INNOVATION, CYBERSECURITY, AND TECHNOLOGY (H) COMMITTEE

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Innovation, Cybersecurity, and Technology (H) Committee
Tampa, Florida
December 13, 2022

The Innovation, Cybersecurity, and Technology (H) Committee met in Tampa, FL, Dec. 13, 2022. The following Committee members participated: Kathleen A. Birrane, Chair (MD); Evan G. Daniels, Co-Vice Chair (AZ); Dana Popish Severinghaus, Co-Vice Chair (IL); Karima M. Woods (DC); John F. King (GA); Amy L. Beard (IN); Chlora Lindley-Myers and Cynthia Amann (MO); Troy Downing (MT); Jon Godfread (ND); Adrienne A. Harris represented by Seema Shah (NY); Judith L. French and Carrie Haughawout (OH); Elizabeth Kelleher Dwyer (RI); Carter Lawrence (TN); Kevin Gaffney (VT); and Mike Kreidler (WA).

1. Adopted its Oct. 14 and Summer National Meeting Minutes

Commissioner Birrane said the Committee met Oct. 14 in a joint meeting with the NAIC/Consumer Liaison Committee. During this meeting, the Committee heard presentations on algorithmic bias and approaches insurance companies are or can implement to manage and mitigate the risk of unintended bias and illegal discrimination when developing and using artificial intelligence (AI)/machine learning (ML). Commissioner Birrane said the Committee also heard presentations on algorithmic bias and a holistic approach to confronting structural racism in insurance.

Commissioner Godfread made a motion, seconded by Commissioner Downing, to adopt the Committee's Oct. 14 minutes (Attachment One). The motion passed unanimously.

Commissioner Birrane said the Committee also met Aug. 10.

Director Daniels made a motion, seconded by Commissioner Lawrence, to adopt the Committee's Aug. 10 minutes (*see NAIC Proceedings – Summer 2022, Innovation, Cybersecurity, and Technology (H) Committee*). The motion passed unanimously.

2. Adopted the Reports of its Working Groups

   A. Big Data and Artificial Intelligence (H) Working Group

Superintendent Dwyer said the Big Data and Artificial Intelligence (H) Working Group met Dec. 13 and exposed draft model and data regulatory questions related to the use of third parties for a 62-day public comment period ending Feb. 13 and issued a report on the AI/ML Private Passenger Auto (PPA) survey results.

   B. Cybersecurity (H) Working Group

Amann said the Cybersecurity (H) Working Group continues to work on a baseline review of its survey results. She said they also: 1) heard an update on international work related to cyber; 2) adopted the "Summary of Cybersecurity Tools" memorandum; 3) received an update on the cybersecurity workstreams document; and 4) discussed cybersecurity with the Cybersecurity and Infrastructure Security Agency (CISA).

C. E-Commerce (H) Working Group

Commissioner Downing said he has nothing additional to report regarding the activities of the E-Commerce (H) Working Group beyond what is in the summary.

D. Innovation in Technology and Regulation (H) Working Group

Director Daniels said he has nothing additional to report regarding the activities of the Innovation in Technology and Regulation (H) Working Group beyond what is in the summary.

D. Privacy Protections (H) Working Group

Amann said the Privacy Protections (H) Working Group will be exposing a new draft of the new *Insurance Consumer Privacy Protection Model Law* (#674) at the end of January, which will be followed by a 60-day comment period.

Director French made a motion, seconded by Director Daniels, to adopt the reports of the Big Data and Artificial Intelligence (H) Working Group (Attachment Two), the Cybersecurity (H) Working Group (Attachment Three), the E-Commerce (H) Working Group, the Innovation in Technology and Regulation (H) Working Group (Attachment Four), and the Privacy Protections (H) Working Group (Attachment Five). The motion passed unanimously.

3. Adopted its 2023 Proposed Charges

Commissioner Birrane reviewed the background and process regarding the development of the 2023 proposed charges for the Committee. She asked if there were any comments regarding the proposed charges.

Hearing none, Commissioner Downing made a motion, seconded by Director Popish Severinghaus, to adopt the Committee's 2023 proposed charges (Attachment Six). The motion passed unanimously.

4. Received a Status Report on Model Law Development Efforts

Director Popish Severinghaus provided a status report regarding the Committee's charge to track the implementation of and issues related to model laws pertaining to innovation, technology, data privacy, and cybersecurity. She said 21 states have adopted the *Insurance Data Security Model Law* (#668), and it is pending in two states. She said 10 states have adopted the *Unfair Trade Practices Act* (#880) revisions, and it is being considered in one state. She also said five states have insurance regulatory sandbox laws in place, and nine have indicated that they have an innovation regulatory initiative or regulatory flexibility allowing for innovation in insurance products and services.

5. Discussed Other Committee-Level Projects

Commissioner Birrane described several committee-level projects currently underway, including a portal, or entry point for understanding what is happening throughout the NAIC on issues related to innovation, cybersecurity, and technology. She asked Scott Morris (NAIC) to provide the status of those projects. Morris said the project that has been referred to as the ICT-Hub is intended to assist in coordinating the work of all NAIC committees on issues related to innovation, cybersecurity, and data privacy. He said during the July Collaboration Forum on Algorithmic Bias, NAIC staff presented a concept to be built on the current website to identify "related groups" and link to their work pages and a summary of the relevant work, as well as a library of resources. He said the team has developed a mockup of the hub focusing on topics covered by the Committee, and it would welcome feedback on

those. He said while this larger project is being worked on and delivered in late spring or early summer 2023, the team is looking to deliver some content earlier.

Morris said NAIC staff are also creating a Committee web page that summarizes the work of "related groups," especially in relation to the Collaboration Forum. He said it would be available after the first of the year or at the very latest, by the 2023 Spring National Meeting. He said another project is the vocabulary project defining foundational terms. He said a draft of that work product would be ready for review by a regulatory drafting group soon. Lastly, he said the NAIC team is working on a resource guide that will aggregate presentations, materials, and key resources related to the topic. He said this educational process is ongoing, and he reviewed all of the related sessions and events held during 2022. He said the plan is to continue these at the direction of the "related groups."

6. Heard an Update on the Collaboration Forum Plans and Deliverables

Commissioner Birrane said the goal of the Collaboration Forum is to ensure, to the extent possible and appropriate, that the work on this important topic is transparent, efficient, collaborative, and consistent in addition to developing a common vocabulary for state insurance regulators. She said state insurance regulators considered whether the NAIC should move forward with guidance or directives now and what form that would take in terms of a principled or prescriptive approach among other topics. She said there is a clear consensus that: 1) the NAIC should develop and adopt a regulatory framework for the use of AI by the insurance industry; 2) it should take the form of a model bulletin; 3) the framework should be principles-based and not prescriptive; and 4) members prefer a focus on governance requirements and the establishment of AI use protocols that rely on external and objective standards, such as the National Institute of Standards and Technology (NIST). She said members agree that efforts to validate the process should be part of the requirements, but with recognition of the practical difficulties and limitations associated with testing at this time. She said with respect to third parties, there is a strong preference among members to place responsibility on licensees to conduct appropriate diligence with respect to third-party data and model vendors as opposed to attempting to directly regulate unlicensed third-party vendors.

Commissioner Birrane said it is with those concepts in mind that the Committee, through the Collaboration Forum and the many working groups that make up the Collaboration Forum, will draft a model interpretative bulletin. She said the development of the current table of contents for the bulletin, at a very high level, is just now getting underway. She said it would include: 1) an introduction background and anchoring legislative authority for the bulletin; 2) a definitional section incorporating the vocabulary project already underway; 3) regulatory expectations for the use of AI by the insurance industry, which will include corporate governance and enterprise risk management (ERM) expectations; and 4) a section on regulatory oversight and examination standards, which will address market conduct, financial examination, and rate filing reviews.

Commissioner Birrane said the drafting of these four sections will be divided among the working groups that currently make up the Collaboration Forum, but all members are welcome to participate. She said a timeline will be developed, and sufficient work will be completed to enable a robust conversation about it in advance of the 2023 Spring National Meeting in Louisville, KY, affording plenty of time to discuss the details.

7. Heard Presentations on the Feasibility of Transparency and Explainability to Consumers Regarding Adverse Decisions from the Use of Big Data and AI

Commissioner Birrane introduced the panel presenting on the topic of the feasibility and transparency regarding adverse decisions that are derived from the use of AI/ML driven automated decisions: the moderator, Dorothy L. Andrews (NAIC); and the panelists, Brenda J. Cude (University of Georgia), Anthony Habayeb (Monitaur), Frank O'Brien (American Property Casualty Insurance Association—APCIA), and Rachel Jrade-Rice (Next Insurance).

Andrews began the discussion asking panelists about what transparency and explainability means for consumers. Jrade-Rice said for Next Insurance, explainability is a key part of transparency. Habayeb said it is important to remove the complexity around transparency and think of it as who did what and why. He said consistently using the words "decision" and "understanding" is very important. O'Brien said transparency is easy and supported by everyone. He said doing transparency is the hard part, and the key things to consider are whether it is doable, desirable, understandable, and scalable. He said operationalizing that within programs that provide a meaningful level of transparency is what we should be pursing, and it is the hard part. Dr. Cude said the important thing is conveying what consumers want to know, which includes why the decision was made and less about how the information is used. She said consumers need to know that so they can better understand what they can change to get a better result. She said this is not new, as consumers make adverse decisions all the time, so consideration should be given to how the introduction of big data and AI into the equation changes things.

The panel discussed what might affect consumer's understanding. Dr. Cude said instead of asking what consumers can understand, it should be about what insurance companies can explain. She said there are consumers that will not pay attention to any of this and people who are expert consumers who already know a lot about this. She said those two groups are not the concern. She said everyone else and the intermediaries that are helping those people are the ones to be concerned about, as well as whether insurers can get that information to those people when they need it. She said there will also be educational and generational issues. Jrade-Rice said it is not a question of whether insurers can do this because they can, but the question is whether it is going to be understandable and actionable for the consumer. She said Next Insurance does a lot of market research to try to figure this out. Habayeb said there is a very positive approach to this, and insurance products can be improved using AI. He said they already have transparency standards in Europe, so there is some global precedence already set. Jrade-Rice agreed and said this can create more transparency. O'Brien said the term adverse needs to be defined within this context, and it is important to present information that assures the consumer they are being treated fairly. He said it is about trust.

Habayeb said the conversation around governance and what questions state insurance regulators will be asking needs to take place. He said in defining what needs to be communicated to consumers, depending on where that discussion lands, there will need to be some operational system that can deliver that, and companies will need some time to build it. Andrews added that diversity in thought is important in making good decisions. Dr. Cude said that as an educator, researcher, and advocate, she wants to know about the audience and ask what they need to know. She said a best practice is to learn more about consumers and what they know about big data, algorithms, and AI, as well as do consumer testing. Jrade-Rice said the federal Fair Credit Reporting Act (FCRA) provides a good lens into how to translate complex processes into something a consumer will understand, and that path should be followed. O'Brien said the NAIC has sought to provide some level of flexibility and scalability in terms of requirements and processes expected of insurers, such as with the cyber model. He said one size will not fit all. Jrade-Rice said the insurer can provide a lot of detail behind how the decision was made, but the question is what is useful to the consumer and actionable. She said consumers want to know the variables upfront and then the outcomes on the backend. Habayeb said insurance has this foundation of actuarial practices in insurance that can influence this area. He said state insurance regulators want to know the inner workings, but consumers do not as they are trusting the state insurance regulator to be on top of that. He said some information provided to the state insurance regulator should not have to be a public asset or record. Dr. Cude said it might be important to ask what consumers have a right to know that does not necessarily have to be automatically provided.

Andrews asked the panel what they believe is practical to be disclosed to consumers. Jrade-Rice said it is about whether it is understandable and actionable to the consumer. She said how much the consumer wants to know and the purpose of the disclosure should be considered. She said certain variables represent a hard decline, and those factors should be disclosed as such, especially when they are actionable and can be used to mitigate risk. Habayeb said being able to say what factors are involved should be table stakes. He said there are also factors

that have been approved to be used, and the consumer should know what factors were involved. He said setting a number on how many factors need to be disclosed may not make sense, but which ones are the most important should definitely be disclosed. O'Brien said the number of factors that should be disclosed is being discussed at the National Conference of Insurance Legislators (NCOIL), and the APCIA has some significant concerns with that and how it would practically work.

Commissioner Birrane said as a consumer, she would want to know what was driving her score or her denial because that represents consumer shopping power. Amann said governance and a framework for it is already covered by the NIST, and much of the disclosure issue is included in the privacy model that will be exposed at the end of January 2023. She encouraged those in attendance to provide comments during that exposure period. Commissioner Birrane said she hears different things regarding what is doable, and knowing what factors were involved that carried the most weight would be of value to her as a consumer. She asked the panel what is actually doable. O'Brien said his members vary in terms of their position on that question. He said it depends on who you talk to. He said more is doable now than was years ago, but he asked what the expectations are, stating that just because it is doable does not make it desirable or scalable. Dr. Cude said from the public policy perspective, we need to be sure this is not just another way of gathering more information about consumers and making rating factors based on correlation and not causation. She said we should be looking at what is good for the consumers as a whole and the industry as well. Jrade-Rice says it is doable, but the question is how much it will cost to do; since that cost is passed on to consumers, there should be a sensitivity to that. She said if we are going to take it on, we should be sure it is useful to the consumer, so it is about finding the right balance. Habayeb said the question is scalability and being reasonable on expectations regarding the time to implement, as different companies will have different capabilities to do this.

Director Popish Severinghaus said if insurance companies can get there on their own, and there is a way for them to do that, they can help to drive where this goes. She said it is the state insurance regulators' job to facilitate that and help consumers to better understand what they need to know. She said facilitating that will help consumers be a part of driving that forward as well.

Having no further business, the Innovation, Cybersecurity, and Technology (H) Committee adjourned.

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Innovation, Cybersecurity, and Technology (H) Committee and the
NAIC/Consumer Liaison Committee
Virtual Meeting
October 14, 2022

The Innovation, Cybersecurity, and Technology (H) Committee met Oct. 14, 2022, in joint session with the NAIC/Consumer Liaison Committee. The following Committee members participated: Kathleen A. Birrane, Chair (MD); Evan G. Daniels, Co-Vice Chair (AZ); Dana Popish Severinghaus, Co-Vice Chair, represented by Erica Weyhenmeyer and C.J. Metcalf (IL); Karima M. Woods represented by Joselyn Bramble(DC); John F. King represented by Martin Sullivan (GA); Amy L. Beard represented by Jerry Ehlers and Meghann Leaird (IN); Chlora Lindley-Myers (MO); Troy Downing (MT); Jon Godfread represented by John Arnold and Chris Aufenthie (ND); Adrienne A. Harris represented by Seema Shah (NY); Judith L. French (OH); Elizabeth Kelleher Dwyer (RI); Carter Lawrence represented by Stephanie Cope (TN); Kevin Gaffney (VT); and Mike Kreidler (WA). The following Liaison Committee members participated: Andrew R. Stolfi, Chair (OR); Grace Arnold, Vice Chair (MN); Mark Fowler (AL); Elizabeth Perri (AS); Evan G. Daniels (AZ); Ricardo Lara represented by Ken Allen (CA); Andrew N. Mais (CT); Karima M. Woods represented by Joselyn Bramble(DC); David Altmaier (FL); Colin M. Hayashida (HI); Dean L. Cameron represented by Weston Trexler (ID); Vicki Schmidt represented by Brenda Johnson and Shannon Lloyd (KS); James J. Donelon represented by Nichole Torblaa (LA); Kathleen A. Birrane (MD); Anita G. Fox represented by Chad Arnold (MI); Chlora Lindley-Myers and Cynthia Amann (MO); Mike Chaney represented by David Browning (MS); Jon Godfread represented by John Arnold and Chris Aufenthie (ND); Chris Nicolopoulos represented by Christian Citarella (NH); Barbara D. Richardson (NV); Adrienne A. Harris represented by Seema Shah (NY); Judith L. French (OH); Michael Humphreys (PA); Scott A. White represented by Don Beatty (VA); Mike Kreidler (WA); Allan L. McVey (WV); and Nathan Houdek (WI). Also participating were: Jason Lapham (CO); Doug Ommen (IA); Sharon P. Clark (KY); Timothy N. Schott (ME); and Larry D. Dieter (SD).

1. Heard Presentations on Algorithmic Bias and Approaches Insurance Companies Are or Can Implement to Manage and Mitigate the Risk of Unintended Bias and Illegal Discrimination When Developing and Using AI/ML

Commissioner Birrane said the goal of the joint meeting is to continue the education of state insurance regulators on the topic of algorithmic bias. She said during the Summer National Meeting, the Committee had such a full agenda that there was no time to hear comments from interested parties, and she committed to holding an interim virtual meeting prior to the Fall National Meeting to provide that opportunity. At the Summer National Meeting, Commissioner Stolfi also ran short on time to hear all the presentations scheduled for the Liaison Committee, so it made sense to meet jointly to complete that work. Commissioner Birrane said this meeting would not only provide an opportunity to hear presentations, but it would also provide ample opportunity for interested parties to speak.

Commissioner Stolfi said he agrees, and he is looking forward to hearing these presentations and engaging in meaningful dialogue. He said this is consistent with the goals of the Committee to look for ways to be more engaged outside of national meetings. He said the group discussed and agreed to hold interim meetings and get more involved with other committees. He said this meeting is an example of following through on that.

a. NAMIC

Tony Cotto (National Association of Mutual Insurance Companies—NAMIC) said NAMIC is opposed to unfair discrimination of any kind, and he understands the pressures policymakers are under, but he urges caution as they pursue developing solutions and mitigation techniques to minimize bias. He said in insurance, fairness is determined by actuarial soundness and risk of loss. He said insurers price based on risk, and they should analyze inputs rather than outcomes other than loss ratios. He stressed the benefits of risk-based pricing, but he said NAMIC agrees that there needs to be common terms defined, and that should be done in statute; however, he stressed that this will be a massive undertaking but must be done because of the importance of getting this right and ensuring understanding. In addition, he said limiting accuracy does nothing to reduce the cost of coverage, and it hurts access, which is what really matters. He said the good news is that there are many benefits, including helping to educate and incentivize risk avoidance. He said the use of this data and algorithms can reduce the cost to consumers.

Cotto said industry's use of data and models is nothing new; state insurance regulators have the authority to ask questions and get explanations if needed, and disparate impact has no place in insurance law. He added that state insurance regulators should not embrace frameworks from other industries, as insurance is very different. He said it should be flexible, principle-based, tailored to insurance, and considering company size and complexity.

b. ACLI

Karen Melchert (American Council of Life Insurers—ACLI) said the first pillar of the ACLI's Economic Empowerment & Racial Equity Initiative is expanding access to financial products to underserved communities. She said new methods for doing this are raising some regulatory concerns around algorithmic accountability. She said the ACLI has been working on this since the NAIC adopted its Artificial Intelligence (AI) Principles back in 2020. She said the ACLI started looking at algorithmic accountability and began with identifying proxy discrimination within the context of insurance. She said the goals of the algorithmic accountability framework are: 1) identify any potential unfair discrimination from the use of algorithms; 2) preserve innovation within the industry; 3) maintain a holistic view of the relationship between new technologies and their use in underwriting; 4) maintain consistency with existing underwriting requirements; and 5) allow for flexibility to accommodate unique uses of algorithms across the industry.

Melchert said the ACLI suggests a principle-based risk management approach that embraces the following four areas: 1) governance process; 2) testing requirements; 3) reporting requirements related to governance and testing; and 4) documentation and attestations related to the governance, testing, and reporting processes. She said a principle-based approach benefits all stakeholders, including consumers and state insurance regulators, and this should be an ongoing dialogue between insurers and state insurance regulators. She said the ACLI has submitted this proposal to the Colorado Insurance Department and presented it during the SB21-169 Stakeholder Engagement Process meeting on July 8. She said it could be used for a draft bulletin or regulation. She said this proposal focuses on unfair discrimination based on race and proxy discrimination because it is the only protected class for which there is any chance to test for given data currently available. She said it is also focused on underwriting because that is the most important use case in terms of the life insurance business, but it could be used for others as well. She said it also addresses third parties, mentioning the need to be compliant in all cases, with the *Unfair Trade Practices Act* (#880). She went on to describe the pillars in more detail, noting that it can also be found on the website supporting the Colorado Stakeholder Engagement Process.

c. APCIA

David F. Snyder (American Property Casualty Insurance Association—APCIA) said the APCIA is very committed to this effort. He said the APCIA agrees with the NAIC on the need to collectively determine how to tackle concerns related to fairness and preventing unlawful discrimination while seeking improvements that strengthen competitive markets and addressing potential inequities while preserving the risk-based foundation of insurance. He said this requires a balanced approach that considers competitive issues and protects investments that benefit consumers. He said the narrative too often starts with the negative. He reviewed the key benefits of AI/machine learning (ML), noting more efficiently meeting customer expectations; more rapidly responding to, settling, and paying claims; more accurately and objectively assessing risk; and providing the ability to analyze company performance to improve product offerings, customer service, and compliance.

Snyder said definitions are very important and present a challenge to provide constructive responses when they are unclear. He said the general definition of "bias" does not consider long-standing legislated insurance regulatory and judicial standards. He said robust governance is very important and should be a priority as a critical foundational element to focus on, as well as the prominent role of human review and decision-making. He said it should be flexible, proportionate, scalable, and explainable. He said in testing for bias, the APCIA found a lack of bias but a firm adherence to risk-based pricing. He said when considering transparency, information regarding what, how, and to whom should be provided and considered. He reviewed the attributes put forth by the National Institute of Standards and Technology (NIST) and encouraged state insurance regulators to consider them.

Snyder said this area is already subject to legislated, regulatory, and judicial standards, and they should neither be expanded nor contracted based on using AI/ML for activities previously performed by humans. He said risk-based pricing should continue to rule the day, and courts have defined the elements related to disparate impact, so that should continue to be recognized. He said data on many of these classes sought to be protected is simply not available.

In conclusion, Snyder said the APCIA is committed to working constructively with the NAIC and state insurance regulators in their work on AI/ML: 1) there is a need for clear definitions; 2) governance is paramount; 3) it is important to avoid inhibiting beneficial uses of AI/ML and legislated regulatory standards; and 4) judicial decisions should be applied. He said the APCIA is committed to addressing systemic racism where it is evident, but using pricing mechanisms to do that does not address the underlying issues.

2. Heard Presentations on Algorithmic Bias and a Holistic Approach to Confronting Structural Racism in Insurance

a. CEJ

Birny Birnbaum (Center for Economic Justice—CEJ) reviewed the importance of insurance products as financial security tools for individuals and community economic development. He reviewed two types of discrimination—actuarial and protected classes. He also reviewed why race and protected class characteristics are carved out regardless of actuarial fairness, noting that historical discrimination has left a legacy of outcomes that are embedded in data used for actuarial analysis. He said addressing proxy discrimination is easy; the data are not predicting insurance outcomes, so they violate both the actuarial and protected class requirements for unfair discrimination.

Birnbaum said "intent" in structural racism and its impacts are often unrecognized, unintentional, and cannot be a determining factor. He provided several examples. He said algorithms learn bias in data and models, and the fact that an insurer does not see race in an algorithm does not logically or factually result in no discrimination on the basis of race, and the only way to eliminate it is to measure the impact by explicit consideration of race and other protected class factors. He said there are statistical techniques that enable testing for proxy discrimination and disparate impact. He said principle-based governance is essential but not sufficient, and the testing of outcomes is essential and must be done simultaneously.

Birnbaum defined these terms as:

- ***Disparate Intent:*** The intentional use of race.
- ***Proxy Discrimination:*** Disproportionate racial outcomes tied to the use of proxies for race, not to outcomes.
- ***Disparate Impact:*** Disproportionate racial outcomes tied to historic discrimination and embedded in insurance outcomes.

Birnbaum said while pricing and rating has gotten the most regulatory attention, it is imperative for insurers and state insurance regulators to test algorithms used in all aspects of the insurance life cycle for racial bias, expanding on the use of algorithms in marketing. He said it is important to do holistic testing and not just individual factors in isolation. In closing, he said the property/casualty (P/C) trades routinely seek to justify pricing freedom, noting the use of any data source or characteristic of the consumer, vehicle, property, or built or natural environment; i.e., if it is predictive of risk and more refined, the risk prediction is always better and more fair. He said this formulation is problematic for several reasons, making the following key points:

- The purpose of insurance is to create a risk pool through which individuals can transfer risk to that pool. Risk-based pricing is a means to manage that mechanism safely and fairly, but it is not the purpose of insurance.
- Testing for and addressing structural racism in insurance is 100% consistent with and improves risk- and cost-based practices.
- Unfettered risk-based pricing without attention to structural racism will reflect and perpetuate historic discrimination.

b. <u>NFHA</u>

Dr. Michael Akinwumi (National Fair Housing Alliance—NFHA) introduced himself and talked about what the NFHA does. He said the NFHA has published a framework for identifying and removing risks that are associated with algorithmic systems related to disparate impact and proxy discrimination. He said the NIST risk management framework could be used to manage identified risks by the auditing framework published.

Morgan Williams (NFHA) said the NFHA Tech Equity Initiative can be found on the NFHA's website. He said compliance and regulatory oversight ultimately flow from the basis and scope of legal liability. He said the basis of civil rights causes of action involving a review of compliance principles of proxy testing and civil rights law prohibit policies and practices when there is evidence of disparate impact, intentional discrimination, and disparate impact that results in discriminatory outcomes. He said the NFHA focuses on disparate impact outcomes, such as facially neutral policy or practice, when the practice does not advance a legitimate business justification and the policy is not the least discriminatory means to advance that interest. He provided several examples of civil rights actions in insurance, and he reviewed civil rights management systems controls.

Dr. Akinwumi reviewed proxy testing control variables, the equation for rate-making using a generalized linear model (GLM), and how to mitigate for bias and discrimination using control variables. He said it introduces race as a control variable using a clustering technique and claims frequency and loss. He explained this technique in detail and the possible outcomes. He mentioned Bayesian Improved Surname Geocoding (BISG) as one of the techniques commonly used. He also said imageomics is also a brand of science that attempts to infer biological traits and biometrics from a person's image using ML techniques that use computer vision algorithms to infer gender and age.

c. Southern University Law Center and University of Connecticut School of Law

Peter Kochenburger (Southern University Law Center and University of Connecticut School of Law) said he wants to address a few points made by the industry presentations. He said it is often said that fairness in insurance is determined by actuarial fairness, but that is only one element in determining what is fair and not discriminatory. He said risk-based pricing is an important element, but it does not determine the regulatory structure (e.g., pre-existing conditions are not allowed to be used in health insurance plans). He said it is relevant, but there are other goals. He said secondly, industry says anything done should be within the existing regulatory framework, and it is already well regulated. He said that is not correct, and there is not a sufficient regulatory structure for this in place today, or we would not be having these discussions. He said the existing structure should be built upon, but we should not be confined to it, as it must evolve and respond to new things being introduced. He said there is a need to study and evaluate this area carefully, but the idea that everything must be defined and well understood before moving forward is simply not true and is merely a delay tactic. He stressed the need to move forward expeditiously or the development of the regulatory framework will fall to other regulatory bodies and be taken away from state insurance regulators.

3. Received Comments from Interested Parties

Brendan Bridgeland (CEJ) asked what steps industry has taken to prevent the duplication of risks by use of the same data elements in different data categories to prevent double counting. Birnbaum said that is handled through multi-variant analysis by simultaneously evaluating many factors and removing the correlation between them, so each factor is making a unique contribution.

Snyder said testing is fundamental and evolving. He said there is not a singular methodology, and industry is trying to see which best serves the purpose of determining what is socially acceptable. He said the key is accuracy regarding the testing methodologies, and all of this is under active consideration, but there is no one way to do this yet.

Michael DeLong (Consumer Federation of America—CFA) said there is a need for strong public input, but this work should not be delayed. If consensus cannot be achieved, the group should keep in mind that justice delayed is justice denied.

Dr. Akinwumi said when it comes to testing, looking at outcomes and loss ratios represents a retrospective look, whereas testing out variables and factors being used needs to happen before there are outcomes.

Melchert said it is important to have defined terms and a strong foundation, and it is not just a delay tactic. She said the ACLI has demonstrated that it wants to move forward, but definitions are important. Kochenburger said he did not mean to imply definitions are not important, but it would be a substantial undertaking to try to define everything and get consensus, which could take years and be an obvious delay tactic. Birnbaum said testing can take place by removing the correlative factor and seeing the outcome; industry already does this in their testing. Snyder said governance is improving, and the work with the NIST is noteworthy; industry shares concerns related to structural racism, and testing is important but complicated. Although, he said it is very important to get it right, and industry does not want to delay getting a framework in place for overseeing this space.

Having no further business, the Innovation, Cybersecurity, and Technology (H) Committee and the NAIC/Consumer Liaison Committee adjourned.

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Big Data and Artificial Intelligence (H) Working Group
Tampa, Florida
December 13, 2022

The Big Data and Artificial Intelligence (H) Working Group of the Innovation, Cybersecurity, and Technology (H) Committee met in Tampa, FL, Dec. 13, 2022. The following Working Group members participated: Elizabeth Keller Dwyer, Chair (RI); Amy L. Beard, Co-Vice Chair, represented by Victoria Hastings (IN); Doug Ommen, Co-Vice Chair (IA); Adrienne A. Harris, Co-Vice Chair, represented by Seema Shah and John Finston (NY); Kevin Gaffney, Co-Vice Chair (VT); Lori K. Wing-Heier (AK); Mark Fowler (AL); Evan G. Daniels (AZ); Michael Conway and Peg Brown (CO); George Bradner and Wanchin Chou (CT); John Reilly (FL); Shannon Hohl (ID); Erica Weyhenmeyer (IL); Shawn Boggs (KY); Tom Travis (LA); Christopher Joyce (MA); Nour Benchaaboun (MD); Sandra Darby (ME); Kevin Dyke (MI); Grace Arnold (MN); Cynthia Amann (MO); John Arnold (ND); Christian Citarella (NH); Barbara D. Richardson (NV); Tom Botsko (OH); Teresa Green (OK); Eric Cutler (OR); Shannen Logue (PA); Travis Jordan and Tony Dorschner (SD); Bill Huddleston (TN); Jon Pike (UT); Eric Lowe (VA); Mike Kreidler and Molly Nollette (WA); Nathan Houdek (WI); and Ellen Potter (WV).

1. Adopted its Summer National Meeting Minutes

Commissioner Gaffney made a motion, seconded by Director Daniels, to adopt the Working Group's Aug. 10 minutes (*see NAIC Proceedings – Summer 2022, Innovation, Cybersecurity, and Technology (H) Committee, Attachment Two).* The motion passed unanimously.

2. Received the AI/ML PPA Report

Commissioner Gaffney said the 2021 Artificial Intelligence (AI)/Machine Learning (ML) Private Passenger Auto (PPA) survey was conducted to accomplish three primary goals: 1) to gain a better understanding of the insurance industry's use and governance of big data and AI/ML; 2) to seek information that could aid in the development of guidance or a potential regulatory framework to support the insurance industry's use of big data and AI/ML; and 3) to inform state insurance regulators as to the current and planned business practices of companies.

Commissioner Gaffney said the PPA survey was conducted under the market conduct examination authority of nine states: Connecticut, Illinois, Iowa, Louisiana, Nevada, North Dakota, Pennsylvania, Rhode Island, and Wisconsin. The survey was sent to larger companies, defined as those PPA writers with more than $75 million in 2020 direct premium written. The survey call letter was distributed on Sept. 28, 2021, and survey responses were requested by Oct. 28, 2021. A total of 193 responses were received, and almost 90% of those indicated that they are doing something pertaining to AI/ML. Commissioner Gaffney said the requesting states agreed that the collected data will not be used to evaluate or determine a company's compliance with applicable laws and regulations, and all company-specific information would be kept confidential under state examination authority.

Commissioner Gaffney said 169 companies currently use, plan to use, or plan to explore using AI/ML as defined for this survey. This equates to approximately 88% of reporting companies. Commissioner Gaffney said companies reported varying levels of AI/ML use, from only 2% in the loss prevention area to 70% in claims operations. In order from maximum to minimum use, the percentage of companies using AI/ML are claims (70%), marketing (50%), fraud detection (49%), rating (27%), underwriting (18%), and loss prevention (2%).

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Commissioner Gaffney said the report provides additional detail on the level of decision making and whether models were developed in-house by an insurer or developed by a third-party vendor. For example, models used to detect first-party and third-party liability tend to be developed by third parties. The report provides a list of third parties by operation area. There are 28 vendors for claims models, 15 for fraud detection, and 39 for marketing. Commissioner Gaffney said the survey results also address the type of data elements used by insurers by operational area, how consumers are notified of the use of data and their ability to request a correction to data being used, and how governance is documented in the company's governance framework.

Commissioner Gaffney said insurers were asked to identify if they are providing additional information about data elements to consumers other than what is required by law. He said the answer, although the number of reporting companies is lower than expected, is almost unanimously "no" for each of the insurer operations, except for rating, which had about 32% of the responses reporting "yes." Many companies discussed having a consumer dispute process. The form of the dispute process ranged from calling the company or agent to dispute erroneous data to allowing policyholders to correct erroneous data themselves through an app.

Commissioner Gaffney said many companies did not answer the question of whether consumers can challenge or correct their specific data outside of processes for the federal Fair Credit Reporting Act (FCRA). Of those companies that answered this question, about 50% said "yes" for rating and underwriting, 40% said "yes" for claims and marketing, 15% said "yes" for fraud detection, and less than 10% said "yes" for loss prevention.

Commissioner Gaffney said the survey asked about documented governance practices tied to the adopted NAIC AI Principles of fairness and ethics considerations; accountability for data algorithms' compliance with laws; appropriate resources and knowledge to ensure compliance with laws, including those related to unfair discrimination; transparency with appropriate disclosures; and secure, safe, and robust systems for privacy risk protections. While the percentage of "yes" responses averaged 67% for most questions, he said the transparency question only received 56% "yes" responses. The answers for rating tended to be higher percentages of "yes" than for the other insurer operations, and the transparency question received noticeably fewer affirmations than others.

Commissioner Gaffney said the report has the following recommendations, which include some activities already in progress:

1. Determine whether to further explore the following subjects:
    a. Insurer AI/ML model usage and the level of decision making; i.e., the amount of human involvement in decision making.
    b. Insurer data elements.
    c. Insurers' governance frameworks and the documentation of such.
    d. Consumer data recourse.
    e. Third-party regulatory framework.
2. Create a risk hierarchy to prioritize the need for more model governance and insurer oversight. The general concept is that more oversight of a model will be needed as the consumer risk or impact increases from the modeling or models.

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3. Evaluate consumer data recourse. Insurers report a wide variety of methods for consumers to evaluate and correct data used by insurers. Some methods are short and easy, such as using an app to correct data, and other methods are more time-consuming and require personal contact with the agent or company. In some cases, consumers may not know their data is being used, so consumer transparency is a priority. This is on the radar of the Privacy Protections (D) Working Group.
4. Evaluate the regulatory framework around the use of third-party models and third-party data, including evaluating the ability of insurers and state insurance regulators to obtain needed information from third parties and state insurance regulators to oversee this work either through the insurers or third parties in some way.
5. Evaluate concerns about third-party concentration by insurer use.
6. Determine whether additional white papers on best practices would be useful on subjects in the AI/ML space.

Commissioner Gaffney concluded his remarks to clarify that the report is a report of the nine requesting states (Attachment Two-A), and it is being provided to the Big Data and Artificial Intelligence (H) Working Group for guidance; therefore, the report should be received rather than exposed for additional comment or adopted by the Working Group.

3. Received an Update on the AI/ML Home Survey

Commissioner Gaffney said the AI/ML Home survey is patterned after the PPA survey. The purpose of the Home survey is to gain a better understanding of the industry's use of big data, AI/ML, and what governance and risk management controls are being put in place. The survey also seeks to gather information that may inform the development of guidance or a potential regulatory framework that would support the insurance industry's use of big data and AI/ML in accordance with the expectations outlined in the NAIC AI Principles.

Commissioner Gaffney said the 10 requesting states of Connecticut, Illinois, Iowa, Louisiana, Nevada, North Dakota, Pennsylvania, Rhode Island, Vermont, and Wisconsin issued an informational notice to 194 companies on Sept. 15 and the formal examination call letter on Nov. 1. Any company licensed to write home insurance in one of the 10 requesting states and has at least $50 million in national home insurance premium for 2020 is required to complete the survey. After receiving a request on behalf of several responding companies, Commissioner Gaffney said the requesting states extended the response deadline for the AI/ML Home survey to Dec. 15.

4. Received Comments on the AI/ML Life Insurance Survey

Commissioner Gaffney said the 14 states of Colorado, Connecticut, Illinois, Iowa, Louisiana, Minnesota, Nebraska, North Dakota, Oregon, Pennsylvania, Rhode Island, Vermont, Virginia, and Wisconsin have collaborated to develop a survey to understand how life insurance companies are deploying AI/ML technologies in the following operational areas: 1) pricing and underwriting; 2) marketing; and 3) loss prevention. Similar to the PPA survey and the Home survey, he said the goal of the Life Insurance survey is to learn from the industry about the current level of risk and exposure associated with their use of AI/ML, how the industry is managing or mitigating risks, and what might be the most meaningful regulatory approach for overseeing the industry's use of AI/ML. The survey also attempts to understand the minimum and maximum face amount thresholds at which AI/ML is used. Commissioner Gaffney said the purpose of the Life Insurance survey is not to have insurers provide details of trade secret components or determine company compliance with existing laws and regulations.

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Commissioner Gaffney said the following criteria were used to identify which companies should receive the survey: 1) a company with more than $250 million in premiums on all individual policies in 2021; 2) a term writer that has issued policies on more than 10,000 lives; or 3) a specifically selected InsurTech Company. He said the 14 states will issue a formal examination call letter to a total of 192 life insurance companies. He said the draft survey was circulated on Nov. 10 for a 30-day public comment period, and comments were received from the American Council of Life Insurers (ACLI) and the Center for Economic Justice (CEJ).

David Leifer (ACLI) said the ACLI supports the work of the NAIC, but it believes the survey is more detailed than the PPA survey and Home survey. He said the survey seeks a lot of granular information, and he is not sure how useful this level of detail will be for the discussions of the Working Group. He said the ACLI has some concerns regarding the confidentiality of responses because aggregated information has the potential to identify a company. He said the definitions for the survey could use some additional work, and companies may not provide consistent responses based on the current definitions in the survey.

Birny Birnbaum (CEJ) questioned how state insurance regulators will use the survey information and receive updated information from companies as the market changes. He said it is difficult to determine whether the use of specific data is reasonable unless the use of the data is mapped to a specific company practice. He said the definitions could be clarified. He said the survey should ask if a company tests its AI/ML practices for bias against protected classes, and this is critical information that will help inform other workstreams of the NAIC. He said the survey should address the use of biometrics, and he said he has additional suggestions on how to make the data categories more exclusive of one another.

Commissioner Gaffney said the requesting states will review the submitted comments for possible revisions to the survey. NAIC staff will deploy a Life Insurance survey web page in early January 2023. Commissioner Gaffney said the requesting states plan to issue a thirty-day informational letter to companies identified to receive the formal examination call letter. He said he anticipates that the informational letter will be distributed in early January 2023, and the formal examination call letter is to be issued in early February 2023. Companies will then have 30 days to respond to the survey after the issuance of the formal examination call letter.

5. Discussed Draft Model and Data Regulatory Questions

Commissioner Ommen said Workstream Two of the Working Group was charged with determining the appropriate regulatory evaluation of third-party data and model vendors and producing a recommended regulatory framework for monitoring and overseeing industry's use of third-party data and model vendors. In accordance with this charge, the workstream developed examination standards or questions state insurance regulators can ask about any data and models used by insurance companies, whether that data or model is developed internally or obtained from external sources.

Commissioner Ommen said these questions would form the base questions, and then other NAIC working groups would add additional task-specific questions. For example, the Casualty Actuarial and Statistical (C) Task force has rate modeling and data questions in its *Regulatory Review of Predictive Models* white paper, and the Accelerated Underwriting (A) Working Group has accelerated underwriting (AU) questions in its recent work products. These working groups could eliminate any of their current questions that overlap with these base questions and then maintain the task-specific questions of the Big Data and Artificial Intelligence (H) Working Group.

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Commissioner Ommen said the document consists of three main sections. The first section is titled, "Main General Questions," and it includes a list of suggested questions to obtain a high-level understanding of the model or data. The second section, "Detailed and Technical Questions," expands on the first section by including additional details and questions to obtain a more in-depth understanding of the model or data. The third section in the document contains draft definitions of key terms used throughout the document.

Eric Ellsworth (Consumers' Checkbook/Center for the Study of Services) said this is a good document, but he said there is still a need to look at model outputs. He said the NAIC should add staff, such as data scientists, and develop the capacity to collect and analyze data on behalf of state insurance departments while also protecting industry trade secrets.

David F. Snyder (American Property Casualty Insurance Association—APCIA) said preventing unfair discrimination is important, but regulatory policy should help ensure that there is a competitive marketplace because a compression of the marketplace could harm consumers. He said the property/casualty (P/C) industry has experienced catastrophe losses, inflation, and higher loss costs. He said a uniform state insurance regulator approach is good, but the use of all questions could be a strain on company resources. He said the questions could also create de facto regulatory standards that are not established legal standards in states.

Birnbaum said the document should include questions about the status of a third-party vendor as an advisory organization and the licensure status as an advisory organization because of antitrust concerns. He said a choice between strong consumer protections and competitive markets is a false choice, and state insurance regulators setting standards of conduct allows insurance markets to flourish. He encouraged state insurance regulators to ask questions that do not result in lengthy, narrative answers.

The Working Group agreed to expose the questions for comment until Feb. 13, 2023.

6. Received an Update from the Accelerated Underwriting (A) Working Group

Commissioner Arnold said an ad hoc group of state insurance regulators has been meeting to consider specific guidance for state insurance regulators with respect to AU in life insurance. She said the ad hoc group identified market conduct as an area where additional guidance could be helpful. She said the discussion of AU needs to be consistent with, and supportive of, all the related initiatives and work being undertaken by other NAIC groups, including the Collaboration Forum of the Innovation, Cybersecurity, and Technology (H) Committee; the Market Conduct Examination Guidelines (D) Working Group; and the Big Data and Artificial Intelligence (H) Working Group. She said the Accelerated Underwriting (A) Working Group has received feedback on the guidance being drafted and will hold an open call to discuss the draft guidance in Q1 2023.

Birnbaum questioned why life insurers' use of credit information is not subject to the same standards as the P/C industry. He said the guidance should address the life insurance industry's use of biometrics, and a life insurer should not be allowed to use biometric information unless the insurer has demonstrated that the use of biometric information does not result in racial basis. He said guidance to the life insurance industry is extremely important because the practices of a life insurer can have a long-term impact on a consumer; whereas, a consumer has more opportunities to change insurers in the P/C marketplace since P/C products have annual renewal periods.

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Having no further business, the Big Data and Artificial Intelligence (H) Working Group adjourned.

Sharepoint/NAICSupportStaffHub/Member Meetings/H CMTE/2022_Fall/BDAIWG/Minutes/BDAI Minutes121322-Final.docx

MEMORANDUM

To: Superintendent Elizabeth Kelleher Dwyer,
Chair of the Big Data and Artificial Intelligence (H) Working Group

From: Commissioner Kevin Gaffney,
Chair of Workstream One (Surveys) of the Big Data and Artificial Intelligence (H) Working Group

Cc: Nine-State Subject Matter Expert Group; Kris DeFrain (NAIC)

Date: December 8, 2022

Re: 2021 Private Passenger Auto Artificial Intelligence/Machine Learning Survey Analysis

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The 2021 Private Passenger Auto Artificial Intelligence/Machine Learning Survey (PPA AI/ML Survey) [1] was conducted to inform the work of the Big Data and Artificial Intelligence (H) Working Group in support of its charge to:

> *Research the use of big data and artificial intelligence (AI) in the business of insurance, and evaluate existing regulatory frameworks for overseeing and monitoring their use. Present findings and recommend next steps, if any, to the Innovation and Technology (EX) Task Force, which may include model governance for the use of big data and AI for the insurance industry.*

The survey was conducted under the market examination authorities of nine (9) requesting states (Connecticut, Illinois, Iowa, Louisiana, Nevada, North Dakota, Pennsylvania, Rhode Island, and Wisconsin) and completed by insurers who write private passenger auto (PPA) insurance in one of the nine participating states and have at least $75 million in national PPA insurance premium for 2020. The following subject matter experts (SMEs) represented the nine states:

CT: George Bradner
IL: Erica Weyhenmeyer
IA: Andria Seip
LA: Nichole Torblaa
ND: Mike Andring and Chris Aufenthie
NV: Gennady Stolyarov

[1] The 2021 PPA AI/ML survey was conducted under the market conduct examination authority of nine states: Connecticut, Illinois, Iowa, Louisiana, Nevada, North Dakota, Pennsylvania, Rhode Island, and Wisconsin. Subject matter experts (SMEs) from these states opted to limit the survey request to only larger companies, defined as those PPA writers with more than $75 million in 2020 direct premium written. The SMEs also limited the scope to only "advanced" AI/ML models (which excludes models like generalized linear models [GLMs], which are used by 85% of companies in rate filings). A total of 193 responses were received.

PA: Michael McKenney
RI: Matt Gendron
WI: Timothy Cornelius

This memorandum contains the SMEs' summary of the survey analysis, key takeaways, and some recommendations for next steps. The SMEs also approved public distribution of the attached NAIC staff's survey analysis, which provides more detail about the survey results.

SURVEY ANALYSIS SUMMARY

"More Advanced" Artificial Intelligence/Machine Learning Model Use by Companies

The survey was intentionally limited to the reporting of "more advanced" types of AI models, so the data should be interpreted as applying to that subset of insurers' predictive models. Out of 193 companies completing the survey, 169 companies currently use, plan to use, or plan to explore using AI/machine learning (ML) as defined for this survey. This equates to approximately 88% of reporting companies.

Among insurer operations areas, companies reported varying levels of AI/ML use, from only 2% in the loss prevention area to 70% in claims operations. In order from maximum to minimum use, the percentage of companies using AI/ML were: claims, 70%; marketing, 50%; fraud detection, 49%; rating, 27%; underwriting, 18%; and loss prevention, 2%. The following shows the predominant uses, the levels of decision-making, and how often models are developed in-house or externally for each insurer operation.

MODELS BY INSURER OPERATIONS

Claims Models

Uses: In insurance claims operations, companies reported currently using AI/ML claims models mostly as an informational resource for adjusters. Other AI/ML claims model uses identified by at least 50 insurers are: 1) to determine claim settlement amounts; 2) to make claim assignment decisions; 3) to evaluate images of loss; and 4) for "other" claim-related functions.

Level of decision-making: Determination of settlement amount tends to include augmentation. Claim assignment decisions tend to be automated, or at least the models provide augmentation.

In-house or third-party: Models for claim approval, claim assignment decisions, adjusters' informational resource, and other claim-related functions tend to be developed in-house. Models used to determine settlement amounts and evaluate images of the loss tend to be developed by third parties.

Fraud Models

Uses (identified by at least 50 companies: In insurance fraud detection, companies reported currently using AI/ML models mostly to refer claims for further investigation.

Level of decision-making: For the referral of claims for further investigation, most of the levels of decisions are a mixture of augmentation and support. Other fraud-detection models are used for support.

In-house or third-party: Models to detect first-party and third-party liability tend to be developed by third parties. Other fraud detection is a mixture of in-house and third-party models.

Marketing Models

Uses (identified by at least 50 companies): Companies use marketing models for targeted online advertising.

Level of decision-making: Many of the marketing models are automated with no human intervention on execution. Marketing models are mostly automated when used for targeted online marketing, direct online sales, provision of offers to existing customers, and other marketing-related functions. When identifying recipients of mail or phone advertising, there is most often augmentation, where a model provides an answer and advises the human who is making the decision. When identifying potential customer groups, the number of models is evenly split between all three levels of decision-making. Demand modeling is evenly split between augmentation and support to the human.

In-house or third-party: Marketing models being used by insurance companies are equally developed in-house (with or without third-party assistance) and purchased from a third party. Two exceptions are that third-party models are used for targeted online advertising, and in-house models are used for the provision of offers to existing customers.

Rating, Underwriting, and Loss-Prevention Models

With a focus on "more advanced" AI/ML models, there are fewer rating, underwriting, and loss-prevention models reported. Therefore, the data for some detailed questions is less credible. This may, however, simply be a reflection of the limited extent of the deployment of such more advanced models to date. This corroborates the understanding of the SMEs that the majority of rating approaches that PPA insurers use today continue to involve more traditional ratemaking techniques and older-generation static predictive models. The more advanced AI/ML models currently constitute a minority of the models used by insurers in rating and underwriting.

Only 52 companies reported current rating model uses, and the majority of those were for rating class determination or "other" uses; the levels of decision are a mix of all types; and almost all rating models were developed in-house.

Only 34 companies reported current underwriting model uses, and the majority of those were for "other" uses; the levels of decision are a mix of all types; and most underwriting models are developed in-house.

Only three companies reported current loss-prevention uses, and all of those were for "identification of high-risk consumers"; the levels of decision are support only; and most loss-prevention models are developed in-house.

DATA ELEMENTS BY INSURER OPERATIONS

The following are the data elements used by at least 50 companies in the different insurer operations. The data sources vary by data element, but for the most-cited data elements, the source tends to be internal.

- Claims
  - Data Elements: Vehicle-Specific Data, Loss Experience, and Medical
- Fraud Detection:
  - Data Elements: Loss Experience, Vehicle-Specific Data, and Medical
- Marketing:
  - Data Elements: Demographic
- Rating, Underwriting, and Loss Prevention: No data elements were used by at least 50 companies.

CUSTOMER DATA CORRECTION

Many companies discussed having a dispute process. The form of the dispute process ranged from calling the company or agent to dispute erroneous data to allowing policyholders to correct erroneous data themselves through an app.

Data Element Information Provided to Consumers

Insurers were asked to identify if they were providing additional information about data elements to consumers *other than what is required by law*. The answer, although the number of reporting companies is lower than expected, is almost unanimously "no" for each of the insurer operations, except for rating, which had about 32% of the responses reporting "yes." The second question is similar but asks whether consumers are told the purposes of data elements beyond what is required by law. For this question, the answer was almost unanimously "no," except for rating, which had about 26% of the responses reporting "yes."

Consumer Opportunity to Challenge or Correct Data

For the question on whether consumers have the opportunity to challenge or correct their specific data outside of processes for the federal Fair Credit Reporting Act (FCRA), many did not answer. Of those who answered this question, about 50% said "yes" for rating and underwriting; 40% said "yes" for claims and marketing; 15% said "yes" for fraud detection; and less than 10% said "yes" for loss prevention.

GOVERNANCE

The purpose of the model governance questions is to obtain a better understanding regarding a company's awareness of specific risk areas tied to selected categories in the NAIC Artificial Intelligence Principles. A sizable number of companies did not respond to these questions.

Insurers were asked if the following are *documented* in a governance program:

- Fairness and ethics considerations.
- Accountability for data algorithms' compliance with laws, as well as intended and unintended impacts.
- Appropriate resources and knowledge involved to ensure compliance with laws, including those related to unfair discrimination.
- Ensure transparency with appropriate disclosures, including notice to consumers specific to data being used and methods for appeal and recourse related to inaccurate data.
- AI systems are secure, safe, and robust, including decision traceability and security and privacy risk protections.

Insurers' answers were fairly consistent between each question. The answers for rating tended to be higher percentages of "yes" than for the other insurer operations. The transparency question received noticeably fewer affirmations than others. While the percentage of "yes" responses averaged 67% for most questions, the transparency question only received 56% "yes" responses.

THIRD-PARTY DATA SOURCES AND MODELS

Insurers identified third-party vendors they use to purchase models and/or data. There were 2,531 models listed in the survey (with some models being counted more than once because of separate uses for the same model); 1,073 (42%) are developed by a third party, and 1,458 (58%) are developed internally. After grouping the similarly named third parties, there are 76 unique third-party companies listed in the survey whose models are being used by insurers. Marketing has 39 different third parties listed, followed by claims with 28. For data purchases, there were 104 unique third parties listed as data sources in the survey.

CONCLUSION/NEXT STEPS

The insight gained from the survey will be used to supplement state insurance regulators' knowledge of the current regulatory framework around AI/ML, governance, consumers, and third parties and to evaluate whether any changes should be made to the regulatory frameworks.

Following are some potential next steps, including many activities already in progress. This list is not intended to be complete, but it may be helpful as a starting point for discussions and decision-making about what next steps to take at the NAIC:

- Evaluate the survey analysis and determine whether to further explore the following subjects:
    - Insurer AI/ML model usage and the level of decision-making (i.e., the amount of human involvement in decision-making).
    - Insurer data elements.
    - Insurers' governance frameworks and the documentation of such.
    - Consumer data recourse.
    - Third-party regulatory framework.
- Create a risk hierarchy to prioritize the need for more model governance and insurer oversight. The general concept is that more oversight of a model will be needed as the consumer risk or impact increases from the modeling or models.
- Evaluate consumer data recourse. Insurers report a wide variety of methods for consumers to evaluate and correct data used by insurers. Some methods are short and easy, such as using an app to correct data, and other methods are more time-consuming and require personal contact with the agent or company. In some cases, consumers may not know their data is being used, so consumer transparency is a priority. *(Privacy Protections (D) Working Group)*
- Evaluate the regulatory framework around the use of third-party models and third-party data. Evaluate the ability of insurers and state insurance regulators to obtain needed information from third parties and for regulators to oversee this work either through the insurers or third parties in some way. *(Workstream Two of the Big Data and Artificial Intelligence (H) Working Group)*
- Evaluate concerns about third-party concentration by insurer use. *(Workstream Two of the Big Data and Artificial Intelligence (H) Working Group)*
- Determine whether additional white papers on best practices would be useful on subjects in the AI/ML space.

Additional information was collected and analyzed in a confidential June 30, 2022, NAIC staff report, which is available to state insurance regulators by contacting Kris DeFrain, kdefrain@naic.org. This report is confidential because data was collected in a market conduct examination of the nine states and agreed confidentiality protections were applied.

December 8, 2022

Private Passenger Auto Artificial Intelligence/Machine Learning Survey Results

NAIC Staff Report

NAIC SURVEY TECHNICAL TEAM

Kris DeFrain, Director of Research and Actuarial Services
Dorothy L. Andrews, Senior Behavioral Data Scientist and Actuary
Roberto Perez Santiago, Property/Casualty Rate Modeling Actuary and Data Scientist
Justin Cox, Data Analyst III
Paula D. Harms, Center for Insurance Policy and Research (CIPR) Senior Research Analyst

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INTRODUCTION

Purpose of the Survey

At the outset of the Artificial Intelligence (AI)/Machine Learning (ML) surveys, the predecessor to the Big Data and Artificial Intelligence (H) Working Group defined five key objectives. Regulators want to: 1) learn directly from the industry about what is happening in this space; 2) get a sense of the current level of risk and exposure and whether or how the industry is managing or mitigating that risk; 3) develop information for trending, such as how the risk is evolving over time, and the industry's responsive actions; 4) inform a meaningful and useful regulatory approach, framework, and/or strategy for overseeing and monitoring this activity; and 5) learn from prior surveys to inform and improve future surveys.

Goals of the Private Passenger Auto Survey
1. Analyze industry use of artificial intelligence (AI)/machine learning (ML). 2. Identify industry's risk and exposure and mitigation of model risk. 3. Calculate trends. 4. Gather background for regulatory approach/framework. 5. Inform/improve future surveys.

This Private Passenger Auto (PPA) survey is expected to help regulators in terms of 1) consumer protections and 2) areas that regulators might expect companies involved in this type of activity to be, actively and with intention, ensuring that they are putting processes and procedures in place to meet, or at least consider, the expectations laid out in the NAIC's AI Principles.

This initial survey was developed to document industry observations in the PPA insurance market regarding use of data and AI/ML, gain insight from open-ended questions, get a good sense of the current level of risk and exposure, and learn what companies be doing to mitigate and/or manage its risk and exposure.

Purpose of This Report

With the tremendous amount of data submitted for this survey, the subject matter expert (SME) group asked NAIC technical staff to assist in conducting a thorough analysis. The survey analysis team was asked to evaluate the results, provide data analysis, and investigate potential inaccuracies in the data. The team was specifically asked to investigate what types of data are being used by companies in their AI/ML models; evaluate third-party AI/ML model and data use; explore levels of governance; and evaluate transparency, consumer disclosures, and potential consumer actions to correct data.

BACKGROUND

The PPA survey was conducted under market conduct examination authority of nine states: Connecticut, Illinois, Iowa, Louisiana, Nevada, North Dakota, Pennsylvania, Rhode Island, and Wisconsin. SMEs from these states opted to limit the survey request to only larger companies, defined as those PPA writers with more than $75 million in 2020 direct premium written. The survey call letter was distributed on Sept. 28, 2021, and survey responses were requested by Oct. 28, 2021. A total of 193 responses were received, and almost 90% of those indicated they are doing something pertaining to AI/ML.

Survey Web Page

The survey template, filing documentation, frequently asked questions (FAQ), and a link to the submission application can be found on the PPA AI/ML survey web page.

Surveyed Companies and Requesting States

The PPA insurance companies with at least $75 million in 2020 direct written premium transacting ongoing business in at least one of the following states were requested to provide survey responses within 30 days: Connecticut, Illinois, Iowa, Louisiana, Nevada, North Dakota, Pennsylvania, Rhode Island, or Wisconsin (requesting states).

Nine states conducted a market conduct analysis of various property/casualty (P/C) companies to:

- Gain a better understanding of the insurance industry's use and governance of big data and AI/ML.
- Seek information that could aid in the development of guidance or a potential regulatory framework to support the insurance industry's use of big data and AI/ML.
- Inform as to the current and planned business practices of the company.

The requesting states agreed the collected data will not be used to evaluate or determine the company's compliance with applicable laws and regulations.

Regulatory Subject Matter Experts

For each of the requesting states, the following SMEs created the survey and will communicate the survey responses to the Big Data and Artificial Intelligence (H) Working Group.

CT: George Bradner
IL: Erica Weyhenmeyer
IA: Andria Seip
LA: Nichole Torblaa
ND: Mike Andring and Chris Aufenthie
NV: Gennady Stolyarov
PA: Michael McKenney
RI: Matt Gendron
WI: Timothy Cornelius

The following NAIC staff assisted the SMEs with survey development, survey distribution, and data collection: Denise Matthews, Tim Mullen, Teresa Cooper, Paula D. Harms, and Justin Cox.

Artificial Intelligence/Machine Learning Definition

The definition of AI/ML was provided on the PPA AI/ML survey web site with the following link: **PPA AI/ML Filing Guidance & Definitions** (Version 2021.0.0).

"Definition of Artificial Intelligence / Machine Learning (AI/ML) for Survey – Applicable to All Sections

AI/ML describes an automated process in which a system begins recognizing patterns without being specifically programmed to achieve a predetermined 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 predetermined 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 exclude:

- 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 ratemaking 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 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 prerecorded voice prompts.
- Any approach that a company could have realistically utilized in the year 2000 or prior."

A key decision affecting interpretation of results was the definition of AI/ML for purposes of the survey. The SME group drafted the AI/ML definition to exclude some methods, such as linear regression, commonly used models such as GLM and GAMs, and any approach that a company could have realistically used in the year 2000 or prior. The SMEs developed the AI/ML definition to focus on the "more advanced" models. Regulators noted they have extensive experience reviewing the older models used for rating, having completed the NAIC's 2020 white paper *Regulatory Review of Predictive Models* and having conducted numerous training and educational events.

This definition resulted in approximately 80% of the models used in rating, based on the types of models submitted to the NAIC's rate model review team, to be excluded from the survey results. We have no information about the impact of this definition on the reporting of models for companies' non-rating operations. While there is some possibility of a mixed bag of data due to using a definition of AI/ML that is not academically accepted, the SME regulators experienced with rating models said the answers appear to reflect the requested definition accordingly. However, after the survey results were partially revealed, Hartford employees said they are aware of the state of the AI/ML usage in the insurance industry and believe the reporting of models exceed the expected number if the survey's AI/ML definition had been used by all reporting companies. This position is speculation and cannot be proven with the available data. Regulators would need to delve deeper by asking the companies whether the definition was consistently used across company operations.

Confidentiality

The individual company results are confidential. Some combined results have been publicly presented at Big Data and Artificial Intelligence (H) Working Group meetings and are presented in this report.

GENERAL SECTION OF THE SURVEY

Out of 193 companies that completed the survey, 169 companies currently use, plan to use, or plan to explore using AI / ML as defined for this survey. This equates to 88.6% of reporting companies. (Refer to Table 1.)

Table 1: Companies Using or Exploring the Use of AI/ML

Number of Companies Planning to Use or Explore Using AI/ML	
Yes	169
No	24
Total	193

The 24 companies that indicated they had no plan to use or explore use of AI/ML also provided their reason(s) why, with the most often selected reasons being: 1) no compelling business reason; and 2) lack of resources and expertise. In addition to the options listed in the survey and shown in Table 2, a few companies wrote in additional reasons. One company said it was not convinced it will yield a better risk selection and/or product pricing result. Three companies said they use preconfigured programming in their business processes. One company said it does not currently have policies in the requesting states.

Table 2: Companies' Reasons for Not Using AI/ML

If not using AI/ML, why?	
Options listed in the survey:	Number of Companies
No compelling business reason	10
Waiting for regulatory guidance	6
Lack of resources and expertise	9
Lack of reliable data and associated security risk	6
Reliance on legacy systems requiring IT (Information Technology), data, and technology system upgrade before starting AI/ML initiatives	7
Waiting on the availability of a third-party vendor product/service	1
Risk not commensurate with current strategy or appetite	4

Among company operations areas, companies reported varying levels of AI/ML use, from only 2% in the loss prevention area to 70% in claims operations. In order from maximum to minimum use, the percentage of companies using AI/ML for the following operation areas were: claims, 70%; marketing, 50%; fraud detection, 49%; rating, 27%; underwriting, 18%; and loss prevention 2%. Adding in the companies with models under construction, the percentages were: claims, 80%; fraud detection, 58%; marketing, 54%; rating, 40%; underwriting, 31%; and loss prevention, 15%. (Refer to Table 3.)

Intuitively, one might expect to see rating and/or underwriting as the areas with the largest amount of AI/ML use. The results of this survey are purposely affected by the definition of AI/ML to exclude the most-often used types of rating and underwriting models to focus on the more advanced types of AI/ML.

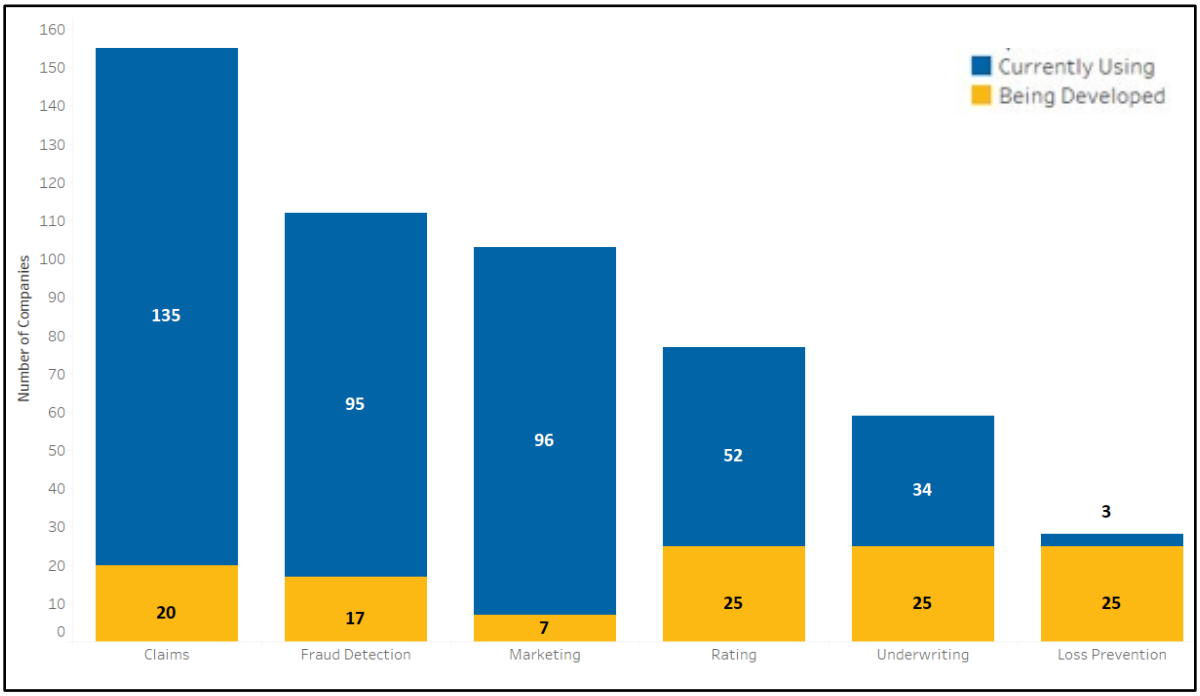
Table 3: Companies with Models in Use or Under Construction by Company Operation Area

Company	Number and Percentage of Companies

Operation Area[1]	In Use		Under Construction[2]		None (N/A)		Total	
	#	%	#	%	#	%	#	%
Rating	52	27%	25	13%	116	60%	193	100%
Underwriting	34	18	25	13	134	69	193	100
Claims	135	70	20	10	38	20	193	100
Fraud Detection	95	49	17	9	81	42	193	100
Marketing	96	50	7	4	90	47	193	100
Loss Prevention	3	2	25	13	165	85	193	100

The same information is shown pictorially in Figure 1.

Figure 1: Number of Companies Currently Using or Developing AI/ML Models



In addition to the company operations areas listed in the survey template, companies provided numerous "other" AI/ML uses. The following are additional uses of AI/ML: agency models (portal effectiveness and insights, agency and sales management, cross-selling); customer interactions (chatbot, customer care operations, call center, customer experience, and customer service); information technology (IT)-related

[1] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

[2] The "under construction" category had options of number of years until expected implementation, but we question the results of the categorization because the choices in the survey were ambiguous. For example, there was not a consistent understanding of whether "< 1 year" meant that the company will be implementing AI/ML in the next year or if the company had been using AI/ML for less than a year.

models (performance monitoring, threat detection/protection); knowledge management; language processing (speech-to-text, event insights); operational efficiency; social media sentiment analysis; premium audits; video imaging to predict accidents; and workload forecasting.

COMPANY OPERATION: CLAIMS[3]

Out of 193 reporting companies, 135 reported using AI/ML for claims operations, and 20 reported having models under construction.

Claims Model Uses

In insurance claims operations, companies reported currently using AI/ML claims models mostly as an informational resource for adjusters (96 companies). Few companies are using AI/ML claims models for claims approvals (9) and none are using them for claims denials. Other AI/ML claims models are currently used to determine claim settlement amounts (50), to make claim assignment decisions (58), to evaluate images of loss (55), and for other claim-related functions (66). The uses of claims models identified in Table 4 were options that could be selected in the survey template. Companies noted some additional uses of claims models in their write-in comments: subrogation potential, claims triage, speech analysis, loss recognition, litigation likelihood, selection of claims for a streamlined liability investigation process, accident detection, listen to voice calls, claim classification, work prioritization, reserving, reserve management, fast-track processing, volume forecasting, leadership quality reviews, call deflection, early total loss recognition, uninsured motorist exposure, physical damage assessment, arbitration, "doc bot," and supplemental requests on claims. One company mentioned the use of AI/ML to recommend repair shops.

Once models under construction begin to be used, companies will most often be using AI/ML claims models for evaluation of images of the loss (114 companies) and other claim-related functions (113).

Table 4: Companies' Use of Claims Models

Claims Model Uses[4]	Number of Companies				
	In Use	Research	Proof of Concept	Prototype	None
Claim Approval	9	5	0	0	179
Claim Denial	0	0	0	0	193
Determine Settlement Amount	50	6	10	3	124
Claim Assignment Decisions	58	15	11	1	108
Informational Resource for Adjusters	96	0	3	0	94
Evaluation of Images of the Loss	55	24	27	8	79
Other Claim-Related Functions	66	21	11	15	80

[3] For definitions, refer to Appendix B: Definitions Specific to Claims.
[4] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

The level of insurance company employee decisions influenced by AI/ML varies by model use. Determination of settlement amount tends to include augmentation, defined as suggesting an answer and advising the human who is making the decision. Claim assignment decisions tend to be automated or at least the models provide augmentation. (Refer to Table 5). Note that Table 5 differs from the previous tables because the data represents the number of models instead of the number of companies.

Table 5: Level of Decision-Making by Use of Claims Models

Claims Model Uses[5]	Number of Models (In Use or Under Construction) by Level of Decisions Influenced by AI/ML			
	Automation*	Augmentation*	Support*	Other
Claim Approval	9	6	0	0
Claim Denial	0	0	0	0
Determine Settlement Amount	30	94	11	0
Claim Assignment Decisions	106	81	8	0
Informational Resource for Adjusters	6	82	164	0
Evaluation of Images of the Loss	16	201	35	0
Other Claim-Related Functions	34	95	92	2

*"Automation" was defined as no human intervention on execution. "Augmentation" was defined as a model that suggests an answer and advises the human making a decision. "Support" was defined as a model that provides information but does not suggest a decision or action.

Models being used by insurance companies are developed in-house (with or without third-party assistance) or purchased from a third party. Models for claim approval, claim assignment decisions, adjusters' informational resource, and other claim-related functions tend to be developed in-house. Models used to determine settlement amounts and evaluate images of the loss tend to be developed by third parties. (Refer to Table 6.)

Table 6: Claims Model Sources by Model Use

Claims Model Uses[6]	Model Source					
	In-House	In-House	Third-Party	Third-Party	Total	Total
	#	%	#	%	#	%
Claim Approval	11	73%	4	27%	15	100%
Claim Denial	0	0	0	0	0	100
Determine Settlement Amount	27	20	108	80	135	100
Claim Assignment Decisions	155	79	40	21	195	100
Informational Resource for Adjusters	222	88	30	12	252	100
Evaluation of Images of the Loss	70	28	182	72	252	100

[5] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

[6] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Claims Model Uses[6]	Model Source					
	In-House	In-House	Third-Party	Third-Party	Total	Total
	#	%	#	%	#	%
Other Claim Related Functions	172	77	51	23	223	100

Data Elements

It is well known that insurers use big data for many purposes and models. Given this survey is focused on the use of the "more advanced" AI/ML, the data element information here is similarly focused on the use of data elements only when used in "more advanced" AI/ML models.

For claims, the following five data elements were the most frequently reported as being used for AI/ML:

- Vehicle-specific data (123 companies)
- Loss experience (74)
- Medical (63)
- Geocoding (22)
- Telematics (21)

There are at least some companies using a consumer or other type of "score" (16), driving behavior (10), criminal convictions (9), voice analysis (8), online media (7), education (2), and personal financial information (2). Companies also reported using "other" nontraditional data elements (32). (Refer to Table 7.)

Table 7: Companies' Use of Claims Data Elements

Claims Data Elements[7]	Number of Companies Using/Not Using the Data Element in a Claims AI/ML Model*		
	Yes	No	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	9	153	31
Demographic	40	122	31
Driving Behavior	10	152	31
Education	2	160	31
Vehicle-Specific Data	123	39	31
Facial Detection/Recognition/Analysis	0	162	31
Geocoding	22	140	31
Natural Catastrophe	0	162	31
Job Stability	0	162	31
Income	0	162	31
Occupation	0	162	31
Personal Financial Information	2	160	31
Loss Experience	74	88	31

[7] For definitions, refer to Appendix H: Data Use Table Definitions.

Claims Data Elements[7]	Number of Companies Using/Not Using the Data Element in a Claims AI/ML Model*		
	Yes	No	Blank
Medical	63	99	31
Online Media	7	155	31
Telematics	21	141	31
Voice Analysis	8	153	32
Consumer or Other Type of "Score"	16	147	30
Other Nontraditional Data Elements	32	130	31

*The question is not whether the data element is used, but only whether the data element is used in an AI/ML model.

The data elements used in claims models tend to be internal data sources or a mix of internal and external sources. (Refer to Table 8.)

Table 8: Claims Model Sources (Internal vs. Third Party) by Data Elements

Claims Data Elements[8]	# of Companies Using the Data Element in a Claims AI/ML model*			
	Internal Data Source	External Data Source	Both Internal and External Data Sources	Blank
Criminal Conviction (Excluding auto-related convictions)	0	9	0	184
Demographic	20	2	18	153
Driving Behavior	7	0	3	183
Education	0	2	0	191
Vehicle-Specific Data	51	21	51	70
Facial Detection/Recognition/Analysis	0	0	0	193
Geocoding	13	7	2	171
Natural Catastrophe	0	0	0	193
Job Stability	0	0	0	193
Income	0	0	0	193
Occupation	0	0	0	193
Personal Financial Information	0	2	0	191
Loss Experience	50	16	8	119
Medical	45	4	14	130
Online Media	0	7	0	186
Telematics	1	7	13	172
Voice Analysis	6	0	2	185
Consumer or Other Type of "Score"	7	2	7	177
Other Non-Traditional Data Elements	31	1	0	161

[8] For definitions, refer to Appendix H: Data Use Table Definitions.

Very few companies reported using a consumer or other type of "score" as an input for claims models. (Refer to Table 9.)

Table 9: Companies' Use of Consumer or Other Type of "Score" as an Input for Claims Data Elements

Claims Data Elements[9]	Number of Companies Using a Consumer or Other Type of "Score" as an Input		
	Yes	No	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	61	132
Demographic	0	69	124
Driving Behavior	0	58	135
Education	0	58	135
Vehicle-Specific Data	3	110	80
Facial Detection/Recognition/Analysis	0	58	135
Geocoding	1	59	133
Natural Catastrophe	0	58	135
Job Stability	0	58	135
Income	0	58	135
Occupation	0	58	135
Personal Financial Information	0	58	135
Loss Experience	0	73	120
Medical	0	68	125
Online Media	0	58	135
Telematics	0	65	128
Voice Analysis	0	58	135
Consumer or Other Type of "Score"			
Other Nontraditional Data Elements	0	83	110

Refer to the "Customer Data Correction," "Governance," and "Third-Party" sections of this report for additional data analysis regarding company operations areas.

COMPANY OPERATION: FRAUD DETECTION[10]

Out of 193 reporting companies, 95 companies reported using AI/ML for fraud-detection operations, and 17 reported having models under construction.

<u>Fraud-Detection Model Uses</u>

In insurance fraud detection, companies reported currently using AI/ML models mostly as a referral of claims for further investigation (83 companies). Other AI/ML fraud-detection models are currently used in the following areas: detect medical producer fraud (27), detect third-party liability (17), fast-tracking of likely non-fraudulent claims (10), detect first-party liability (10), and "other" fraud detection-related

[9] For definitions, refer to Appendix H: Data Use Table Definitions.
[10] For definitions, refer to Appendix C: Definitions Specific to Fraud Detection.

functions (four). The uses of fraud-detection models identified in Table 10 were options that could be selected in the survey template. Companies noted some additional uses of fraud-detection models in their write-in comments: fraudulent quote detection, organized crime rings identification, social network analysis, facial recognition, behavior models, detect prefill information harvesters, device risk, and claims watch list.

Some models are under construction for fraud detection, but there appears to be no significant development planned in the near future.

Table 10: Companies' Use of Fraud-Detection Models

Fraud-Detection Model Uses[11]	Number of Companies				
	In Use	Research	Proof of Concept	Prototype	None (N/A)
Fast-Tracking of Likely Non-Fraudulent Claims	10	15	3	1	164
Referral of Claims for Further Investigation	83	3	6	3	98
Detect Medical Producer Fraud	27	3	2	9	152
Detect First-Party Liability	10	2	2	1	178
Detect Third-Party Liability	17	2	2	1	171
Other Fraud Detection-Related Functions	4	2	12	4	171

The level of decisions influenced by AI/ML varies by model use. Most fraud detection model uses provide support. For referral of claims for further investigation, there is an even split between augmentation and support. (Refer to Table 11. Note that Table 11 differs from the previous tables because the data represents the number of models instead of the number of companies.)

Table 11: Level of Decision-Making by Use of Fraud-Detection Models

Fraud-Detection Model Uses[12]	Number of Models (In Use or Under Construction) by Level of Decisions Influenced by AI/ML			
	Automation*	Augmentation*	Support*	Other
Fast-Tracking of Likely Non-Fraudulent Claims	1	5	23	1
Referral of Claims for Further Investigation	0	89	93	2
Detect Medical Producer Fraud	0	17	44	0
Detect First-Party Liability	1	4	13	0
Detect Third-Party Liability	1	11	13	0

[11] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.
[12] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Fraud-Detection Model Uses[12]	Number of Models (In Use or Under Construction) by Level of Decisions Influenced by AI/ML			
	Automation*	Augmentation*	Support*	Other
Other Fraud Detection-Related Functions	0	8	26	0

*"Automation" was defined as no human intervention on execution. "Augmentation" was defined as a model that suggests an answer and advises the human making a decision. "Support" was defined as a model that provides information but does not suggest a decision or action.

Models to detect first-party and third-party liability tend to be developed by third parties. The model use of "Other Fraud Detection-Related Functions" tended to be developed by third parties. All other uses of fraud detection models result from a mixture of in-house and third-party models. (Refer to Table 12.)

Table 12: Fraud-Detection Model Sources by Model Use

Fraud-Detection Model Uses	Model Source					
	In-House	In-House	Third-Party	Third-Party	Total	Total
	#	%	#	%	#	%
Fast-Tracking of Likely Non-Fraudulent Claims	15	50%	15	50%	30	100%
Referral of Claims for Further Investigation	120	65	64	34	184	100
Detect Medical Producer Fraud	39	64	22	36	61	100
Detect First-Party Liability	3	17	15	83	18	100
Detect Third-Party Liability	10	40	15	60	25	100
Other Fraud Detection-Related Functions	9	26	25	74	34	100

Data Elements

The survey was limited to the use of the "more advanced" AI/ML. Therefore, the data element information here does not represent the industry's entire use of big data (which would require adding in the data element information from excluded models (e.g., regression-type models, etc.).

For fraud detection, the following five data elements were the most frequently reported as being used for AI/ML:

- Loss experience (80 companies)
- Vehicle-specific data (68)
- Medical (67)
- Criminal conviction (43)
- Online media (29)

There are at least some companies using demographic (28 companies), geocoding (21), driving behavior (6), personal financial information (3), consumer or other type of "score" (3), occupation (1), and telematics (1) for fraud-detection purposes. Companies also reported using "other" nontraditional data elements (12). Some of the other uses were: identification of fraudulent quotes and organized crime rings, detection of prefill information, device risk, claims watch list, social network analysis, facial recognition, and behavior models. (Refer to Table 13.)

Table 13: Companies' Use of Fraud-Detection Data Elements

Fraud-Detection Data Elements[13]	Number of Companies Using/Not Using the Data Element in a Fraud-Detection AI/ML Model*		
	Yes	No	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	43	79	71
Demographic	28	94	71
Driving Behavior	6	116	71
Education	0	122	71
Vehicle-Specific Data	68	54	71
Facial Detection/Recognition/Analysis	0	122	71
Geocoding	21	101	71
Natural Catastrophe	0	122	71
Job Stability	0	120	73
Income	0	122	71
Occupation	1	121	71
Personal Financial Information	3	119	71
Loss Experience	80	42	71
Medical	67	55	71
Online Media	29	93	71
Telematics	1	121	71
Voice Analysis	0	122	71
Consumer or Other Type of "Score"	3	119	71
Other Nontraditional Data Elements	12	110	71

*The question is not whether the data element is used, but only whether the data element is used in an AI/ML model.

There are differences in data sources for the data elements. The data elements used in fraud-detection models are most often from external data sources for criminal conviction, geocoding, and online media. Other fraud-detection models tend to use internal data sources or a mix of internal and external sources. (Refer to Table 14.)

[13] For definitions, refer to Appendix H: Data Use Table Definitions.

Table 14: Fraud-Detection Model Sources (Internal vs. Third Party) by Data Elements

Fraud-Detection Data Elements[14]	Number of Companies Using the Data Element in a Fraud-Detection AI/ML model*			
	Internal Data Source	External Data Source	Both Internal and External Data Sources	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	36	7	150
Demographic	16	2	10	165
Driving Behavior	3	0	3	187
Education	0	0	0	193
Vehicle-Specific Data	35	2	31	125
Facial Detection/Recognition/Analysis	0	0	0	193
Geocoding	3	18	0	172
Natural Catastrophe	0	0	0	193
Job Stability	0	0	0	193
Income	0	0	0	193
Occupation	1	0	0	192
Personal Financial Information	0	3	0	190
Loss Experience	39	0	41	113
Medical	45	4	18	126
Online Media	0	18	11	164
Telematics	1	0	0	192
Voice Analysis	0	0	0	193
Consumer or Other Type of "Score"	1	2	0	190
Other Nontraditional Data Elements	12	0	0	181

Few companies reported using a consumer or other type of "score" as an input for fraud-detection models. (Refer to Table 15.)

Table 15: Companies' Use of Consumer or Other Type of "Score" as an Input for Fraud-Detection Data Elements

Fraud-Detection Data Elements[15]	Number of Companies Using a Consumer or Other Type of "Score" as an Input		
	Yes	No	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	64	129
Demographic	0	65	128
Driving Behavior	0	57	136
Education	0	57	136
Vehicle-Specific Data	1	75	117

[14] For definitions, refer to Appendix H: Data Use Table Definitions.
[15] For definitions, refer to Appendix H: Data Use Table Definitions.

Fraud-Detection Data Elements[15]	Number of Companies Using a Consumer or Other Type of "Score" as an Input		
	Yes	No	Blank
Facial Detection/Recognition/Analysis	0	57	136
Geocoding	1	58	135
Natural Catastrophe	0	57	136
Job Stability	0	57	136
Income	0	57	136
Occupation	0	57	136
Personal Financial Information	0	57	136
Loss Experience	0	76	117
Medical	0	66	127
Online Media	0	57	136
Telematics	0	57	136
Voice Analysis	0	57	136
Consumer or Other Type of "Score"			
Other Nontraditional Data Elements	5	57	131

Refer to the "Customer Data Correction, "Governance," and "Third-Party" sections of this report for additional data analysis regarding company operations areas.

COMPANY OPERATION: MARKETING[16]

Out of 193 reporting companies, 96 companies reported using AI/ML for fraud-detection operations, and seven (7) reported having models under construction. So, approximately half of the companies are using AI/ML for marketing.

Marketing Model Uses

Companies are using many marketing models for multiple uses. Companies use marketing models for targeted online advertising (56 companies), identification of recipients of mail and phone advertising (42), provision of offers to existing customers (42), and direct online sales (41). Only 19 companies are currently using models for identification of potential customer groups, and only seven (7) companies are currently using AI/ML for demand modeling. Companies are also using marketing models for other marketing-related functions (46).

The uses of marketing models identified in Table 16 were options that could be selected in the survey template. Companies noted some additional uses of marketing models in their write-in comments: customer service, customer-related metrics, customer interactions using natural language processing (NLP), mixed media modeling, marketing content variation, alternative quote recommendation, creative optimization, budget and channel spend allocation, customer retention and acquisition (including lifetime value), referrals, agency rank, and click analysis on third-party sites (web searching).

[16] For definitions, refer to Appendix D: Definitions Specific to Marketing.

Table 16: Companies' Use of Marketing Models

Marketing Model Uses[17]	Number of Companies				
	In Use	Research	Proof of Concept	Prototype	None (N/A)
Targeted Online Advertising	56	2	3	0	132
Identification of Recipients of Mail or Phone Advertising	42	2	0	0	149
Provision of Offers to Existing Customers	42	2	3	11	135
Identification of Potential Customer Groups	19	3	7	0	164
Demand Modeling	7	10	0	0	176
Direct Online Sales	41	5	0	0	147
Other Marketing-Related Functions	46	10	0	3	134

Many of the marketing models are automated with no human intervention on execution. Marketing models are mostly automated when used for targeted online marketing (136 models), direct online sales (88), provision of offers to existing customers (56), and other marketing-related functions (75). When identifying recipients of mail or phone advertising, there is most often augmentation (68), where a model provides an answer and advises the human who is making the decision. When identifying potential customer groups, the number of models is evenly split between all three levels of decision-making. Demand modeling is evenly split between augmentation and support to the human. (Refer to Table 17.)

Table 17: Level of Decision-Making by Use of Marketing Models

Marketing Model Uses[18]	Number of Models (In Use or Under Construction) by Level of Decisions influenced by AI/ML			
	Automation*	Augmentation*	Support*	Other
Targeted Online Advertising	136	45	23	1
Identification of Recipients of Mail or Phone Advertising	28	68	23	1
Provision of Offers to Existing Customers	56	27	24	1
Identification of Potential Customer Groups	32	28	22	1
Demand Modeling	2	13	14	0
Direct Online Sales	88	40	12	5
Other Marketing-Related Functions	75	23	16	2

[17] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.
[18] For definitions, See Appendix A: "Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention"

*"Automation" was defined as no human intervention on execution. "Augmentation" was defined as a model that suggests an answer and advises the human making a decision. "Support" was defined as a model that provides information but does not suggest a decision or action.

Marketing models being used by insurance companies are equally developed in-house (with or without third-party assistance) and purchased from a third party. Two exceptions are that third-party models are used for targeted online advertising, and in-house models are used for the provision of offers to existing customers. (Refer to Table 18.)

Table 18: Marketing Model Sources by Model Use

Marketing Model Uses[19]	Model Source					
	In-House	In-House	Third-Party	Third-Party	Total	Total
	#	%	#	%	#	%
Targeted Online Advertising	19	9%	186	91%	205	100%
Identification of Recipients of Mail or Phone Advertising	46	38	74	62	120	100
Provision of Offers to Existing Customers	78	72	30	28	108	100
Identification of Potential Customer Groups	48	58	35	42	83	100
Demand Modeling	16	55	13	45	29	100
Direct Online Sales	76	52	69	48	145	100
Other Marketing-Related Functions	69	59	47	41	116	100

Data Elements

The survey was limited to the use of the "more advanced" AI/ML. Therefore, the data element information here does not represent the industry's entire use of big data (which would require adding in the data element information from excluded models (e.g., regression-type models, etc.).

For marketing, the following five data elements were the most frequently reported as being used:

- Demographic (79 companies)
- Education (42)
- Consumer or other type of "score" (42)
- Geocoding (40)
- Vehicle-specific data (39)

There are at least some companies using driving behavior (33 companies), occupation (32), online media (29), loss experience (21), personal financial information (13), telematics (11), job stability (11), income (4), and natural catastrophe (1) for fraud-detection purposes. Companies also reported using "other" nontraditional data elements (26). (Refer to Table 19.)

[19] For definitions, See Appendix A: "Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention"

Table 19: Companies' Use of Marketing Data Elements

Marketing Data Elements[20]	Number of Companies Using/Not Using the Data Element in a Marketing AI/ML Model*		
	Yes	No	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	128	65
Demographic	79	48	66
Driving Behavior	33	94	66
Education	42	85	66
Vehicle-Specific Data	39	88	66
Facial Detection/Recognition/Analysis	0	127	66
Geocoding	40	87	66
Natural Catastrophe	1	126	66
Job Stability	11	116	66
Income	4	123	66
Occupation	32	95	66
Personal Financial Information	13	114	66
Loss Experience	21	106	66
Medical	0	127	66
Online Media	29	98	66
Telematics	11	116	66
Voice Analysis	0	127	66
Consumer or Other Type of "Score"	42	99	52
Other Nontraditional Data Elements	26	101	66

*The question is not whether the data element is used, but only whether the data element is used in an AI/ML model.

There are differences in data sources for the data elements. For example, demographic, driving behavior, education, geocoding, job stability, occupation, loss experience, and telematics are most often sourced externally, while income, personal financial, and consumer or other "score" were more frequently sourced internally. Other data elements, such as vehicle-specific data and online media, are sourced almost equally from both external and internal data. (Refer to Table 20.)

[20] For definitions, see Appendix H: "Data Use Table Definitions."

Table 20: Marketing Model Sources (Internal vs. Third Party) by Data Elements

Marketing Data Elements[21]	Number of Companies Using the Data Element in a Marketing AI/ML model*			
	Internal Data Source	External Data Source	Both Internal and External Data Sources	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	0	0	193
Demographic	40	14	25	114
Driving Behavior	20	9	4	160
Education	21	6	15	151
Vehicle-Specific Data	20	14	5	154
Facial Detection/Recognition/ Analysis	0	0	0	193
Geocoding	36	8	0	149
Natural Catastrophe	0	1	0	192
Job Stability	11	0	0	182
Income	0	4	0	189
Occupation	22	10	0	161
Personal Financial Information	0	6	7	180
Loss Experience	13	1	7	172
Medical	0	0	0	193
Online Media	14	15	0	164
Telematics	11	0	0	182
Voice Analysis	0	0	0	193
Consumer or Other Type of "Score"	11	31	0	151
Other Nontraditional Data Elements	24	2	0	167

A few companies use a consumer or other type of "score" as an input for the following marketing data elements: demographic (5 companies), occupation (4), and personal financial information (2). One company uses consumer or other type of "score" as an input for the following market data elements: driving behavior, education, vehicle-specific data, income, and online media. (Refer to Table 21.)

[21] For definitions, see Appendix H: "Data Use Table Definitions."

Table 21: Companies' Use of Consumer or Other Type of "Score" as an Input for Marketing Data Elements

Marketing Data Elements[22]	Number of Companies Using a Consumer or Other Type of "Score" as an Input		
	Yes	No	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	46	147
Demographic	5	61	127
Driving Behavior	1	45	147
Education	1	60	132
Vehicle-Specific Data	1	46	146
Facial Detection/Recognition/Analysis	0	46	147
Geocoding	0	59	134
Natural Catastrophe	0	46	147
Job Stability	0	46	147
Income	1	46	146
Occupation	4	40	149
Personal Financial Information	2	45	146
Loss Experience	0	46	147
Medical	0	46	147
Online Media	1	59	133
Telematics	0	47	146
Voice Analysis	0	46	147
Consumer or Other Type of "Score"			
Other Nontraditional Data Elements	0	60	133

Refer to the "Customer Data Correction," "Governance," and "Third-Party" sections of this report for additional data analysis regarding company operations areas.

COMPANY OPERATION: RATING[23]

Out of 193 reporting companies, 52 companies reported using AI/ML for rating operations, and 25 reported having models under construction.

Rating Model Uses

While numbers are small, the most common use case within the rating area of operations is Rating Class determination, with 37 companies indicating they have models either in use (23 companies) or under construction (14). The second most common use case within the rating area of operations is numerical relativity determination, with 27 companies indicating that they have models either in use (19) or under construction (8). Only seven (7) companies reported using AI/ML models for retention modeling, with six (6) companies reporting models under construction for the area. No companies reported using or having plans to use AI/ML models for price optimization.

[22] For definitions, see Appendix H: "Data Use Table Definitions."
[23] For definitions, See Appendix E: Definitions Specific to Rating

The uses of rating models identified in Table 22 were options that could be selected in the survey template. Companies noted some additional uses of rating models in their write-in comments: telematics, close rate expectation, loss development expectation, loss performance monitoring, ground-up loss prediction, and frequency trend forecasting. Additional write-ins were policy application pre-filling and bad-debt mitigation.

Table 22: Companies' Use of Rating Models

Rating Model Uses[24]	Number of Companies				
	In Use	Research	Proof of Concept	Prototype	None (N/A)
Rating Class Determination	23	9	0	5	156
Price Optimization	0	0	0	0	193
Retention Modeling	7	3	0	3	180
Numerical Relativity Determination	19	4	0	4	166
Other Rate-Related Functions	24	4	0	0	165

Most of the rating models are automated, requiring no human intervention for execution. The types of models most often automated are retention models and other rate-related functions. Rating Class determinations and numerical relativity determinations tend to be augmented, where the model suggests an answer and advises a human who is making a decision. (Refer to Table 23.)

Table 23: Level of Decision-Making by Use of Rating Models

Rating Model Uses[25]	Number of Models (In Use or Under Construction) by Level of Decisions Influenced by AI/ML			
	Automation*	Augmentation*	Support*	Other
Rating Class Determination	9	33	8	3
Price Optimization	0	0	0	0
Retention Modeling	22	0	5	2
Numerical Relativity Determination	10	21	9	2
Other Rate-Related Functions	29	2	27	0

*"Automation" was defined as no human intervention on execution. "Augmentation" was defined as a model that suggests an answer and advises the human making a decision. "Support" was defined as a model that provides information but does not suggest a decision or action.

Rating models tend to be developed by companies and not third parties. About 75%–90% of the rating models are developed by companies "in-house." (Refer to Table 24.)

[24] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.
[25] For definitions, See Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Table 24: Rating Model Sources by Model Use

Rating Model Uses[26]	Model Source					
	In-House	In-House	Third-Party	Third-Party	Total	Total
	#	%	#	%	#	%
Rating Class Determination	47	89%	6	11%	53	100%
Price Optimization	0	0	0	0	0	100
Retention Modeling	25	86	4	14	29	100
Numerical Relativity Determination	33	79	9	21	42	100
Other Rate-Related Functions	44	76	14	24	58	100

Data Elements

The survey was limited to the use of the "more advanced" AI/ML. Therefore, the data element information here does not represent the industry's entire use of big data (which would require adding in the data element information from excluded models; e.g., regression-type models, etc.).

For rating, the following five data elements were the most frequently reported as being used for AI/ML:

- Vehicle-specific data (40 companies)
- Loss experience (35)
- Driving behavior (33)
- Demographic (30)
- Telematics (27)

There are at least some companies using vehicle-specific data (39 companies), driving behavior (33), occupation (32), online media (29), loss experience (21), personal financial information (13), telematics (11), job stability (11), income (4), and natural catastrophe (1) for fraud-detection purposes. Companies also reported using "other" nontraditional data elements (26). (Refer to Table 25.)

Table 25: Companies' Use of Rating Data Elements

Rating Data Elements[27]	Number of Companies Using/Not Using the Data Element in a Rating AI/ML Model*		
	Yes	No	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	113	80
Demographic	30	83	80
Driving Behavior	33	80	80
Education	7	106	80
Vehicle-Specific Data	40	73	80

[26] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.
[27] For definitions, refer to Appendix H: Data Use Table Definitions.

Rating Data Elements[27]	Number of Companies Using/Not Using the Data Element in a Rating AI/ML Model*		
	Yes	No	Blank
Facial Detection/Recognition/Analysis	0	113	80
Geocoding	11	102	80
Natural Catastrophe	6	107	80
Job Stability	0	113	80
Income	0	113	80
Occupation	6	107	80
Personal Financial Information	14	99	80
Loss Experience	35	78	80
Medical	0	113	80
Online Media	0	113	80
Telematics	27	86	80
Voice Analysis	0	113	80
Consumer or Other Type of "Score"	21	94	78
Other Nontraditional Data Elements	6	107	80

*The question is not whether the data element is used, but only whether the data element is used in an AI/ML model.

There are differences in data sources for the data elements. For example, driving behavior, telematics, natural catastrophe, and a consumer or other "score" tend to be externally sourced, while vehicle-specific data, loss experience, and occupation are more frequently sourced internally. Other data elements—such as geocoding, personal financial information, and demographic information—are sourced from both external and internal data. (Refer to Table 26.)

Table 26: Rating Model Sources (Internal vs. Third Party) by Data Elements

Rating Data Elements[28]	Number of Companies Using the Data Element in a Rating AI/ML Model*			
	Internal Data Source	External Data Source	Both Internal and External Data Sources	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	0	0	193
Demographic	11	6	13	163
Driving Behavior	0	27	6	160
Education	7	0	0	186
Vehicle-Specific Data	20	6	14	153
Facial Detection/Recognition/Analysis	0	0	0	193
Geocoding	5	6	0	182
Natural Catastrophe	0	6	0	187
Job Stability	0	0	0	193
Income	0	0	0	193

[28] For definitions, refer to Appendix H: Data Use Table Definitions.

Rating Data Elements[28]	Number of Companies Using the Data Element in a Rating AI/ML Model*			
	Internal Data Source	External Data Source	Both Internal and External Data Sources	Blank
Occupation	6	0	0	187
Personal Financial Information	7	7	0	179
Loss Experience	26	0	9	158
Medical	0	0	0	193
Online Media	0	0	0	193
Telematics	1	9	17	166
Voice Analysis	0	0	0	193
Consumer or Other Type of "Score"	4	17	0	172
Other Nontraditional Data Elements	0	6	0	187

Most companies do not use a consumer or other type of score as a data element. Table 27 illustrates that the only rating data elements for which consumer or other type of "score" was listed as an input are as follows: demographic (4 companies), driving behavior (4), vehicle specific data (1), and personal financial information (4). The numbers are low; recall the AI/ML definition excludes the most-often used rating models.

Table 27: Companies' Use of Consumer or Other Type of "Score" as an Input for Rating Data Elements

Rating Data Elements[29]	Number of Companies Using a Consumer or Other Type of "Score" as an Input		
	Yes	No	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	31	162
Demographic	4	36	153
Driving Behavior	4	29	160
Education	0	31	162
Vehicle-Specific Data	1	32	160
Facial Detection/Recognition/Analysis	0	31	162
Geocoding	0	31	162
Natural Catastrophe	0	33	160
Job Stability	0	31	162
Income	0	31	162
Occupation	0	31	162
Personal Financial Information	4	33	156
Loss Experience	0	37	156
Medical	0	31	162
Online Media	0	31	162
Telematics	0	47	146

[29] For definitions, refer to Appendix H: Data Use Table Definitions.

Rating Data Elements[29]	Number of Companies Using a Consumer or Other Type of "Score" as an Input		
	Yes	No	Blank
Voice Analysis	0	31	162
Consumer or Other Type of "Score"			
Other Nontraditional Data Elements	0	36	157

Refer to the "Customer Data Correction, "Governance," and "Third-Party" sections of this report for additional data analysis regarding company operations areas.

COMPANY OPERATION: UNDERWRITING[30]

Out of 193 reporting companies, 34 companies reported using AI/ML for fraud-detection operations, and 25 reported having models under construction.

Underwriting Model Uses

Most underwriting models in use are reported in the "all other" use category of other underwriting-related functions. There are 14 models under construction for the use of automated denial. No companies reported using or having plans to use AI/ML models for underwriting tier determination or to automate processing through the agency channel. We suspect the reason (there are no reported models) stems from the exclusion of the most-often used models in the AI/ML definition.

The uses of underwriting models identified in Table 28 were options that could be selected in the survey template. Companies noted some additional uses of underwriting models in their write-in comments: renewal evaluations, the need for renewal inspections, reinstatements, motor vehicle report (MVR) ordering, policy characteristics verification, quote display determination, rating facility determination, work triage, telematics app discount eligibility, policy anomaly detection, production implementation, pre- and post-underwriting fraud detection, network detection, premium audits, and book evaluation.

Table 28: Companies' Use of Underwriting Models

Underwriting Model Uses[31]	Number of Companies				
	In Use	Research	Proof of Concept	Prototype	None (N/A)
Automated Approval	1	3	0	0	189
Automated Denial	0	3	0	11	179
Underwriting Tier Determination	0	0	0	0	193
Company Placement	0	2	0	0	191
Input into Non-Automated Approval Decision	1	0	0	1	191

[30] For definitions, refer to Appendix F: Definitions Specific to Underwriting.
[31] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Underwriting Model Uses[31]	Number of Companies				
	In Use	Research	Proof of Concept	Prototype	None (N/A)
Input into Non-Automated Denial Decision	0	0	0	3	190
Automate Processing Through the Agency Channel	0	0	0	0	193
Other Underwriting-Related Functions	33	3	0	2	155

Underwriting models are evenly split between automation, augmentation, and support. (Refer to Table 29.)

Table 29: Level of Decision-Making by Use of Underwriting Models

Underwriting Model Uses[32]	Number of Models (In Use or Under Construction) by Level of Decisions Influenced by AI/ML			
	Automation*	Augmentation*	Support*	Other
Automated Approval	0	1	0	3
Automated Denial	11	1	0	2
Underwriting Tier Determination	0	0	0	0
Company Placement	0	0	0	2
Input into Non-Automated Approval Decision	0	1	2	0
Input into Non-Automated Denial Decision	0	3	0	0
Automate Processing Through the Agency Channel	0	0	0	0
Other Underwriting-Related Functions	28	27	23	0

*"Automation" was defined as no human intervention on execution. "Augmentation" was defined as a model that suggests an answer and advises the human making a decision. "Support" was defined as a model that provides information but does not suggest a decision or action.

Most underwriting models are developed by companies (67%–100%). However, companies tend to use more third-party models for input into non-automated approval decisions (67%). (Refer to Table 30.)

Table 30: Underwriting Model Sources by Model Use

[32] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Underwriting Model Uses[33]	Model Source					
	In-House	In-House	Third-Party	Third-Party	Total	Total
	#	%	#	%	#	%
Automated Approval	3	75%	1	25%	4	100%
Automated Denial	13	93	1	7	14	100
Underwriting Tier Determination	0	0	0	0	0	100
Company Placement	2	100	0	0	2	100
Input into Non-Automated Approval Decision	1	33	2	67	3	100
Input into Non-Automated Denial Decision	2	67	1	33	3	100
Automate Processing Through the Agency Channel	0	0	0	0	0	100
Other Underwriting-Related Functions	72	92	6	8	78	100

Data Elements

The survey was limited to the use of the "more advanced" AI/ML. Therefore, the data element information here does not represent the industry's entire use of big data (which would require adding in the data element information from excluded models (e.g., regression-type models, etc.).

The following four data elements were the most frequently reported as being used for AI/ML underwriting systems:

- Vehicle-specific data (35 companies)
- Demographic (28)
- Consumer or other type of "score" (28)
- Loss experience (20)

There are at least some companies using the following data elements for AI/underwriting systems: driving behavior (12 companies), education (12), geocoding (12), natural catastrophe (9), telematics (5), personal financial information (2), and occupation (1). (Refer to Table 31.)

Table 31: Companies' Use of Underwriting Data Elements

Underwriting Data Elements[34]	Number of Companies Using/Not Using the Data Element in an Underwriting AI/ML Model*		
	Yes	No	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	90	103

[33] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.
[34] For definitions, refer to Appendix H: Data Use Table Definitions.

Underwriting Data Elements[34]	Number of Companies Using/Not Using the Data Element in an Underwriting AI/ML Model*		
	Yes	No	Blank
Demographic	28	62	103
Driving Behavior	12	78	103
Education	12	78	103
Vehicle-Specific Data	35	55	103
Facial Detection/Recognition/Analysis	0	90	103
Geocoding	12	78	103
Natural Catastrophe	9	81	103
Job Stability	0	90	103
Income	0	90	103
Occupation	1	89	103
Personal Financial Information	2	88	103
Loss Experience	20	70	103
Medical	0	90	103
Online Media	0	90	103
Telematics	5	85	103
Voice Analysis	0	90	103
Consumer or Other Type of "Score"	28	68	97
Other Nontraditional Data Elements	0	90	103

*The question is not whether the data element is used, but only whether the data element is used in an AI/ML model.

There are differences in data sources for the data elements. For example, driving behavior and consumer or other type of "score" are almost always sourced externally (almost 100% externally sourced either fully or partially), while vehicle-specific data was more frequently sourced internally (69% internally sourced). Other data elements, such as loss experience and demographic information, are sourced from both external and internal data. (Refer to Table 32.)

Table 32: Underwriting Model Sources (Internal vs. Third Party) by Data Elements

Underwriting Data Elements[35]	Number of Companies Using the Data Element in an Underwriting AI/ML Model*			
	Internal Data Source	External Data Source	Both Internal and External Data Sources	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	0	0	193
Demographic	14	0	14	165
Driving Behavior	1	10	1	181
Education	12	0	0	181
Vehicle-Specific Data	24	2	9	158

[35] For definitions, refer to Appendix H: Data Use Table Definitions.

Underwriting Data Elements[35]	Number of Companies Using the Data Element in an Underwriting AI/ML Model*			
	Internal Data Source	External Data Source	Both Internal and External Data Sources	Blank
Facial Detection/Recognition/Analysis	0	0	0	193
Geocoding	3	7	2	181
Natural Catastrophe	1	7	1	184
Job Stability	0	0	0	193
Income	0	0	0	193
Occupation	1	0	0	192
Personal Financial Information	0	1	1	191
Loss Experience	4	0	16	173
Medical	0	0	0	193
Online Media	0	0	0	193
Telematics	2	2	1	188
Voice Analysis	0	0	0	193
Consumer or Other Type of "Score"	1	26	1	165
Other Nontraditional Data Elements	0	0	0	193

There were no companies reporting the use of consumer or other type of "score" as an input for underwriting data elements. (Refer to Table 33.)

Table 33: Companies' Use of Consumer or Other Type of "Score" as an Input for Underwriting Data Elements

Underwriting Data Elements[36]	Number of Companies Using a Consumer or Other Type of "Score" as an Input		
	Yes	No	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	36	157
Demographic	0	33	160
Driving Behavior	0	36	157
Education	0	36	157
Vehicle-Specific Data	0	39	154
Facial Detection/Recognition/Analysis	0	36	157
Geocoding	0	38	155
Natural Catastrophe	0	36	157
Job Stability	0	36	157
Income	0	36	157
Occupation	0	36	157
Personal Financial Information	0	36	157
Loss Experience	0	37	156

[36] For definitions, refer to Appendix H: Data Use Table Definitions.

Medical	0	36	157
Online Media	0	36	157
Telematics	0	36	157
Voice Analysis	0	36	157
Consumer or Other Type of "Score"			
Other Nontraditional Data Elements	0	36	157

Refer to the "Customer Data Correction," "Governance," and "Third-Party" sections of this report for additional data analysis regarding company operations areas.

COMPANY OPERATION: LOSS PREVENTION[37]

Out of 193 reporting companies, three (3) companies reported using AI/ML for loss prevention operations, and 12 reported having models under construction.

Loss Prevention Model Uses

Out of all the areas of company operations, the least number of companies use loss prevention models. Only three (3) companies have AI/ML currently implemented in production. All three of those companies are using AI/ML for the identification of high-risk customers. However, eight (8) companies are in the research phase, and one (1) company is in the prototype phase to use AI/ML for the identification of high-risk customers.

Two (2) companies indicated that they are in the prototype phase for using AI/ML for risk-mitigation advice to consumers, and one company is in the research phase for an other loss prevention-related function. No companies indicated that they are or plan to use AI/ML for the determination of advance payments.

The uses of loss prevention models identified in Table 34 were options that could be selected in the survey template. Companies noted an additional use of loss prevention models in their write-in comments: guidance for loss control inspections.

Table 34: Companies' Use of Loss Prevention Models

Fraud-Detection Model Uses[38]	Number of Companies				
	In Use	Research	Proof of Concept	Prototype	None (N/A)
Identification of High-Risk Customers	3	8	0	1	181
Risk-Mitigation Advice to Consumers	0	0	0	2	191

[37] For definitions, refer to Appendix G: Definitions Specific to Loss Prevention.
[38] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Fraud-Detection Model Uses[38]	Number of Companies				
	In Use	Research	Proof of Concept	Prototype	None (N/A)
Determination of Advance Payments	0	0	0	0	193
Other Loss Prevention-Related Functions	0	1	0	0	192

Almost all the loss prevention models are used for support. (Refer to Table 35.)

Table 35: Level of Decision-Making by Use of Loss Prevention Models

Loss Prevention Model Uses[39]	Number of Models (In Use or Under Construction) by Level of Decisions Influenced by AI/ML			
	Automation*	Augmentation*	Support*	Other
Identification of High-Risk Customers	0	1	11	0
Risk-Mitigation Advice to Consumers	0	0	0	2
Determination of Advance Payments	0	0	0	0
Other Loss Prevention-Related Functions	0	0	1	0

*"Automation" was defined as no human intervention on execution. "Augmentation" was defined as a model that suggests an answer and advises the human making a decision. "Support" was defined as a model that provides information but does not suggest a decision or action.

Of the few reported loss prevention models, most are developed by companies in-house, and some are developed by a third party. (Refer to Table 36.)

Table 36: Loss Prevention Model Sources by Model Use

Loss Prevention Model Uses[40]	Model Source					
	In-House	In-House	Third-Party	Third-Party	Total	Total
	#	%	#	%	#	%
Identification of High-Risk Customers	8	67%	4	33%	12	100%
Risk-Mitigation Advice to Consumers	2	100	0	0	2	100
Determination of Advance Payments	0	0	0	0	0	100
Other Loss Prevention-Related Functions	1	100	0	0	1	100

Data Elements

[39] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.
[40] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

The survey was limited to the use of the "more advanced" AI/ML. Therefore, the data element information here does not represent the industry's entire use of big data (which would require adding in the data element information from excluded models (e.g., regression-type models, etc.).

The following four data elements were the most frequently reported as being used for AI/ML loss prevention:

- Driving behavior (10 companies)
- Vehicle-specific data (10)
- Geocoding (10)
- Loss experience (10)

There is one (1) company using demographic data. No other data elements are being used. (Refer to Table 37.)

Table 37: Companies' Use of Loss Prevention Data Elements

Loss Prevention Data Elements[41]	Number of Companies Using/Not Using the Data Element in a Loss Prevention AI/ML Model*		
	Yes	No	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	59	134
Demographic	1	58	134
Driving Behavior	10	49	134
Education	0	59	134
Vehicle-Specific Data	10	49	134
Facial Detection/Recognition/Analysis	0	59	134
Geocoding	10	49	134
Natural Catastrophe	0	59	134
Job Stability	0	59	134
Income	0	59	134
Occupation	0	59	134
Personal Financial Information	0	59	134
Loss Experience	10	49	134
Medical	0	59	134
Online Media	0	59	134
Telematics	0	59	134
Voice Analysis	0	59	134
Consumer or Other Type of "Score"	0	66	127
Other Nontraditional Data Elements	0	59	134

*The question is not whether the data element is used, but only whether the data element is used in an AI/ML model.

[41] For definitions, refer to Appendix H: Data Use Table Definitions.

Almost all loss prevention data is internally sourced. Only geocoding data is sometimes also eternally sourced. (Refer to Table 38.)

Table 38: Loss Prevention Model Sources (Internal vs. Third Party) by Data Elements

Loss Prevention Data Elements[42]	Number of Companies Using the Data Element in a Loss Prevention AI/ML Model*			
	Internal Data Source	External Data Source	Both Internal and External Data Sources	Blank
Criminal Conviction (Excluding Auto-Related Convictions)	0	0	0	193
Demographic	1	0	0	192
Driving Behavior	10	0	0	183
Education	0	0	0	193
Vehicle-Specific Data	10	0	0	183
Facial Detection/Recognition/ Analysis	0	0	0	193
Geocoding	7	3	0	183
Natural Catastrophe	0	0	0	193
Job Stability	0	0	0	193
Income	0	0	0	193
Occupation	0	0	0	193
Personal Financial Information	0	0	0	193
Loss Experience	10	0	0	193
Medical	0	0	0	193
Online Media	0	0	0	193
Telematics	0	0	0	193
Voice Analysis	0	0	0	193
Consumer or Other Type of "Score"	0	0	0	193
Other Nontraditional Data Elements	0	0	0	193

No companies indicated they are using a consumer or other type of "score" as an input for any of the data elements. (Refer to Table 39.)

Table 39: Companies' Use of Consumer or Other Type of "Score" as an Input for Loss Prevention Data Elements

Loss Prevention Data Elements[43]	Number of Companies Using a Consumer or Other Type of "Score" as an Input		
	Yes	No	Blank
Criminal Conviction	0	8	185

[42] For definitions, refer to Appendix H: Data Use Table Definitions.
[43] For definitions, refer to Appendix H: Data Use Table Definitions.

Loss Prevention Data Elements[43]	Number of Companies Using a Consumer or Other Type of "Score" as an Input		
	Yes	No	Blank
(Excluding Auto-Related Convictions)			
Demographic	0	8	185
Driving Behavior	0	15	178
Education	0	8	185
Vehicle-Specific Data	0	15	178
Facial Detection/Recognition/Analysis	0	8	185
Geocoding	0	15	178
Natural Catastrophe	0	8	185
Job Stability	0	8	185
Income	0	8	185
Occupation	0	8	185
Personal Financial Information	0	8	185
Loss Experience	0	15	178
Medical	0	8	185
Online Media	0	8	185
Telematics	0	8	185
Voice Analysis	0	8	185
Consumer or Other Type of "Score"			
Other Nontraditional Data Elements	0	8	185

Refer to the "Customer Data Correction," "Governance," and "Third-Party" sections of this report for additional data analysis regarding company operations areas.

CUSTOMER DATA CORRECTION

The following two consumer data correction questions ask if consumers are provided information about data elements—other than what is required by law. The number of companies not reporting is slightly more than expected, based on the number of companies reporting non-use of AI/ML for a particular company operation area (compared to the "none" and "under construction" column in Table 3). For the companies that did answer, few said "yes." (Refer to Table 40 and Table 41.)

Table 40: Companies' Disclosure to Consumers About the Data Elements by Company Operation Area

Are consumers provided information regarding the **data elements being used**? *(Answer should be no if not disclosing any information other than what is required by law.)*			
Company Operation Area[44]	Number of Companies		
	Yes	No	Blank
Rating	23*	49	121

[44] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Are consumers provided information regarding the **data elements being used**? *(Answer should be no if not disclosing any information other than what is required by law.)*			
Company Operation Area[44]	Number of Companies		
	Yes	No	Blank
Underwriting	4	46	143
Claims	0	140	53
Fraud Detection	0	96	97
Marketing	2	87	104
Loss Prevention	0	17	176

*Three of the "yes" responses for rating are models in progress and not yet implemented. The answer is interpreted as: "When the model is implemented, the answer will be 'yes.'"

Table 41: Companies' Disclosure to Consumers About the Purposes of Data Elements by Company Operation Area

Are consumers provided information regarding the **purposes for which data elements** are being used? *(Answer should be no if not disclosing any information other than what is required by law.)*			
Company Operation Area[45]	Number of Companies		
	Yes	No	Blank
Rating	19*	53	121
Underwriting	0	50	143
Claims	0	139	54
Fraud Detection	0	98	95
Marketing	2	88	103
Loss Prevention	0	16	177

*Three of the "yes" responses for rating are models in progress and not yet implemented. The answer is interpreted as: "When the model is implemented, the answer will be 'yes.'"

Most companies also did not answer the next question about whether the company has more consumer data correction processes than required by the federal Fair Credit Reporting Act (FCRA). The number of companies not reporting is slightly more than expected, based on the number of companies reporting non-use of AI/ML or under construction for a particular company operation area. The existence of consumer data correction opportunities varies by company operation area, but fewer companies have additional processes than the number that adhere to the FCRA only. (Refer to Table 42.)

Table 42: Consumers' Ability to Correct Data by Company Operation Area

[45] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Outside of processes required because of FCRA, do consumers have an opportunity to challenge or correct their specific data?			
Company Operation Area[46]	Number of Companies		
	Yes	No	Blank
Rating	35	37	121
Underwriting	23	27	143
Claims	54	77	62
Fraud Detection	15	80	98
Marketing	41	65	87
Loss Prevention	1	15	177

If the company has more than the FCRA for consumers to have an opportunity to challenge or correct their specific data, the following write-ins explain the process:

Many companies discussed having a dispute process, which ranged from calling the company or agent to dispute erroneous data to allowing policyholders to correct erroneous data themselves through an app. In future surveys, it might be useful to ask more detailed questions to determine consumer awareness of dispute processes and ask companies to provide statistics on how often consumers avail the company dispute processes to correct erroneous data.

Future surveys might pose one or more of the following questions:

1. How do consumers learn about your customer-dispute processes?
2. Are your customer-dispute processes discussed with consumers at the time of sale?
3. How often do consumers avail themselves of your customer-dispute process on average per year?
4. What aspects of the policies do consumers dispute more, the insurance rate or the data? What data elements are the most disputed?
5. How do consumers gain access to the data used to calculate their insurance rate?
6. For direct writers, how often on average each year do consumers ask how their insurance rate was calculated? How much interaction do consumers have with the company?
7. Who explains the calculation to the consumers? Is all the data used in the calculation provided at the time of the discussion?

Other considerations might include:

- How are companies, on an annual basis, letting customers know about the customer-dispute process?
- If an application is denied, can the customer dispute the denial?
- In third-party claims (when the person making the claim is not the person who bought the policy), how does the dispute process work?
- Where risk differentiation is used and bias might be present, how is the actuarial justification explained to customers?

[46] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

GOVERNANCE[47]

The purpose of the model governance questions is to obtain a better understanding regarding a company's awareness of specific risk areas tied to selected categories in the NAIC's AI Principles. While companies may consider a principle, the governance responses represent whether the company has the principle "documented" within its governance program. (Refer to Tables 43–50.)

A sizable number of companies did not respond to these questions for some company operation areas. We would expect to find that the number of "blank" answers in Tables 43-50 would be less than or equal to those in the "under construction" plus "none" columns of Table 3. If companies answered these questions when expected, the "Blank" column should be less than the following: Rating (141); Underwriting (159); Claims (58); Fraud Detection (98); Marketing (97); and Loss Prevention (190).

Table 43: Governance Documentation of NAIC AI Principle: Fairness and Ethics Considerations

Are "Fairness and Ethics Considerations" documented in the governance program?			
Company Operation Area[48]	Number of Companies		
	Yes	No	Blank
Rating	41	9	143
Underwriting	26	16	151
Claims	67	45	81
Fraud Detection	48	31	114
Marketing	38	34	121
Loss Prevention	9	3	181

Table 44: Governance Documentation of NAIC AI Principle: Accountability for Data Algorithms' Compliance with Laws, as Well as Intended and Unintended Impacts

Are "Accountability for Data Algorithms' Compliance With Laws, as Well as Intended and Unintended Impacts" documented in the governance program?			
Company Operation Area[49]	Number of Companies		
	Yes	No	Blank
Rating	45	5	143
Underwriting	26	16	151
Claims	77	37	79
Fraud Detection	55	24	114
Marketing	44	28	121
Loss Prevention	9	3	181

[47] For definitions, refer to Appendix I: Model Governance Definitions.
[48] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.
[49] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Table 45: Governance Documentation of NAIC AI Principle: Appropriate Resources and Knowledge Involved to Ensure Compliance With Laws, Including Those Related to Unfair Discrimination

Are "Appropriate Resources and Knowledge Involved to Ensure Compliance With Laws, Including Those Related to Unfair Discrimination" documented in the governance program?			
Company Operation Area[50]	Number of Companies		
	Yes	No	Blank
Rating	41	9	143
Underwriting	26	16	151
Claims	69	45	79
Fraud Detection	48	31	114
Marketing	38	34	121
Loss Prevention	9	3	181

Table 46: Governance Documentation of NAIC AI Principle: Ensure Transparency With Appropriate Disclosures, Including Notice to Consumers Specific to Data Being Used and Methods for Appeal and Recourse Related to Inaccurate Data

Are "Ensure Transparency with Appropriate Disclosures, Including Notice to Consumers Specific to Data Being Used and Methods for Appeal and Recourse Related to Inaccurate Data" documented in the governance program?			
Company Operation Area[51]	Number of Companies		
	Yes	No	Blank
Rating	36	14	143
Underwriting	21	21	151
Claims	57	57	79
Fraud Detection	40	39	114
Marketing	45	27	121
Loss Prevention	8	4	181

Table 47: Governance Documentation of NAIC AI Principle: AI Systems Are Secure, Safe, and Robust Including Decision Traceability and Security and Privacy Risk Protections

[50] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.
[51] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Are "AI Systems Are Secure, Safe, and Robust Including Decision Traceability and Security and Privacy Risk Protections" documented in the governance program?			
Company Operation Area[52]	Number of Companies		
	Yes	No	Blank
Rating	44	6	143
Underwriting	25	17	151
Claims	77	37	79
Fraud Detection	56	23	114
Marketing	42	30	121
Loss Prevention	9	3	181

Table 48: Companies Following "Other" Existing Standards or Guidance in Regard to a Governance Framework

Do you follow some other existing standards or guidance in regard to governance framework?			
Company Operation Area	Number of Companies		
	Yes	No	Blank
Rating	61	11	121
Underwriting	43	6	144
Claims	105	35	53
Fraud Detection	68	22	103
Marketing	60	46	87
Loss Prevention	11	7	175

Table 49: Source (Internal or External) of "Other" Existing Standards or Guidance in Regard to a Governance Framework

If the company cited it uses "some other existing standards or guidance in regard to a governance framework," are the standards developed internally, provided by a third party, or both?			
Company Operation Area	Number of Companies		
	Internal	External	Both
Rating	50	5	6
Underwriting	41	0	2
Claims	91	1	13
Fraud Detection	54	1	13
Marketing	53	46	7
Loss Prevention	10	1	0

Table 50: Existing "Other" Standards or Guidance in Regard to a Governance Framework

[52] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

If the company cited it uses "some other** existing standards or guidance in regard to a governance framework," those standards/guidance are:		
Company Operation Area	Cited Standard	Number of Times Cited
Rating	"All" (Undefined)	5
Underwriting		
Claims	Actuarial Standards of Practice	1
Fraud Detection	Actuarial Standards of Practice	1
Marketing		
Loss Prevention	Actuarial Standards of Practice	1

THIRD-PARTY DATA SOURCES AND MODELS

Some AI/ML models being used by companies are developed by third parties. Many of these products are used by multiple companies. Risks exist that some "off-the-shelf" tools may not be fully understood by companies and may pose risks to consumers when data is inaccurate. In addition to using third-party models, companies are using big data from third-party data sources.

There are 2,531 models listed in the survey; 1,073 (42%) are developed by a third party, and 1,458 (58%) are developed internally. After grouping the similarly named third parties, there are 76 unique third-party companies listed in the survey whose models are being used by companies. Marketing has 39 different third parties listed, followed by claims with 28.

There are 104 unique third parties listed as data sources in the survey.

Third-Party Models Used in Claims

Insurers purchased claims models from 28 third-party vendors. Third-party vendors are identified 443 times for claims models. (Refer to Table 51.)

Table 51: Third Parties' Claims Models Used by Companies

Claims Model Uses[53]	If Model is Developed by a Third Party, List the Third Party
	Third-Party Name
Claim Approval	Optum
	Mitchell
	Guidewire
Claim Denial	---
Determine Settlement Amount	CCC*
	Tractable
	Mitchell Medical**
	CoPart
	Medlogix

[53] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Claims Model Uses[53]	If Model is Developed by a Third Party, List the Third Party
	Third-Party Name
	Colossus
Claim Assignment Decisions	CCC***
	Mitchell
	Guidewire
Informational Resources for Adjustors	EXL
	TrueMotion/Cambridge Mobile Telematics
	CCC
	Infinilytics
	Verisk
	Assured
Evaluation of Images of the Loss	CCC****
	Tractable
	Google
	Briefcam Ltd.
	Developed by a third party
	Auto Glass Inspections Services a.k.a NCS
	Amazon Web Services (AWS)
	Next Gear Solutions
	Mitchell International*****
	Claim Genius
	Verisk
	Shift Technology
Other Claim-Related Functions	Also developed with AWS
	TrueMotion/Cambridge Mobile Telematics******
	Cognizant Worldwide Ltd.
	Hi Marley
	Verisk
	Verint
	Optum
	Five9
	Eleveo
	Amazon
	TBD
	Shift Technology
	I.P. Soft
	CCC
	Assured

*Includes CCC Intelligent Solutions.
**Includes Mitchell.
***Includes CCC Information Services Inc. and CCC IS.
****Includes CCC Information Services, CCC Intelligent Solutions, CCC Information Services Inc., CCC Intelligent Systems, and CCC Intelligent Solutions.
*****Includes Mitchell.

******Includes TrueMotion and True Motion.

Third-Party Data Sources used in Claims

Eleven (11) third parties are used for vehicle-specific data, and eight (8) third parties are used for medical.

Table 52: Third-Party Claims Data Element Sources Used by Companies

Claims Data Elements[54]	If External or Both, List Each Data Vendor
	Third-Party Name
Criminal Conviction (Excluding Auto-Related Convictions)	Carpe Data ClaimsX
	Lexis Nexis Claim Datafill
	Verisk ISO ClaimSearch
Demographic	LexisNexis
	ESRI
	EASI (for population density)
	Lexis Nexis Claim Datafill
	Verisk ISO ClaimSearch
	Easi
	Shift Technology
Driving Behavior	Lexis Nexis Claim Datafill
	Verisk ISO ClaimSearch
	Internal Claims data
	Motor Vehicle Report
Education	Lexis Nexis Claim Datafill
Vehicle-Specific Data	CCC*
	Allant Group
	Polk
	HLDI
	LexisNexis**
	Advocates for Highway and Safety
	Infinilytics
	TransUnion
	Verisk ISO ClaimSearch
	Internal Policy Data
	Shift Technology
Facial Detection/Recognition/ Analysis	---
Geocoding	HR3
	PLRB
	LexisNexis Claim Datafill
	CCC One

[54] For definitions, refer to Appendix H: Data Use Table Definitions.

Claims Data Elements[54]	If External or Both, List Each Data Vendor
	Third-Party Name
Natural Catastrophe	---
Job Stability	---
Income	---
Occupation	---
Personal Financial Information	Lexis Nexis Claim Datafill
Loss Experience	ISO/Verisk
	CCC Information Services*
	Internal Loss Data
Medical	Mitchell Medical
	ABM
	CCC
	ODG
	Provider Information
	Claim Director Tool
	Next Gear Settle Assist
	Verisk ISO ClaimSearch
Online Media	Carpe Data
Telematics	TrueMotion***
Voice Analysis	Amazon
	Eleveo
	Five9
	HiMarley
	Verint
Consumer or Other Type of "Score"	CCC
	Tractable
	Lexis Nexis Claim Datafill
	Verisk ISO ClaimSearch
Other Nontraditional Data Elements	National Recall Database
	News Articles
	Shift Technology
	Weather Data

*Includes CCC Information Services Inc., CCC Intelligent Solutions, CCC Information Services, CCC IES, CCC Smart Estimate, CCC Data, CCC One.
**Includes Lexis Nexis Claim Datafill.
***Includes Cambridge Mobile Telematics, CMT.

Third-Party Models Used in Fraud Detection

Insurers purchased fraud detection models from 15 third-party vendors. (Refer to Table 53.)

Table 53: Third Parties' Fraud-Detection Models Used by Companies

Fraud-Detection Model Uses[18]	If Model is Developed by a Third Party, List the Third Party
	Third-Party Name
Fast-Tracking of Likely Non-Fraudulent Claims	Shift Technology (Shift)
	IBM
	Verisk
	Not Yet Named
	Guidewire
Referral of Claims for Further Investigation	Shift Technology (Shift, Shift Technologies)
	Developed by a third party
	Carpe Data
	Verisk
	ISO
	SAS Institute Inc.
	IBM
	Not Yet Named
	Mitchell
	Guidewire
	CCC Intelligent Solutions
Detect Medical Provider Fraud	Shift (Shift Technology, Shift Technologies)
	Verisk
	SAS Institute Inc.
Detect First-Party Liability	Shift Technology (Shift Technologies)
	SAS, Institute Inc.
	IBM
	Verisk
	Mitchell
	Guidewire
Detect Third-Party Liability	Shift Technology (Shift Technologies)
	SAS Institute, Inc.
	IBM
	Verisk
	Mitchell
	Guidewire
Other Fraud Detection-Related Functions	Shape, Neustar, TransUnion
	TransUnion
	NeuroID
	Shift Technology
	SkopeNow
	PinDrop
	Carpe Data

Table 54: Third-Party Fraud-Detection Data Element Sources Used by Companies

Fraud-Detection Data Elements[55]	If External or Both, List Each Data Vendor
	Third-Party Name
Criminal Conviction (Excluding Auto-Related Convictions)	NICB*
	Shift Technology's models leverage the NICB's prosecution and administrative action convictions
	AIS
	Shift
	TransUnion
Demographic	LexisNexis
	Shift Technology**
	"Age is used to clear potentially suspicious cases (e.g., Injuries are more likely for elderly passengers, so that can lessen the suspicion of an injury claim). Address is used to identify possible personal relationships in fraud ring detection. Gender, marital status, race, etc., are never used in fraud detection."
	Easy Analytics Software Inc.
	Open Source Python Package uszipcode 0.2.6 (Massachusetts Institute of Technology [MIT] owns license)
Driving Behavior	LexisNexis (for driving violations)
Education	---
Vehicle-Specific Data	Verisk – ISO***
	CCC
	LexisNexis
	NICB Forewarn Alerts
	CARFAX
	Not Yet Named
	Shift
	TransUnion
Facial Detection/Recognition/Analysis	---
Geocoding	Shift Technology provides geocoding capabilities as an input into its models (e.g., calculating distances between addresses)
	IBM
	Census Bureau

[55] For definitions, refer to Appendix H: Data Use Table Definitions.

Fraud-Detection Data Elements[55]	If External or Both, List Each Data Vendor
	Third-Party Name
Natural Catastrophe	---
Job Stability	---
Income	---
Occupation	---
Personal Financial Information	TransUnion
	Insurance Score
Loss Experience	NICB Questionable Claims****
	Verisk*****
	Internal Loss Data
	Not Yet Named
Medical	AIS
	CMS NPI
	Internal medical bills
	LEIE
	Claims Director tool
	Shift
Online Media	Shift crawls publicly available social media activity to detect activity inconsistent with the facts of loss******
	Carpe Data
	SkopeNow
Telematics	---
Voice Analysis	---
Consumer or Other Type of "Score"	LexisNexis
	Shift
	TLO
	Verisk
Other Nontraditional Data Elements	---

*Includes ISO and Verisk/NICB.
**Includes Shift Technology.
***Includes ISO and Verisk.
****Includes NICB Forewarn Alerts, NICB, NICB Questionable Claims, and NICB Questionable Claims.
*****Includes Verisk-ISO, ISO, and ISO Loss Data/Reports.
******Includes Shift.

Third-Party Models Used in Marketing

Marketing is the only operational area in which most models are developed by third parties at 56% with 454 models (vs. 352 developed internally). For targeted online advertising, 186 models were from third parties compared to 19 models developed internally.

Insurers purchased marketing models from 39 third-party vendors. (Refer to Table 55.)

Table 55: Third Parties' Marketing Models Used by Companies

Marketing Model Uses[56]	If Model is Developed by a Third Party, List the Third Party
	Third-Party Name
Targeted Online Advertising	Google
	Facebook
	The Trade Desk
	Yahoo
	Universal McCann
	Pinterest
	Ebay
	Buzzfeed
	BING
	Amazon
	Google, Microsoft, Facebook
	Google, Facebook, LinkedIn
	Verizon
	Deployed advertising agency
	Facebook/Instagram
	AT&T
	Various display advertising firms
	Used by Google for Ad Buying
	Used by Google and Facebook for Ad Buying
	Transunion
	Seismic
	Salesforce
	LinkedIn
	Digital Remedy
	Amsive
	Acxiom
Identification of Recipients of Mail or Phone Advertising	Merkle
	EXL
	DataLab
	Salesforce
	Pegasystems
	IBM
	Amsive
	Ameriprise

[56] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Marketing Model Uses[56]	If Model is Developed by a Third Party, List the Third Party
	Third-Party Name
Provision of Offers to Existing Customers	Merkle
	Pegasystems
	IBM
	Amsive
Identification of Potential Customer Groups	Merkle
	Google
	The Trade Desk
	EXL
	Yahoo
	Facebook/Instagram
	AT&T
	TransUnion
	Amsive
	Acxiom
Demand Modeling	Pegasystems
	IBM
	Google
	Yahoo
Direct Online Sales	Multiple, depends on advertising platform; e.g., Facebook, Cognitiv
	Microsoft
	Kibo/Monetate
	Google and Bing
	Google
	Pegasystems
	IBM
Other Marketing-Related Functions	Google, Facebook, LinkedIn
	Persado
	Xplain
	Google, Microsoft, Facebook, LinkedIn
	Nielson
	Neustar
	Marketing Evolution
	Rocket Referrals
	Qualtrics
	PPC Protect
	Matlen Silver
	Human
	Google

Third parties are listed 277 times under marketing. Twenty-three (23) different third parties are used as a data source for the demographic data element. (Refer to Table 56.)

Table 56: Third-Party Marketing Data Element Sources Used by Companies

Marketing Data Elements[57]	If External or Both, List Each Data Vendor Third-Party Name
Criminal Conviction (Excluding Auto-Related Convictions)	---
Demographic	Acxiom
	EASI
	DMS
	MediaAlpha
	Equifax
	Facebook
	Facebook/Instagram
	The Trade Desk*
	Xandr
	Ameriprise Advisor Information
	Amsive
	Claritas
	Costco
	DataLab (uses marketing data to develop models; unsure of data sources it licenses)
	Experian
	Google
	Google DV360 + YouTube
	Lead Provider
	LinkedIn
	Self-reported information from consumer, provided by lead aggregators such as Everquote
	TransUnion
	Various programmatic display advertising vendors
	Yahoo
Driving Behavior	CARFAX
	DMS
	MediaAlpha
	Lead Provider
	TransUnion

[57] For definitions, refer to Appendix H: Data Use Table Definitions.

Marketing Data Elements[57]	If External or Both, List Each Data Vendor
	Third-Party Name
Education	Acxiom
	DMS
	MediaAlpha
	Equifax
	Amsive
	Experian
	Google
	Lead Provider
	Self-reported information from consumer, provided by lead aggregators such as Everquote
	TransUnion
	Yahoo
Vehicle-Specific Data	CARFAX
	DMS
	MediaAlpha
	Acxiom
	Google
	Lead Provider
	Self-reported information from consumer, provided by lead aggregators such as Everquote
	TransUnion
	Yahoo
Facial Detection/Recognition/Analysis	---
Geocoding	Facebook
	Google DCM
	Google Maps Application Programming Interfaces (API)
	DataLab – uses territory in its models
	Lead Provider
	LinkedIn
	Various programmatic display advertising vendors
Natural Catastrophe	Lead Provider
Job Stability	---
Income	Equifax
	Experian
	Google
	Google DV360 + YouTube
	The Trade Desk
	TransUnion
	Yahoo

Marketing Data Elements[57]	If External or Both, List Each Data Vendor
	Third-Party Name
Occupation	Acxiom
	Equifax
	Facebook
	Amsive
	Experian
	Lead Provider
	LinkedIn
	Various programmatic display advertising vendors
Personal Financial Information	Credit Bureaus
	Trans Union
	Acxiom
	TransUnion
	Amsive
	EXL
	Experian
Loss Experience	LexisNexis
	Lead Provider
Medical	---
Online Media	Acxiom
	Google
	"Inherent in programmatic display advertising. We do not have an internal model, but AI/ML is inherently used in digital advertising placement, leveraging online activity."
	Facebook
	Google DCM
	Social Media
	4USocial
	Amsive
	Bing
	Google DV360 + YouTube
	LinkedIn
	Rocket Referrals
	The Trade Desk
	Various programmatic display advertising vendors
	Yahoo
Telematics	---
Voice Analysis	---

Marketing Data Elements[57]	If External or Both, List Each Data Vendor
	Third-Party Name
Consumer or Other Type of "Score"	TransUnion
	Acxiom
	Equifax
	FICO
	Zeta
	Experian
	Facebook Total Value Score
	Lead Provider
	TransUnion, Equifax (Credit)
Other Nontraditional Data Elements	Ameriprise Advisor Business Information
	Experian
	TransUnion

*Includes Trade Desk.

Third-Party Models Used in Rating

Insurers purchased "more advanced AI/ML" rating models from three (3) third-party vendors. (Refer to Table 57.)

Table 57: Third Parties' Rating Models Used by Companies

Rating Model Uses[58]	If Model is Developed by a Third Party, List the Third Party
	Third-Party Name
Rating Class Determination	Cambridge Mobile Telematics
	TransUnion
Price Optimization	---
Retention Modeling	Willis Towers Watson
Numerical Relativity Determination	TrueMotion (CMT)
	Cambridge Mobile Telematics
	TransUnion
Other Rate-Related Functions	Cambridge Mobile Telematics

Third parties are listed 258 times under the "rating" category. (Refer to Table 58.)

[58] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Table 58: Third-Party Rating Data Element Sources Used by Companies

Rating Data Elements[59]	If External or Both, List Each Data Vendor
	Third-Party Name
Criminal Conviction (Excluding Auto-Related Convictions)	---
Demographic	EASI
	American Community Survey
	U.S. Census Bureau
	Applied Geographic Solutions
	Integrated Public Use Microdata Series
Driving Behavior	CARFAX
	LexisNexis
	Explore
	TransUnion
	Cambridge Mobile Telematics
	CLUE
	TrueMotion
	Motor Vehicle Record (MVR)
	State Departments of Motor Vehicles (DMVs) (MVRs)
Education	---
Vehicle-Specific Data	CARFAX
	HLDI*
	ISO**
	Polk
	TransUnion
Facial Detection/Recognition/Analysis	---
Geocoding	Precisely
	Pitney-Bowes
Natural Catastrophe	Applied Geographic Solutions
	Oak Ridge National Laboratory
	Property and Liability Resource Bureau
	CoreLogic
	Hazardhub
	National Oceanic and Atmospheric (NOAA)
Job Stability	---
Income	---
Occupation	---
Personal Financial Information	LexisNexis
	TransUnion

[59] For definitions, refer to Appendix H: Data Use Table Definitions.

Rating Data Elements[59]	If External or Both, List Each Data Vendor
	Third-Party Name
Loss Experience	LexisNexis
	CLUE
Medical	---
Online Media	---
Telematics	Cambridge Mobile Telematics***
Voice Analysis	---
Consumer or Other Type of "Score"	Equifax
	TransUnion****
	LexisNexis
	Cambridge Mobile Telematics
Other Nontraditional Data Elements	Environmental Systems Research Institute (ESRI)
	Federal Highway Administration (FHWA)
	Highway Loss Data Institute (HLDI)
	Precisely
	PRISM Climate Group
	United States Geologic Survey (USGS)

*Includes HLDI and HLDI.
**Includes ISO/Verisk and ISO Verisk.
***Includes TrueMotion and CMT.
****Includes TransUnion Credit.

Third-Party Models Used in Underwriting

Insurers purchased "more advanced AI/ML" underwriting models from five (5) third-party vendors. (Refer to Table 59.)

Table 59: Third Parties' Underwriting Models Used by Companies

Underwriting Model Uses[60]	If Model is Developed by a Third-Party, List the Third Party
	Third-Party Name
Automated Approval	Shift Technology
Automated Denial	Shift Technology
Underwriting Tier Determination	---
Company Placement	---
Input Into Non-Automated Approval Decision	Shift Technology
	Verisk

[60] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Underwriting Model Uses[60]	If Model is Developed by a Third-Party, List the Third Party
	Third-Party Name
Input Into Non-Automated Denial Decision	Shift Technology
Automate Processing Through the Agency Channel	---
Other Underwriting-Related Functions	Cambridge Mobile Telematics
	Shift Technology*
	Clyde Analytics
	Betterview

*Includes SHIFT.

Third parties are listed 145 times under the "underwriting data elements" category. (Refer to Table 60.)

Table 60: Third-Party Underwriting Data Element Sources Used by Companies

Underwriting Data Elements[61]	If External or Both, List Each Data Vendor
	Third-Party Name
Criminal Conviction (Excluding Auto-Related Convictions)	---
Demographic	EASI
	U.S. Census Data Web site
Driving Behavior	Explore
	LexisNexis
	TransUnion
	Cambridge Mobile Telematics
	State DMVs, MVR
Education	---
Vehicle-Specific Data	HLDI (HLDI-1)
	ISO
	HLDI/CARFAX
	Polk
	Vehicle Symbol
Facial Detection/Recognition/Analysis	---
Geocoding	Precisely
	Claritas
	Pitney Bowes
	U.S. Census Bureau

[61] For definitions, refer to Appendix H: Data Use Table Definitions.

Underwriting Data Elements[61]	If External or Both, List Each Data Vendor
	Third-Party Name
Natural Catastrophe	AIR Worldwide (Applied Insurance Research)
	CoreLogic
	ISO and NOAA
Job Stability	---
Income	---
Occupation	---
Personal Financial Information	Insurance Score
	LexisNexis
Loss Experience	LexisNexis
	CLUE
Medical	---
Online Media	---
Telematics	Cambridge Mobile Telematics
Voice Analysis	---
Consumer or Other Type of "Score"	TransUnion
	Equifax
	LexisNexis
	Verisk
Other Nontraditional Data Elements	---

Third-Party Models Used in Loss Prevention

Insurers purchased loss prevention models from two (2) third-party vendors. (Refer to Table 61.)

Table 61: Third Parties' Loss Prevention Models Used by Companies

Loss Prevention Model Uses[62]	If Model is Developed by a Third-Party, List the Third Party
	Third-Party Name
Identification of High-Risk Customers	Flyreel
	Shift Technology
Risk-Mitigation Advice to Consumers	---
Determination of Advance Payments	---
Other Loss Prevention-Related Functions	---

[62] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

Third-Party Models Used in Loss Prevention

The only third party as a data source for loss prevention is Flyreel, which is listed for geocoding. (Refer to Table 62.)

Table 62: Third-Party Loss Prevention Data Element Sources Used by Companies

Loss Prevention Data Elements[63]	If External or Both, List Each Data Vendor
	Third-Party Name
Criminal Conviction (Excluding Auto-Related Convictions)	---
Demographic	---
Driving Behavior	---
Education	---
Vehicle-Specific Data	---
Facial Detection/Recognition/Analysis	---
Geocoding	Flyreel
Natural Catastrophe	---
Job Stability	---
Income	---
Occupation	---
Personal Financial Information	---
Loss Experience	---
Medical	---
Online Media	---
Telematics	---
Voice Analysis	---
Consumer or Other Type of "Score"	---
Other Nontraditional Data Elements	---

REGULATORS' ACCESS TO DATA: DASHBOARD

The aggregated survey responses for the PPA AI/ML survey are created in a dashboard and will be made available to all regulators. The information included is the aggregated data on AI/ML usage in the specific company operations areas. Detail in the dashboard includes implementation status, how AI/ML is used, how models are developed, governance, and data elements.

Given the project was conducted under individual states' market conduct authority, functionality to drill down to an individual company's response is not available within the dashboard. Also, due to confidentiality issues, free-form answers regarding other specific uses within operational areas, names of models, names of third parties, and processes for customers to correct data are not included in the dashboard.

[63] For definitions, refer to Appendix H: Data Use Table Definitions.

CONCLUSION/NEXT STEPS

As requested by the SME group, the NAIC's technical team completed an analysis of the data submitted in the PPA AI/ML survey. Insight was gained around the general use of AI/ML by insurance companies, uses of AI/ML in insurance company operations, data elements and sources used in insurance company operations, governance frameworks and documentation, consumer data recourse, and third-party sources for AI/ML models and/or data.

The insight gained from the survey will be used to supplement regulators' knowledge of the current regulatory framework around AI/ML, governance, consumers, and third parties and to evaluate whether any changes should be made to the regulatory frameworks.

The SME group, other regulators, and NAIC staff have identified some potential next steps, including many activities already in progress. The following list of next steps is not intended to be complete, but it may be helpful as a starting point for discussions and decision-making about what next steps to take at the NAIC:

- Evaluate the survey analysis and determine whether to further explore the following subjects:
    - Company AI/ML model usage and the level of decision-making (i.e., the amount of human involvement in decision-making).
    - Company data elements.
    - Companies' governance frameworks and the documentation of such.
    - Consumer data recourse.
    - Third-party regulatory framework.
- Create a risk hierarchy to prioritize the need for more model governance and company oversight. The general concept is that more oversight of a model will be needed as the consumer risk or impact increases from the modeling or models.
- Evaluate consumer data recourse. Companies report a wide variety of methods for consumers to evaluate and correct data used by companies. Some methods are short and easy, such as using an app to correct data, and other methods are more time consuming and require personal contact with the agent or company. In some cases, consumers may not even know about their data being used, so consumer transparency is a priority. *(Privacy Protections (H) Working Group)*
- Evaluate the regulatory framework around the use of third-party models and third-party data. Evaluate the ability of companies and regulators to obtain needed information from third parties and for regulators to oversee this work either through the companies or third parties in some way. *(Workstream Two of the Big Data and Artificial Intelligence (H) Working Group)*
- Evaluate concerns about third-party concentration by company use. *(Workstream Two of the Big Data and Artificial Intelligence (H) Working Group)*
- Determine whether additional best-practices white papers would be useful on subjects in the AI/ML space.

APPENDIX A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention

The respondent will only need to complete the corresponding sections for which artificial intelligence (AI)/machine learning (ML) is being used by their company as indicated in the "General Section of the Survey."

For the purposes of this survey, the operational areas are: rating, underwriting, claims, fraud detection, marketing, and loss prevention. This survey is primarily focused on consumer-facing models used for these operational areas. However, the respondent can include other operational areas listed in the "other" line (question 3) in the "General" section of the survey.

Each operational area has specific uses listed for AI/ML. For example, "Rating Class determination is a use listed under the "Rating" section. The respondent should select the highest level of deployment of AI/ML.

• Research: This is the investigation into and study of materials and sources to establish facts and reach new conclusions, as well as the collection of information about a particular subject.

• Proof of Concept (POC): The POC is a small exercise to test the design idea or assumption. The main purpose of developing a POC is to demonstrate the functionality and to verify that a certain concept or theory can be achieved in development. It is testing the model for functional viability to be sure it runs and delivers a result.

• Prototype: Prototyping provides the opportunity to visualize how the product will function; it is a working interactive model of the end product that gives an idea of the design, navigation, and layout. Prototyping involves testing the model with actual data, in a limited, controlled environment. A prototype brings the POC idea to life.

• Implemented in Production: The model is being used in a live, production environment using real data. In addition to the highest level of deployment, the survey seeks information on the level of decisions influenced by an AI/ML model.

• Automation: There is no human intervention on execution.

• Augmentation: The model advises the human, who makes a decision; the model suggests an answer.

• Support: The model provides information but does not suggest decision or action.

APPENDIX B: Definitions Specific to Claims

• Claim Approval: Approving a claim without human intervention on that particular claim.

• Claim Denial: Denying a claim without human intervention on that particular claim.

• Determine Settlement Amount: Recommending which amount to offer to a claimant in order to resolve the company's obligations on the claim.

• Claim Assignment Decisions: Recommending which adjusters are assigned to which claims.

• Informational Resource for Adjusters: Providing facts, data, and analysis to claim adjusters without recommending a decision or limiting the adjusters' authority over handling the claim.

• Evaluation of Images of the Loss: Analysis of photographic, video, or other visual evidence pertaining to a potentially insured loss in order to extract facts relevant to a company's decision and/or provide guidance and recommendations based on the information obtained in this manner.

APPENDIX C: Definitions Specific to Fraud Detection

• Fast Tracking of Likely Non-Fraudulent Claims: For claims that are identified to be at a low risk of fraud, establishing a rapid process for approving and paying those claims without further scrutiny or follow-up with the claimant.

• Referral of Claims for Further Investigation: For claims that are identified to be at a higher risk of fraud or other potential issues that affect the legitimacy of those claims, determining that those claims should be assigned to investigators for a more intensive and human-driven review process.

• Detect Medical Provider Fraud: Identification of claims where medical providers may have submitted inappropriate or questionable amounts for reimbursement.

• Detect First-Party Liability: Identification of potential situations where a first-party insured may have been at fault for a claim and/or may have misrepresented information to the company.

• Detect Third-Party Liability: Identification of potential situations where a third-party claimant may have been at fault for a claim and/or may have misrepresented information to the company.

APPENDIX D: Definitions Specific to Marketing

Definitions Specific to Marketing

• Targeted Online Advertising: Determination of which individuals on the Internet should receive or see advertisements from the company.

• Identification of Recipients of Mail or Phone Advertising: Determination of which individuals would be desirable recipients of a company's advertisements via the telephone or physical mail.

• Provision of Offers to Existing Customers: Determination of which customers should be notified of new insurance products, discounts, options to be written in a different book of business, or any other benefit or favorable treatment that the company seeks to extend.

• Identification of Potential Customer Groups: Determination regarding which consumer subpopulations could become additional likely customers of the company and/or benefit from the company's products and services.

• Demand Modeling: Identification of consumers' needs for and interest in specific types of insurance and insurance products that the company is offering or whose development or sale the company may be considering or exploring.

• Direct Online Sales: Selling insurance policies to consumers through a direct Internet-based channel in a manner that does not rely solely on preprogrammed decision rules.

APPENDIX E: Definitions Specific to Rating

Definitions Specific to Rating

• Rating Class Determination: Decisions regarding which insureds to place within which rating category and which criteria to use to establish a given rating category.

• Price Optimization: NAIC Casualty and Actuarial Statistical (C) Task Force white paper: https://content.naic.org/sites/default/files/inline-files/committees_c_catf_related_price_optimization_white_paper.pdf

• Retention Modeling: Estimation of the effects of a particular company-initiated rate change on the decisions of existing insureds to remain with the company.

• Numerical Relativity Determination: Decisions regarding which quantitative rating factor to assign to a particular rating category.

APPENDIX F: Definitions Specific to Underwriting

• 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) that use combinations of attributes that affect a company'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 artificial intelligence (AI)/machine learning (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 Through 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.

APPENDIX G: Definitions Specific to Loss Prevention

• Identification of High-Risk Customers: The goal of such identification in a loss-prevention context is not to make an underwriting or rating decision, but rather to recognize which specific customers may benefit most from loss-prevention advice and mitigation techniques that the company may be able to provide, thereby reducing such customers' frequency and/or severity of losses. For example, an artificial intelligence (AI)/machine learning (ML) system might determine that certain households with youthful drivers are more likely to benefit from risk-mitigation advice and other approaches.

• Risk-Mitigation Advice to Consumers: AI/ML systems might be used to target messaging to consumers based on specific risks identified for a given policy. For example, in a household with youthful drivers, AI/ML-targeted messaging and incentives could focus on ways those drivers could gain experience in a low-risk manner and drive more carefully in day-to-day context. For households in mountainous areas, AI/ML systems could provide targeted advice about safe driving in rugged terrain.

• Determination of Advance Payments: In many situations, small payments issued at or shortly after the time of loss, prior to the full adjustment of the claim, can help the insured or third-party claimant prevent much larger amounts of damage that would otherwise greatly raise the costs of the claim for the company. In a private passenger automobile (PPA) context, examples could include, but are not limited to:

- Making a payment for minor repairs that restore the vehicle to a drivable condition, whereas the insured and/or company would have otherwise needed to spend much more money to rent another vehicle or to pay for storage of a non-functional vehicle.
- Making a payment for prompt, inexpensive medical treatment of a claimant, which could prevent the emergence of a longer-term, chronic, and much more costly health condition.
- Making a payment for expenses related to towing an insured's or claimant's vehicle away from the scene of the accident and reasonable costs of storage for the vehicle until the company or vehicle owner is able to gain possession of the vehicle. In the absence of such prompt payments, vehicles at towing-company storage yards may accumulate significant charges for which the company may ultimately become responsible.

APPENDIX H: Data Use Table ("Data Elements") Definitions

1. Consumer or Other Type of "Score": A numeric value generated based on a combination of any underlying attributes or behaviors of the consumer, insured risk, or any items considered by the company to be relevant to the consumer or insured risk. Scores are computed using deterministic algorithms or models that are not themselves considered to be artificial intelligence (AI)/machine learning (ML) systems. Inquiries in this survey regarding such scores seek to understand whether these scores are used as input data elements within AI/ML systems.

2. Criminal Convictions: Exclude auto-related convictions.

3. Demographic: Age, gender, address, marital status, other non-behavioral attributes of a consumer, or population attributes of an area.

4. Driving Behavior: Tickets, years of driving experience, or annual miles driven.

5. Education: Level of education or GPA.

6. Vehicle-Specific Data: Type of vehicle(s) driven or owned, history of the vehicle(s), or value of contents inside the car.

7. Facial Detection/Recognition/Analysis: Picture to confirm identity, estimate biological age, or gender of the consumer.

8. Geocoding: Latitude and longitude coordinates of a physical address.

9. Natural Catastrophe Hazard: Frequency and severity of natural hazards.

10. Job Stability: Current employment, length of employment at prior employers, or unemployment.

11. Income: Annual income or income source.

12. Occupation: Primary profession, service, or trade for which a person is paid.

13. Personal Financial Information: Net worth, type of bank account or credit account, number of bank accounts or credit accounts, available credit, or payment history data.

14. Loss Experience: Claim history for private passenger auto (PPA) or claims from other lines of insurance.

15. Medical: Medical history, medical condition, prescription data, or lab data.

APPENDIX I: Model Governance Definitions

The purpose of the question related to model governance is to obtain a better understanding regarding a company's awareness of specific risk areas tied to the NAIC's Artificial Intelligence (AI) Principles. In addition, the survey seeks information to understand if guidelines and/or best practices are documented. Specifically, if the company is involved in using AI/machine learning (ML) models, does the company have a documented process in place that addresses:

• Fairness and Ethics Considerations: Ensuring responsible adherence to fairness and ethical considerations. It is clear there is debate regarding the definition of "fairness and ethics," so for the purposes of this survey, and assuming a general understanding of the terms, the response should be consistent with how the company defines those terms. Generally, respect the rule of law and implement trustworthy solutions designed to benefit consumers in a manner that avoids harmful or unintended consequences including unfair or proxy discrimination.

• Accountability for Data Algorithms' Compliance with Laws as Well as Intended and Unintended Impacts: Ensuring the data used and the algorithms/models within the scope of the AI/ML system are delivering the intended benefit, and there are proactive processes in place to ensure there is no unacceptable unintended impact. Simply put, be responsible for the creation, implementation, and impacts of any AI system.

• Appropriate Resources and Knowledge Involved to Ensure Compliance with Laws, Including Those Related to Unfair Discrimination: Ensuring the requisite and appropriate resources, skill sets, and knowledge needed to ensure compliance with laws, including those related to unfair discrimination, are actively involved in these programs and decision-making—including oversight of third parties' understanding and competence related to compliance with relevant laws and the issue of unfair discrimination.

• Ensure Transparency With Appropriate Disclosures, Including Notice to Consumers Specific to Data Being Used and Methods for Appeal and Recourse Related to Inaccurate Data: Ensuring documented processes and best practices are in place that govern and actively address the issue of transparency, ensuring adequate and complete/understandable consumer disclosure regarding the data being used and how the data is used, as well as providing a way for consumers to appeal or correct inaccurate data. This is intended to be specific for data not already protected by legislation such as the federal Fair Credit Reporting Act (FCRA), as the assumption is all companies would be compliant with that law. This pertains to consumer data not specified in the FCRA.

• AI Systems are Secure, Safe, and Robust, Including Decision Traceability and Security and Privacy Risk Protections: Ensuring an appropriate governance process is in place and documented specific to the company's AI/ML activity or program that focuses on protecting security, in terms of its data and intellectual property, from potentially compromising interference or risk and relevant and necessary privacy protections are in place. Ensuring the data and the AI/ML models are sufficiently transparent and explainable so that they can be reviewed for compliance with laws and best practices and proven to not be unfairly discriminatory or used for an unethical purpose.

It is understood that governance models vary in terms of components and terms used to describe these risk areas. However, there is a common thread across most governance models, and this language was specifically used in this survey as it ties directly to the NAIC's AI Principles. Where there may be concerns about overlap, the intention is for this additional information to clarify the unique intent of each. The company should reply to each component as specifically as possible.

Draft: 11/16/2022

Cybersecurity (H) Working Group
Virtual Meeting
November 15, 2022

The Cybersecurity (H) Working Group of the Innovation, Cybersecurity, and Technology (H) Committee met Oct. 11, 2022. The following Working Group members participated: Cynthia Amann, Co-Chair (MO); Wendy Erdly, Co-Chair (NY); C.J. Metcalf, Co-Vice Chair (IL); Michael Peterson, Co-Vice Chair (VA); Sian Ng-Ashcraft (AK); Chris Erwin (AR); Lance Hirano (HI); Alex Borkowski (MD); Jake Martin (MI); Troy Smith (MO); Martin Swanson (NE); Colton Schulz and Chris Aufenthie (ND); Barbara D. Richardson (NV); Don Layson (OH); Dan Petterson (VT); John Jacobson (WA); and Rachel Cissne Carabell (WI).

1. Adopted its October 11 Meeting Minutes

Schulz made a motion, seconded by Amann to adopt the Working Group's October 11 minutes (Attachment Three-A). The motion passed unanimously.

2. Discussed Cybersecurity with the Cybersecurity and Infrastructure Security Agency (CISA)

Erdly led a discussion with CISA's Executive Director, Brandon Wales. The discussion touched on several topics.

Wales said that CISA's work consists of two broad missions. CISA is responsibility for coordinating national efforts around critical infrastructure, security, and resilience. Because CISA is not a part of the law enforcement community or the intelligence community, the organization is purpose built for partnership with industry. The second mission is related to operational responsibility for the security of federal, civilian executive branch networks. CISA provides information, guidance, and technical advisories related to cybersecurity.

Related to the Cyber Incident Reporting for Critical Infrastructure Act of 2022 (CIRCIA), Erdly asked about the act, what makes it important, and how CIRCIA will determine who is critical infrastructure and therefore will be subject to the reporting requirements of the Act. Wales responded that CIRCIA will help the federal government have better visibility to cybersecurity trends noting that currently the federal government estimates that it only knows about 20 to 30% of the cyber attacks that hit the United States which prevents the government from providing early warning to additional victims which further allows campaigns to spread more quickly. Therefore the law now requires incident reporting with CISA working on what will qualify as a covered incident who will qualify as a covered entity. CISA wants to make sure that when they issue their final rule to apply the authority given to them in CIRCIA, that result in a clear definition allowing members of industry to understand whether they qualify as critical infrastructure or not. Lastly, CISA also wants to make sure that they are receiving the most relevant information for covered incidents understanding that incidents evolve quickly and that limited information may be available at times. Erdly asked further about the type of information CISA anticipates gathering with Wales responding that the information will be of the sort that helps CISA advise the rest of the community about emerging threats including information on tactics and techniques used by adversaries. Erdly asked if the incident information CISA gathers could be shared with state insurance regulators. Wales responded that there are restrictions in how information can be used, for instance criminal proceedings, and so there may be information they have to remove for privacy reasons, but that CISA anticipates being able to share information with state insurance regulators. Miguel Romero (NAIC) asked if CISA anticipated taking an active aiding in the investigation of cybersecurity incidents or passive role largely focused on gathering information. Wales responded that CISA's role can vary based on what is needed but that generally they expect to gather information when working with industry representatives. Romero asked if the information gathered would include consumer level information.

Wales responded that given CISA's focus on protecting all companies, consumer level information may not be relevant.

Erdly next asked about CISA's Cybersecurity Performance Goals. Erdly indicated that the goals originate from a National Security Memorandum signed by President Biden on July 2021. The memorandum required that CISA work with the National Institute of Standards of Technology (NIST) to develop baseline cybersecurity performance goals that are consistent across all critical infrastructure. The goals are a voluntary set of cybersecurity practices intended to help those deemed to be critical infrastructure, especially small and medium sized organizations. Wales added that the goals were developed with industry input and that the goals are a focused set of controls most essential to achieving positive cybersecurity outcomes. They draw on the NIST Cybersecurity Framework (CSF), but don't cover every practice referenced in the CSF. The goals also include insights on the anticipated cost and complexity of implementation so organizations can evaluate their own capacity as they decide which controls to implement.

Erdly next asked how state insurance regulators can support CISA's work. Wales talked about the importance of having sound due diligence related to cybersecurity insurance underwriting because he views cyber insurance as a really critical mechanism to improve cybersecurity risk mitigation. Wales further indicated that the Department of Treasury is studying at the possibility of a federal backstop for cyber insurance.

Erdly next asked about CISA's Shield's Up Program. Wales indicated that the program originated in 2021 as the US government recognized that Russia was likely to invade Ukraine and that there may be implications for US cybersecurity based on the US's support for Ukraine. The program recommends a series of steps a company should take to mitigate risk possibly as a reprisal from Russia. Suggested practices include using multi-factor authentication on administrative accounts and segmenting networks as much as possible. The program also suggests other practices for instance lowering the threshold for reporting incidents to governmental agencies and making sure the company has adequate equipment for operations in case of supply chain issues.

3. Discussed Other Matters

Having no further business, the Cybersecurity (H) Working Group adjourned.

Https://naiconline.sharepoint.com/sites/NAICSupportStaffHub/Member Meetings/H CMTE/2022_Fall/Cybersecurity/C(H)WG 11-15-2022 Minutes.docx

Draft: 1/5/23

Cybersecurity (H) Working Group
Virtual Meeting
October 11, 2022

The Cybersecurity (H) Working Group of the Innovation, Cybersecurity, and Technology (H) Committee met Oct. 11, 2022. The following Working Group members participated: Cynthia Amann, Co-Chair (MO); Wendy Erdly, Co-Chair (NY); C.J. Metcalf, Co-Vice Chair (IL); Michael Peterson, Co-Vice Chair (VA); Sian Ng-Ashcraft (AK); Damon Diederich (CA); Wanchin Chou (CT); Matt Kilgallen (GA); Lance Hirano (HI); Shane Mead (KS); Van Dorsey (MD); Jake Martin (MI); John Harrison (NC); Colton Schulz and Chris Aufenthie (ND); Don Layson and Todd Oberholtzer (OH); Dan Petterson (VT); John Jacobson (WA); and Rachel Cissne Carabell (WI).

1. Adopted its Summer National Meeting Minutes

Schulz made a motion, seconded by Erdly to adopt the Working Group's July 14 minutes (*see NAIC Proceedings – Summer 2022, Innovation, Cybersecurity, and Technology (H) Committee*). The motion passed unanimously.

2. Heard an Update on International Work Related to Cyber

Rashmi Sutton (NAIC) started by introducing herself to the Working Group. She has worked with the NAIC on the international team for eight years. In that capacity, she is a member of the International Association of Insurance Supervisors' (IAIS') Operational Resilience Task Force (ORTF). By way of background, Sutton noted that the NAIC is a founding member of the IAIS, which was founded in 1994. The ORTF started meeting in the fall of 2020 to pull in all things resilience, including cybersecurity resilience. The mandate of the ORTF is to identify and assess factors and developments that may affect operational resilience in the insurance sector regarding information technology (IT) third-party outsourcing and insurance sector cyber resilience. The ORTF was tasked with taking stock of and reviewing relevant best practices from both the reinsurers' and supervisors' perspective. The ORTF's work will also consider the impact of the COVID-19 pandemic, specifically in the area of business continuity planning, both from the perspective of how it affected insurers and supervisors around the world.

The initial work of the ORTF was focused on information gathering. As part of its information gathering, the ORTF has heard from NAIC staff on the *Insurance Data Security Model Law* (#668 and about how examination processes have been enhanced in recent years to add cybersecurity questions to the work performed by state insurance regulators in the U.S. Other jurisdictions presented on their own efforts related to cybersecurity. As the information gathering came to a close, the ORTF settled on the first effort being an issues paper broadly focusing on insurer operational resilience, including cybersecurity resilience, third-party outsourcing, and business continuity management. Sutton explained that IAIS issues papers introduce a topic and its background while providing areas for future work that the IAIS could focus on. In contrast, IAIS application papers provide recommendations on best practices for supervisors to consider as they evaluate how their framework does or does not address international standards. The ORTF's work has progressed to where a public consultation will be held soon after the Working Group's meeting and would collect comments through early January 2023. This would represent an opportunity for state insurance regulators to provide feedback on the IAIS' work. Within the NAIC, feedback on international work is usually provided via the International Insurance Relations (G) Committee. However, given the subject matter, the Working Group and associated regulators could provide beneficial input.

Amann thanked Sutton for the presentation and asked that state insurance regulators consider volunteering to give feedback on the IAIS' issues paper when the comment period opens up. Romero further noted how important it can be for state insurance regulators to engage in this work to make sure the end product adequately incorporates U.S. insurance regulator views, as appropriate.

3. Adopted the "Summary of Cybersecurity Tools" Memorandum

The Working Group next discussed the formerly exposed "Summary of Cybersecurity Tools" Memorandum. Amann noted that the document was exposed for a public comment period after the Working Group's last meeting on July 18 with a comment period ending August 16. No comments were received, but NAIC staff did identify minor revisions for state insurance regulators to consider. Romero discussed the attached "Summary of Cybersecurity Tools" memorandum drafted by NAIC staff as a resource for state insurance regulators. The memorandum describes the various tools that state insurance regulators have available, and it is intended to be a reference guide for future regulators who follow the Working Group's work. The revision reflected in the meeting materials clarifies that if state insurance regulators inquire pursuant to the Cybersecurity Vulnerability Response Plan, they may determine that an insurer was subject to a cybersecurity event. In that case, the revisions clarify that the intention is that the response plan would cease to be the right tool to guide the state insurance regulators' efforts and that they should instead consider a more detailed inquiry via other regulatory guidance. Romero further clarified that this "Summary of Cybersecurity Tools" is intended as an informative reference guide describing the tools available to state insurance regulators and is not intended as an authoritative piece of guidance.

Martin made a motion, seconded by Ng-Ashcraft, to adopt the "Summary of Cybersecurity Tools" memorandum as amended (Attachment Three-A1). The motion passed unanimously.

4. Received an Update on the Cybersecurity Workstreams Document

Romero provided an update on the cybersecurity workstreams document (Attachment Three-A2). The document describes the various workstreams underway related to cybersecurity that Romero was aware of as an aide to state insurance regulators interested in tracking cybersecurity-related work. The workstreams are not assignments of the Working Group but may still represent relevant projects that the Working Group may wish to be aware of. Romero noted the intention to post the document on the Working Group's page as a means of being transparent on the ongoing cybersecurity work being undertaken at or through the NAIC. He then provided an update on the contents of the workstreams document, noting how it included references to the following projects:

- Model #668
- *Financial Condition Examiners Handbook*
- *Market Regulation Handbook*
- Cybersecurity Tabletop Exercises
- Cybersecurity Research (Center for Insurance Policy and Research [CIPR])
- Incident Response Best Practices Guidelines for State Insurance Departments
- Coordination and Communication in Addressing Cyber Events
- European Union (EU)-U.S. Cyber Exercise Template (non-active workstream)
- Macroprudential (E) Working Group – Global Insurance Market Report (GIMAR)
- Operational Resilience Task Force – Issues Paper

5. Received a Preview of the Working Group's Meeting

Amann and Romero provided a preview of the Working Group's next meeting, which will feature a discussion with the Cybersecurity and Infrastructure Security Agency (CISA). This meeting builds on the update provided during the Working Group's last meeting on July 14 from Brooke Stringer (NAIC), who talked about CISA's new role in cybersecurity incident reporting. NAIC staff are working with CISA staff to finalize the logistics, but the meeting is currently scheduled for Nov. 15. Amann requested input on discussion topics and questions, with Amann's goal being to understand the role CISA will play going forward on cybersecurity events. Romero further added that the discussion may be beneficial in allowing state insurance regulators to understand the work of this federal agency. Moreover, he suggested that the group discuss CISA's Shields Up program, which provides good insights that companies may find beneficial to bolster their security. Also, a dialogue with CISA may help ensure both CISA and state insurance regulators are comfortable sharing information when cybersecurity events take place.

6. Discussed Other Matters

Amann shared a development that the White House released a *Blueprint for an AI Bill of Rights* providing insights on the use of artificial intelligence (AI) and on cybersecurity matters.

Additionally, Mead promoted a cybersecurity summit in Kansas intended to unite the public sector and critical infrastructure resources of Kansas. He said the summit's aim is to build a stronger cybersecurity community in the state of Kansas but that it is open to all people that are interested. The event is scheduled for Oct. 25.

Having no further business, the Cybersecurity (H) Working Group adjourned.

Https://naiconline.sharepoint.com/sites/NAICSupportStaffHub/Member Meetings/H CMTE/2022_Fall/Cybersecurity/c(h)wg_minutes-att1.docx

MEMORANDUM

TO: Members of the Cybersecurity (H) Working Group

FROM: NAIC Staff

DATE: May 2, 2022

RE: Summary of Cybersecurity Tools

With the creation of the Cybersecurity (H) Working Group and the addition of new voices to our discussion, NAIC staff have created this primer describing currently available NAIC cybersecurity-related regulatory tools.

There are three key NAIC resources regulators that relate to insurer cybersecurity – the NAIC's *Insurance Data Security Model Law* (Model #668), the *Financial Condition Examiners Handbook*, and the *Market Regulation Handbook*. This memo will summarize how each tool addresses the topic of cybersecurity as well as the interrelationship between each tool.

Insurance Data Security Model Law (#668)

The Model Law was adopted in 2017 and it builds on the existing broad regulatory authority vested in state insurance regulators. Specifically, it establishes standards for data security and standards for the investigation of and notification to the Commissioner of a Cybersecurity Event. Among the sections of the Model Law are:

- Information Security Program – This section sets expectations for what shall be included within a security program for licensees, with a specific discussion of mitigation practices that should be considered. The section also sets forth expectations for board oversight and oversight of third-party service providers.
- Notification of Cybersecurity Event – This section sets a 72-hour notification notice to the Commissioner for security events.
- Power of the Commissioner – This section gives the Commissioner the power to investigate licensees to determine if the licensees have engaged in any conduct in violation of the law.

Financial Condition Examiners Handbook

Financial exams serve a broad purpose but generally give regulators a chance to review and evaluate the financial condition and prospective solvency of insurers.

As part of the exam process, regulators perform a General Information Technology Review which has historically been focused on evaluating IT general controls and application controls. However, given the rise of cybersecurity concerns and the potentially for overlapping concepts/questions, the IT review also allows regulators to evaluate cybersecurity specific risks and controls.

The *Financial Condition Examiners Handbook* includes guidance based on the COBIT 5 Framework that provides regulators with possible questions aiding in the process of investigation. However, starting with the 2016 edition of the *Financial Condition Examiners Handbook* and in subsequent editions, the guidance has been revised based on industry trends, to align with the Model Law, and to benefit from NIST Cybersecurity Framework concepts.

IT review guidance in the *Financial Condition Examiners Handbook* is maintained by the Information Technology (IT) Examination (E) Working Group. Moreover, the Working Group has an ongoing mandate to monitor cybersecurity trends and develop updates to guidance as needed.

Working with NAIC staff, the Working Group also developed a mapping tool that allows regulators to see how examination procedures relate to the Model Law and the guidance in the *Market Regulation Handbook* with the intent of creating efficiencies where possible.

Market Regulation Handbook

Following the adoption of the NAIC's Model Law, Market Conduct regulators added guidance in the *Market Regulation Handbook* to aid jurisdictions in reviewing a regulated entity's insurance data security program and response to a Cybersecurity Event.

The Market Conduct guidance comes in the form of two checklists. A "Insurance Data Security Post-Breach Checklist" was developed to allow market regulators to review a regulated entity's insurance data security program and response to a Cybersecurity Event, for compliance with applicable state statutes, rules or regulations relating to Model #668. The "Insurance Data Security Pre-Breach Checklist" was also developed; it is used by market regulators proactively, to understand regulated entity compliance with applicable state statutes, rules or regulations relating to Model #668, in the absence of a Cybersecurity Event.

The Insurance Data Security Pre-and Post-Breach Checklists are in the *Market Regulation Handbook* and are maintained by the Market Conduct Examination Guidelines (D) Working Group.

Cybersecurity Vulnerability Response Plan

To aid states in addressing matters related to vulnerabilities, the Information Technology Examination (E) Working Group developed a *Cybersecurity Vulnerability Response Plan* (Response Plan).

The document guides examiners and/or analysts through the ad-hoc inquiry that may be necessary when a cybersecurity exposure or vulnerability has been identified or alleged in the period between full-scope examinations. If, during such inquiry, regulators identify the occurrence of a cybersecurity event, the Response Plan then directs regulators to use the post-breach checklist from the *Market Regulation Handbook.* It is, however, up to those examiners or analysts to use sound professional judgement when deciding to undertake such inquiries.

The results of the ad-hoc inquiry may warrant additional investigation, which could include calling a targeted examination, performing interim work, and/or follow-up on recommendations by the department analyst. If additional investigation is warranted, the vulnerability plan directs regulators consult the *Financial Condition Examiners Handbook* to identify relevant follow up procedures.

If there are any questions or concerns, please contact Miguel Romero at maromero@naic.org.

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NAIC CYBERSECURITY WORKSTREAMS

ISSUE	DESCRIPTION	NAIC COMMITTEE/STAFF	STATUS
Domestic Initiatives & Projects			
NAIC Insurance Data Security Model Law (#668)	State adoption of the model and implementation.	Executive (EX) Committee Legal • Holly Weatherford • Jennifer McAdam	Model complete/implementation in process with 21 states having adopted the model and 1 state with action under consideration as of September 16, 2022. See "State Adoption Map" for additional details.
Updates to *Financial Condition Examiners Handbook*	As part of the exam process, regulators perform a General Information Technology Review which has historically been focused on evaluating IT general controls and application controls. However, the IT review also allows regulators to evaluate cybersecurity specific risks and controls.	Information Technology (IT) Examination (E) Working Group • Jacob Steilen • Bailey Henning	The *Financial Condition Examiners Handbook* includes guidance based on the COBIT 5 Framework that provides regulators with possible questions aiding in the process of investigation. Starting with the 2016 edition of the *Financial Condition Examiners Handbook* and in subsequent editions, the guidance has been revised and will continue to be revised based on cybersecurity trends, to align with the Model Law, and to benefit from NIST Cybersecurity Framework concepts.
Updates to *Market Regulation Handbook*	D Committee updated the *Market Regulation Handbook* to strengthen sections regarding cybersecurity, including development of a pre-	Market Conduct Examination Guidelines (D) Working Group	In 2020, the *Market Regulation Handbook* was updated with the adopted insurance data security pre-breach checklist and an insurance

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NAIC CYBERSECURITY WORKSTREAMS

ISSUE	DESCRIPTION	NAIC COMMITTEE/STAFF	STATUS
	breach and a post-breach market conduct examination checklist.	• Tim Mullen • Lois Alexander • Petra Wallace	data security post-breach checklist to provide guidance for market conduct examinations.
Cyber Tabletop Exercises (Domestic)	Working with State and Federal Regulators, the NAIC facilitates tabletop exercises with insurers and regulators to explore cyber incident response and recovery back. These exercises are a useful means for regulators and the insurance industry to test their ability to respond effectively to these incidents. The exercises follow a cybersecurity event (i.e., ransomware) and result in dialogue among attendees as the event progresses.	E Committee, D Committee, DC staff (govt. relations) • Frosty Mohn • Skyler Gunther • Lindsay Bartholomew • Tim Mullen • Miguel Romero • Brooke Stringer • Jeff Czajkowski	The NAIC has hosted tabletops with regulators of the following states: • South Carolina (2019) • Joint session with Kansas and Missouri (2019) • Connecticut (2021) The following sessions are also planned into the future: • 2022 – Maryland • 2023 – Ohio and joint North Dakota/South Dakota session
Cybersecurity Research	The CIPR has several ongoing research projects. Paired with each recent and future tabletop exercise, the CIPR surveys insurers in the host state to gain information on cybersecurity practices and views of risk.	CIPR • Jeff Czajkowski	Pending

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NAIC CYBERSECURITY WORKSTREAMS

ISSUE	DESCRIPTION	NAIC COMMITTEE/STAFF	STATUS
	Additionally, the CIPR has acquired an Advisen cyber event data set which has led to two presentations at the NAIC's Insurance Summit on cybersecurity event trends using both the Advisen data and the NAIC's data acquired via the cybersecurity surveys.		
Incident Response Best Practices Guidelines for State Insurance Departments	Through the tabletops and FBIIC discussions, industry and government officials have recommended developing a best practices guideline for cyber incident response. The SEC and CFTC have developed plans that may be helpful resources.	H Committee, DC staff (govt. relations) • Miguel Romero • Frosty Mohn • Brooke Stringer	The Cybersecurity (H) Working Group has a charge to consider the development of a response plan and will likely begin work later in 2022.
Coordination and Communication in Addressing Cyber Events	NAIC staff and various regulator groups (i.e., MAWG, FAWG, Chief Regulators) continue to play a key role in facilitating communication and coordination across states in addressing cybersecurity events. This includes coordination with federal bodies as necessary (i.e., FBIIC, Treasury) to coordinate efforts on emerging vulnerabilities and events.	E Committee, D Committee • Bruce Jenson • Miguel Romero • Tim Mullen • Randy Helder • Paul Santillanes • Brooke Stringer	Recent activities include coordination around several known insurance company breaches, as well as outreach regarding various high-profile vulnerabilities (i.e., Solar Winds, Qualys, Microsoft Exchange). Given the increased frequency of these events, state insurance

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NAIC CYBERSECURITY WORKSTREAMS

ISSUE	DESCRIPTION	NAIC COMMITTEE/STAFF	STATUS
			regulators are considering whether a more formalized process and structure for coordination and communication activities is necessary.
International Initiatives & Projects			
EU-U.S. Cyber Exercise Template	As part of the EU-U.S. Insurance Project, FIO, the NAIC, European Commission, EIOPA and EU member states have discussed potential development of an exercise template or process.	G Committee, H Committee • Gita Timmerman • Miguel Romero	This project is currently on hold with participants discussing whether the project should be restarted.
Macroprudential Monitoring Working Group – Global Insurance Market Report (GIMAR)	The IAIS develops a GIMAR special topic edition each year, which delves deeper into a specific area of focus. The focus of the 2022 GIMAR special topic is the potential financial stability impact of cyber risk, including how cyber risk underwriting activities of insurers could potentially mitigate or amplify these risks.	G Committee, H Committee • John Hopman • Miguel Romero	IAIS has sent out a request for data that NAIC staff will take the lead in responding to.
Operational Resilience Task Force – Issues Paper	The IAIS' Operational Resilience Task Force (ORTF) is developing an Issues Paper on operational resilience in the insurance sector, specifically on IT third-party outsourcing and insurance sector cyber resilience. The paper will build on work undertaken by the FSB on a cross-sector basis. The ORTF will also consider how to integrate lessons from Covid-19 on ensuring business continuity (over an extended period) into supervisory guidance.	G Committee, H Committee • Rashmi Sutton • Ryan Workman • Miguel Romero	A draft of an issues paper has been circulated for comments among group participants.

Draft: 1/5/23

Innovation in Technology and Regulation (H) Working Group
Virtual Meeting
September 14, 2022

The Innovation in Technology and Regulation (H) Working Group of the Innovation, Cybersecurity, and Technology (H) Committee met Sept. 14, 2022. The following Working Group members participated: Evan G. Daniels, Chair (AZ); Dana Popish Severinghaus, Co-Vice Chair, and C.J. Metcalf (IL); Judith L. French and Lori Barron, Co-Vice Chairs (OH); Erick Wright and Yada Horace (AL); Lucy Jabourian (CA); George Bradner (CT); Dana Sheppard (DC); Tim Li (DE); Weston Trexler (ID); Brenda Johnson and Shannon Lloyd (KS); Alexander Borkowski and Kory Boone (MD); Leah Piatt (ME); Chad Arnold (MI); Carrie Couch (MO); Andy Case and Ryan Blakeney (MS); Chris Aufenthie and Colton Schulz (ND); Connie Van Slyke (NE); Jennifer Catechis (NM); Aeron Teverbaugh and TK Keen (OR); Shannen Logue (PA); Nancy Clark (TX); Eric Lowe (VA); Timothy Cornelius, Jennifer Stegall, Jody Ullman, and Rebecca Rebholz (WI); and Juanita Wimmer (WV).

1. Heard Presentations from Boost Insurance and Degree Insurance on Innovation Collaboration with State Insurance Regulators

Director Daniels said the presentations from Boost Insurance and Degree Insurance will focus on how state insurance regulators have facilitated innovation in insurance over the last several years. He said the last Working Group meeting emphasized different approaches three states have taken, such as sandboxes and the use of existing laws, to allow state insurance regulators some flexibility in addressing new ideas. He said that meeting was an inward focus on how state insurance regulators are thinking about these approaches, and this meeting is an outward focus on companies' experiences in working with states on innovation.

Dennis Murashko (Degree Insurance) said his company has built a new product that did not previously exist in the market that guarantees students make money after college. He said his company sells insurance products to colleges and universities that then offer coverage to incoming freshmen. He said that coverage ensures a certain salary level, and Degree Insurance would cover the difference if the graduate is not making the guaranteed salary after five years. He said there is not another product like this on the market, and it is difficult for state insurance regulators to see how this product performs since claims are 10 to 12 years delayed from when the policy is sold.

Mr. Murashko said Degree Insurance began its regulatory process in Illinois because it has a particularly innovative insurance department. He said by having a regulatory guide, much of the complexity of regulation gets reduced to a checklist of a couple dozen items. He said the checklist makes the process much easier from an industry perspective, especially in innovative companies where the founders and employees are not necessarily coming from an insurance background. He said Illinois state insurance regulators made it easy for Degree Insurance to price its products in a way that made it easier to satisfy risk-based capital (RBC) compliance. He said additionally, Illinois worked with Degree Insurance and the NAIC to determine which line of business this new product would be filed under. He said after a positive regulatory experience with the Illinois Department of Insurance (DOI), Degree Insurance expanded into other states where it met the regulatory requirements. He said Degree Insurance also meets the requirements of the industrial insured exemption in many states, which allows it to have a sales channel in certain states while working with state insurance departments to become an admitted carrier of an innovative insurance product.

Mr. Murashko said a positive outcome of a state insurance department being open to innovation is working to promote innovation and protecting consumers. He said Degree Insurance looked at states with sandboxes, but it ultimately decided that was not the best approach for them and instead chose to take the path of the traditional approval process. He said even in states where Degree Insurance cannot yet file, it is important to have open conversations with state insurance regulators that set the groundwork for a smoother process in the future.

Jeremy Deitch (Boost Insurance) said his company is focused on digital distribution, empowering any company to engage with its customers and increase its sales by offering insurance through its own digital experience. He said Boost Insurance is an insurance infrastructure platform that packages compliance, capital, operational, and technical components of an insurance program and puts them together into a turnkey white label solution.

Mr. Deitch said when thinking about bringing innovative products to the market, there is the need to protect consumers using modern technology and the need for insurers to write profitable business. He said any company that is trying to take a technology-forward approach should create and maintain a vital translation layer between stakeholders. He said that happens internally when building products, and it happens externally in open conversations between companies and state insurance regulators. He said these are the things that foster innovation and, ultimately, regulatory approval. He said innovative companies should be able to explain the what and the why behind their utilization of new technology and innovative datasets.

Mr. Deitch said there needs to be a change in the mindset of how companies are viewing the regulatory review and approval process. He said instead of viewing it as a hurdle, companies should look at the process as something that will ultimately create the best product. He said if both state insurance regulators and companies can look at where the other party is coming from, it will lead to moving innovation forward. He said commissioners are putting together initiatives that are vital for fostering innovation, and the enthusiasm behind these initiatives needs to trickle down to front line reviewers.

Mr. Deitch said Boost Insurance has found that proactive approaches to innovation from state insurance regulators have been the most beneficial thing in terms of understanding what the regulations are and how they apply to the specific product. He said open communication before a company has begun regulatory filings is important. He said one example of this was a product that had an innovative approach to underwriting. He said sitting down with states and their actuaries, reviewing the product, and talking through issues that might lead to a disapproval was a proactive step.

Director Daniels asked how easy it was to find the right people in the insurance departments to discuss innovative ideas. Mr. Murashko said it was quite easy after talking with many different people at NAIC meetings and industry gatherings. He said on top of meeting state insurance regulators at these events, others in the industry that have been in the innovation space can lead newer companies to the right people. He said he would like to see the innovation contacts list maintained by the NAIC updated more frequently and possibly broken out by contacts for certain issues within the regulatory process. Mr. Deitch agreed that having separate contacts for more granular issues would help in speeding up response time and moving the process forward more quickly.

Director French asked if either company could put a time frame on their acceptable length of time to hear back from regulatory inquiries. Mr. Deitch said it would depend on the situation, but he would expect some a response within 30 days. He said companies need to be flexible and cognizant that state insurance regulators are not working on the same timeline as companies when they are trying to push out a new product.

Director Daniels asked both presenters to address pain points they have come across in the regulatory process. Mr. Deitch said there can sometimes be a sense of treating all filings the same and not evolving the review process or the application of statutes as innovative products come into the market. Mr. Murashko agreed, and he said in terms of Degree Insurance's product, some seasoning requirements in states could not apply to the product because even after two or three years, states would not have claim activity to review. He said in those instances, it would be more helpful to look at the product as a whole instead of just applying standard length of seasoning requirements.

Mr. Trexler asked Mr. Deitch why Boost Insurance took the route of becoming a managing general agent (MGA) rather than an insurance carrier. Mr. Deitch said Boost Insurance operates with delegated authority and handles filings on behalf of carriers and reinsurers. He said even as an MGA, Boost Insurance has some of the same regulatory hurdles that it is navigating on behalf of carriers.

Having no further business, the Innovation in Technology and Regulation (H) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/H Cmte/2022_Fall/ITRWG/Minutes/ITRWG Minutes091422-Final.docx

Draft Pending Adoption

Draft: 1/5/23

Privacy Protections (H) Working Group
Tampa, Florida
December 12, 2022

The Privacy Protections (H) Working Group of the Innovation, Cybersecurity, and Technology (H) Committee met in Tampa, FL, Dec. 12, 2022. The following Working Group members participated: Katie Johnson, Chair, represented by Don Beatty (VA); Cynthia Amann, Co-Vice Chair (MO); Chris Aufenthie, Co-Vice Chair (ND); Chelsy Maller (AK); Shane Foster (AZ); Damon Diederich (CA); George Bradner and Kristin Fabian (CT); Erica Weyhenmeyer and C.J. Metcalf (IL); LeAnn Crow (KS); Ron Kreiter (KY); Van Dorsey (MD); Robert Wake and Benjamin Yardley (ME); Martin Swanson (NE); Teresa Green (OK); Raven Collins represented by Numi Griffith (OR); Gary Jones (PA); Frank Marnell (SD); Todd Dixon (WA); and Lauren Van Buren, Rachel Cissne Carabell, and Timothy Cornelius (WI). Also participating were Sarah Bailey (AK); Glenda Haverkamp (KS); Kathleen A. Birrane (MD); John Arnold (ND); and Tanji J. Northrup (UT).

1. Adopted its Summer National Meeting Minutes and Noted an Updated Work Plan

Amann said the Working Group met Aug. 9.

Commissioner Birrane made a motion, seconded by Diederich, to adopt the Working Group's Aug. 9 minutes (*see NAIC Proceedings – Summer 2022, Innovation, Cybersecurity, and Technology (H) Committee, Attachment Four*). The motion passed unanimously.

Amann noted that an updated Nov. 11, 2022, work plan for the Working Group was posted to the Working Group's web page.

2. Heard Updates on State Privacy Legislation

Jennifer Neuerburg (NAIC) said there was little action on state privacy legislation, and both updated charts were posted to the Working Group's web page.

3. Heard a Presentation from a Consumer Perspective on General Market Practices Regarding the Use of Personal Information During the Insurance Process

Matthew J. Smith, Esq. (Coalition Against Insurance Fraud—CAIF) said the data onslaught is here, and insurance consumers need state insurance regulators to make sure they are protected. He said data, if used correctly, can be used in helping consumers with lower premiums; tailoring coverages; and making the insurance process of application, payment, and claims easier. However, he said regulatory oversight and accountability are crucial. He said there is support for the appropriate use of data in the world of insurance, and consumers are not data-ignorant according to "The Ethical Use of Data to Fight Insurance Fraud Study" commissioned by the CAIF and executed by Dynata with a recommendation from NAIC consumer representative, Brenda J. Cude (University of Georgia). He said this study was done to help guide state insurance legislators and regulators because it includes valuable insight to guide the proper oversight of data both in antifraud and beyond. He said the study had over 2,000 American respondents, with 67% of those responding being consumers; 17% insurance professionals; 6% federal and state legislators, regulators, or government agency respondents; and 10% from the legal or data

Draft Pending Adoption

service industry. He said the data collected was cross-analyzed and confirmed by data scientists as having no difference from consumers to companies to other respondents. The study showed that 85% of all American consumers are concerned about data fraud in insurance transactions. Smith said when consumers were asked about whom they trust with their personal data, 75% said they were okay with insurance companies using their data, but 61% wanted a national data protection standard enforced by state insurance departments, and 85% supported data laws and guidance for insurance companies' use of such data. He said disclosure regarding data usage and clarity—i.e., requiring companies to have a straightforward and easy-to-read privacy policy—are key to insurer data trust. He said when the premium is reduced to receive data, 61% of respondents said they had no expectations; however, 46% said they expected a 10% reduction in premium. He said when asked if insurers are properly overseeing personal data, insurance professionals said 47% of their companies had strong data protections in place, and 53% said their companies had little, not good, or no policy of personal data protection in place.

Smith recommended that state insurance regulators play a strong role by using the results of this study in consultation with data scientists to: 1) apply this data to their work both nationally and at the state level; 2) encourage others to undertake similar research; 3) address data usage at all parts of the insurance transaction; 4) create clear policies with accountability; 5) share information with other states; 6) control the use of personal data for marketing; 7) create standards for data use and retention after cancellation or non-renewal; 8) determine if data is being de-identified and, if so, by whom; 9) include third parties who aggregate or oversee programs for insurers; 10) track the shipping of data overseas; 11) address bias and prejudice; and 12) determine whether the misuse of personal data is intentional or unintended. In closing, he said the challenge moving forward is getting it right and right away, as there is no time to continue to simply wait and see what happens with the use of insurance consumers' personal data.

4. Heard a Presentation from a Company Perspective on General Market Practices Regarding the Use of Personal Information During the Insurance Process

Scott Fischer (Lemonade Insurance Company) said we all use data in our daily lives; however, a balance is needed for the necessary use of data and the consumers' need for privacy. He said insurance is unique with open questions that still need to be addressed. He said one question has to do with the best way to handle tradeoffs, because we need to ensure that users cannot manipulate data for fraud detection and how much transparency companies can provide. He said another question is regarding what level of control users can have, because users who choose to delete their data give up a less personalized experience. For auto insurance, he said allowing for consumer deletion of data would skew the company's perception of risk.

Fischer said the question includes determining the best way to provide users with the appropriate context; whether it should be through disclosures, terms of service, or privacy policies; as well as what such notices could or should look like. He said this unique insurance industry should think about privacy by its intentional collection and use of a user's data.

Fischer said companies should look at: 1) what type of data is being collected from users and why it is being collected; 2) who has access to that data and what they can use it for; 3) what users know about their data and what control they have; and 4) how it is collected.

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Fischer said data that is sensitive and personal should come directly from the user; data that relates to user behavior in other domains, such as a house purchase, comes from third-party sources; user behavior data, like scrolling through the product online, is provided indirectly; and data about a user that is generated via machine learning (ML), such as whether the user has a swimming pool, is generated within the company itself.

Fischer said user data ranges in its sensitivity from less sensitive data that is not user-identifiable, such as scrolling patterns, to more sensitive data that is considered sensitive personally identified information (SPII), such as one's Social Security Number (SSN) or biometrics that could cause significant harm if compromised, with the midpoint data being user identifiable and personal, such as video footage. He said the sensitivity of the data should be used to control how each category of data is collected, what user controls should exist, and who can access the data internally and externally. He said the more sensitive the data is, the more guarded access to the data should be and the more control and awareness users should have. He said less sensitive data can be indirectly collected and stored without explicit consent and provided more broad access and use across use cases and features. He said access to more sensitive data should be extremely limited internally and used only for a handful of purposes where no other data can be used and explicit user permission to collect or generate data must be sought, and it should allow users controls to be able to access and delete data. At the midpoint, he said limited access is allowed for purposes that are pre-defined for users, and it provides users with appropriate levels of awareness and control depending on the use case.

Fischer said state insurance regulators need to hold third-party sources accountable for clarity during collection; the purpose should be clear to users throughout the user experience for data obtained directly from users; indirect behavioral data should not contain any sensitive information, such as personally identified information (PII); and when users provide information for generation within the company, users should be informed of how data may be used, especially for more sensitive cases.

Fischer said companies should provide users with the proper context while the data is being collected; provide a common help center or space for users to understand what data is being collected, and for what purposes; clearly indicate to users that account deletion equals data deletion; and identify what data makes sense for a user to have control over in terms of deletion, access, and usage. He said there are technical innovations like differential privacy and federated learning in this space that are making it possible to add noise to or silo a user's data, while still providing access to train models. However, he said these innovations are not being used in the insurance space yet. It would provide a secure environment where personal data could be stored and subjected to a differentially private computation with access to analysts' queries via noisy results.

5. <u>Discussed General Market Practices Regarding the Use of Personal Information During the Insurance Process from Both Perspectives</u>

Eric Ellsworth (Consumers' Checkbook) said as a data scientist, he believes data becomes much more sensitive, as data is linked to other data; it is necessary to flag the linkage aspect and relevancy coalescent, as well as tangential relationships. Harry Ting (Health Consumer Advocate) said Smith's survey clearly indicates that state insurance regulators can and should regulate insurance companies' use of consumer data even though the Metas like Google are too big to fail and control. Wake said there is a strong push from the federal government to put together a list of things states can and cannot regulate. He said identity theft protection is not all there is to protect; there is also the universe of third parties to consider. He said federal Health Insurance Portability and Accountability Act of 1996 (HIPAA)-like concessions are needed, with third parties agreeing to keep all data protected like it is under HIPAA. He said state insurance regulators need to think about the purposes for which data is to be used and the

Draft Pending Adoption

companies who do things behind the scenes to support insurance companies. He said there is a dichotomy between universally available data and non-public data. He said telematics are needed by auto insurance companies with things like coverage, uber, etc. included. Smith said according to the CAIF's study, car trackers are not all altruistic.

Amann said the new *Insurance Consumer Privacy Protection Model Law* (#674) draft includes all lines of business. She said the drafting group discussed federal acts and focused on being technologically current. Commissioner Birrane said she has confidence in state insurance regulators to develop a model that all states can use to effectively regulate and serve consumers.

6. Discussed Other Matters

Amann reminded attendees about the upcoming exposure draft of Model #674 at the end of January for a two-month comment period to be followed by open meetings resuming in March to discuss all comments received in the coming months.

Having no further business, the Privacy Protections (H) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/H Cmte/2022_Fall/Privacy/PPWG Minutes121222-Final.docx

Draft: 11/2/22
Adopted by the Executive (EX) Committee and Plenary,
Adopted by the Innovation, Cybersecurity, and Technology (H) Committee, 12/13/22

2023 Proposed Charges

INNOVATION, CYBERSECURITY, AND TECHNOLOGY (H) COMMITTEE

The mission of the Innovation, Cybersecurity, and Technology (H) Committee is to: 1) provide a forum for state insurance regulators to learn and have discussions regarding: cybersecurity, innovation, data security and privacy protections, and emerging technology issues; 2) monitor developments in these areas that affect the state insurance regulatory framework; 3) maintain an understanding of evolving practices and use of innovation technologies by insurers and producers in respective lines of business; 4) coordinate NAIC efforts regarding innovation, cybersecurity and privacy, and technology across other committees; and 5) make recommendations and develop regulatory, statutory, or guidance updates, as appropriate.

Ongoing Support of NAIC Programs, Products, or Services

1. The **Innovation, Cybersecurity, and Technology (H) Committee** will:
   A. Provide forums, resources, and materials for the discussion of insurance sector developments in cybersecurity and data privacy to educate state insurance regulators on how these developments affect consumer protection, insurer and producer oversight, marketplace dynamics, and the state-based insurance regulatory framework.
   B. Discuss emerging issues related to cybersecurity, including cybersecurity event reporting and consumer data privacy protections. Monitor and advise on the cybersecurity insurance market, including rating, underwriting, claims, product development, and loss control. Report on the cyber insurance market, including data reported within the Cybersecurity Insurance and Identity Theft Coverage Supplement.
   C. Coordinate with various subject matter expert (SME) groups on insurer and producer internal cybersecurity. Discuss emerging developments; best practices for risk management, internal control, and governance; and how state insurance regulators can best address industry cyber risks and challenges. Work with the Center for Insurance Policy and Research (CIPR) to analyze cybersecurity-related information from various data sources.
   D. Provide forums, resources, and materials for the discussion of innovation and technology developments in the insurance sector, including the collection and use of data by insurers, producers, and state insurance regulators, as well as new products, services, and distribution platforms. Educate state insurance regulators on how these developments affect consumer protection, data privacy, insurer and producer oversight, marketplace dynamics, and the state-based insurance regulatory framework.
   E. Discuss emerging technologies and innovations related to insurance and insurers, producers, state insurance regulators, licensees, or vendors, as well as the potential implications of these technologies for the state-based insurance regulatory structure—including reviewing new products and technologies affecting the insurance sector and their associated regulatory implications.
   F. Consider and coordinate the development of regulatory guidance and examination standards related to innovation, cybersecurity, data privacy, the use of big data and artificial intelligence (AI) including machine learning (ML) in the business of insurance, and technology, including drafting and revising model laws, white papers, and other recommendations as appropriate. Consider best practices related to cybersecurity event tracking and coordination among state insurance regulators, and produce guidance related to regulatory response to cybersecurity events to promote consistent response efforts across state insurance departments.

G. Track the implementation of and issues related to all model laws pertaining to innovation, technology, data privacy, and cybersecurity, including the *Insurance Data Security Model Law* (#668), the *NAIC Insurance Information and Privacy Protection Model Act* (#670), the *Privacy of Consumer Financial and Health Information Regulation* (#672), and the *Unfair Trade Practices Act* (#880) rebating language and providing assistance to state insurance regulators as needed.
H. Coordinate with other NAIC committees and task forces, as appropriate, and evaluate and recommend certifications, continuing education (CE), and training for regulatory staff related to technology, innovation, cybersecurity, and data privacy.
I. Follow the work of federal, state, and international governmental bodies to avoid conflicting standards and practices.

2. The **Big Data and Artificial Intelligence (H) Working Group** will:
   A. Research the use of big data and AI including ML in the business of insurance, and evaluate existing regulatory frameworks for overseeing and monitoring their use. Present findings and recommendations to the Innovation, Cybersecurity, and Technology (H) Committee, including potential recommendations for development of a regulatory bulletin that would include, but not be limited to: 1) explanatory introduction/background; 2) identifying existing underlying statutory/regulatory authority; 3) vocabulary; 4) regulatory expectations for use of AI techniques to accomplish regulated activity, including : governance framework; risk management components; tolerances/standards/controls; validation methods; third-party diligence/oversight; and appropriate transparency, including disclosures/ explanations; and 5) regulatory oversight framework for the use of big data and AI, including ML for the insurance industry.
   B. Review current audit and certification programs and/or frameworks that could be used to oversee insurers' use of consumer and non-insurance data and models using intelligent algorithms including AI and in alignment with the NAIC AI Principles. If appropriate, issue recommendations and coordinate with the appropriate SME committees on the development of or modifications to model laws, regulations, handbooks, and regulatory guidance regarding data analysis, marketing, rating, underwriting and claims, regulation of data and model vendors, regulatory reporting requirements, and consumer disclosure requirements.
   C. Assess data and regulatory tools needed for state insurance regulators to appropriately monitor the marketplace, and evaluate the use of big data, algorithms, and ML, including AI/ML in underwriting, rating, claims, and marketing practices This assessment shall include a review of currently available data and tools, as well as recommendations for development of additional data and tools, as appropriate. Based on this assessment, propose a means to include these tools in existing and/or new regulatory oversight and monitoring processes to promote consistent oversight and monitoring efforts across state insurance departments.

3. The **E-Commerce (H) Working Group** will:
   A. Examine e-commerce laws and regulations and work toward meaningful, unified recommendations. The Working Group will also examine whether a model bulletin would be appropriate for addressing some of the identified issues and draft a proposed bulletin if determined appropriate.

4. The **Cybersecurity (H) Working Group** will:

   A. Monitor cybersecurity trends such as vulnerabilities, risk management, governance practices, and breaches with the potential to affect the insurance industry.
   B. Interact with and support state insurance departments responding to insurance industry cybersecurity events.

C. Promote communication across state insurance departments regarding cybersecurity risks and events.
D. Oversee the development of a regulatory cybersecurity response guidance document to assist state insurance regulators in the investigation of insurance cyber events.
E. Monitor federal and international activities on cybersecurity engaging on efforts to manage and evaluate cybersecurity risk.
F. Coordinate NAIC committee cybersecurity work, including cybersecurity guidance developed by the Market Conduct Examination Guidelines (D) Working Group and the Information Technology (IT) Examination (E) Working Group.
G. Advise on the development of cybersecurity training for state insurance regulators.
H. Work with the CIPR to receive updates on cybersecurity research efforts, by the CIPR and others, and to analyze publicly available cybersecurity-related information.
I. Support the states with implementation efforts related to the adoption of Model #668.

5. The Privacy Protections (H) Working Group will:

A. Use state insurance privacy protections regarding the collection, data ownership and use rights, and disclosure of information gathered in connection with insurance transactions to draft a new Privacy Protections Model Act to replace NAIC models, such as Model #670 and Model #672.
B. Develop a research paper on state insurance privacy protections regarding the collection, data ownership and use rights, and disclosure of information gathered in connection with insurance transactions that states can use to support their implementation efforts related to the adoption of the new *Privacy Protections Model Act* (#674).

6. ***The Innovation in Technology and Regulation (H) Working Group*** *will:*

A. Develop forums, resources, and materials for discussing innovation and technology regarding companies, producers, state insurance regulators, and licensees relevant to the state-based insurance regulatory structure, including new products, services, business models, and distribution mechanisms.
B. In conjunction with NAIC staff, explore developing a forum that provides insurers or third parties working with insurers the opportunity to confidentially brief state insurance regulators regarding innovation and technology applications, tests, use cases, and results.
C. Identify and discuss regulatory models or programs that may assist state insurance regulators to identify and better understand innovation taking place within the insurance industry.
D. Monitor innovation work occurring in other NAIC letter committees, task forces, and working groups, and identify areas of possible coordination for the Innovation, Cybersecurity, and Technology (H) Committee.

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