December 8, 2022

Private Passenger Auto
Artificial Intelligence/Machine Learning
Survey Results

NAIC Staff Report

NAIC SURVEY TECHNICAL TEAM

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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 Operation Area[1]	Number and Percentage of Companies							
	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

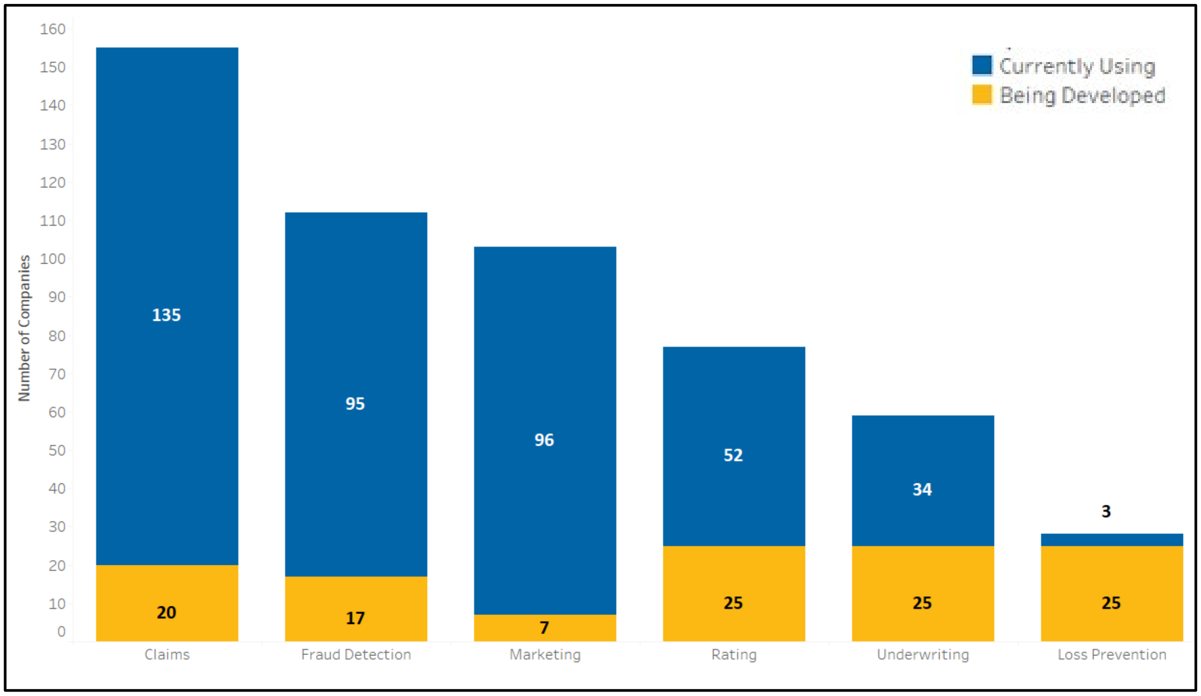
[1] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.

[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.

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 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

[3] For definitions, refer to Appendix B: Definitions Specific to Claims.

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

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

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

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

Claims Model Uses[5]	Number of Models (In Use or Under Construction) by Level of Decisions Influenced by AI/ML			
	Automation*	Augmentation*	Support*	Other
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
Other Claim Related Functions	172	77	51	23	223	100

<u>Data Elements</u>

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)

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

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
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	0	9	0	184

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

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
(Excluding auto-related convictions)				
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

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

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

Claims Data Elements[9]	Number of Companies Using a Consumer or Other Type of “Score” as an Input		
	Yes	No	Blank
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.

Fraud-Detection Model Uses

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 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

[10] For definitions, refer to Appendix C: Definitions Specific to Fraud Detection.
[11] 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[11]	Number of Companies				
	In Use	Research	Proof of Concept	Prototype	None (N/A)
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
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.)

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

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

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

Fraud-Detection Data Elements[13]	Number of Companies Using/Not Using the Data Element in a Fraud-Detection AI/ML Model*		
	Yes	No	Blank
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.)

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

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

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
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.

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

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).

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

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

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

*"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

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

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.)

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.

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

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.)

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.

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[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
Facial Detection/Recognition/Analysis	0	113	80
Geocoding	11	102	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
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
Occupation	6	0	0	187
Personal Financial Information	7	7	0	179
Loss Experience	26	0	9	158

[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
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
Voice Analysis	0	31	162
Consumer or Other Type of "Score"			
Other Nontraditional Data Elements	0	36	157

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

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
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

[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 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

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

[32] For definitions, refer to Appendix A: Guidance for Questions in Each Operational Area: Rating, Underwriting, Claims, Fraud Detection, Marketing, Loss Prevention.
[33] 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
	#	%	#	%	#	%
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
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

[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
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
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

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

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
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

[36] For definitions, refer to Appendix H: Data Use Table Definitions.
[37] For definitions, refer to Appendix G: Definitions Specific to Loss Prevention.

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
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.)

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

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

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

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

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.

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

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

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
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 (Excluding Auto-Related Convictions)	0	8	185
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

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

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
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.)

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

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

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

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

[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.
[52] 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
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

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		

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
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
	Colossus
Claim Assignment Decisions	CCC***
	Mitchell
	Guidewire

[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
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.

<u>Third-Party Data Sources used in Claims</u>

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
Natural Catastrophe	---
Job Stability	---
Income	---
Occupation	---
Personal Financial Information	Lexis Nexis Claim Datafill

[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
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.

<u>Third-Party Models Used in Fraud Detection</u>

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

Fraud-Detection Model Uses[18]	If Model is Developed by a Third Party, List the Third Party
	Third-Party Name
	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

[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
	Census Bureau
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
Provision of Offers to Existing Customers	Merkle
	Pegasystems
	IBM
	Amsive
	Merkle

[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
Identification of Potential Customer Groups	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
Education	Acxiom
	DMS
	MediaAlpha
	Equifax
	Amsive
	Experian
	Google

[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
	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
Occupation	Acxiom
	Equifax
	Facebook
	Amsive
	Experian
	Lead Provider
	LinkedIn
	Various programmatic display advertising vendors

Marketing Data Elements[57]	If External or Both, List Each Data Vendor
	Third-Party Name
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	---
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.)

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)

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

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

[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
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
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

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

	Shift Technology
Risk-Mitigation Advice to Consumers	---
Determination of Advance Payments	---
Other Loss Prevention-Related Functions	---

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

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

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.

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.