AI in Insurance

Top Use Cases, Challenges, and Trends

WHITE PAPER

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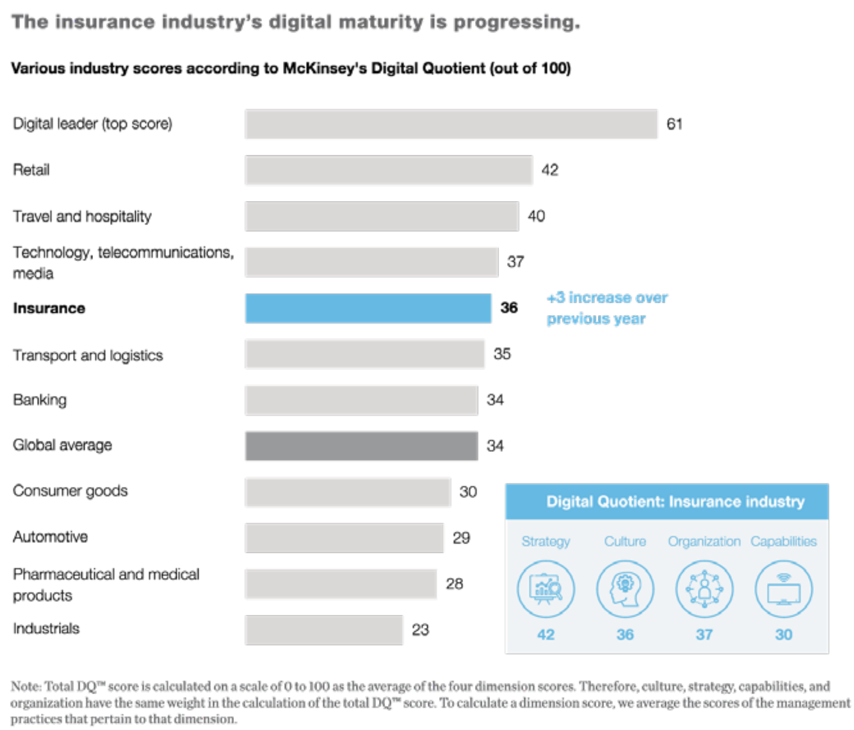
Introduction

Combining mathematics and data analysis in insurance for prediction is not new but has perhaps come into the spotlight with recent worldwide buzz surrounding data science and machine learning. And in the past few years, the pace and scale of data science, machine learning, and ultimately AI adoption has accelerated to enhance or reinvent the processes core to the insurance business.

"During the last 12 months, Gartner has seen great interest in the use cases and application of AI for many tasks, including chatbots for customer service, underwriting assistance platforms, and AI for no-touch claims processing."

- Gartner 2019 CIO Agenda: Insurance Industry Insights, Kimberly Harris-Ferrante, 15 October 2018 (report available to Gartner subscribers)

Exhibit *From McKinsey's Digital Insurance in 2018*



"During the first three quarters of 2019, a total of US$4.36 billion had been deployed to InsurTech companies across 239 transactions. That already marked a 5 percent increase from the total amount of investment in all of 2018."

- Source: Willis Towers Watson

This growth of data science, machine learning, and AI in insurance is driven by a variety of factors, including:

- The breadth of use cases that can be developed using machine learning techniques, particularly those that go well beyond traditional uses of data by actuaries.
- Disruption from fintech (insurtech) and the resulting need to retain and attract clients through a better customer experience.
- Reinforced client price sensitivity.
- The potential business impact in using AI for more and larger use cases.
- Increased pools (and subsequent hiring) of machine learning and AI talent.
- The need to model evolving - and ever more complex - risks.
- The need for increased profit and loss management in a long-term, long-yield environment.

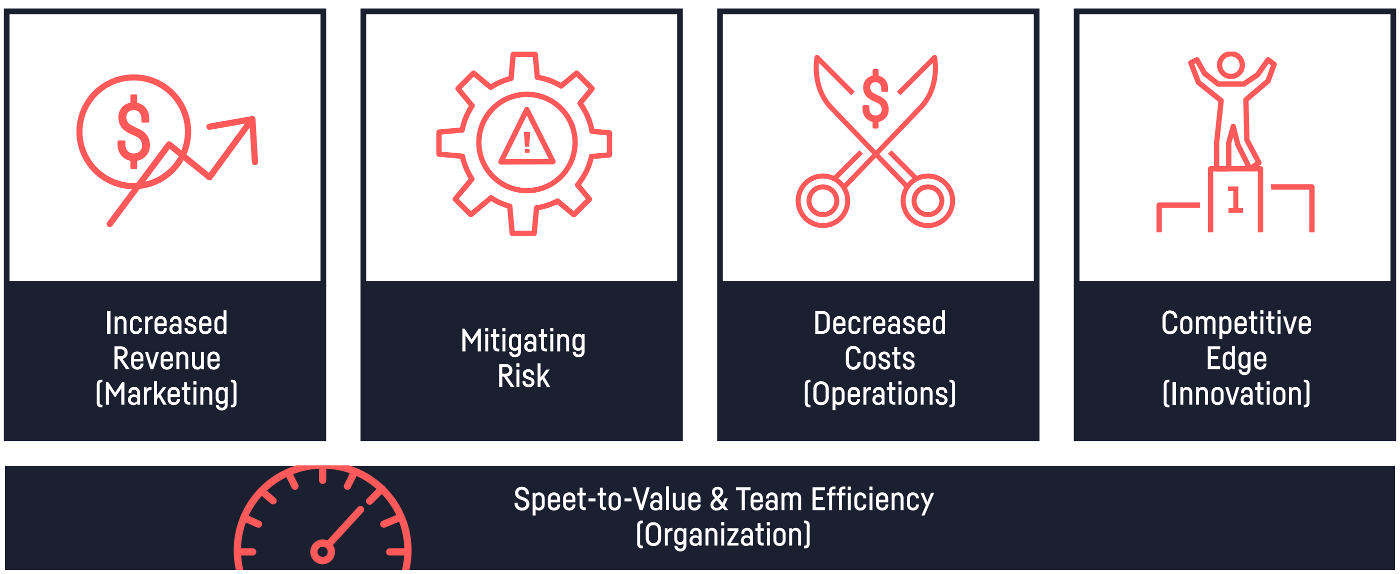
This white paper will explore some of the up-and-coming use cases, challenges that traditional insurance companies face in implementation of those use cases, and ways to address those challenges to be successful in the race to AI. It will also explore trends in how successful companies are executing on AI initiatives.

AI in Insurance: High-Value Use Cases

"As AI becomes more deeply integrated in the industry, carriers must position themselves to respond to the changing business landscape. Insurance executives must understand the factors that will contribute to this change and how AI will reshape claims, distribution, and underwriting and pricing. With this understanding, they can start to build the skills and talent, embrace the emerging technologies, and create the culture and perspective needed to be successful players in the insurance industry of the future."

- McKinsey, Insurance 2030: The Impact of AI on the Future of Insurance

Overall, use cases for data science, machine learning, and AI fall into one of five categories:



These categories are broad, which means there is no shortage of use cases when it comes to data science, machine learning, and AI in the insurance industry. This section takes a (non-exhaustive) look at some of today's most high-value use cases.

INCREASED REVENUE (SALES AND MARKETING)

Customer retention and churn prediction: A 2019 study by TechSee revealed that 50 percent of insurance customers actively search for an alternate insurer at renewal. And even though more than half (54 percent) of insurance companies made efforts to keep those customers, their efforts were largely unfruitful.

That leaves huge opportunities for AI not to simply predict possible churners, (as some customers will leave no matter what) but to take things one step further with a technique called uplift modeling. Since marketing efforts will not change the mind of every potential churner, uplift modeling is a second prediction after the initial prediction that identifies potential churners likely to respond positively to marketing messages.

If Not Treated \ If Treated	+	-
+	**Sure Things** Those that would have had a positive response either way and thus represent wasted marketing costs.	**Do Not Disturbs** Those who would have had a positive response but are then negatively impacted by marketing and thus should not be targeted.
-	**Persuadables** The target group - those that would have had a negative response but are then positively persuaded by marketing.	**Lost Causes** Those that would have responded negatively with or without marketing and thus represent wasted marketing costs.

AI-powered customer acquisition: Businesses can develop machine learning-based systems that help sales prioritize their work by assigning an individual probability of conversion to each prospect, whether that prospect is an individual or a group.

One insurance company working with Dataiku did this by first looking at data on existing clients (specifically, their cost of acquisition and lifetime value). They then used this analysis to establish “look alikes” for each prospect - that is, an existing customer who has similar characteristics and therefore will likely mirror the future actions of the prospect.

The end result of this system is a tool available for sales that allows them to more effectively prioritize their prospects by providing two pieces of information to consider: likelihood of conversion and likelihood of recuperation of acquisition costs. The team also created an interactive map containing this data so that any travel to visit prospects could be maximized by visiting other promising prospects nearby.

Optimal pricing and conversion: Optimal pricing is a delicate balance between understanding what the customer is willing to pay as well as how much risk they bring. The sheer number of factors and amount of data at play make it a great use case for AI; however, accurate price prediction is also incredibly challenging.

For example, AXA used machine learning to predict if a driver may cause a large-loss case during the insurance period and using Random Forest - a common machine learning algorithm that is very accurate for certain use cases - and achieved only 40 percent accuracy. In order to get to nearly 80 percent accuracy, AXA ultimately developed a much more complex deep learning (neural-network) model.

Improved customer service, driven by machine learning-powered customer segmentation: This category is broad, but important, as increasingly, it's the customer experience that provides the "stickiness" needed to retain clients. AI-powered innovations that range from applications delivering personalized offerings to internal recommendation engines allowing representatives to offer relevant services can help drive additional revenue.

A Glance at ADA:
Aviva's Algorithmic Decision Agent

- 33k employees globally (16k in the United Kingdom)
- The UK's largest multi-line insurer
- Global data science practice - called Quantum - has more than 700 data and analytics professionals
- The Customer Data Science Team is the company's customer-first data center-of-excellence and is made up entirely of data scientists

One of the Customer Data Science Team at Aviva's most celebrated projects is ADA (Algorithmic Decision Agent), Aviva's personalization AI, which helps the company be more specific and relevant to its customers. The AI, built using Dataiku, helps the company understand its customers better and delivers tailored marketing experiences based on their needs.

"As a customer data science team, we're always looking at how we can make things better for customers. And happily, that also tends to drive profit."
- Tom Spencer, Head of Customer Data Science | Aviva

"When we started building ADA ... it was taking us quite a long time with the existing legacy systems. But through using Dataiku and the API functionality, we reduced the amount of time from beginning to end to build a model and push out the model into the marketing channel."
- Ayca Kandur, Data Scientist | Aviva

Enhanced client advisory on financial protection services: In some markets, insurers play a key role in providing long-term financial protection and retirement schemes to customers. In this field, fueling deep understanding of clients in recommendation engines capable of adjusting to a wide range of financial profiles help insurers to deliver much more tailored financial advisory. Such recommendation engines, developed as proprietary tools by the insurance companies, enable them to position themselves as long-term advisors to their clients, offering appropriate recommendations for risk-adjusted solutions.

MITIGATING RISK

Claims forecasting and prediction: In the age of AI and algorithms, older modeling techniques fail to incorporate the wide variety of data sources needed to produce forecasts precise enough for the modern enterprise. Traditional claims reserve estimates don't look at the individual characteristics of policyholders, which effects predictability of future claims.

AI-based systems can use machine learning to take into account many more patterns in data than a human could, including those individual characteristics for better accuracy. And because AI-based systems can easily scale with automation, they can predict payments at an individual policy level, not just at the group level.

Regulatory reporting automation: Insurance companies worldwide have to deal with a slew of regulatory reporting standards that are both time consuming and risky if done incorrectly. The very act of having a centralized AI platform in which all data projects are built and stored is, in and of itself, a step in the right direction for smoother regulatory reporting.

With all actions logged and - in the case of Dataiku - a transparent view of all data pipelines, regulatory compliance can be monitored more real-time to ensure that there are no surprises if an audit arises. In case of an audit, AI itself can help automate manual work like validation of customer data, customer data security operations, and more.

Winning the Race for ESG in the Investment Space: A Data and Modeling Game

ESG, SRI, impact investment: all of these names and acronyms point to the same reality, which is that the demand for responsible investment has moved from promise to fact. The need for long-term appreciation of risks beyond pure financial factors - even more so in the face of today's uncertain health crisis - is pushing for accelerated demand from investors toward the full integration of Environment, Social, and Governance dimensions in the investment strategies run by asset managers.

"Our ambition is to better take into account environmental, social, and governance-related risks in investment decisions." What could sound straightforward is turning into a true mind bender for all investment professionals who are confronted with pressure from regulators, NGOs, and clients to act and demonstrate.

At the same time, the markets are still very much trying to get a full grasp on the topic, struggling to put frameworks in place on subjects (not to mention public debate and regulations) that continuously evolve. On top of this uncertainty are strong local specificities plus a general lack of stakeholder alignment on the appropriate KPIs to track the different ESG components, and it's easy to see why the topic is so complex.
But waiting for norms to emerge is not an option: asset managers who do not position themselves in a credible manner will simply fail to survive in a market already marked by increased competition, challenges of traditional active strategies by passives and alternatives, and continuous cost of regulation.

Out of the several ingredients needed to win the race for ESG, two stand out as essentials:

1. Strong convictions, embedded throughout processes and built on…
2. Distinctive ESG models capable of delivering strong ESG-adjusted performance and adapting to ongoing evolutions of the ESG landscape.

It's a Data Jungle Out There (& Getting Thicker by the Minute)

Asset managers who enter into the ESG space have to learn to navigate the world of external data providers with their respective frameworks, coverage, naming conventions, and types of data. To which they need to add all the material provided by brokers, research bodies, specialists, NGOs, and news feeds.

Asset managers who want to be serious about ESG more often than not end up juggling more than a dozen providers on top of their traditional financial data sources. And this jungle only gets thicker by the minute: as some large providers (such as MSCI and Sustainalytics) start emerging as industry standards and become commodities, asset managers are encouraged to combine these new must-haves with data issued by smaller organizations focusing on specific topics to have detailed impact tracking and preserve a differentiating edge.

To build their framework, asset managers will have to make choices, resting on the right selection of large providers, niche organizations, and public data, combined with internal insights and proprietary signals built from unstructured data. The capacity to blend, test, complete data coverage through machine learning, reverse engineer, and quickly review over time will be paramount to win the ESG race. So will be the capacity to enrich the set foundations with new data sources. For example, in an environment marked by new extreme weather hazards, can satellite images step in to assess emerging risks of exposure to flooding?

Turning the Switch to ESG: The Need for Collaboration

For a traditional portfolio manager, entering into the field of ESG starts with data. ESG scores aim at giving an overview of the ESG health of an issuer or asset, including controversy scores, CO2 emissions, or revenue exposure to sensitive activities such as coal and weapons production, etc. But asset managers can't expect all their professionals to become ESG experts over the course of a few days (or even a few weeks or months).

Furthermore, ESG data should not be seen as just a simple addition to existing framework; it behaves fundamentally differently than traditional financial data, and more often than not, it demands full end-to-end rethinking of processes.

If the ambition is to manage portfolios with the objective of alignment with a 2° scenario, should this link to the exclusion of full sectors - and is that manageable from a liquidity and diversification standpoint? What are the appropriate indicators and how do they fit in with traditional financial indicators? Are their ways of developing proprietary signals to give forward views on stock or yield-curve evolution based on environmental performance?

Putting such frameworks in place requires bringing together ESG experts along with traditional portfolio managers, portfolio engineers, and operation process owners around the same environment to jointly build the right models. Keeping this topic a specialist one is a tempting route, but it will not produce the internal buy-in nor the models that can, in the long run, deliver true ESG risk-adjusted performance.

Sharing the Right ESG Impact View

The ultimate objective of responsible investment is to better hedge investors versus emerging ESG risks, aligning their investments with their own beliefs. This might mean covering desire to disinvest from controversial activities such as coal production, tar sands, weaponry, palm oil, or to actively tune exposure toward social wellbeing, green activities development, gender balance, etc.

ESG topics don't stop with asset classes. A growing demand is emerging for cross-asset class views with consolidated perspectives on risks and exposures (beyond traditional ways of reporting and managing assets). To develop this type of ESG fiduciary and advisory service, asset managers will need to build new models as well as demonstrate agility to preserve their operational core foundations while building views and advice adapted to the specific demands of their clients.

Working with traditional frameworks will not solve this complex equation. New data types will need to play a role, along with new types of stress tests and models to help clients make the appropriate decisions. Fully preparing all business lines to foster these models and demonstrating proactive advice to clients using resulting learnings will be among key ingredients to emerge as true ESG leaders.

The Bottom Line

Most asset managers - not to mention investors - are only starting their journey on ESG. The topic remains a true shape-shifter, supported by strong local specificities, which makes it all the more difficult to capture. That makes it even more important to recognize the inherent complexity of the topic and the need to root answers in:

- Solid data and modeling foundations, combined with…
- Collaboration across all experts

Both of these will be paramount for asset managers, putting them on the right track to capture current demand and answer future needs, including the need to leverage AI as the switch from reaction to proactivity becomes a must-have.

ABOUT THE AUTHOR

Sophie Dionnet is VP Strategy at Dataiku where she drives strategic projects and helps financial players on their path to Enterprise AI. She has 14 years of experience in the asset management industry and notably acted as COO for a multi-asset portfolio management division, conducting large scale IT, regulatory, and transformation projects, including active development of responsible investment.

DECREASED COSTS (OPERATIONS)

Claims processing: The potential for AI to improve the claims processes is massive because it not only promises reduced costs from eliminating inefficiencies, but also increased customer satisfaction that has the opportunity to increase revenue.

Today's cutting-edge insurtech and - more recently - traditional insurance businesses are increasingly looking to AI for faster triage (e.g., larger claims with more uncertainty can be started more quickly by specialized teams, letting smaller claims be closed out even faster). Plus, technologies like deep learning (specifically natural language processing, or NLP) and computer vision move automatic processing into the realm of possibility, allowing businesses to move away from time-consuming, manual processing.

In fact, automation and advanced prioritization have the potential to touch nearly every part of the claims process, from intake to assessment to settlement. As an added bonus to speed, automation also can ensure fewer human errors and easier auditing. This is not to say that claims automation removes humans from the loop entirely; rather, much like fraud detection, it allows them to be leveraged more smartly only in cases where a human is truly essential. For example, claims with missing data might be routed to a human who can handle the case (and bonus: a bot could see how the human resolves the missing data and learn for future cases).

AI is allowing for such quick advancement and efficiency gain around claims handling that some companies - including New York-based Lemonade - are able to pay out claims in less than a day, resulting in high satisfaction from its growing base of loyal customers.

Underwriting: Machine learning is well suited for underwriting, identifying patterns in diverse data sources (from imagery to credit bureau data) to create a more tailored risk assessment.

For example, unstructured data can be incorporated to improve underwriting decisions. Public satellite or private imagery can be quickly and automatically analyzed to confirm risks on a property or site, while data from IoT devices (combined with other publicly-available information on individuals) can be instantly parsed for much more accurate - and timely - assessments of coverage.

Of course, insurance rating laws require rates and rating factors that are not excessive, inadequate, or unfairly discriminatory. AI has the potential to reinforce current underwriting approaches if developed with a strict white-box approach with full understanding and traceability of factors and resulting outputs (read more about this in the section **Responsible AI & the Insurance Industry**).

Fraud detection and prevention: Insurance organizations are all exposed to fraud risks, whether dealing with false claims, false billings, unnecessary procedures, staged incidents, withholding of information, and much more. This industry must be on the cutting edge of technology to stay ahead of fraudsters and reduce losses.

With limited resources on fraud investigation teams, every investigation into a case ultimately identified as low risk is wasted time. Hiring more staff to conduct these manual audits is an expensive and inefficient option - instead, the key is optimizing that team's work by using AI to detect fraudulent activity with a higher degree of accuracy. With detailed, specific small data from patients and providers feeding into these large data sets for analysis, audit teams look only at the highest-risk cases and can therefore detect more fraud.

Accurately Identifying Fraudulent Claims

Santéclair, a health network (part of Allianz), found fraudulent reimbursements stemmed both from opticians as well as patients, but they didn't have a system in place that allowed them to effectively analyze the right data and that would adapt with increasingly sophisticated fraudsters. Instead, they relied on "if-then-else" business rules to identify likely fraud cases, which resulted in the manual audit team spending their time on too many low-risk cases. With the increase of reimbursement volume (more than $1.5 million a year), they needed to improve their efficiency and productivity.

Leveraging Automation and Advanced Machine Learning

Santéclair identified these high-risk cases using Dataiku by:

- Outsmarting fraudsters with advanced machine learning algorithms that continually update and automatically learn or retrain using the latest data so that any new fraud patterns are immediately identified and audited. Dataiku handles the entire workflow, from raw data to exposing the predictive model to the operational applications.
- Automatically combining hundreds of variables from different datasets, including patient/prescriber history, interaction graphs, prescription characteristics, and other contextual data.
- Allowing teams to develop their data science skills through Dataiku's collaborative, easy-to-use interface.

Saving Customers Money with 3x More Effective Fraud Detection

Due to the comprehensive solution developed with Dataiku, Santéclair and Eulidia have:

- Enabled fraud detection teams to target actual fraud cases three times more effectively.
- Reduced time-to-market for similar projects by making a POC in a few weeks and then industrializing the project within a few months with a low impact on the IT team, thanks to the production-ready component in Dataiku.
- Saved their customers a lot of money by decreasing fraudulent behaviors in the health network and excluding the fraudsters from the network.
- Saved time with a model automatically updated and monitored along the way to prevent drifting of performance with little human supervision

"In less than a year, Santéclair has developed an unprecedented fraud detection system using Dataiku that allows our company to handle a growing volume of invoices and control costs. By choosing Dataiku, Santéclair was able to internalize its data skills and pursue additional analytics projects."

- Jocelyn Philippe, Head of Partnerships and Development at Santéclair

Improvement and automation of processes: There are still plenty of manual business processes in the industry outside of claims processing that can be improved through robotic process automation (RPA) and AI. One major example is policy management, but even smaller customer-side improvements (like streamlining the application process) can save time and reduce the chance of human error.

FEATURE

AI Meets Mail Processing: AI for Insurance Admin Tasks

Even as we continue to reach new technological milestones and solve the world's most demanding problems, many insurance companies are still confronted with the oldest of administrative nightmares: piles and piles of physical mail.

Head of Dataiku AI Lab Léo Dreyfus-Schmidt offered a scalable solution to the eternal problem of mail processing by using AI and deep learning techniques to solve the four major problems of mail processing, driven by a real use case for an insurance company:

1. Distinguishing if a letter is handwritten or typed
2. Parsing the text from a typed letter
3. Detecting words in handwritten letters
4. Extracting meaning from the images of words

Their goal was ultimately to deliver a production-ready tool that could be used to automatically sort any letters received and send them to their appropriate departments. Traditionally, this would have to be done by hand -- an expensive and time-consuming task.

The first challenge that the data team had to overcome was a very heterogeneous data set. While initially expecting to receive a pretty even mix of handwritten and typed letters, the actual training set contained a mix of letters, envelopes, forms, leaflets, and other forms of written documents.

With the 200,000 unlabeled images that they received, they went through the long process of labeling every document by type using a webapp they built. This allowed them to begin building their deep learning model on a large training set of data.

The Model

In a process that involved constructing a vector representation of the document images using an autoencoder (a process explained more thoroughly in the talk on the subject) and running a Random Forest machine learning model on the dataset, the team was able to successfully distinguish hand-written documents from typed ones.

Extracting text from images now accurately identified as being typed was the first (and perhaps most straightforward) step. They used an open source OCR (Optical Character Recognition) engine called Tesseract to do this.

Then came the hard part -- the handwritten letters. This process involved using computer vision techniques to detect paragraphs on the page and then to detect words from those paragraphs. They then stacked two common layers of deep learning techniques to learn and read the visual characteristics of those words.

Using some open-source datasets (and some augmented versions of those datasets) as the training set, they were then able to create a deep learning model in Dataiku that was able to identify the meaning of those handwritten words with fairly high confidence. Once this step was completed, the team had an operational method of extracting meaning from all of the incoming documents.

BEHIND THE MODEL

Léo Dreyfus-Schmidt is a mathematician and holds a PhD in pure mathematics from University of Oxford and University of Paris VII. After five years focusing on homological algebra and representation theory in Paris, Oxford, and the University of California - Los Angeles, he joined Dataiku where he has been developing solutions for predictive maintenance, personalized ranking systems, price elasticity, and natural language applications.

COMPETITIVE EDGE (INNOVATION)

Seamless customer experience: The idea of a better customer experience by weaving AI throughout processes - from acquisition all the way through claims processing, prevention actions and advisory - in order to retain clients has already been well-covered throughout this section on use cases.

However, it's worth mentioning again the competitive advantage that a truly seamless customer experience can provide. In addition, as more processes become automated and as client information is leveraged in a refined manner, client service operators can switch from being task managers to giving a more human, tailored experience to customers, providing client experiences capable of competing with promises of new fintechs.

Product development: Machine learning and AI open up opportunities for new products that were previously impossible, perhaps because of risk or cost. For example, private insurance coverage for some very risky exposures are unavailable today for lack of a dynamic model that can actually accurately represent the possible losses. More sophisticated and complex models can incorporate data from more sources than ever before to accurately estimate loss outcomes and probabilities.

Improved agility around data and AI also offers insurance companies the opportunity to better adapt to new client demands and emerging risks. For example, the rise of environmental concerns and increase in climate change-related risks, which demands adaptation both in pricing models and products with new types of data lacking maturity of traditional KPIs, is a key area where mastery of data science-related techniqueswill come as an essential differentiator.

Trends in AI for Insurance

Understanding how AI can be valuable in different parts of the business is easy; but actually executing on any of the use cases described in the previous section requires calculated coordination between people, processes, and technology. As more and more insurance companies start their journey in building Enterprise AI, there are a few trends emerging as best practice:

People

Growing collaboration between data scientists and actuaries: Though the two are currently largely working on different projects, the crossover is growing. Finding ways (likely via technology) to encourage and facilitate their collaboration is paramount to the success of insurance companies in AI initiatives. Especially considering that actuaries largely outnumber data scientists in most traditional insurance organizations, getting the two to work toward a common goal is critical.

The center of excellence model: More and more companies in financial services at large are putting in place AI center of excellences to support business adoption.That's not to say that AI projects stay siloed in one team; however, there is a need for one central driver and owner of AI efforts who can then set the framework enabling business units and data scientists deliver impactful results.

GO FURTHER: UBS on How to Build a Data Science Service Center of Excellence

Processes

Self-service analytics: There is an increasing need, in parallel to a center of excellence, to enable line-of-business professionals or analysts to access and work with data to generate insights - predictive or not - and data visualization with little direct support from data scientists, IT, etc. That's where self-service analytics comes into play.

GO FURTHER: Get the White Paper Enabling AI Services through Operationalization and Self-Service Analytics

Getting staff out of spreadsheets: One quick win on the path to Enterprise AI in the insurance industry is making a concerted effort to get staff out of spreadsheets. Not only are they error-prone, but they make regulatory reporting and data privacy standards a nightmare. While not a sexy use case, leveraging an AI platform to consolidate all efforts of working with data is a huge organizational win, with multiple applications across all functions.

GO FURTHER: The Guidebook to Going From Excel to Dataiku

Technology

The ability to work with unstructured data (i.e., text, images, etc.): The year 2019 was a landmark one for the field of natural language processing, more commonly referred to as NLP. Cutting-edge techniques once mainly restricted to the research area are now becoming much more mainstream and translating into real-world business applications. With the amount of automation to be done with documents in the insurance industry, having the technology and skills to execute on NLP is critical.

GO FURTHER: Get the White Paper: **Get Up to Speed With NLP**

Data science, machine learning, and AI platforms These tools allow for the scalability, flexibility, and control required to thrive in the era of Enterprise AI because they provide a framework for data governance, efficiency, reproducibility, automation, responsible AI, operationalization, collaboration, and more.

GO FURTHER: Get the White Paper: **Why Enterprises Need AI Platforms**

Bringing Insurance into the Age of AI: On Growing Data Science Collaboration

Analysts and actuaries have been around practically for centuries to bring mathematical models to the world of insurance. But data science, machine learning, and AI have the potential to take it one step further.

Even so, getting these initiatives off the ground has generally not been easy for most in the insurance business. The industry is often characterized as traditional and slow-moving, or worse, one that is not as customer-centric as it should be. However, there are some working to - and succeeding at - bucking these trends to bring data science to the forefront of insurance, transforming the way the business works with data for the better.

Aviva's Keys to Success

Aviva, the United Kingdom's largest multi-line insurer, developed their Customer Data Science Team around two years ago to compliment their already existing (and robust) global data practice.

We talked to Aviva's Head of Customer Data Science Tom Spencer and Data Scientist Ayca Kandur about what makes their team 5 times faster at going from raw data to production:

1. **Good data.** Upstream to downstream, one of the most important contributors to great data science is great data. For Spencer and his team, that means not only high quality raw data, but having a staff that knows what data is, what it means, and where it comes from.
2. **Proper tooling.** When Spencer started building the Customer Data Science Team at Aviva, his first priority was getting great people, but a close second was getting the tools in place that would allow that team to work together and to be its most productive. Today, the entire data science team uses Dataiku for every step of the data pipeline, from connecting to data to data preparation, building models to deploying them to production, and everything in between.
3. **Staying grounded in results.** The team at Aviva recognizes that data science is neither fun nor useful if the business ultimately isn't actually using what they're producing, so they have a strong focus on pushing to production (not just playing in a sandbox) for real impact.
4. **Staying Agile.** Delivering value fast is also important to Aviva, which means the Customer Data Science Team strikes a balance between quick-and-dirty R&D and more structured push-to-production strategies.

"The answers often aren't from insurance, they're from other disciplines out in the world. Our job, then, is to partner with our colleagues that have deep insurance expertise for a data-driven outlook."

- Tom Spencer, Head of Customer Data Science | Aviva

Read Aviva's full story

Responsible AI & the Insurance Industry

Going from producing one machine learning model a year to thousands a day is well within the average insurance organization's reach, and operationalization has made it possible for a single model to impact millions of decisions (as well as people). Yet, despite the exponential increase in the amount of machine learning models in production, only a few companies have dedicated the time and effort to ensure these models are deployed responsibly.

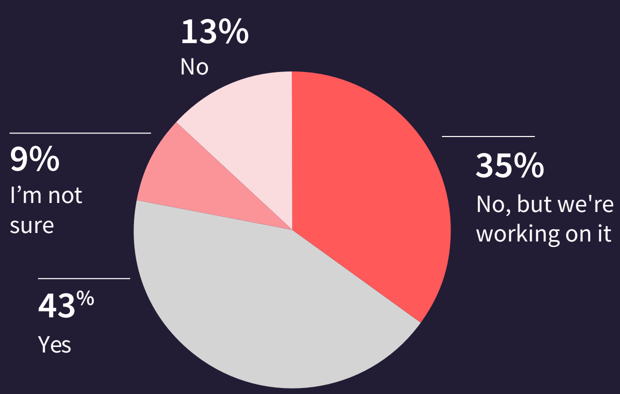
Responsible AI is perhaps even more important to consider for insurance organizations, as they must strike a delicate balance between efficiency and profitability as well as customer satisfaction, trust, and regulatory compliance. A responsible use of AI covers three main dimensions, which should all be considered when developing an organizational implementation strategy:

- **Accountability:** Ensuring that models are designed and behave in ways aligned with their purpose. This includes using white-box over black-box models when it makes sense, which is more inherent in the insurance world due to regulations but still can be a challenge when it comes to increasing model complexity (read more in White-Box vs. Black-Box Models: Balancing Interpretability and Accuracy) as well as taking the right precautions when it comes to model bias (read 3 Steps Toward More Ethical AI).

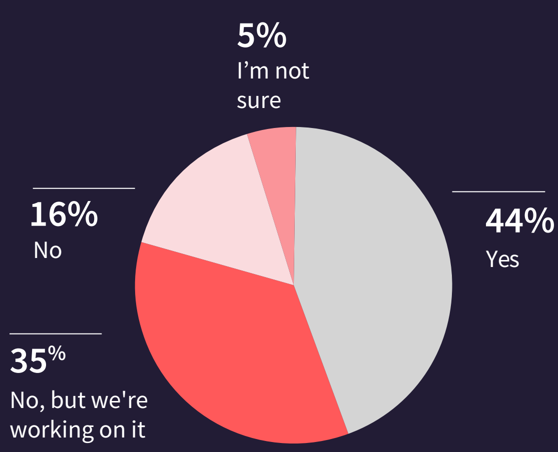
In a 2019 survey of more than 400 data professionals, Dataiku asked: Does your organization have processes in place to ensure data science, machine learning, and AI are leveraged responsibly and ethically?

The overall responses vs. those of respondents in the financial services industry were as follows:

Does Your Organization Have Processes in Place to Ensure Data Science, ML, and AI are Leveraged Responsibly and Ethically?



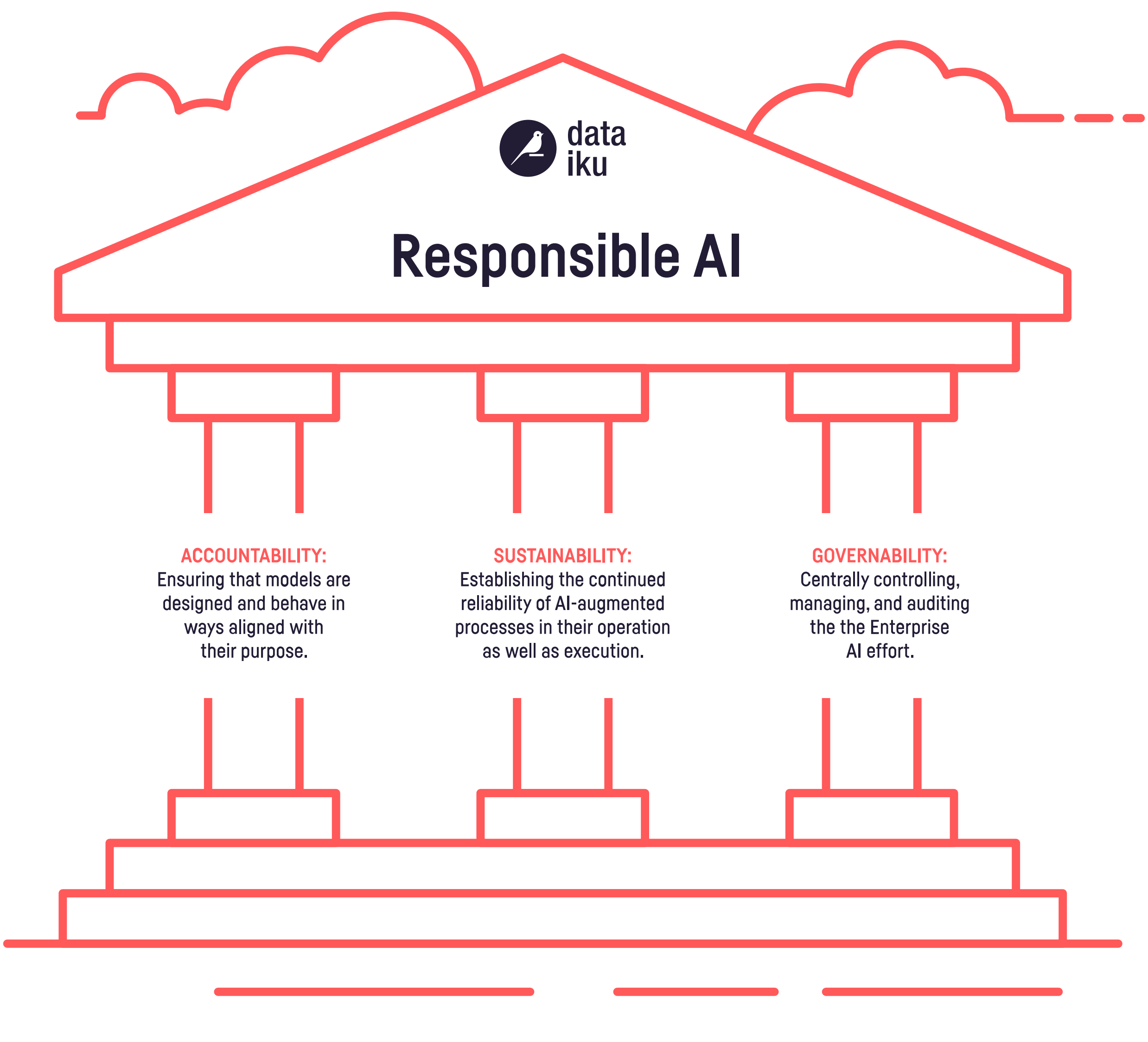
Respondents in the Finance Industry



- **Sustainability:** Establishing the continued reliability of AI-augmented processes in their operation as well as execution. This means that no matter what changes in technology or architecture lie ahead, they don't have adverse effects on existing models in production.
- **Governability:** Centrally controlling, managing, and auditing the Enterprise AI effort. This means expanding the idea of governance beyond the traditional IT sense and instead thinking about it more globally, from access and security all the way up to centralized model management (so-called MLOps).

Given these dimensions (which are each complex in and of themselves), it's clear that having a comprehensive strategy for responsible AI is not easy. So where can organizations begin?

Of course, it's important to empower people, hold them accountable, and develop concrete policies and processes around how responsible AI should be executed. But underpinning all of this is having the right technology, which can enable people and processes while at the same time delivering accountability, sustainability, and governability of data and AI projects. Dataiku, for example, is technology agnostic and built for best-practice methodology and governance throughout a model's entire lifecycle, including concrete features for responsible AI efforts like advanced, granular model explainability.



Challenges & Solutions to Get Started

Despite progress and trends moving the industry in the right direction, there are undoubtedly still challenges that can hinder progress as organizations move forward on the path to Enterprise AI. This section will address just a few and propose solutions:

Finding and hiring data talent: Hiring people with skills in machine learning and AI is extremely difficult across industries due to a shortage of talent and skyrocketing demand. But the insurance industry is better positioned than most to overcome this challenge via upskilling. With tens (possibly hundreds) of statistics-minded actuaries already on staff, providing the right tools to nudge them into the world of AI is a small step. Upskilling business staff is also a great way to fill talent gaps, and in many ways, it's necessary for insurance businesses that want to democratize AI. Ultimately, it's much more difficult to teach a pure AI talent the ins-and-outs of the business than to teach someone who knows the business like the back of their hand some basic skills for using data in their day-to-day work.

Legacy tools: While insurance is undoubtedly more advanced when it comes to technology than some of the financial services players on the banking side (just look at cloud adoption), there is still a lingering issue of legacy tools and systems. It becomes infinitely more difficult to upskill staff per the previous section if data tools are difficult to use, aimed exclusively at the coder population, or even if the user experience is constantly changing with each new technology that gets introduced. AI platforms like Dataiku can help resolve this challenge by being a unified visual abstraction layer for data projects, providing robust features no matter who the audience (coder or non-coder) and a consistent experience no matter what the underlying changes in technology.

Breaking down silos: Today's enterprises tend to be siloed in many ways - from individuals to entire teams and potentially also data, it's difficult to get everything (and everyone) working together across these lines. Again, tools can help when it comes to breaking down the silos of data. But when it comes to people, the answer is collaboration. Insurance organizations should be looking for ways on AI projects that actuaries can work with data scientists and also with excerpts from the business side to come up with the best possible solutions to high-value use cases.

Conclusion

This white paper has covered at a very high level some of the use cases, challenges, and next steps for insurance, but obviously there are many other types of insurance business out there that might have different needs or use cases when it comes to data science, machine learning, and AI.

However, no matter the specific applications, the model for moving into this new era and for success remains the same:

People: It's essential to start educating and upskilling staff on data science and machine learning technologies and initiatives. It's become increasingly clear that the only way to transform a business around data is for the initiative to be democratized; that is, not only supported from the top down, but also the bottom up.

Processes: One of the biggest challenges in democratizing working with data across the business is having the systems and processes to do so. Setting up self-service analytics systems that allow people to access and use data in a controlled way is a good way to get started.

Technology: Of course, mobilizing people and creating processes are difficult to do without the right technology. Data science, machine learning, and AI platforms can facilitate the journey; for example, Dataiku does this at scale by making data accessible to a wider population within the enterprise, facilitating and accelerating the design of machine learning models, and by providing a centralized, controlled, and governable environment.

Your Path to
Enterprise AI

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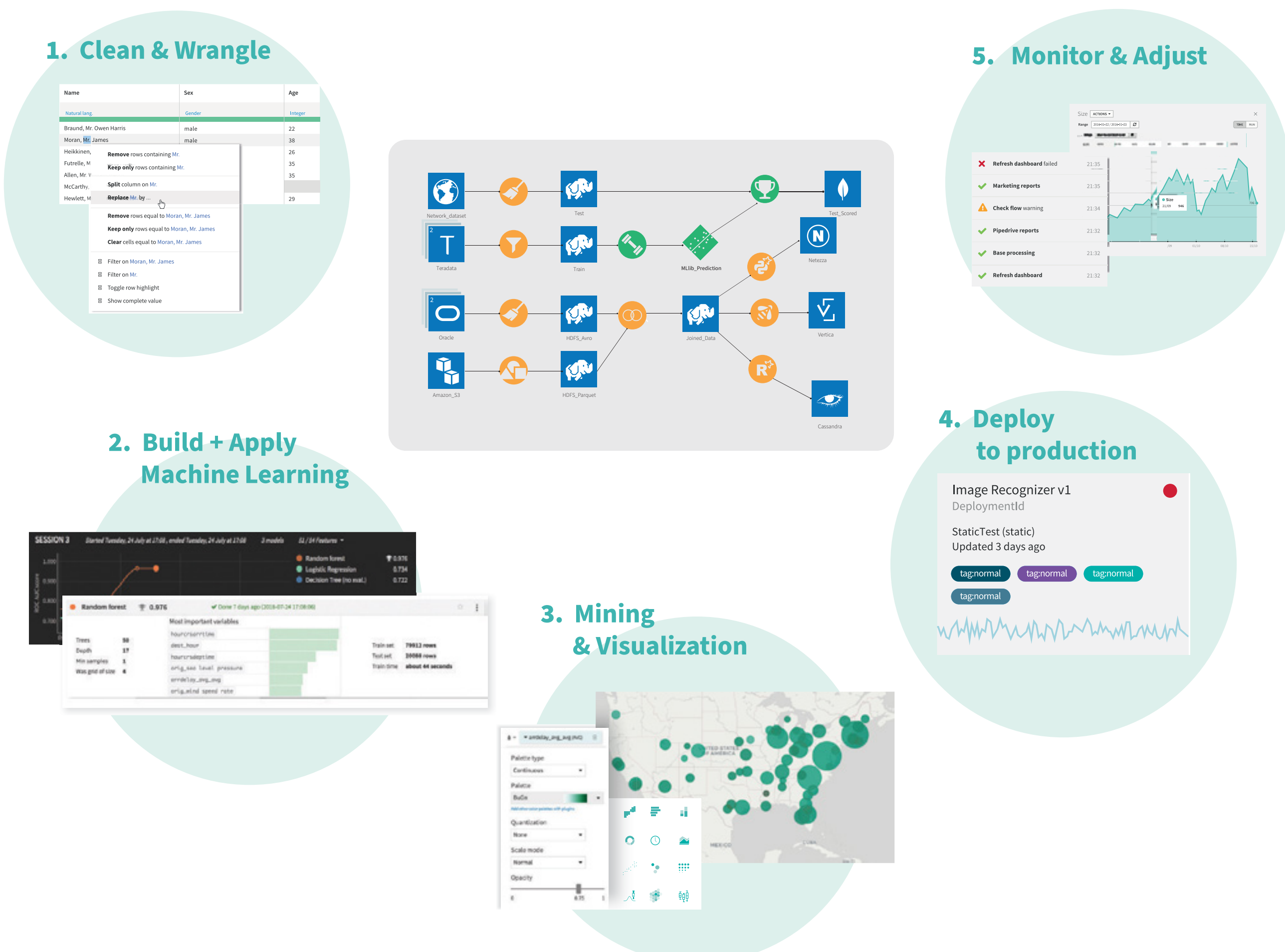

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