Thank you for the opportunity to comment on the AUWG January 25, 2022 draft Educational Paper. We appreciate the significant time and effort the Working Group has put into this process. We also support the December 3, 2021 comments filed by the Center for Insurance Research and the Center for Economic Justice on the November 8, 2021 exposure draft, many of which are applicable to the current draft. Our comments are below; the page numbers refer to the WG’s 1/25/2022 clean draft.

**Page 1, paragraph 2.** “… regulators and insurers should be guided by current law related to fair trade practices and unfair discrimination. Regulators and insurers should continue to monitor accelerated underwriting practices as they develop to avoid unfairly discriminatory practices. Much of the discussion in this paper is framed in these general terms.”

We agree with earlier comments that “should be guided by current law ….” suggests that complying with these laws is optional or a best practice rather than a legal requirement, though we doubt this clause will cause actual confusion. More important, is that even for an introduction to an educational paper, the language quoted above is anodyne and states a conclusion that was clear and obvious before the WG started its work. This – unintentionally – immediately diminishes the credibility or usefulness of the paper, which would be unfortunate given its potential value and the time you have spent on it.

If the intent is to link the two concepts in this paragraph, then perhaps: “When examining accelerated underwriting practices, regulators should be guided by current laws related to fair trade practices and unfair discrimination, and also recognize that the use of big data and artificial intelligence over the last five years has demonstrated that these standards need to be updated to meet these new challenges, and perhaps new regulatory tools added.”

**Page 1, definition of Accelerated Underwriting.** As the AAA, CEJ and Cir pointed out in their earlier comments, parts of this definition are inaccurate. For example, “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.” Page 2, bullet point three, December 3, 2021 AAA letter to the WG.

**Page 3, General Discussion of Issues and Recommendations.** “Life insurers reliance on an increasingly automated underwriting process that uses non-traditional, non-medical data presents new regulatory challenges.”

We think this reference to “new regulatory challenges” is necessary and also more consistent with our proposed language above – “… has demonstrated that these standards need to be updated to meet these new challenges, and perhaps new regulatory tools added” – than the current draft language, which suggests regulatory standards developed decades before are sufficient to protect consumers now.
Pages 3-4, General Discussion, Recommendations – Transparency.

Appropriately, the draft emphasizes the importance of transparency – “the use of accelerated underwriting in life insurance should be fair and transparent to regulators, consumers, and policymakers” (p. 4, first sentence in Recommendations). This statement is unarguable and can be supported by all interested parties, which is why it does not provide meaningful guidance nor advance the determination of what transparency in Accelerated Underwriting would consist of for regulators, consumers, and policymakers. The NAIC’s Principles on Artificial Intelligence already established important baseline standards for future NAIC white papers, model laws, and other regulatory guidance documents to flesh out and put into regulatory practice. This educational paper is an opportunity to begin this difficult but necessary work, rather than repeat what has already been acknowledged, and delaying the time when principles are translated into actual consumer protections. Along with likely every interested party, we would be happy to work with the AUWG to draft specific recommendations on transparency.

Pages 3-4 (and throughout the draft), General Discussion of Issues and Recommendations – Unfair Discrimination.

We believe one of this paper’s most important accomplishments is building upon the Principles of Artificial Intelligence and making clear that the fair treatment of consumers and the definition of “unfair discrimination” is more than not utilizing prohibited classifications and ensuring that the classifications and results are actuarially sound (“actuarially fair”). Similarly, the draft does not limit its definition of unfair discrimination to actions with a discriminatory intent. As North Dakota Commissioner Jon Godfread noted at an Innovation and Technology meeting last year, if our goal is to prevent the harm caused, or remedy it after, then the AI actor’s intent is not relevant as the harm or damage is the same.

Assuming We have interpreted the paper’s intent accurately, then it would be a benefit to state this directly, rather than inferring this principle from various sections of the draft. These provisions could also be modified, for example in page 3:

One particular challenge is the potential for unfair discrimination. Due to the fact accelerated underwriting relies on non-traditional, non-medical data and 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, and the model designers and users did not intend the unfairly discriminatory outcomes. 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 or ones that are not actuarially sound.

Page 4, Input Data. “Because accelerated underwriting relies on predictive models or machine learning algorithms that use non-traditional, non-medical data, it may lead to unexpected or unfairly discriminatory outcomes, even though the input data may be facially neutral and the risk classifications actuarially valid.”
Like the comments above, we think this proposed modification supports AUWG’s position that actuarial fairness and facially neutral input data are necessary, but not by themselves sufficient to demonstrate a fair and acceptable model, as the term is used in the NAIC’s Principles of Artificial Intelligence.

**Page 5, Inclusion of Criminal Records within the list of Traditional Data.** There is no question that criminal records are used in insurance underwriting including life insurance. However, this is an opportunity to recommend its use be significantly curtailed for several reasons, including (1) record accuracy (especially arrest records that are not correlated with an actual conviction or plea), (2) the effects of using criminal history in our country, where it is estimated 1/3 of adult citizens have a criminal record,\(^1\) and most critical, (3) the recognition that our criminal justice system is not neutral, reflects and contributes to systemic racism in our society, and that therefore the data it produces, ranging from records of major felonies to violations of municipal ordinances and motor vehicle infractions, disproportionately affect disadvantaged groups, including people of color and the poor.\(^2\) For these reasons, along with the growing number of risk classifications available to insurers that do not replicate the often harsh results our criminal justice system, the WG can advise that its use should be evaluated and limited to specific risks where criminal history is both directly relevant to the risk (e.g., prior convictions for insurance fraud) and other risk factors cannot adequately replace the established predictive value of criminal record data.\(^3\) If not part of this educational paper, the AUWG should study this issue in more detail for a subsequent addendum or report.

**Page 5, Considerations for use of Traditional Data.** “The relationship of the traditional data elements to the risk is well established and consumers generally understand how most of the elements impact their risk classification or premium charged.”

While we all wish this was true, it is unfortunately not. As has been discussed at many NAIC presentations over the years, and by commentators on this draft,\(^4\) consumers typically have a minimal understanding of how their premiums are calculated, and even less knowledge of how underwriting models comparatively weigh these factors. We agree consumers typically understand that some traditional data elements are important, for example that their life insurance premiums can be affected by their health status, and their auto premiums by a vehicle’s make/model/year, and that traffic infractions may cause premiums to increase. Regardless of whether consumer credit scores are considered traditional or new data, We believe few consumers realize these scores may be a key component in determining their premium in

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\(^1\) This figure includes arrests as well as arrests with convictions: [https://www.brennancenter.org/our-work/analysis-opinion/just-facts-many-americans-have-criminal-records-college-diplomas](https://www.brennancenter.org/our-work/analysis-opinion/just-facts-many-americans-have-criminal-records-college-diplomas). Both types of records are tracked and utilized by AI actors.

\(^2\) Peter Kochenburger made a presentation on this topic at the Fall 2020 NAIC meeting: [https://content.naic.org/sites/default/files/national_meeting/Version%203%20-%20Consumer%20%20Liaison%20commissioners%20Slideshow_Dec3_2020-for%20posting.pdf](https://content.naic.org/sites/default/files/national_meeting/Version%203%20-%20Consumer%20%20Liaison%20commissioners%20Slideshow_Dec3_2020-for%20posting.pdf)

\(^3\) NCOIL has already taken this step. **BE IT FURTHER RESOLVED** that NCOIL views as contrary to public policy and unfairly discriminatory the use of all data in the underwriting of private, non-commercial insurance that is: related to non-pending arrests, charges and indictments that do not result in conviction; related to convictions that do not relate in any way to fraud; or are not related to the insurability of a prospective or existing policyholder, and urges state legislatures to prohibit its use ... “July 17, 2021 Resolution Regarding the Use of Certain Rating Factors.

\(^4\) “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.” Center for Insurance Research’s December 3, 2021 comments, page 5.
multiple lines of insurance, even though insurance credit scoring has been an important underwriting tool since at least the mid 1990s. I [Peter Kochenburger] have taught our law school’s introductory insurance law course for 17 years and only in the last several have a bare majority of law students understood that credit scores affected their insurance premiums in some manner. The growing number of risk classifications that fall under “non-traditional data,” and how they are used, further reduces consumer understanding of risk-based underwriting.

Page 5, Non-Traditional Data – “Biometric data, e.g., voice analysis, facial analysis, and other analytics based on personal physical features and characteristics” (highlighting added).

The NAIC’s own recent events have highlighted how facial recognition software does not properly function for minority populations. Merely changing “facial recognition” to “facial analysis” does not eliminate or diminish any of the objections against its use. As consumer representatives, it is not clear there is any meaningful distinction between “recognition” and “analysis” – if anything, the terms suggest that “analysis” is a more difficult and in-depth process. Yet if recognition does not work, how would a more detailed “analysis” function? Perhaps at some point it will be proven to consumers that facial scanning software provides accurate results for all member of society, but the evidence and transparency is not there yet. Facial analysis may prove to be a vital aid to life insurance underwriting, or it may turn out to be modern-day phrenology. At this point, the ability of consumers to purchase life insurance at a fair price point should not be based on the bumps in the shape of their skull. The paper should make it clear that allowing the development and usage of AUW programs does not permit discrimination based on novel and untested data elements.

Page 6, FCRA Data. While it is useful to acknowledge and compare FCRA protections to those provided (if any) to non-traditional data, this paper should not imply that the FCRA is the gold standard for protecting consumer information. The FCRA’s limitations have been reported on for decades, including the lack of enforcement and the difficulties that consumers and regulators have in obtaining credit bureau cooperation. For example, the CFPB issued a report on January 5, 2022 titled: “Consumer Financial Protection Bureau report “Detailing Consumer Complaint Response Deficiencies of the Big Three Credit Bureaus.”

We recommend that the statement “Non-traditional data may not have the same consumer protections as FCRA and traditional data” revert to the previous draft - “... does not have ...” Most of the non-traditional data examples are not specifically protected by federal and state consumer data, privacy, or consumer protection laws.

Conclusion.

Even with these editorial changes we return to our major concern briefly stated in our first comment. This exposure draft still lacks a firm statement of purpose and principals and an authoritative declaration stating that AUW programs should exclude non-traditional data that may result in unfair discrimination against protected classes. Instead, the draft merely suggests that usage of non-traditional data should be monitored after implementation to determine if they result in unfair discrimination. This position is simply not strong enough and “monitoring” suggests a passive approach rather than a

regulatory one. The paper should state in no uncertain terms that non-traditional data elements which lack a reasonable explanation for correlation with mortality should be excluded if a particular data category has the potential to result in unfair discrimination – particularly if it may impact protected classes. Facial scanning is one such obvious example, as discussed above.

Thank you for considering these suggestions and comments.