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Comments of the Center for Economic Justice

To the NAIC Accelerated Underwriting (A) Working Group

Regarding Draft "Regulatory Guidance and Considerations"

April 14, 2023

The Center for Economic Justice ("CEJ") offers the following comments on the draft "Regulatory Guidance and Considerations" for Accelerated Underwriting in Life Insurance.

CEJ appreciates the efforts of the working group to identify and address consumer protection issues with insurers' use of big data, algorithms and artificial intelligence – collectively referred to as Accelerated Underwriting ("AU"). We recognize the difficulty in carrying out your charge because of the constantly shifting responsibilities that touch on AU that have been assigned to a variety of different working groups and committees at the NAIC.

To an outsider, it appears to be a shell game with AU issues going from the Life Actuarial Task Force in 2016 to, in no particular order, the Life Insurance Committee, the Big Data Working Group, the H Committee, the Market Conduct Annual Statement Blanks Working Group and perhaps others. We suspect that all of this movement of AU-related responsibilities around the NAIC has made your work more difficult as you try to stay in your lane while respecting the work of other group. The description, in the draft guidance document, of the related work of other NAIC entities reflects this fractured approach – nearly two full pages of the five-page document describe potential AU-related activities of other NAIC groups.

While we continue to appreciate the AU WG efforts, the draft regulatory guidance document unfortunately provides little regulatory guidance. In the five-page document, the first page is an introduction. Pages 2 and 3 discuss the work of other NAIC groups. The regulatory guidance provided is limited to the last two pages of the document and much of this is not actually guidance. Page 4 consists largely of "considerations" without reference to statutory authority and without guidance for how to address these considerations. At the bottom of page 4 onto page 5, the draft provides general descriptions of things to do, but, again, fails to link these regulatory requests to statutory authority or to particular issues of concern. The questions on page 5 are similarly without context regarding when and how to ask the questions. In addition, many of the terms used in expectations and questions are undefined.

The two pages of regulatory guidance in the draft are essentially the same general issues of concern raised in 2016 at the Life Actuarial Task Force and raised continuously since at each of the NAIC groups through which AU has migrated. The draft regulatory guidance provides no references for further information, despite a list of 17 documents on the AU WG web page.

Below, CEJ offers for the AU WG's consideration substantive regulatory guidance – guidance that would provide a clear road map based on statutory authorities to examine insurers' AU practices and show how to examine issues of regulatory concern. Included in the guidance are specific referrals to the Market Regulation and Consumer Affairs (D) Committee, marked with a footnote. We ask the AU WG to revise the draft referral to the Market Conduct Examination Standards Guidelines Working Group to reflect the suggestions in the proposed revised draft regulatory guidance. Please see footnotes 5, 6, 7, 9 and 11 in the proposed regulatory guidance document for proposed referrals to the D Committee.

Finally, we request the AU WG hold an interactive meeting with stakeholders, as is the norm for working groups developing regulatory guidance. Examples include the detailed discussion of stakeholder comments at the Restructuring Mechanisms and Privacy Protections working groups, among many others past and current. Those sessions not only allow regulators to ask questions of stakeholders, but provide stakeholders with an understanding of why regulators decide to accept or reject particular recommendations.

Thank you for your consideration.

Proposed Guidance for Regulatory Oversight of Life Insurers' Accelerated Underwriting Practices

Foundation

This section provides foundational information and concepts to provide the basis for the guidance to regulators that follows.

What is Accelerated Underwriting in Life Insurance?

The NAIC Accelerated Underwriting Working Group ("AU WG") developed an educational paper, subsequently adopted by the Life Insurance and Annuities (A) Committee in April 2022. The educational paper provides the following definition / description of Accelerated Underwriting ("AU")

> Accelerated underwriting (AU) is the use of big data, artificial intelligence, and machine learning to underwrite life insurance in an expedited manner. The process generally uses predictive models and machine learning algorithms to analyze applicant data, which may include the use of non-traditional, non-medical data, provided either by the applicant directly or obtained through external sources. The process is typically used to replace all or part of traditional underwriting in life insurance and to allow some applicants to have certain medical requirements waived, such as paramedical exams and fluid collection.[1]

AU as a Continuum of Big Data and Artificial Intelligence ("AI") Practices

Insurers' use of big data, algorithms and AI runs along a continuum from speeding up traditional underwriting through automated processes and access to third party data sets to replacing traditional underwriting completely with algorithms and non-traditional data. On one end of the continuum, the insurer may speed up the underwriting and pricing process by obtaining data from third party sources instead of from the consumer in an application.

For example, instead of asking a consumer about their prescription drug use, the insurer might access a third party prescription database. Instead of obtaining a consumer credit report to review for financial distress / bankruptcy, the insurer might obtain a credit score based on the consumer's credit information.

[1] https://content.naic.org/sites/default/files/inline-files/AUWG%20DRAFT%203-4-22%20for%20SNM_0.pdf at page 2.

At the other end of the continuum is total replacement of traditional underwriting through an algorithm that takes basic information identifying a consumer to access personal consumer information about that consumer from third party sources to perform underwriting without a medical examination or analysis of body fluids. AU may involve the use of biometric algorithms, described in more detail below, which analyze biometric information – facial or body analytics – in real time during a video application interview.

While all or nearly all insurers have embarked on some degree of AU, there is a diversity among insurers in where they are along the continuum. An important take away from this diversity is that the term "AU" is likely to mean different things to different insurers based upon their business models and degree of data sophistication. The description / definition of AU in the NAIC AU Education Paper recognizes and reinforces this understanding. Consequently, regulators should frame information requests in terms of data and algorithms and technologies used by the insurer instead of asking for information about "AU" to ensure consistency in understanding by insurers about the information requested.

Profound Benefits Possible, Not Guaranteed

This document focuses on regulatory guidance for consumer protection and fair competition among insurers. Consequently, the document identifies a variety of issues of concern for regulators and potential problems with insurers' use of big data, algorithms and AI.

It is important to state that insurers' use of AU holds tremendous promise for consumer benefit – from lower costs and greater convenience for consumers to greater availability and affordability of essential life insurance protection to new types of insurer-consumer relationships to promote greater health and longevity.

The potential benefits are profound, but not guaranteed. The purpose of the regulatory guidance document is to alert regulators to practices that may thwart the realization of these consumer and insurer benefits and that may create unfair competition. But, the document should not be interpreted as doubting the great potential consumer and societal benefits of insurers' use of AU.

Traditional Underwriting / AU Predicting Mortality or Traditional UW Results

Like AU, "traditional underwriting" is a term that may vary based on the insurer, the insurer's business model and product mix and the time frame being referenced. At one time, traditional underwriting was largely based on age, gender and smoker/non-smoker mortality tables supplemented by information provided by the applicant in an application (family medical history, medical condition, dangerous hobbies) and, in some cases, medical exams with or without body fluid analysis.

The foundation of traditional underwriting has been – and continues to be – mortality tables that review many decades of insurer life insurance experience. These tables have historically been developed by the Society of Actuaries, subject to approval and adoption by the NAIC's Life Actuarial Task Force (and subsequent adoption by parent committees).

Over time, some of the manual underwriting processes were automated or semi-automated, but still remain part of a traditional underwriting approach – analyzing the same information, but getting it from sources other than the applicant and/or analyzing the traditional information in more granular detail to allow greater use of predictive models to produce greater segmentation among consumers – i.e., more price levels.

With new sources of data and advanced analytics, some insurers, reinsurers and vendors developed new approaches to underwriting – AU – that replace some or all of traditional underwriting data with different types of information. But since there is no set of mortality tables associated with these new sources of data, it is not possible to analyze, say, 50 years of mortality experience with the new data. Consequently, some AU applications are based on predicting what the traditional underwriting outcome would be as opposed to directly predicting mortality.

The distinction between an AU algorithm developed on the basis of actual mortality experience versus one developed on the basis of predicting or replicating the traditional underwriting result is significant. If a regulator seeks assurance that an insurer's underwriting is producing actuarial fair outcomes, then the relevant outcome to analyze is mortality. The fact that an AU algorithm faithfully mirrors the outcomes of traditional underwriting is, at best, a proxy for actuarial fairness and deserves careful scrutiny to ensure the traditional underwriting results were not biased on either actuarial or protected class basis.

Regulatory Authority

Regulatory oversight of insurers' use of AU represents both a continuation of traditional regulatory responsibilities and oversight and the need for new approaches. With traditional underwriting, the number of risk classifications used were limited and largely reviewed and overseen by regulators in the form of mortality tables. With AU, insurers are now using a variety of data and analytic approaches for which regulators do not have the same direct oversight as with mortality tables and, consequently, new approaches are needed for regulators to ensure AU meets statutory standards of fairness.

Regulators generally have broad authority to examine insurer practices. While insurers' use of big data and AI, generally, and AU, specifically, may require additional regulatory authorities or different approaches from traditional regulatory oversight, there is a solid foundation of regulatory authority for insurance regulators today.

- Information and Data Requests: Regulators have broad authority to request information form regulated entities. This authority works well for information maintained by the insurer or the insurer's agents or third parties acting under the authority of the insurer (such as a third party administrator), but may be problematic for third party vendors supplying data or algorithms for the insurer's AU practices.

  Regulators may ask third party providers of data and algorithms for information and many are willing to respond to the regulatory requests. For example, vendors providing credit-based mortality scores have indicated a willingness to share information with regulators – just as these same vendors do with credit-based insurance scores for auto and home insurance.

  However, some third-party vendors of data and algorithms may not be willing to provide the information sought by regulators. If the absence of information from third party vendors prevents the regulator from ensuring the insurer's compliance with statutory requirements, then the regulator may need to resort to disapproving or disallowing a particular insurer practice or algorithm unless and until the relevant third party vendors provide the information needed by the regulator.

- Unfair Discrimination on the Basis of Protected Class Status: Most states have laws in place that prohibit insurers, including life insurers, from discriminating on the basis of protected class characteristics. The protected class characteristics typically include race, religion and national origin, but may include other characteristics.

- Unfair Discrimination on An Actuarial Basis: Most states require that insurers treat similarly situated consumers the same, meaning that any difference in treatment of consumers for underwriting, pricing or claims settlement must be based on sound actuarial analysis and reflect a difference in the expect costs of the transfer of risk. If there is no actuarial basis for treating consumers differently, those consumers have experienced unfair discrimination.

- Unfair and Deceptive Trade Practice: For life insurance, unfair discrimination prohibitions are often found in unfair trade practices statutes or regulations. In addition, the unfair trade practices regulatory authority may be used to address deceptive and misleading practices by insurers. This is particularly relevant for issues of disclosure and consent for the insurers to collect, use and share personal consumer information.

Unfair Discrimination Definitions

With the advent of new data sources, data mining, and AI generating new models and algorithms used by insurers, there is increased potential for some data and models to reflect, perpetuate or amplify historical discrimination, particularly discrimination on the basis of race.

Regulators need precise definitions for different types of unfair discrimination to ensure a consistent understanding across all stakeholders and to facilitate consistent regulatory analysis and treatment. Using the protected class characteristic of race:

Disparate Intent is intentional use of race to discriminate in any aspect of the insurance life cycle. Regulators hope and believe that life insurers no longer use race explicitly for underwriting, pricing, claims settlement or antifraud activities.

Proxy Discrimination means disproportionate racial outcomes tied to the use of proxies for race, not to outcomes. The data source or algorithm is actually predicting race and not the insurance outcome.

Disparate Impact means disproportionate racial outcomes tied to historic discrimination and embedded in insurance outcomes. The data source is correlated to race, but also predicts the insurance outcome because the racial discrimination is baked into the insurance outcomes.

Regulatory guidance for how to use these definitions is provided below.

Dark Patterns

Dark Patterns is a term used to describe digital manipulation.

> *"Dark patterns are user interface techniques that benefit an online service by leading consumers into making decisions they might not otherwise make. Some dark patterns deceive consumers, while others exploit cognitive biases or shortcuts to manipulate or coerce them into choices that are not in their best interests."*
>
> *"As documented in several research studies, consumers may encounter dark patterns in many online contexts, such as when making choices to consent to the disclosure of personal information or to cookies, when interacting with services and applications like games or content feeds that seek to capture and extend consumer attention and time spent, and in e-commerce, including at multiple points along a purchasing journey".*[2]

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[2] https://freedom-to-tinker.com/2022/08/10/recommendations-for-updating-the-ftcs-disclosure-guidelines-to-combat-dark-patterns
Two resources on dark patterns are:
https://content.naic.org/sites/default/files/national_meeting/Consumer_Handout_CEJ_dark_patterns_SpNM.pdf
and

> *"At their core, dark patterns are a specific type of choice architecture in website and app design that interfere with user autonomy and choice. Dark patterns modify the presentation of choices available to users or manipulate the flow of information so that users make selections that they would not otherwise have chosen—to their own detriment and to the benefit of the website or app provider. Hallmarks of dark patterns include imposing asymmetric burdens to achieve competing choices, restricting the choices available at the same time (or at all), and hiding information or presenting information deceptively."*[3]

The issue of dark patterns or digital manipulation is directly relevant for regulatory oversight of AU because of disclosure for and consumer consent to the use by the insurer of consumer personal consumer information. As discussed in the section below on the Fair Credit Reporting Act ("FCRA"), not all data sources used by insurers for AU are subject to the consumer protections of the FCRA and the FCRA itself has some limitations.

Regulatory oversight of insurers' AU practices should include review of insurers' privacy notices and consumer consent methods to ensure consumers are not misled into sharing personal information for uses they did not intend. Ensuring the absence of dark patterns in AU is a necessary aspect of ensuring insurers are not engaging in unfair or deceptive practices.

Fair Credit Reporting Act

The FCRA (other than HIPAA which relates to consumers' personal health information) is the core federal law regarding the collection, use and sharing of personal consumer information. The FCRA can enforced by the state agencies as well as the federal Consumer Financial Protection Bureau. The basic structure of the FCRA is as follows:

An organization that collects and distributes personal consumer information is a consumer reporting company. A report of personal consumer information produced by a consumer reporting company is a "consumer report."

Businesses that collect personal consumer information may report that information to a consumer reporting company, which, in turn, can provide consumer reports to eligible business and persons.

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https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3431205
[3] https://www.bytebacklaw.com/2022/03/how-do-the-cpra-cpa-and-vcdpa-treat-dark-patterns/

The major credit reporting agencies are FCRA consumer reporting agencies and the consumer credit reports they produce and sell are consumer reports. But there are dozens of other consumer reporting companies covering employment screening, tenant screening, check and bank account screening, personal property insurance, medical, utilities and more. The CFPB publishes a list of consumer reporting companies with basic information about consumer rights.[4]

In addition to consumer credit reports (which may be used in credit-based scores) for AU, any of the consumer reports might be used by an insurer as part of a data mining and predictive analytics exercise. Insurers and health care providers contribute data to consumer reporting companies, including the following. However, insurers may use any consumer report from a consumer reporting agency – not just the ones to which they contribute:

- A-Plus by Verisk – claims and loss history associated with homes, auto or personal property

- Drivers History by TransUnion – information and data from public sources and government agencies regarding driving violations.
- Insurance Information Exchange by Verisk – collects and reports motor vehicle records, including traffic violations, employment and education verification services, government sanctions searches, and criminal background checks.

- C.L.U.E. by LexisNexis -- Comprehensive Loss Underwriting Exchange is a claims information exchange for auto and property insurance. It collects and reports up to seven years of auto and personal property claims. It also provides insurance risk scores to help inform pricing and underwriting decisions for the insurance industry

- MIB by MIB, Inc – Collects information about medical conditions and hazardous avocations with your authorization. It reports this information to life and health insurance companies to assess your risk and eligibility during the underwriting of individual (rather than as a member of a group) life, health, disability income, critical illness, and long-term care insurance policies.

- IntelliScript by Milliman – Collects prescription drug purchase history for quantifying the relative mortality risk of life insurance applicants and provides risk scores for underwriting decision

[4] https://files.consumerfinance.gov/f/documents/cfpb_consumer-reporting-companies-list_2023.pdf

A business seeking to obtain a consumer report must do the following:

- Disclose the business's intent to obtain a consumer report
- Obtain the consumer's consent to obtain the consumer report
- Use the consumer report only for permitted uses
- Protect the consumer's personal consumer information
- Advise the consumer if the business's use of the consumer report resulted in an adverse action through an adverse action notice.
- Advise the consumer of their rights to obtain a copy of the consumer report, dispute inaccuracies in the consumer report, correct information in the consumer report and have the adverse action reviewed based on an accurate consumer report.
- For certain types of consumer reports, a consumer can place a freeze on the report to prevent third party access to the consumer reports.

The FCRA has requirements for both consumer reporting agencies and businesses that seek to obtain a consumer report from a consumer reporting company. The consumer reporting agencies are subject to oversight by the CFPB and to requirements for data accuracy, protection of data, provision of reports about individual consumers to those consumers, dispute resolution and error correction, among others.

Non-FCRA Data

There are suppliers of personal consumer information who are not subject to the FCRA, including data brokers, social media companies, companies obtaining social media data and the big web and mobile phone data vacuums – Google, Amazon, Apple and others.

Generally, none of the FCRA consumer protections apply to these entities and data sources. In some cases, organizations that are FCRA-compliant for some types of personal consumer information also provide other types of personal consumer information marketed as non-FCRA data, meaning not subject to the requirements of the FCRA.

Because of the absence of FCRA consumer protections, life insurers' use of non-FCRA data may raise concerns about transparency, disclosure, consent, accuracy, error correction, ability to dispute and notice of adverse action as well as racial or other protected class unfair discrimination.

Getting Started

Lay of the Land Information Requests

Regulators should start with data and information requests to all life insurers to get information about life insurers' use of big data, algorithms, models and AI – all of which comprise AU.

Information Request 1: Data Sources and Uses: This request should go to all life insurers with the following information requests:[5]

- Date of Report
- Data Type –What is the Data?
- Source of Data – Consumer via Application, Consumer via Wearable Device or other internet-connected device, Insurer Internal, Third Party, Other
- FCRA Compliant – Yes or No
- Use Category – Marketing, Underwriting (Eligibility/Terms), Pricing, Claims, Anti-Fraud, Risk Prevention, Loss Mitigation, Consumer Relations/Retention
- Models Utilizing These Data – Which of the insurer's' models utilize this data type

With this information, the regulator can quickly assess the state of AU in your jurisdiction. A best practice would be, following the initial reporting by insurers, to require insurers to provide updates every six months identifying any changes from the previous report.

Based upon this initial review, the regulator may want to dig deeper by asking insurers about their AU algorithms identified in the Data Sources and Uses reports.

Information Request 1A – Algorithms and Models: This information request provides the regulator with information to take the deeper dive into AU models:[6]

- Date of Report
- Name of Model or Algorithm
- Internally Developed or Third Party Algorithm
- If Third Party, Name of Vendor
- Date First Deployed
- Date Current Version Deployed

[5] The detailed development of this information request has been referred to the Market Regulation and Consumer Affairs (D) Committee.
[6] The detailed development of this information request has been referred to the Market Regulation and Consumer Affairs (D) Committee.

- Current Version Number
- Purpose(s) of Algorithm (Marketing, Underwriting, Pricing, Claims Settlement, Antifraud, Risk Mitigation Partnership, Other)
- Data Inputs, Sources of Data Inputs (Consumer, Insurer, Third Party, Other) and whether Data are FCRA-compliant (subject to FCRA requirements).
- Unfair Discrimination Test Results
- Actions Taken to Address Unfair Discrimination Test Results
- Consumer Complaints Arising from Use of the Model (since last report)
- Actions Taken with Respect to the Model to Address Consumer Complaints
- Results of Tests to Ensure Model is Performing as Intended
- Actions Taken in Response to Testing of Actual Model Performance

Disclosure and Consent for Collection and Use of Personal Consumer Information

Regulators expect that insurers' AU practice will be transparent and fair to consumers. Transparency requires meaningful disclosure of the personal information the insurer intends to collect or has already collected and the opportunity for the consumer to consent to specific uses by the insurer. This transparency requires a clear notice and disclosure to the consumer as well as a meaningful opportunity to decline some or all of the data collection and uses proposed by the insurer.

With AU – and, more generally, with more digital applications and consumer interactions – the issue of dark patterns or digital manipulation takes center stage. When a consumer goes to a life insurer's web site and seeks to obtain a quote, does the digital interface clearly disclose what personal consumer information will be obtained with the consumers' consent and without the consumers consent? Does the digital interface make it straightforward for the consumer to identify and decline data uses not essential to the insurance transaction?

Information Request 2: Privacy Policies and Screenshots of Disclosure and Consent Architecture for Collection and Use of Personal Consumer Information[7]

- Privacy Policies (Text)
- Screenshots of Disclosure of Personal Consumer Information Collected
- Screenshots of Consumer Consent Architecture

[7] The detailed development of this information request and guidance for identifying dark patterns has been referred to the Market Regulation and Consumer Affairs (D) Committee

Review of this information allows the regulator to identify misleading, deceptive or insufficiently transparent disclosures to the consumer regarding the collection and use of their personal information as well as identifying potential dark patterns. Given the use of both FCRA and non-FCRA data sources by life insurers with AU, such review is essential to ensure the absence of unfair and deceptive practices and a level playing field among life insurers. The regulator will likely follow up on the review of these documents with a hands-on use of the insurer's web site.

Unfair Discrimination – Insurer Model Governance and Testing

All life insurers will have some approach to governance of data use, models, algorithms and AI applications. This regulatory guidance will focus on testing for unfair discrimination on the actuarial and protected class bases.

While regulators are likely familiar with methods of testing for actuarial fairness, testing for protected class unfair discrimination – proxy discrimination and disparate impact may be new concepts. Testing for protected class unfair discrimination has much greater relevance and importance in an era of big data, complex algorithms, AI and AU than ever before because the new sources of data used for AU may reflect historical discrimination. Intent is not a requirement for protected class unfair discrimination. Facially neutral data sources, individually and collectively within an algorithm, may reflect historic discrimination. When an algorithm is trained on data that reflects racial bias, the algorithm will learn that bias and replicate it, absent a conscious effort to identify the racial bias. This potential is well recognized. Barocas and Selbst state the issue succinctly:[8]

> 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.

Most data sets of personal consumer information as well data sets of the built environment reflect historical discrimination against protected classes. For example, TransUnion has an insurance score used for pricing based on criminal violations filed with the courts – not just convictions, but all criminal filings regardless of the eventual outcome. TransUnion's marketing materials state:

[8] http://www.californialawreview.org/wp-content/uploads/2016/06/2Barocas-Selbst.pdf

> "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."

It did not take the recent murders of Black Americans by police to recognize that this "criminal history score" will reflect historic discrimination in policing against Black Americans and perpetuate that discrimination in insurance. Consider policing records in Ferguson, Missouri.

> <u>US DOJ Investigation of the Ferguson Police Department</u>
> 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.
>
> 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.

One of the oft-cited benefits of big data analytics in insurance is greater personalization – the ability of insurers to develop products and pricing tailored to individual needs and characteristics. But the other side of personalization is exclusion. Insurers' use of algorithmic techniques called price optimization, claim optimization and customer lifetime value are examples of the flip side of big data personalization – differential treatment of groups of consumers that may reflect and perpetuate inherent bias and systemic racism.

The TransUnion Criminal History Score is just one example data sources and algorithms that may reflect and perpetuate historic discrimination against protected classes in insurance – algorithms that reinforce inherent bias and systemic discrimination. Another example relevant to regulators' review of life insurers' use of AU is facial recognition technology or, more broadly, biometrics. A number of cities – as well as Google and IBM – have stopped using facial recognition technology because of the biases against Black Americans.

Protected Class Unfair Discrimination Analysis is Straightforward and Particularly Suited to Insurance.

The insurance industry has the precise skill set needed to identify and eliminate proxy discrimination and minimize disparate impact.

Let us revisit proxy discrimination and disparate impact forms of protected class unfair discrimination. Proxy Discrimination occurs when a predictive factor or data source 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. Since proxy discrimination violates both the actuarial and protected class versions of unfair discrimination, the particular factor or data source should be discarded.

Disparate Impact occurs when the insurance outcomes are racially-biased because the racial bias in embedded in the insurance outcomes. For example, certain health conditions disproportionately impact African Americans. Historic residential property redlining is associated with a variety of disproportionate health impacts on communities of color.

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.

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.

There is a long history of and many approaches to identifying and minimizing disparate impact in employment, credit and insurance. However, 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.

Regulators should expect that life insurers would test their AU algorithms for both actuarial and protected class unfair discrimination during the development of the AU algorithm and following the deployment of the AU algorithms. Information request 1A, noted above, asks insurers to report information that describes this testing as well as actions taken to address any problems found from testing.

Unfair Discrimination – Regulatory Data Collection and Independent Testing

In addition to reviewing insurers' self-testing of the AU algorithms for unfair discrimination, regulators should also collect granular consumer market outcome data for independent regulator testing. There are several reasons for independent regulator testing in addition to insurer self-testing. First, models don't always perform as intended. While an insurer model may not intend to produce racially biased results, the outcomes may, in fact, be racially biased in a manner that can be prevented or minimized. Second, regulators can utilize a common testing method across all insurer market outcomes to produce metrics comparable across insurers. Third, trust but verify. Insurer testing may be flawed. Fourth, the aggregate industry results may show racial bias even if individual insurer results do not. Fifth, testing based on data containing final quotes – including both policies issued and not issued – provides insight into potential bias in marketing algorithms.

Information Request 3 – Granular Consumer Market Outcome Data – These data should include a record for each final life insurance quote with all the risk characteristics utilized by the life insurer. Each record will include, among other things, whether the quote resulted in policy issuance and demographic information about the applicant collected by the insurer.

The AU WG has identified three possible options for the Market Regulation and Consumer Affairs (D) Committee to consider in developing detailed speculations and approaches for this information request[9]:

- Revise the current life insurance Specialized Data Request developed for market conduct examinations;
- Revise the Market Conduct Annual Statement;
- Supplement Life Insurance reporting for principles based reserving. Life insurers will be reporting granular sales and claims data to the NAIC pursuant to the PBR valuation manual sections VM 50 and VM 51.
- Develop a separate statistical plan for life insurance and appoint a statistical agent to collect the data from insurers on behalf of the regulations. This approach would eliminate the need for the Life Insurance MCAS.

<u>Regulatory Testing for Unfair Discrimination Using Granular Consumer Market Outcome Data</u>

As noted above, there are well-accepted methods of testing for protected class bias. One common approach is to add a data element to each consumer market outcome data to infer the racial characteristic of the applicant. While insurers do not collect this information during the application process – and, consequently, cannot report it – there are well-accepted methods of

[9] The detailed development of this information request and has been referred to the Market Regulation and Consumer Affairs (D) Committee.

inferring a race to individual consumer market outcome records. A commonly used approach is the Bayesian Improved First Name Surname and Geocoding (BIFSG) method which uses surnames, first names, and residential addresses to indirectly estimate race and ethnicity.[10][11]

Data Categories and Models of Particular Concern

There are several categories of data and algorithms used in life insurance AU that raise particular concern and may warrant specific regulator treatment.

Consumer Credit

Several vendors, including some credit reporting companies, have developed credit-based mortality scores. Regulators should consider the following. Most states have adopted laws governing insurers' use of consumer credit information to supplement general unfair discrimination prohibitions and general FCRA requirements. A few states prohibit insurers from using consumer credit information for underwriting or pricing auto and home insurance. Most states' laws insurance credit scoring laws are based on or are similar to a model law created by the National Council of Insurance Legislators (NCOIL).[12]

For states that permit the use of consumer credit information in insurance, your state's insurance credit scoring model provides a basis for evaluating the fairness of a life insurer's credit-based scoring model.

Genomic Information

Millions of consumers have utilized DNA testing services like 23 and Me or Ancestry.com. In some cases, these services have provided consumer genomic data to others without knowledge or conscious consent by the consumers. Regulators should make sure that insurers are not accessing consumers' genomic information without clear consent by the consumer.

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[10] See https://aspe.hhs.gov/sites/default/files/documents/931e1e3edec745ea7fdd364f9e28d6c6/aspe-rand-imputation-race-ethnicity-mktplc-rpt.pdf. In addition, as of April 2023, the Colorado Division of Insurance and District of Columbia Department of Insurance Securities and Banking had retained O'Neil Risk Consulting & Algorithmic Auditing to employ the BIFSG method to test for unintentional racial bias.
[11] The detailed development of testing for unfair discrimination has been referred to the Market Regulation and Consumer Affairs (D) Committee.
[12] https://33afce.p3cdn2.secureserver.net/wp-content/uploads/2020/10/Credit-Model-readopted-9-26-20.pdf

Biometric Information

Biometrics refers to the measurement and statistical analysis of an individual's physical and behavioral characteristics. The technology associated with biometrics has many uses but frequently is used to verify personal identity. Examples of physiological characteristics include: DNA, fingerprints, face, hand, retina or ear features, and odor. Examples of behavioral characteristics include gestures, voice, typing rhythm, and gait.[13]

Facial recognition is the most common form of biometrics and, as discussed above, has been identified and racially biased.[14] Other algorithms either used by or marketed to life insurers include biometric analysis of video interviews or assessing the truthfulness of an applicant or the biological age of the applicant. New algorithms score consumers based on how they fill in / complete online forms.

Regulators should quickly identify any biometric data sources and algorithms used by life insurers and require the insurers to demonstrate that any use of such data or algorithms are fair and not unfairly discriminatory.

Criminal Histories and Criminal History Scores / Motor Vehicle Records

Regulatory concern with criminal histories and criminal history scores was discussed above. Some life insurer AU models utilize driving records – moving violations, for example – in AU models. Because of documented bias in policing, regulators should require insurers to demonstrate that their AU models that utilize these data sources do not produce unfairly discriminatory outcomes

Other AU data sources and algorithms that raise particular concern about unfair discrimination and for which regulators should require insurers to demonstrate the absence of unfair discrimination include:

- Consumer Lifetime Value Scores
- Fraud or Propensity for Fraud Scores
- Social Media
- Telematics / Wearable Devices

[13] https://www.jacksonlewis.com/sites/default/files/docs/IllinoisBIPAFAQs.pdf
[14] The NAIC hosted an event on facial recognition and racial bias in 2021. Regulators may want to view a recording of that session for background on the issue.

Availability of AU Products

Another issue for regulators to consider with AU is whether all consumers have the same access to AU life insurance products. Analysis of information request 3: Granular Consumer Market Outcome Data enables regulators to determine whether AU products are being sought by or offered to consumers from all communities.