NATIONAL ASSOCIATION OF INSURANCE COMMISSIONERS

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

Date: August 10, 2023

Re: 2022-23 Home Artificial Intelligence/Machine Learning Survey Analysis

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The 2022-23 Home Artificial Intelligence/Machine Learning Survey (Home 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 recommended 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 10 requesting states (Connecticut, Illinois, Iowa, Louisiana, Nevada, North Dakota, Pennsylvania, Rhode Island, Vermont, and Wisconsin) and completed by insurers who write Home insurance in one of the ten participating states and have at least $50 million in national Homeowners insurance premium for 2020. The following subject matter experts (SMEs) represented the ten states:

CT: George Bradner
IL: Erica Weyhenmeyer and CJ Metcalf
IA: Jared Kirby
LA: Nichole Torblaa and Arthur Schwartz

[1] The 2022-2023 Home AI/ML survey was conducted under the market conduct examination authority of ten states: Connecticut, Illinois, Iowa, Louisiana, Nevada, North Dakota, Pennsylvania, Rhode Island, Vermont, and Wisconsin. Subject matter experts (SMEs) from these states opted to limit the survey request to only larger companies, defined as those Home (NAIC Type of Insurance--TOI 4.0) writers with more than $50 million in 2020 direct premium written. Type of Insurance (TOI) 4.0 includes policies for residential owners of stand-alone homes, tenants, and condominium unit-owners. The SMEs also limited the scope to only "advanced" AI/ML models but still asked companies to estimate the number of excluded models such as generalized linear models (GLMs). A total of 194 responses were received.

ND: Mike Andring and Chris Aufenthie
NV: Gennady Stolyarov
PA: Michael McKenney
RI: Matt Gendron
VT: Commissioner Kevin Gaffney
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 194 companies completing the survey, 136 companies currently use, plan to use, or plan to explore using AI/machine learning (ML) as defined for this survey. This equates to approximately 70% of reporting companies. For comparison, approximately 88% of the companies responding to the PPA Survey reported they currently use, plan to use, or plan to explore using AI/machine learning (ML).

Among insurer operations areas, companies reported varying levels of AI/ML use, from 14% in the loss prevention area to 54% in claims operations[2]. In order from maximum to minimum use, the percentage of companies using AI/ML by insurer function were: claims, 54%; underwriting and marketing (both at 47%); fraud detection, 42%; rating, 35%; and loss prevention, 14%.

The top two most popular reasons reported for not using, not planning to use, and not exploring use of AI/ML were "no compelling business reason", and "waiting for regulatory guidance".

The following shows the predominant insurer uses of AI/ML, the levels of decision-making when there are AI/ML models in place, 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 for subrogation and claims triage (44 companies each) and evaluation of images of loss (36). Few companies are using AI/ML claims models to determine the settlement amount (2) and a couple are researching how they might use them for claim approval and claim denial. Companies noted some additional uses of claims models in their write-in comments: identification of contractor outcomes, workforce management, legal bill review or automatic payment decisions, method of inspection, DocBot document classification, customer satisfaction, and NLP analysis of complaint intensity. In comparison, the main uses of AI/ML models for claims reported in the PPA Surveys were for informational resources for adjusters (96 companies), claim assignment decisions (58), evaluation of images to estimate losses (55), and to determine settlement amount (50).

[2] 'Other' areas included: routing or triage of customer service calls, customer service chat for property, social media sentiment analysis, document processing/identification/routing, and chatbots.

Level of decision-making: Over 60% of the AI/ML models used to help determine subrogation and claims triage *augment* human decision-making. In contrast, over 60% of the models used to evaluate images to estimate loss amounts *support* human decision-making.

In-house or third-party: Models were developed in-house for most of the claims applications (subrogation, claims triage, adjuster information, claim assignment, litigation, approval and denial). Models used to evaluate images to determine loss and for speech analysis tend to be developed by third parties.

Types of models: About a third of the types of AI/ML models used for Claims consisted of machine learning ensembles/automated machine learning techniques which are effective to estimate claim amounts and probability of litigation, and another third were neural networks/deep learning which are effective for image and speech analysis.

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. Interestingly, 26 companies are using AI/ML to detect organized crime rings, as compared to very few respondents reporting this use in PPA Survey. Further, 24 companies reported using social network data on the Home Survey, but this was not a listed data source for those responding to the PPA Survey.

Level of decision-making: For the referral of claims for further investigation, most of the models *augmented* human decisions. Other fraud-detection models were a mixture of *augmentation* and *support*. This is consistent with the findings reported in the PPA AI/ML Surveys.

In-house or third-party: Fraud detection models are mostly from third-party sources but for some uses, the models are just as frequently in-house as they are from third parties.

Types of Models: A variety of models were used to help determine Fraud, including deep learning/neural networks, machine learning ensembles and other techniques.

Marketing Models

Uses: Companies use marketing models mainly for customer acquisition and retention, and targeted online advertising.

Level of decision-making: Many of the marketing models were used to *augment* human decision-making. Marketing models are mostly used as *augmentation* when used for customer acquisition and retention and provision of offers to existing customers. *Automated* models, with no human intervention on execution, were most often used for targeted online advertising and customer interactions using NLP. For comparison, the PPA AI/ML Surveys reported a greater degree of *automated* Marketing model implementations than the Home AI/ML Surveys.

In-house or third-party: Marketing models being used by insurance companies combine in-house and third-party sources in all but click analysis on third-party sales. In-house sources are predominately used for customer acquisition and retention, provision of offers to existing customers, and identification of potential customer groups. Third-party sources are prevalent in targeting online advertising, identification of recipients of mail or phone advertising, and media mix modeling.

Types of Models: A majority of the models used for Marketing were machine learning ensembles.

Rating, Underwriting, and Loss-Prevention Models

Similar to the PPA AI/ML Surveys, there were fewer "more advanced" AI/ML models used for rating, underwriting, and loss prevention. 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 due to the transparency required by state departments of insurance. This corroborates the understanding of the SMEs that the majority of rating approaches that Home 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, underwriting, and loss prevention.

Only 68 companies reported current rating model uses, and the majority of those were for rating class determination, retention modeling, or other rate-related functions. The levels of decision were mixed between *automated* and *support*; and as similarly reported in the PPA Surveys, almost all rating models were developed in-house mainly using machine learning ensembles.

A greater number of companies than reported in the PPA Surveys (91 vs. 34) reported current underwriting model uses, and the majority of those were for automated denial/inputs into non-automated denial decisions, and for verification of policy characteristics. About half of the models were used for *automation*, with a third used for *support* and a sixth of the models were used for *augmentation*. Most of the models used in underwriting were developed in-house, using deep learning and machine learning ensembling techniques, consistent with the PPA Surveys.

Only 28 companies reported current loss-prevention uses (compared to 3 companies using models for loss prevention in the PPA Surveys), mainly for guidance on loss control inspections, and with 12 companies reporting active research in providing risk-mitigation advice, where most of the models were reported used to *augment* or *support* human decisions. Models were split between being developed internally and by third parties. A variety of neural network and other machine learning models were reported being used to develop models for loss prevention.

DATA ELEMENTS BY INSURER OPERATIONS

The following are the most frequent data elements used in the different insurer operations.

- Claims
    - Home loss Experience (internal), Roof data (from external source), and Geocoding (mix of internal and external sources)
- Fraud Detection:
    - Mainly home loss experience (split between internal and externally-sourced)
- Marketing:
    - Insured demographic/Geo-demographic data, Consumer or other type of Score, Occupation, Education, Personal Finance Information, Home loss experience, geo-coding, and Income; these data elements were mixed between internally and externally sourced.
- Rating:
    - Insured demographic/Geo-demographic data, Consumer or other type of Score, Geo-coding, and Home loss experience; these data elements were mixed between internally and externally sourced.

- Underwriting:
    - Roof data, Consumer or other type of Score, Defect identification in images, and Insured demographic data; these data elements were mixed between internally and externally sourced.
- Loss Prevention:
    - Of the data elements listed, very few data elements were reported being used in AI/ML loss prevention models, implying that other data elements were used but not reported in the Surveys.

CUSTOMER DATA CORRECTION

The response rate to the consumer data correction questions in the Home Surveys was low. Less than 10% of the companies responded they provide information regarding the data elements used and the purposes of use to consumers beyond what is required by law. Of these companies, half responded they had more consumer data correction processes than required by the federal Fair Credit Reporting Act (FCRA).

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 was lower than expected, was almost unanimously "no" for each of the insurer operations. The second question was similar but asked whether consumers are told the purposes of data elements beyond what is required by law. For this question, the answer was almost unanimously "no." This response was consistent with the PPA Surveys.

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, 60% responded "yes" for rating and underwriting; a little less than half responded "yes" for claims; over 40% responded "yes" for marketing and fraud detection; and 35% responded "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.

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 to the fairness and ethics consideration, accountability, transparency, and secure/safe/robust questions were fairly consistent between each question, where approximately 50% of insurers reported "yes" in the Home Surveys, as compared to approximately 25% of insurers reporting "yes" in the PPA Surveys. The answers for the appropriate resources question tended to be higher percentages of "yes" (approximately 90%) than for the other questions.

THIRD-PARTY DATA SOURCES AND MODELS

Insurers identified third-party vendors they use to purchase models and/or data. There were 2,413 models listed in the survey (with some models being counted more than once because of separate uses for the same model); 1,006 (42%) are developed by a third party, and 1,407 (58%) are developed internally. The proportions of models developed internally vs. a third party reported in the PPA Surveys were nearly identical. After grouping the similarly named third parties, there are 95 unique third-party companies listed in the survey whose models are being used by insurers (vs. 76 third parties reported in the PPA Surveys). Marketing has 48 different third parties listed as providing models, followed by claims with 37. There were 76 third-party companies listed as data providers used by insurers (vs. 104 unique third parties reported in the PPA Surveys).

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 but not documented due to the confidential nature. Regulators may contact Kris DeFrain, kdefrain@naic.org to seek additional, but non-company identifying information. This report is confidential because data was collected in a market conduct examination of the ten states and agreed confidentiality protections were applied.