial basis.

My question to you to start things off. Why is race a prohibited factor for underwriting or pricing even if there is an actuarial basis for such discrimination?

We know, at least for some lines of insurance, that race is predictive of insured loss. Black Americans have a lower life expectancy than other Americans – why are life insurers prohibited from using race as an underwriting or pricing factor? And, if race were predictive of auto insurance claims, why shouldn't insurers be able to use that or any factor predictive of claims? One reason could be that a person has no control over their race – they're born with it. But, there are plenty of pricing factors based on characteristics that consumers have little or no control over – like age or gender for auto insurance. So, again, why do state and federal laws declare racial discrimination as unfair discrimination in insurance?

Move to Slide 7

Slide 7 shows a map of Cleveland – What Information Does This Map of Cleveland Present?

- a. Concentration of Minority Population
- b. Eviction Rates
- c. COVID Infections and Deaths Rates
- d. Flood Risk
- e. Environment-related Illnesses
- f. Intensity of Policing

- g. Predatory Lending
- h. Federal Home Loan Eligibility 1930's to 1960's

Of course, this is a map of federal home loan eligibility from 1940 – The red areas represent parts of Cleveland that were excluded from federal housing loans because Black Americans were the predominant inhabitants of these areas. But, in fact, the map shows all the things I mentioned – all the legacy of historic racial discrimination.

Next Slide, 8

Let me suggest the reason that race and protected class characteristics are carved out regardless of actuarial fairness is that there is a history of discrimination that, at best, has left a legacy of outcomes that are embedded in the data used for actuarial analysis and, at worst, continues today with racist practices – whether intentional or unintentional – that are unrelated to risk or cost of insurance. The protected class unfair discrimination in insurance recognizes that historical discrimination has long-lasting effects that have disadvantaged these groups. The shorter life expectancy of Black Americans is not caused by their skin color, but by the historical and ongoing discrimination in housing, health care, policing and other parts of our lives.

That's why US federal civil rights and anti-discrimination laws in employment, credit and housing have always been understood to prohibit not just intentional discrimination, but practices – intentional or unintentional – that result in disparate outcomes based on race. Federal laws – and every court that has opined on the issue – have recognized both disparate treatment and disparate effect as unfair discrimination – that is intentional discrimination as well as facially-neutral practices that have the same effect as intentional discrimination.

Move to Slide 10

We continue to see those legacies of historical discrimination today both directly and indirectly in policing and criminal justice, housing, and the impacts of the Covid-19 pandemic.

Systemic racism refers to policies, practices, or directives that result in advantages or disadvantages to individuals or communities **based on race**, including harm caused by infrastructures that determine access and quality of resources and services.

Slide 11

Let me identify 3 ways in which systemic racism can manifest in any aspect of the insurance life-cycle:

Intentional discrimination on the basis of race – disparate intent.

For today's presentation, I want to focus on two types of, hopefully, unintentional forms of racial bias.

Proxy Discrimination -- Disproportionate Outcomes On the Basis of Race Resulting from Proxies for Race; and

Disparate Impact -- Disproportionate Outcomes on the Basis of Race Because of Historic Discrimination Embedded in Insurance Outcomes

Next Slide 12

Proxy Discrimination – this is when a predictive factor – say, a rating variable – is actually predicting race and not the intended outcome. The result is unnecessary racial bias because the predictive factor is not, in fact, predicting the outcome. For example, consider the use of criminal history information in, say, Ferguson Missouri. Using criminal history as a predictive variable would simply be a proxy for the racist policing.

The other category is disparate impact – this occurs when the insurance outcomes are racially-biased because the racial bias is embedded in the insurance outcomes. Recall the map of Cleveland from earlier, an accurate assessment of flood risk will have a racial bias because of racial bias in housing.

It is important to distinguish between proxy discrimination and disparate impact. With proxy discrimination, insurers have or should have interest in stopping this unnecessary discrimination.

Disparate impact, however, requires a policy decision based on equity considerations – specifically – does prohibiting the use of a particular data source or consumer characteristic compromise the cost-based and risk-based foundation of insurance? We know that such equity-based policy decisions have been made – that’s why intentional use of race is prohibited.

Next Slide 13

While there is an important distinction between disparate impact and proxy discrimination, **there is a common methodology to test for both and** such testing is consistent with the predictive analytic methods that insurers already use.

In the Big Data / AI era, it is essential for insurers to test their algorithms and for regulators to test actual consumer market outcomes for proxy discrimination and disparate impact.

There is a long history of and many approaches to identifying and minimizing disparate impact in employment, credit and insurance. But, the general principle is to identify and remove the correlations between the protected class characteristic and the predictive variables by explicit consideration of the protected class characteristic.

The techniques to analyze proxy discrimination and disparate impact are the same techniques insurers use in developing predictive models for all aspects of the insurance life cycle.

Next Slide 14

Insurer trades argue that anything that restricts their ability to segment the population for any aspect of the insurance life cycle will destroy the cost-based foundation of insurance, will lead to “good risks” subsidizing “bad risks” and lead to insurer financial ruin.

In fact, the existence of protected class characteristics demonstrates that risk segmentation – “predicting risk” – is not the goal of insurance but a tool to help achieve the real goal of insurance – a risk pooling mechanism providing financial security for as many as possible and particularly for those with modest resources. Insurers’ arguments for unfettered risk classifications are inconsistent with the goal of insurance.

While some risk segmentation is necessary to avoid adverse selection, the logical extension of that argument is not unlimited risk segmentation.

We also hope that you reject as absurd the p/c trades argument that they can't discriminate on the basis of race because they don't consider race. Anyone who works with predictive modeling and algorithms knows that algorithms will reflect and perpetuate any bias in historical outcomes embedded in the historical data.

Move to Slide 16

It is Reasonable and Necessary to Recognize Proxy Discrimination and Disparate Impact as Unfair Discrimination in Insurance.

1. It makes no sense to permit insurers to do indirectly what they are prohibited from doing directly. If we don't want insurers to discriminate on the basis of race, why would we ignore practices that have the same effect?
2. It improves risk-based and cost-based practices.
3. In an era of Big Data, systemic racism means that there are no "facially-neutral" factors.

Next Slide 17

At the urging of the P/C Trades, NCOIL adopted a definition of proxy discrimination that profoundly misunderstands how structural racism affects insurance. NCOIL's defines proxy discrimination only 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.**

At best, this action represents a profound misunderstanding of how systemic racism affects insurance. At worst, it is a conscious act of stopping insurance regulators and states from even attempting to address racial justice. The language memorializes insurer practices that indirectly discriminate on the basis of race, discourages insurers from examining such racial impact and restricts current regulatory efforts. It is based on a profoundly-flawed legal argument and NCOIL's mistaken belief that actuarial soundness requires only a simple correlation.

If there is to be any progress towards racial justice in insurance, the NCOIL definition of proxy discrimination must be rejected.



**Presentation to Property / Casualty Work Stream of
NAIC Special Committee on Race**

Proxy Discrimination and Disparate Impact in Insurance

December 1, 2021

Birny Birnbaum
Center for Economic Justice

The Center for Economic Justice

CEJ is a non-profit consumer advocacy organization dedicated to representing the interests of low-income and minority consumers as a class on economic justice issues. Most of our work is before administrative agencies on insurance, financial services and utility issues.

On the Web: www.cej-online.org

About Birny Birnbaum

Birny Birnbaum is the Director of the Center for Economic Justice, a non-profit organization whose mission is to advocate on behalf of low-income consumers on issues of availability, affordability, accessibility of basic goods and services, such as utilities, credit and insurance.

Birny, an economist and former insurance regulator, has worked on racial justice issues for 30 years. He performed the first insurance redlining studies in Texas in 1991 and since then has conducted numerous studies and analyses of racial bias in insurance for consumer and public organizations. He has served for many years as a designated Consumer Representative at the National Association of Insurance Commissioners and is a member of the U.S. Department of Treasury's Federal Advisory Committee on Insurance, where he co-chairs the subcommittee on insurance availability. Birny is also a member of the U.S. Federal Reserve Board's Insurance Policy Advisory Committee.

Birny served as Associate Commissioner for Policy and Research and the Chief Economist at the Texas Department of Insurance. At the Department, Birny developed and implemented a robust data collection program for market monitoring and surveillance.

Birny was educated at Bowdoin College and the Massachusetts Institute of Technology. He holds Master's Degrees from MIT in Management and in Urban Planning with concentrations in finance and applied economics. He holds the AMCM certification.

Why CEJ Works on Insurance Issues

Insurance Products Are Financial Security Tools Essential for Individual and Community Economic Development:

CEJ works to ensure ***fair access*** and ***fair treatment*** for insurance consumers, particularly for low- and moderate-income consumers.

Insurance is the Primary Institution to Promote Loss Prevention and Mitigation, Resiliency and Sustainability:

CEJ works to ensure insurance institutions maximize their role in efforts to reduce loss of life and property from catastrophic events and to ***promote resiliency and sustainability*** of individuals, businesses and communities.

Fair and Unfair Discrimination in Insurance

In the U.S., Provisions regarding fair and unfair discrimination are generally found in two parts of insurance statutes: rating and unfair trade practices.

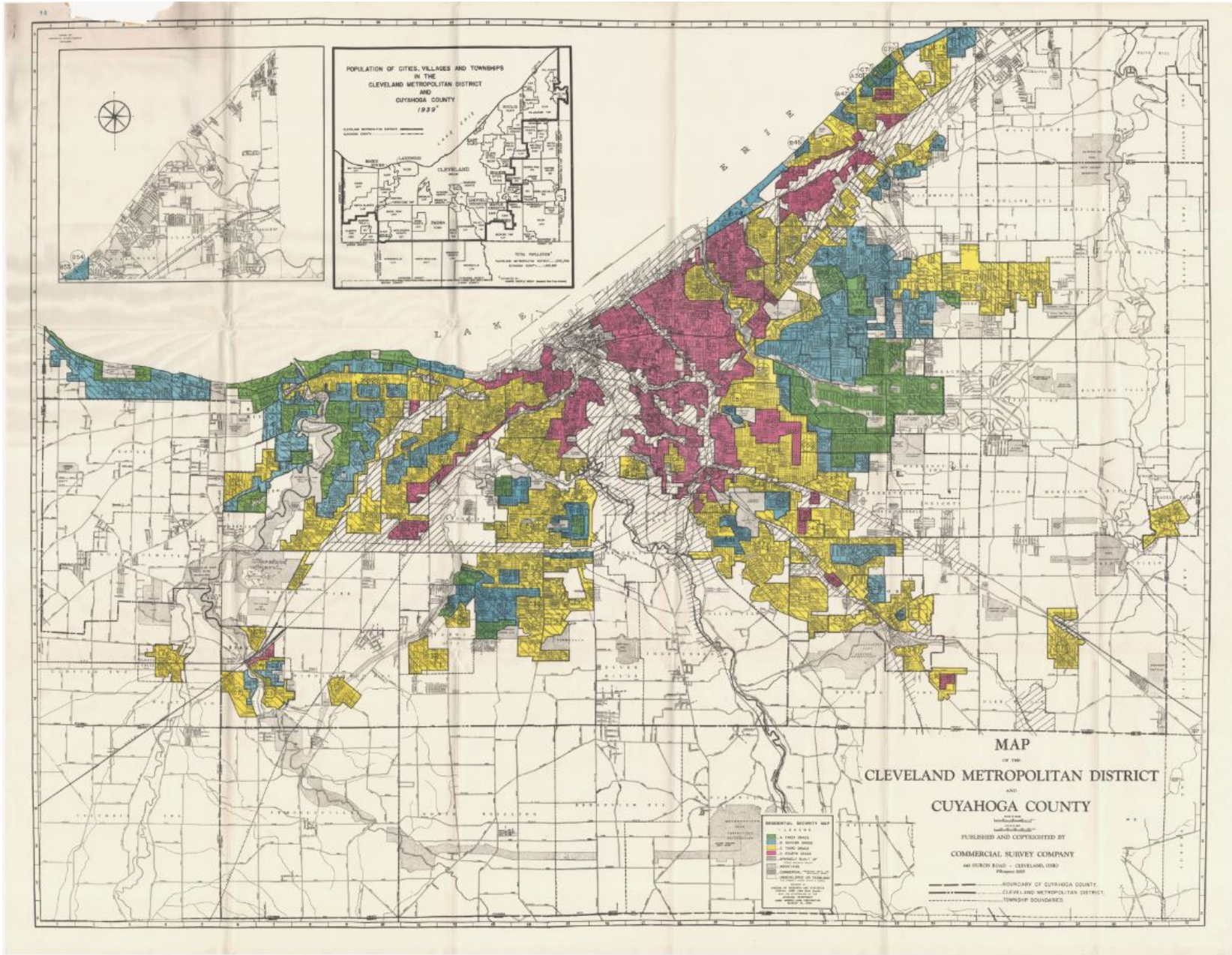
We find two types of unfair discrimination:

- Actuarial – there must be an actuarial basis for distinction among groups of consumers; and
- Protected Classes – distinctions among groups defined by certain characteristics – race, religion, national origin – prohibited regardless of actuarial basis.

Why do state and federal laws prohibit discrimination on the basis of certain characteristics even if there is an actuarial basis for such discrimination?

What Information Does This Map of Cleveland Present?

- a. Concentration of Minority Population
- b. Eviction Rates
- c. COVID Infections and Deaths Rates
- d. Flood Risk
- e. Environment-related Illnesses
- f. Intensity of Policing
- g. Predatory Lending
- h. Federal Home Loan Eligibility 1930's to 1960's



Why Do State and Federal Laws Prohibit Discrimination on the Basis of Race?

Justice Kennedy for the Majority in the U.S. Supreme Court's 2015 *Inclusive Communities* Opinion upholding disparate impact as unfair discrimination under the Fair Housing Act.

Recognition of disparate-impact claims is also consistent with the central purpose of the FHA, which, like Title VII and the ADEA, was enacted to eradicate discriminatory practices within a sector of the Nation's economy.

Recognition of disparate-impact liability under the FHA plays an important role in uncovering discriminatory intent: it permits plaintiffs to counteract unconscious prejudices and disguised animus that escape easy classification as disparate treatment.

Why Are Race and Other Protected Class Characteristics Carved Out of Fair Actuarial Discrimination?

The existence of historical, intentional discrimination based on these characteristics – discrimination that violates state and federal constitutions. But, also, the recognition that the historical discrimination has long-lasting effects that disadvantage those groups. Stated differently, you can't enslave a population for two hundred years and then expect the legacy of that enslavement will disappear overnight.

We continue to see those legacies of historical discrimination – systemic racism -- today both directly and indirectly in policing and criminal justice, housing, and the impacts of the Covid-19 pandemic.

Systemic Racism¹

Structural racism is the policies and practices that normalize and legalize racism in a way that creates differential access to goods, services, and opportunities based on race.

Systemic racism refers to policies, practices, or directives that result in advantages or disadvantages to individuals or communities based on race, including harm caused by infrastructures that determine access and quality of resources and services.

¹ <https://new.finalcall.com/2021/03/09/death-by-zip-code-housing-discrimination-neighborhood-contamination-and-black-life/>

How Can Systemic Racism Manifest Itself in Insurance – Whether for Marketing, Pricing or Claims Settlement?

1. Intentional Use of Race – Disparate Intent
2. Disproportionate Outcomes Tied to Historic Discrimination and Embedded in Insurance Outcomes – Disparate Impact
3. Disproportionate Outcomes Tied to Use of Proxies for Race, Not to Outcomes – Proxy Discrimination

Definitions

Disparate Impact: Use of a non-prohibited factor that causes disproportionate outcomes on the basis of prohibited class membership and that such disproportionate outcomes cannot be eliminated or reduced without compromising the risk-based framework of insurance.

Proxy Discrimination: Use of a non-prohibited factor that, due in whole or in part to a significant correlation with a prohibited class characteristic, causes unnecessary, disproportionate outcomes on the basis of prohibited class membership.

Or

Proxy Discrimination: Use of an external consumer data and information source, algorithm, or predictive model whose predictive capability is derived in substantial part from its correlation with membership in one or more of such protected classes.

Testing for Disparate Impact and Proxy Discrimination:

A Natural Extension of Typical Insurer Practices

While proxy discrimination and disparate impact are different forms of unfair discrimination, there is a common methodology to test for both.

There is a long history of and many approaches to identifying and minimizing disparate impact in employment, credit and insurance. But, the general principle is to identify and remove the correlations between the protected class characteristic and the predictive variables by explicit consideration of the protected class characteristic.

The techniques to analyze proxy discrimination and disparate impact are the same techniques insurers use in developing predictive models for all aspects of the insurance life cycle. See below for more technical explanation.

Risk Segmentation is not the Purpose of Insurance

Insurer trades argue that anything that restricts their ability to segment the population for any aspect of the insurance life cycle will destroy the cost-based foundation of insurance, will lead to “good risks” subsidizing “bad risks” and lead to insurer financial ruin.

In fact, the existence of protected class characteristics demonstrates that risk segmentation – “predicting risk” – is not the goal of insurance but a tool to help achieve the real goal of insurance – a risk pooling mechanism providing financial security for as many as possible and particularly for those with modest resources. Insurers’ arguments for unfettered risk classifications are inconsistent with the goal of insurance.

While some risk segmentation is necessary to avoid adverse selection, the logical extension of that argument is not unlimited risk segmentation. In fact, if unlimited risk segmentation was necessary, we would see all insurers using all risk characteristics – they don’t – and collapsing markets in states where some limitations on risk characteristics exist – they aren’t.

Disparate Impact Analysis Improves Cost-Based Pricing

With proxy discrimination, an insurer is using a factor – a characteristic of the consumer, vehicle, property or environment – that is predicting race and not the insurance outcome. Proxy discrimination is, therefore, a spurious correlation and eliminating such spurious correlation improves cost-based pricing. Since proxy discrimination is indirect racial discrimination, it is currently a prohibited practice. Testing would therefore both improve risk-based pricing and stop unintentional or intentional racial discrimination.

There is a long history and many approaches to identifying and minimizing disparate impact in employment, credit and insurance. But, the general principle is to identify and remove the correlations between the protected class characteristic and the predictive variables. Testing identifies true disparate impact that may require a public policy that recognizes equity – such as the prohibition against using race itself as a factor.

Why is it Reasonable and Necessary to Recognize Disparate Impact as Unfair Discrimination in Insurance?

1. It makes no sense to permit insurers to do indirectly what they are prohibited from doing directly. If we don't want insurers to discriminate on the basis of race, why would we ignore practices that have the same effect?
2. It improves risk-based and cost-based practices.
3. In an era of Big Data, systemic racism means that there are no “facially-neutral” factors.

NCOIL's "Definition" of Proxy Discrimination Must Be Rejected

At the urging of the P/C Trades, NCOIL recently adopted the following:

For purposes of this Act, as well as for the purpose of any regulatory material adopted by this State, or incorporated by reference into the laws or regulations of this State, or regulatory guidance documents used by any official in or of this State, "Proxy Discrimination" means 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.**

At best, this action represents a profound misunderstanding of how systemic racism affects insurance. At worst, it is a conscious act of stopping insurance regulators and states from even attempting to address racial justice. The language memorializes insurer practices that indirectly discriminate on the basis of race, discourages insurers from examining such racial impact and restricts current regulatory efforts.

Algorithms Learn the Bias Reflected in Data and Modelers

*Advocates of algorithmic techniques like data mining argue that they eliminate human biases from the decision-making process. **But an algorithm is only as good as the data it works with.** Data mining can inherit the prejudices of prior decision-makers or reflect the widespread biases that persist in society at large. **Often, the “patterns” it discovers are simply preexisting societal patterns of inequality and exclusion. Unthinking reliance on data mining can deny members of vulnerable groups full participation in society.**²*

The fact that an insurer doesn't use race in an algorithm does not logically or factually result in no discrimination on the basis of race.

In fact, the only way to identify and eliminate the impacts of structural racism in insurance is to measure that impact by explicit consideration of race and other protected class factors.

² Barocas and Selbst

Consider Criminal History Scores

“TransUnion recently evaluated the predictive power of court record violation data (including criminal and traffic violations)

“Also, as court records are created when the initial citation is issued, they provide insight into violations beyond those that ultimately end up on the MVR—such as violation dismissals, violation downgrades, and pre-adjudicated or open tickets.”

What is the likelihood that TU Criminal History Scores have a disparate impact against African-Americans? Consider policing records in Ferguson, Missouri.

US DOJ Investigation of the Ferguson Police Department

Ferguson's approach to law enforcement both reflects and reinforces racial bias, including stereotyping. ***The harms of Ferguson's police and court practices are borne disproportionately by African Americans, and there is evidence that this is due in part to intentional discrimination on the basis of race.***

Ferguson's law enforcement practices overwhelmingly impact African Americans. Data collected by the Ferguson Police Department from 2012 to 2014 shows that African Americans account for 85% of vehicle stops, 90% of citations, and 93% of arrests made by FPD officers, despite comprising only 67% of Ferguson's population.

US DOJ Investigation of the Ferguson Police Department (2)

FPD appears to bring certain offenses almost exclusively against African Americans. For example, from 2011 to 2013, African Americans accounted for 95% of Manner of Walking in Roadway charges, and 94% of all Failure to Comply charges.

Our investigation indicates that this disproportionate burden on African Americans cannot be explained by any difference in the rate at which people of different races violate the law. Rather, our investigation has revealed that these disparities occur, at least in part, because of unlawful bias against and stereotypes about African Americans.

Why Test for Disparate Impact and Proxy Discrimination in All Aspects of Insurers' Operations?

Among the various parts of the insurance life-cycle – marketing, underwriting, pricing, claims settlement, antifraud – new data sources and complex algorithms for pricing currently get the most attention from regulators because in most states most insurers file personal lines rates. Data and algorithms used for marketing, in contrast, get little or no attention. ***Yet, it is the marketing function – and the new data sources and algorithms used in micro-targeting consumers – that has become the true gatekeeper for access to insurance.***

Consider the following quotes from 2005 to present. In 2005, in a meeting with investment analysts, the CEO of a major publicly-traded insurer was effusive about the benefits of the then relatively new use of consumer credit information— referred to as tiered pricing.

Tiered pricing helps us attract higher lifetime value customers who buy more products and stay with us for a longer period of time. That's Nirvana for an insurance company.

This year, we've expanded from 7 basic price levels to 384 potential price levels in our auto business.

Tiered pricing has several very good, very positive effects on our business. It enables us to attract really high quality customers to our book of business.

The key, of course, is if 23% or 20% of the American public shops, some will shop every six months in order to save a buck on a six-month auto policy. ***That's not exactly the kind of customer that we want.*** So, the key is to use our drawing mechanisms and our tiered pricing to find out of that 20% or 23%, to find those *that are unhappy with their current carrier*, are likely to stay with us longer, likely to buy multiple products and that's where tiered pricing and a good advertising campaign comes in.

Now fast forward to 2017, when the new CEO of that insurer told investment analysts:

The insurer's "universal consumer view" keeps track of information on 125 million households, or 300 million-plus people, Wilson said.

"When you call now they'll know you and know you in some ways that they will surprise you, and give them the ability to provide more value added, so we call it the trusted adviser initiative"

And just recently, the telematics subsidiary of this insurer pitched its ability to identify the most valuable customers in real time:

Attract the most profitable drivers with telematics-based targeting

Traditionally, insurance marketing has relied on demographic and behavioral data to target potential customers. While useful at a high level, these proxies fall short when it comes to considering customer value and retention. Now, you can reach the most profitable customers from the outset using the nation's first telematics-based marketing platform.

Company intelligently layers driving score onto insurer campaign targeting criteria to purchase the ideal audience based on quartiles of driving risk. [The] Scored user receives a targeted offer via awareness and performance channels

Not to be outdone, another telematics data vendor announced a partnership with an auto manufacturer

Insurers can harness the power of connected Hyundai vehicles as a new marketing channel to support the profitable growth of their behavior- or mileage-based programs. Discount Alert allows insurers to deploy personalized marketing offers directly to drivers through Hyundai's online owner portal and contains robust tools to anonymously segment ideal risk targets—ensuring your offers are only sent to qualified leads.

All of this begs the questions, what about consumers and businesses who don't have the wealth to provide the value sought by insurers? How do these strategies line up with public policies against discrimination on the basis of race and promoting widespread availability of insurance?

The Murder of George Floyd Raised Awareness of Systemic Racism How Did Insurer CEOs React?

“In the coming days, I encourage each of us to step outside of our comfort zones, seek to understand, engage in productive conversations and hold ourselves accountable for being part of the solution. We must forever stamp out racism and discrimination.” Those are the words of Kirt Walker, Chief Executive Officer of Nationwide.

Floyd’s death in Minneapolis is the latest example of “a broken society, fueled by a variety of factors but all connected by inherent bias and systemic racism. Society must take action on multiple levels and in new ways. It also requires people of privilege—white people—to stand up for and stand with our communities like we never have before,” Those are the words of Jack Salzwedel, the CEO of American Family.

How Have the U.S. Insurer Trades – Particularly NAMIC and APCIA – Responded to the Insurer CEOs’ Calls?

- Opposed the inclusion of “Consistent with the risk-based foundation of insurance, AI actors should proactively . . . avoid proxy discrimination against protected classes” in the NAIC Principles for Artificial Intelligence.
- Have opposed the application of disparate impact liability under the federal Fair Housing Act to home insurance.
- Supported the gutting of the U.S. Housing and Urban Development’s disparate impact rule – despite pleas from several insurers to leave the rule alone in the aftermath of the murder of Black Americans at the hands of police.
- Pushed NCOIL to adopt a resolution opposing the CASTF White Paper because it suggested that regulators could ask insurers to show a rational relationship between new data sources and insurance outcomes.

How Have the Insurer Trades – Particularly NAMIC and APCIA – Responded to the Insurer CEOs’ Calls? (con’t)

- Opposed state bills to limit the impacts of credit-based insurance scores during a pandemic, citing insurers’ need for “risk-based pricing,” while supporting efforts to permit such deviations when insurers find it convenient – price optimization, consumer lifetime value.
- Sued regulators in NV and WA who sought temporary limits on the use of credit-based insurance scores disrupted by the pandemic and the CARES Act.
- Pushed NCOIL to adopt a definition of proxy discrimination that would block any efforts to identify and address disparate impact and proxy discrimination and shield insurers from any accountability for their practices.

Practices That Raise Concerns About Disparate Impact and Proxy Discrimination on the Basis of Race

Price Optimization and Consumer Lifetime Value Scores

By definition, these algorithms used by insurers utilize non-cost factors to differentiate among consumers and the factors and data reflect bias against communities of color.

Credit-Based Insurance Scores

The consumer credit information factors used in CBIS are highly correlated with race. The Missouri Department of Insurance found that the single best predictor of the average CBIS in a ZIP Code was minority population.

Criminal History Scores

Here, the problem is not just the legacy of historical discrimination, but ongoing discrimination in policing and criminal justice.

Why Do Efforts to Address Discrimination on the Basis of Race Require Explicit Consideration of Race?

New York Times, August 10, 2015: Algorithms and Bias: Q. and A. With Cynthia Dwork

Q: Some people have argued that algorithms eliminate discrimination because they make decisions based on data, free of human bias. Others say algorithms reflect and perpetuate human biases. What do you think?

A: Algorithms do not automatically eliminate bias. . . .Historical biases in the . . .data will be learned by the algorithm, and past discrimination will lead to future discrimination.

Fairness means that similar people are treated similarly. ***A true understanding of who should be considered similar for a particular classification task requires knowledge of sensitive attributes, and removing those attributes from consideration can introduce unfairness and harm utility.***

Steve Bellovin, “Yes, ‘algorithms’ can be biased. Here’s why. A computer scientist weighs in on the downsides of AI.”³

This is what's important: machine-learning systems—“algorithms”—produce outputs that reflect the training data over time. If the inputs are biased (in the *mathematical* sense of the word), the outputs will be, too. Often, this will reflect what I will call “sociological biases” around things like race, gender, and class.

One thing is to exercise far more care in the selection of training data. Failure to do that was the likely root cause of Google Images labeling two African-Americans as gorillas. Sometimes, fixing the training data can help.

Of course, this assumes that developers are even aware of the bias problem. Thus, another thing to do is to test for biased outputs—and some sensitive areas, such as the criminal justice system, simply do not use these kinds of tools.

³ <https://arstechnica.com/tech-policy/2019/01/yes-algorithms-can-be-biased-heres-why/>

There are several reasons to be wary of the "algorithmic" approach. One reason is that people put too much trust in computer output. Every beginning programmer is taught the acronym "GIGO:" garbage in, garbage out. To end users, though, it's often "garbage in, gospel out"—if the computer said it, it must be so. (This tendency is exacerbated by bad user interfaces that make overriding the computer's recommendation difficult or impossible.) We should thus demand less bias from computerized systems precisely to compensate for their perceived greater veracity.

The second reason for caution is that computers are capable of doing things—even bad things—at scale. There is at least the perceived risk that, say, computerized facial recognition will be used for mass surveillance. Imagine the consequences if a biased but automated system differentially misidentified African-Americans as wanted criminals. Humans are biased, too, but they can't make nearly as many errors per second.

Our test, then, should be one called disparate impact. "Algorithmic" systems should be evaluated for bias, and their deployment should be guided appropriately. Furthermore, the more serious the consequences, the higher the standard should be before use.

“The Real Reason Tech Struggles with Algorithmic Bias”⁴

These are mistakes made while trying to do the right thing. But they demonstrate why tasking untrained engineers and data scientists with correcting bias is, at the broader level, naïve, and at a leadership level insincere.

No matter how trained or skilled you may be, it is 100 percent human to rely on cognitive bias to make decisions. Daniel Kahneman’s work challenging the assumptions of human rationality, among other theories of behavioral economics and heuristics, drives home the point that human beings cannot overcome all forms of bias. But slowing down and learning what those traps are—as well as how to recognize and challenge them—is critical. As humans continue to train models on everything from stopping hate speech online to labeling political advertising to more fair and equitable hiring and promotion practices, such work is crucial.

⁴ Yael Eisenstat at <https://www.wired.com/story/the-real-reason-tech-struggles-with-algorithmic-bias/>

The Evolution of Insurers' Analytics: Univariate to Multivariate Analysis

In the past 30 years, insurers have moved away from univariate analysis to multivariate analysis – from analyzing the effects of one risk characteristic at a time to simultaneous analysis of many risk characteristics.

What the problem with univariate analysis?

If I analyze the relationship of age, gender and credit score – each individually – to the likelihood of a claim, the individual results for each risk characteristic are likely capturing some of the effects of the other risk characteristics – ***because age, gender and credit score (or other risk classifications) may be correlated to each other*** as well as to the outcome variable.

How does multi-variate analysis address this problem?

Testing for Disparate Impact and Proxy Discrimination:

A Natural Extension of Typical Insurer Practices

Here's a simple illustration of a multivariate model. Let's create a simple model to predict the likelihood of an auto claim:

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + e = y$$

$X_1, X_2 + X_3$ are the predictive variables trying to predict y .

Say that $X_1, X_2 + X_3$ are age, gender and credit score and we are trying to predict y – the likelihood of an auto insurance claim

Let's assume that all three X s are statistically significant predictors of the likelihood of a claim and the b values are how much each X contributes to the explanation of claim. The b values can be tested for statistical significance – how reliable are these estimates of the contribution of each X ?

By analyzing these predictive variable simultaneously, the model removes the correlation among the predictive variables.

Use of Control Variables in Multivariate Insurance Models

Suppose an insurer want to control for certain factors that might distort the analysis? For example, an insurer developing a national pricing model would might want to control for different state effects like different age distributions, different occupation mixes or differences in jurisprudence. An insurer would add one or more control variables.

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4C_1 + e = y$$

C_1 is a control variable – let's say for State. By including State as a control variable, the correlation of the Xs to State is statistically removed and the new b values are now the contribution of the Xs, independent of their correlation to State, to explaining the likelihood of a claim. When the insurer deploys the model, it still only uses the X variables, but now with more accurate b values.

Disparate Impact as Both a Standard and a Methodology

Let's go back to multi-variate model, but now use Race as a control variable:

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4R_1 + e = y$$

R_1 is a control variable – by including race in the model development, the correlation of the Xs to race is statistically removed and the new b values are now the contribution of the Xs, independent of their correlation to race, to explaining the likelihood of a claim

How Do We Interpret the Disparate Impact Analysis?

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4R_1 + e = y$$

Result: No Proxy Discrimination or Disparate Impact

Outcome	Interpretation	Indicated Action
R is not statistically significant and there is little change to b1, b2 and b3.	There is little correlation between X1, X2 and X3 and race, little or no disparate impact or proxy discrimination	None, utilize the model.

How Do We Interpret the Disparate Impact Analysis?

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4R_1 + e = y$$

Result: Proxy Discrimination

Outcome	Interpretation	Indicated Action
R is statistically significant and b1 has lost its statistical significance	X1 was largely a proxy for race and the original predictive value of X1 was spurious. This is an example of proxy discrimination	Remove X1 from the marketing, pricing, claims settlement or anti-fraud model.

How Do We Interpret the Disparate Impact Analysis?

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \mathbf{b_4R_1} + e = y$$

Result: Disparate Impact

Outcome	Interpretation	Indicated Action
R is statistically significant and has a large impact on the outcome, but b1, b2 and b3 remain largely unchanged and statistically significant	This is an example of disparate impact.	Are X1, X2 or X3 essential for the insurer's business purposes? Are there less discriminatory approaches available? Would eliminating a predictive variable significantly reduce the disparate impact but not materially affect the efficiency or productiveness of the model?

How Do We Interpret the Disparate Impact Analysis?

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \mathbf{b_4R_1} + e = y$$

Result: Some Proxy Discrimination, Some Disparate Impact

Outcome	Interpretation	Indicated Action
R is statistically significant, but b1, b2 and b3 remain statistically significant with different values from the original.	X1, X2 and X3 are correlated to race, but also predictive of the outcome, even after removing the variables' correlation to race. This is an example of some proxy discrimination and some disparate impact.	Depending on the significance of the racial impact, utilize the model with the revised predictive variable coefficients, consider prohibiting a variable on the basis of equity or both.

Insurers Don't Collect Applicant's Race – How Can an Actuary Get Data on Race to Perform a Disparate Impact Analysis?

1. Assign a racial characteristic to an individual based on racial characteristic of a small geographic area – Census data at the census block level.
2. Utilize the Bayesian Improved Surname Geocoding Method, based on census geography and surname data.⁵
3. Reach out to data brokers and vendors for a new data service.

⁵ See Consumer Financial Protection Bureau, "Using publicly available information to proxy for unidentified race and ethnicity."
<https://www.consumerfinance.gov/data-research/research-reports/using-publicly-available-information-to-proxy-for-unidentified-race-and-ethnicity/>
and Yin Zhang, "Assessing Fair Lending risks Using Race/Ethnicity Proxies."

Ethical Algorithms -- Sources

Pauline T. Kim, "Auditing Algorithms for Discrimination"

<https://www.pennlawreview.com/online/166-U-Pa-L-Rev-Online-189.pdf>

Claire Whitaker, "Ethical Algorithms"

<https://www.kdnuggets.com/2019/03/designing-ethical-algorithms.html>

Erin Russel, "The Ethical Algorithm"

<https://www.cognitivetimes.com/2019/01/the-ethical-algorithm/>

Barocas and Selbst

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2477899

Kroll, et al, "Accountable Algorithms:

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2765268

Virginia Eubanks, *Automating Inequality: How High Tech Tools Profile, Police and Punish the Poor*

Selbst and Barocas, "The Intuitive Appeal of Explainable Machines

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3126971

Levy and Barocas, "Designing Against Discrimination in Online Markets

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3084502

New York Times, "Algorithms and Bias, Q and A with Cynthia Dwork," 10 August 2015

<https://www.nytimes.com/2015/08/11/upshot/algorithms-and-bias-q-and-a-with-cynthia-dwork.html>

Martin, Kirsten E. M., What Is an Ethical Algorithm (And Who Is Responsible for It?) (October 21, 2017). Available at SSRN:

<https://ssrn.com/abstract=3056692> or <http://dx.doi.org/10.2139/ssrn.3056692>

Kirsten Martin, "Ethical Implications and Accountability of Algorithms"

<http://kirstenmartin.net/wp-content/uploads/2013/11/Martin-JBE-Ethics-and-Accountability-of-Algorithms.pdf>

Kirsten Martin, DATA AGGREGATORS, BIG DATA, & RESPONSIBILITY ONLINE

<http://kirstenmartin.net/wp-content/uploads/2013/11/AAPOR-Martin-Info-Value-Chain-v2.pdf>

AIandBigData: A blueprint for human rights, social and ethical impact assessment Alessandro Mantelero

<https://reader.elsevier.com/reader/sd/pii/S0267364918302012?token=3836947F0CAD3C145A1F273E3CBE6C38F67E777DD7E4D590548F481916130DAACA8D57BED4667BD1FE1F4D8FC80E7C56>

Center for Insurance Research

145 South Main Street • Haverhill, MA 01835

December 3, 2021

Commissioner Mark Afable, Chair
Commissioner Grace Arnold, Vice-Chair
Jennifer Cook
Accelerated Underwriting (A) Working Group
NAIC Central Office
1100 Walnut Street, Suite 1500
Kansas City, MO 64106-2197

RE: Comments on Educational Paper on AUW Draft 11-8-21

Dear Members of the Working Group:

I am writing to offer my comments on the exposure draft of the Educational Paper on Accelerated Underwriting in Life Insurance (dated November 8, 2021). I am one of the members of the NAIC consumer liaison program and the Director of the Center for Insurance Research. The Center for Insurance Research (CIR) is a nonprofit, public policy and advocacy organization founded in 1991 that represents consumers on insurance matters nationally.

First, I wish to echo and support the comments submitted by my colleague Birny Birnbaum. Birny's detailed analysis and recommendations thoroughly highlight the numerous consumer issues arising from the use of Accelerated Underwriting (AUW) programs. In particular, I urge the adoption of the definitions suggested by Birny. I will not repeat the points Birny raised, but did wish to offer some of my own editorial suggestions.

Introduction (Draft page No. 2)

- This paper is the output of over a year's work by regulators to ~~understand~~ ~~survey~~ ~~the~~ current ~~state-of-the~~ industry trends and ~~its use~~ ~~develop a high level view~~ of accelerated underwriting.

While I believe the publicly accessible presentations received by the Working Group have provided some useful insight, given the numerosity and complexity of AUW models, I do not believe a comprehensive understanding of

current AUW practices can be obtained without the aid of detailed examination of algorithms and machine learning programs or review by data scientists and other neutral experts. The vast majority of the presentations made to the Working Group were from market participants who have a vested interest in the continuation of current AUW programs and while additional information has no doubt been provided in the “regulator only” Working Group sessions, I do not believe there has been enough data analysis to thoroughly test and develop a comprehensive understanding of existing AUW programs. I think the Educational Paper should be clear about its scope – a broad overview of AUW as a concept and a summary of key elements to AUW programs – but not suggest the paper reflects a comprehensive review of specific, real-world AUW programs currently in use.

- “In order to fairly deliver the benefits of more convenient and cost-effective processes, regulators and insurers should be guided by current law related to fair trade practices and unfair discrimination [and continue to monitor AUW practices as they develop to avoid unfairly discriminatory practices.](#)”

It is not enough to comply with historical standards in the advent of new technologies. As Birny Birnbaum’s submissions have illustrated, existing laws have not always prevented unfair (even if accidental) discrimination. Regulators, industry and consumers should all endeavor to prevent any unfair discrimination, particularly when technological evolution may out-pace the drafting of laws and regulations. It should be assumed that insurers will do their best to comply with existing laws and they should be encouraged think proactively about the impact of using new sources of non-traditional data, not simply be reactive.

- The Working Group believes the charge to specifically address the impact on minority populations is included in these terms, ~~and we have provided examples to illustrate the impact on minority populations.~~

I do not believe the latter clause is required to show the Working Group if following the charge it has been given, and as the draft does not contain any specific examples as of yet, is an unnecessary statement.

Page 3

- “Life insurance underwriting is the process of ~~determining eligibility~~ ~~and~~ classifying applicants into risk categories to determine the appropriate rate to charge for transferring the financial risk associated with insuring the applicant.”

I do not believe that “determining eligibility” needs to be included in the statement. The risk classification is what an insurer will use to determine if it will issue a policy to an applicant or not, “eligibility” is not a separate step.

- “Companies presenting to the Working Group stated that the accelerated underwriting process is less cumbersome, costs less than traditional underwriting, improves the underwriting experience for consumers, shortens issue times, and increases policy acceptance rates. [The Working Group has not conducted a data call or analysis to confirm these claims.](#)”

I do not doubt that companies see A UW programs as providing them with numerous benefits, otherwise they would not fund their development. But the paper should make it clear this is perspective of the companies and industry consultants who have a vested interest in the continuation of their A UW programs and that the Working Group has not conducted its own cost/benefit analysis to verify these claims.

Page 4

- “Such scrutiny is especially important when behavioral data is utilized. Behavioral data may include gym membership, one’s profession, marital status, family size, grocery shopping habits, wearable technology, and credit attributes. [Not all jurisdictions may allow the use of these behavioral data.](#)”

The paper should not imply the listed types of behavioral data have been approved by regulators in all jurisdictions and it should be clear that individual

states retain the power to make judgments about what is permitted in their marketplaces.

- “To accomplish these objectives, regulators should dialogue with [consumers](#), life insurers and third-party vendors to determine if consumer data is being used in problematic or unfair ways or generating unfair outcomes.

Consumers should not be excluded from discussions on the appropriateness of certain types of external data. Moreover, while I believe the bullet point recommendations included in the Draft are helpful, the list of recommendations needs more emphasis on two points: 1) the importance of ensuring that AUW mechanisms do not – even inadvertently – unfairly discriminate on the basis of prohibited categories such as race; and 2) require transparency of the types of external data used in AUW programs to both regulators and consumers. Mitigation has always been an important part of the insurance marketplace – but consumers cannot take steps to lower their risk when they do not know what criteria are being used.

Page 5

This section of the paper defines what “traditional data” sources have been used in underwriting, including:

- “Financial and tax information”

My presumption is that “financial” information is meant to refer to FCRA data such as credit reports or insurance scores. However, as I have noted in prior meetings, under many AUW programs a personal bankruptcy within the last 5-10 years disqualifies a consumer from the accelerated underwriting process.¹ Including both credit or insurance scores and bankruptcy in an AUW program is potentially problematic, as it counts a single risk-factor twice. To date, nobody has been able to explain clearly to me why credit and bankruptcy records should both be used together.

¹ https://content.naic.org/sites/default/files/inline-files/Accelerated_Underwriting-NAIC%20December%202019.pdf

Furthermore, it is unclear to me what “tax information” is considered part of traditional underwriting data. Admittedly, while it has been some years since I applied for a new life insurance policy, I do not recall being asked to submit my federal or state tax income tax filings. I think further clarification is required if “tax information” is to be kept as part of the traditional data list.

- ~~“The relationship of the traditional data elements to the risk is well established and consumers understand how the elements impact their risk classification or premium charged.”~~

Birny identified this sentence as problematic, and I agree. In my long experience as a consumer advocate, I can tell you it simply is not true that most consumers understand “the elements” of their risk classification as defined in the paper. Modern day risk classifications are extremely robust and complex and not something a typical consumer is at all familiar with. In my experience, most consumers understand that being overweight, having a history of medical conditions or smoking will impact their life insurance rates – but not “financial or tax information” or “bankruptcy records, civil litigation.”

- ~~“State statutes and case laws were developed based on the use of traditional data containing consumer protections created under the assumption that this was the type of data collected or reviewed during an underwriting process.”~~

I find this blanket statement overly broad and believe that some citation or source would be required to support such an expansive conclusion. Laws related to life insurance in many states have been in place for decades, and in many cases, certainly before the creation of modern-day prescription record databases. Unless an analysis on the legislative history of life insurance statutes in every state will be included in the paper, I think this sentence should be stricken.

- “FCRA data is already used in property/casualty lines of business in many jurisdictions, but has also been prohibited in other states over concern that such data is unfairly discriminatory or disproportionately impacts lower income consumers.”

While the usage of credit scores and insurance scores are widespread, they are not without controversy and not permitted in all jurisdictions for all lines of business and the paper should reflect this.

- “FCRA data may be used to predict mortality, but there may not be a reasonable explanation for that correlation.”

I do not disagree with this statement, but note it shows that FCRA data is inappropriate for use in AUW programs. As noted on page 4 of the paper “behavioral data may lead to questionable conclusions as correlation may be confused with causation” and given that the recommendations require “valid explanation or rationale for any claimed correlation.” As there is no reasonable correlation with mortality for FCRA data, it should not be used in AUW programs.²

The paper also provides a list of “nontraditional data” used in AUW programs, but a number of these data categories are clearly inappropriate and the paper should not suggest they should be used by insurers:

- “assessor data”

Why is assessor data being used in AUW programs and how is it in anyway appropriate? Real estate value would seem to indicate nothing more than the respective wealth of an applicant – which does not necessarily correlate with personal health. It could easily create bias against low income or minority consumers who lack the resources to invest in real estate, but may still take care of their health. Moreover, it could prove misleading. An individual may have inherited a home, which would not demonstrate a level of “personal responsibility” required to save and invest. In which case it would merely reflect generational wealth, which again would create bias against low income or minority consumers.

² Insurers have insisted for years that credit and insurance scores provide an indicator of “personal responsibility” that reflect the sort of risks an insured might take. Clearly, a “personal responsibility” measure is “behavioral data” and should be subject to the standards for the usage of such data.

- “voter information”

Further information is required about the potential usage of voter information before it could be permitted in an AUW program, as the use of such data is potentially problematic.

- “Marketing and social data, e.g., shopping habits, mortgage amount/lender, occupation and education, and social media, etc.”
- “Professional licenses”

These data categories are concerning for the same reason that “assessors data” is – they appear to reflect income levels and generational wealth rather than “personal responsibility.” Moreover, categories such as “shopping habits” are rife with the potential for misleading conclusions. If a parent buys pizzas for a youth sports team frequently, or a large amount of hot dogs for school picnic or fundraiser, should they be tagged as having an unhealthy lifestyle? Classifying applicants based on their chosen mortgage lender would also raise the prospect of redlining. Should life insurance applicants be punished because only certain types of lenders issue mortgages in their neighborhoods? All of these should be identified as data categories that require further examination before being allowed to put into use in AUW.

- “Voice recognition used to determine smoking status”

As someone with a naturally raspy voice who has never smoked a day in my life, I find this particular data category particularly worrisome. Has the Working Group viewed or analyzed any scientific testing of voice recognition patterns? Like the “marketing and social data” listed above, this is concept is too underbaked to be included in a list of potentially acceptable data factors.

- “Facial recognition”

There should not even be the slightest suggestion that facial recognition software is appropriate to use in AUW programs. The NAIC has held a screening of the film “Coded Bias” which amply demonstrated that facial recognition

programs currently in use discriminate against people of color.³ Even if such discrimination is inadvertent and unintended, the outcome would be detrimental to consumers rather than beneficial.

Page 7

- “Form and rate reviewers may:
 - Request that the life insurer provides information about how a predictive model or machine learning algorithm will be used.
 - ~~Consider~~ ~~r~~ ~~Require~~ ~~ing~~ the filing of models used to analyze data.
 - ~~Consider~~ ~~q~~ ~~Question~~ ~~ing~~ the extent to which data elements correlate to applicant risk.
 - Request information about source data regardless of whether the data or score is provided by a third party.
 -

The filing of models and probing the basis for correlation should not merely be “considered” – they should be an essential part of regulatory review.

- “Life insurers have a responsibility to understand the data they are using. To accomplish this, life insurers should conduct post-issue audits and data analysis. For example, analyses such as evaluating claims and lapse rates may be helpful. [These audits and analyses should be available for review by regulators \(pursuant to appropriate confidentiality protections\)](#). Life insurers and third-party vendors should ensure data inputs are accurate and reliable.”

I agree that life insurers should be responsible for understanding the impact of the data they are using and how it impacts consumers. Any audits or analyses should be shared with regulators with appropriate trade secret protections.

³https://content.naic.org/article/news_release_naic_host_screening_and_panel_discussion_focused_big_data_and_artificial_intelligence.htm

Page 11

- “Any approach that an insurer ~~could have realistically~~ utilized in the year 2000 or prior.”

This standard is vague and unworkable, as it is unclear what the limits of “realistically utilized in the year 2000” might be. It would take far less interpretation simply to state that systems already in use in the year 2000 or earlier are not addressed by this paper. However, it begs the question – did the Working Group examine what programs and resources were available in the year 2000? If not, the entire sentence should be stricken.

Thank you for the consideration of these comments and I wish to thank the Working Group for the all the hard work done to date.

Sincerely,

/s/

Brendan Bridgeland
Director



AMERICAN ACADEMY *of* ACTUARIES

Objective. Independent. Effective.™

December 3, 2021

Honorable Mark Afable, Chair
Honorable Grace Arnold, Vice Chair
Accelerated Underwriting (A) Working Group
National Association of Insurance Commissioners (NAIC)

Dear Commissioner Afable and Commissioner Arnold:

One of the goals of the Life Underwriting and Risk Classification Work Group of the American Academy of Actuaries¹ is to monitor public policy developments regarding underwriting and risk classification for life insurance and annuities. We have reviewed the Ad Hoc Drafting Subgroup exposure draft of Nov. 8, 2021, and are pleased to have the opportunity to provide the following general comments. Due to the brief comment period, we were unable to provide more detailed comments.

- In general, we believe the recommendations contained in the paper are sound concepts. However, we note that some of the recommendations may be challenging to implement from a practical standpoint and others may require more detail in order to assure that they support the working group's charge related to the use of external data and data analytics in accelerated life underwriting.
- Although many of the comments provided to the working group included consumer benefits of accelerated underwriting, the paper tends to focus on the potential issues. We believe the paper might be more balanced if it included more discussion of the favorable impacts to the consumer and believe the table of contents may be a useful guide in such an effort.
- Throughout the development process of this draft paper, the working group has heard from a variety of stakeholders regarding different practices and with different perspectives. Not all of the information provided should be generalized across the life insurance industry, and we suggest revisions throughout the paper to avoid overgeneralizations. For example:
 - The paper generally assumes that accelerated underwriting uses predictive models or machine learning algorithms. However, the use of these tools is not a defining characteristic of accelerated underwriting, because some accelerated underwriting programs use only human underwriters. In addition, the use of these tools is not exclusive to accelerated underwriting, because the tools are used in all types of life insurance underwriting (e.g., simplified issue, full underwriting, etc.).
 - The draft paper implies that there is a distinct definition for "traditional" underwriting and that there is a differentiation between traditional underwriting and accelerated underwriting.

¹ The American Academy of Actuaries is a 19,500-member professional association whose mission is to serve the public and the U.S. actuarial profession. For more than 50 years, the Academy has assisted public policymakers on all levels by providing leadership, objective expertise, and actuarial advice on risk and financial security issues. The Academy also sets qualification, practice, and professionalism standards for actuaries in the United States.

- However, underwriting is an ever-changing continuum, and many of the practices used in accelerated underwriting are also used in full underwriting.
- “FCRA data is already used in property/casualty lines of business” may imply that Fair Credit Reporting Act (FCRA) data has not been used in life insurance, but FCRA data is already used in life insurance.
 - Common types of underwriting data are listed with uncommon data types, which may imply that there is a higher prevalence of less common data in the underwriting process.
- The definition of accelerated underwriting used in the draft paper is important, as it potentially paves the way for use of the term in other policy documents. The proposed definition conflates the general concept of accelerated underwriting and the use of data and predictive models in underwriting, but data and predictive models are used in all forms of underwriting. We recommend revisiting this definition and the use of these terms.
 - We do not understand why the bullet point “FCRA data may be used to predict mortality, but there may not be a reasonable explanation for that correlation” has a footnoted reference to Actuarial Standard of Practice (ASOP) No. 12. We do not find any portion of the bullet point that is specifically related to ASOP No. 12. The specific section of ASOP No. 12 should either be referenced and quoted if applicable or the reference to the ASOP should be removed.

We are available to support your efforts to refine this paper and would be able to provide a more thorough and nuanced review with an extended comment period.

If you have any questions or would like further dialogue on these topics, please contact Khloe Greenwood, the Academy’s life policy analyst, at greenwood@actuary.org.

Sincerely,

Sue Bartholf, MAAA, FSA
Chairperson, Life Underwriting and Risk Classification Work Group
American Academy of Actuaries

CC: Jennifer Cook

David Leifer

Vice President & Senior Associate General Counsel
(202) 624-2128 t
davidleifer@acli.com

Gabrielle Griffith

Sr. Policy Analyst & NAIC Coordinator
(202) 624-2317 t
gabriellegriffith@acli.com

December 3, 2021

The Honorable Mark Afable
Commissioner of Insurance, State of Wisconsin
Chair, NAIC Accelerated Underwriting (A) Working Group

The Honorable Grace Arnold
Commissioner of Commerce, State of Minnesota
Vice Chair, NAIC Accelerated Underwriting (A) Working Group

Sent via email to: Jennifer R. Cook, Sr. Health & Life Policy Counsel, NAIC Government Relations

Re: Comments Regarding Draft Part 3 of the Accelerated Underwriting White Paper

Dear Mr. Afable & Ms. Arnold:

On behalf of the American Council of Life Insurers (ACLI), thank you for the opportunity to again comment on the Accelerated Underwriting (A) Working Group draft white paper on accelerated underwriting. We appreciate the thoughtful work that has gone into developing this paper. There is much useful information contained in the current draft that should be helpful to regulators and stakeholders as accelerated underwriting evolves. We do have several suggestions we hope the Working Group can consider as it develops the next iteration of the white paper.

ACLI is supportive of establishing a clear process for understanding accelerated underwriting, however, we are concerned that the paper in places mischaracterizes the types of data used in traditional underwriting vs accelerated underwriting. The paper states that traditional underwriting assesses an applicant's physical health for determining coverage. While true, it also involves a financial and behavioral evaluation as is indicated in the list of sources reviewed in traditional underwriting. This statement implies limitation to physical health. We recommend including financial

American Council of Life Insurers | 101 Constitution Ave, NW, Suite 700 | Washington, DC 20001-2133

The American Council of Life Insurers (ACLI) is the leading trade association driving public policy and advocacy on behalf of the life insurance industry. 90 million American families rely on the life insurance industry for financial protection and retirement security. ACLI's member companies are dedicated to protecting consumers' financial wellbeing through life insurance, annuities, retirement plans, long-term care insurance, disability income insurance, reinsurance, and dental, vision and other supplemental benefits. ACLI's 280 member companies represent 95 percent of industry assets in the United States.

and behavioral evaluation as part of the statement.¹ We also recommend clarifying that accelerated underwriting is a process, and not a method. The methods can differ for this process, which is essentially fluidness underwriting.

Presentations made to the Working Group indicated that life insurers use accelerated underwriting in primarily two ways: to triage and rate applicants. The terminology “unsuccessful” and “successful” is misleading here, as accelerated underwriting may triage to a human underwriting, but that does not mean the applicant will be unsuccessful in obtaining coverage.

We recommend in the General Discussions section that the Working Group emphasize that while the technology is new, its risk for unfair discrimination should not be viewed differently than traditional underwriting. Accelerated underwriting utilizes technology to perform the same processes that a human underwriter would perform. Therefore, the focus of regulators should not be on how to regulate it further, but how to create requirements for transparency and explainability.

On page 3, paragraph 5, we recommend adding the following language in red “the accelerated underwriting process is less cumbersome, costs less than traditional underwriting, **it expedites the process and requires less consumer involvement in the purchase and** improves the underwriting experience for consumers. ~~shortens issue times, and increases policy acceptance rates~~ **Accelerated underwriting also holds the promise of improving and refining the underwriting outcomes.**”

On page 4, paragraph 1, there are various references in the paper to correlation or “claimed correlation,” and the idea of having a “valid explanation or rationale.” We recommend the following change in red: “Although medical data has a scientific linkage with mortality, behavioral data may lead to questionable conclusions ~~as correlation may be confused with causation~~ **as the observed correlation may not have a valid explanation or rationale.**” (i.e. ~~diabetes – diabetes causes~~ **health problems that are directly correlated with life expectancy. Most medical data is correlated with a medical condition. Underwriting is based on correlation, as opposed to causation, the latter of which reflects the manifested medical condition or disease. Underwriting, which is inherently predicative in nature, cannot function if it is confined entirely to causation.**

On page 4, bullet 2 in the list of recommendations we recommend adding the following language in red “Ensure that the **use of** external data sources...”

On page 4, bullet 4 we recommend the following: ~~Ensure that the predictive models or machine learning algorithm achieve an outcome that is not unfairly discriminatory.~~ **Monitor the use of predictive models and adjust as necessary, so that outcomes are not unfairly discriminatory.**

Below, we again identify themes for clarification:

- Characterization of Data

The paper in our view mischaracterizes types of data sources in several places, combining those that are more typically or traditionally used with more novel ones that are not used with prevalence (if at all) by the life industry. For example, the paper classifies use of data elements such as wearables and social media as “typical” by carriers, whereas very few life insurers utilize

¹ Traditional life insurance underwriting involves assessing the applicant’s physical health, then determining whether an applicant is eligible for coverage and the risk class to which that individual belongs.

these data sources. The paper conversely identifies traditionally used sources such as court records as “nontraditional” and implies FCRA is “new” in its use by the life industry. The life insurance industry has utilized these data sources (FCRA and non-FCRA) for many decades as part of the underwriting process. We understand the benefit of “flagging” new or novel data sources for regulator awareness, but it is critical in our view that regulators have a solid understanding of the existing and traditional use of data vs. the new or novel sources that are not being used by industry prevalently, if at all. It is also important not to create undue concern around practices that likely are not taking place.

- Public records is listed under both Traditional Data and Nontraditional Data, which may be fine since it is a broad category. However, it seems confusing to have example of “criminal records” listed under both.
- Negative Inferences

The paper seems to draw several conclusions relative to potential negative impacts without providing an opportunity for analysis. These might be more appropriate as questions for analysis and review rather than conclusions. Regulators are rightfully exploring accelerated underwriting and related issues within this Working Group and elsewhere. However, there is no evidence to date that accelerated underwriting has been used in a manner harmful to consumers. To the contrary, consumers seem very pleased with the speed and convenience offered by accelerated underwriting.

ACLI opposes racial discrimination and supports access for all consumers. Accelerated underwriting is an important tool for insurers to improve the underwriting experience, and it may hold the promises of helping insurers reach traditionally underserved markets. It may also be the case that accelerated underwriting can ultimately help reduce human bias. We think it important to bear in mind much of the technology involved in accelerated underwriting is still in the early stages of development. We are committed to advancing this technology while at the same time curtailing any unfair discriminatory effects that may lie within such structure. There is no empirical evidence that accelerated underwriting methods are unfairly discriminatory, but we continue to work on methods to help ensure that they are not.



Another continuing concern we have is over the use of the term “fair” throughout the draft. ACLI appreciates that this term is used in the NAIC AI Principles adopted in 2020, but the concept of “fairness” in insurance underwriting is not as straight forward as a lay person may conceive. Life insurance underwriting at its most basic level involves grouping similar risks together and charging a sufficient premium to the members of that group to cover expected claims, administration, etc. Not everyone is going to be in the same group, nor will every individual be insurable. This may strike some as “unfair”, but it is how the life insurance functions in a solvent fashion. We would urge that the white paper utilize the “unfair discrimination” standard that is well-understood in the industry.

- FCRA and non-FCRA Data

We question the usefulness in distinguishing between FCRA and non-FCRA data. Life insurers have long used FCRA and non-FCRA data and the use of it in accelerated underwriting is no different. We do think the list of “Traditional Data” is very accurate. Some of the discussion under “FCRA Data” is confusing. For example, the term “non-usable credit attributes” is unknown to us. More broadly, the assertion that more data is collected than used may or may not be accurate, but seems out of place in a paper about accelerated underwriting. As a point of correction, life insurers historically use FCRA data along with property/casualty lines.

Thank you again for the opportunity to comment on the White Paper. The drafting Subgroup has produced excellent work, and ACLI and our member companies look forward to reviewing and providing input on future iterations of the paper. As always, please let us know if there is specific information we can provide in furtherance of this project.

Sincerely,

 <p>David M. Leifer Vice President & Associate General Counsel 202-624-2128 DavidLeifer@acli.com</p>	 <p>Gabrielle Griffith Senior Policy Analyst and NAIC Coordinator 202-624-2371 gabriellegriffith@acli.com</p>
---	---