MILLIMAN REPORT

The use of artificial intelligence and data analytics in life insurance

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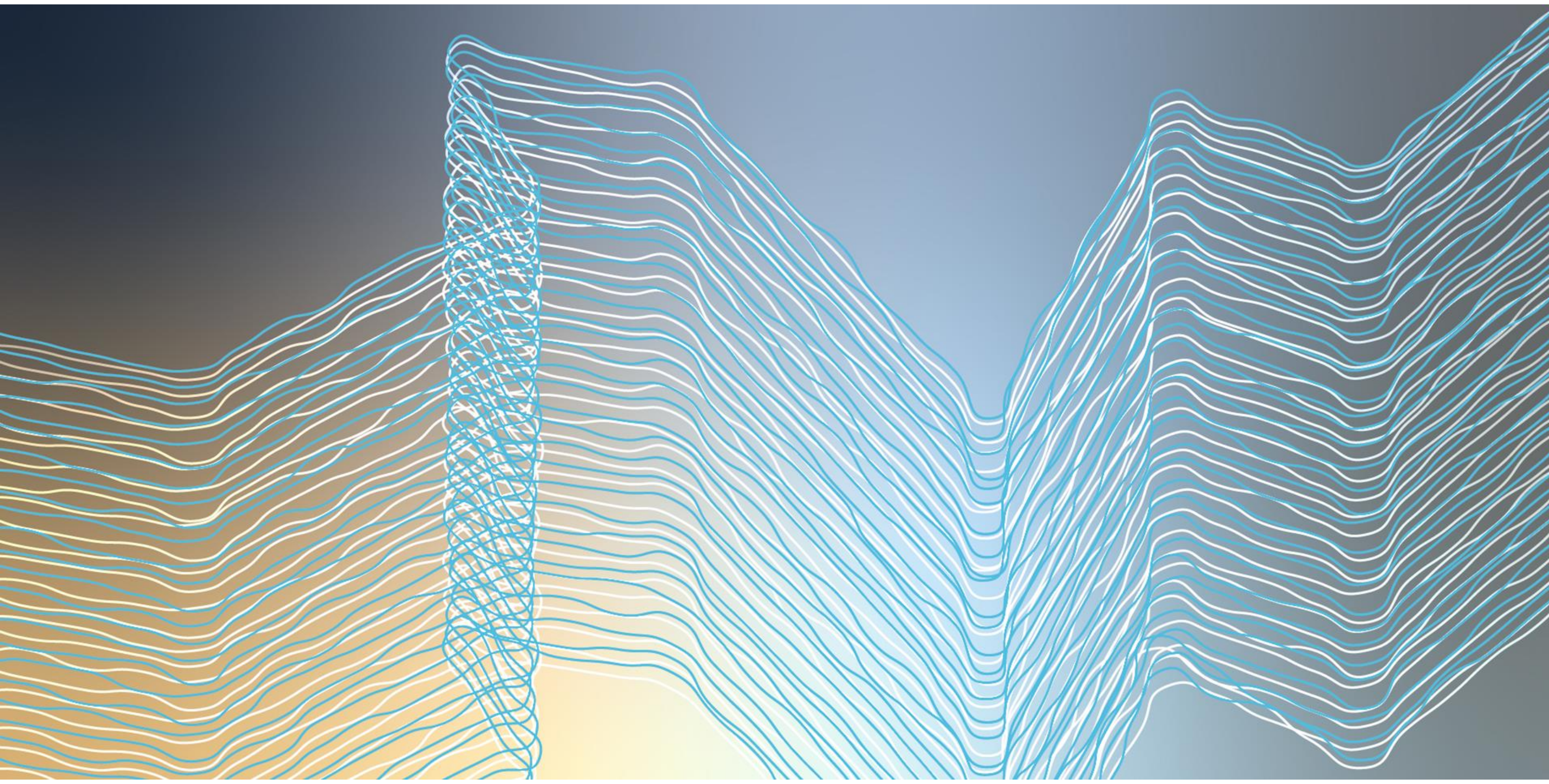

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1. Introduction

The emergence of data analytics and machine learning (ML) methods is providing insurers and reinsurers with new insights into the way they drive and monitor their business. These innovative methods are facilitated by the expansion and availability of new data sources. Examples of applications of artificial intelligence (AI) in non-life insurance are historically numerous (analysis of customer subscriptions and cancellations, modernization of pricing approaches and use of telematics data, automation of reserving approaches, anticipation of the cost of claims, image and text recognition to accelerate some processes, etc.).

Innovative techniques are also now more and more used in the life business. Using technology, AI and data can help life insurers assess risk and adjust coverage and premiums on a recurring basis. Companies can also adjust their offer based on life events. AI and data analytics are now used in various steps of the life insurance value chain: Underwriting simplification, customer targeting, targeted insurance, dynamic insurance considering life changes, risk assessment, prevention, or fraud are non-exhaustive examples of applications which can be seen in the industry.

These approaches are developed not only by traditional insurers or reinsurers but also by insurtechs that have developed innovative solutions in life insurance and are partnering with traditional life insurance players. Milliman is also strongly acting in life insurance analytics as a leader in developing and applying analytics solutions to improve decision making, measure and manage risk, increase predictive accuracy, and automate complex tasks.

After having presented the technical foundations and key principles of data analytics techniques, this research paper outlines use which has been developed by life insurers or reinsurers or by insurtechs partnering with the life insurance industry. It aims to stimulate further thinking on how life insurers could leverage data analytics to support their business ambitions.

In **Section 3** of this research paper, we provide an overview of the technical framework and key considerations to conduct a successful data analytics project in life insurance.

In **Section 4**, we provide concrete examples of use cases developed in the life insurance business. We will notably cover different processes, such as the following:

- Pricing and product development
- Acquisition and underwriting process, including marketing actions
- Life cycle management of the contracts, including claims management
- Investment management
- Financial reporting processes
- Risk management processes
- Management steering

In **Section 5**, we present feedback from life insurance industry data leaders, sharing their experience and convictions on AI and data analytics.

2. Executive summary

Life insurance data analytics and predictive modelling developments combined with significant new data sources offer massive opportunities for life insurance business on the entire value chain. Indeed, as outlined in this research paper, business processes (claims, underwriting and sales) which could be costly and time-consuming for life insurance can be considerably improved. All the possibilities offered by data and analytics will also help life insurers to better understand the customer, improve quality of touch points and provide better experiences and outcomes. Last but not least, life insurance risk management with its specificities (policyholders' behaviour risks, mortality/longevity risks, sensitivity to market risk) also benefit from new data sources and modelling capabilities which are complementing existing actuarial and modelling approaches.

The data to be used in AI models may come from various sources. Traditional models use mostly data points provided by policyholder such as: age, sex, marital status, addictions, health history or medical results. In addition, other data is also collected by the insurer, such as contact details, history of interactions with a client (via email, chat box, telephone or by agent) and information gathered while selling other products. Modern data mining techniques allow to extract value from such variables and to improve models. Thanks to methods such as **natural language processing and deep learning** it is possible to analyse unstructured data such as text, images, audio, or videos and to understand underwriting risks better based on this information.

The ability of machine learning models to automatically interpret patterns in the data and use them to make predictions has unlocked new use cases and opportunities for companies across all sectors. However, building such models is not an easy process. On the technical side, **training machine learning models** requires several pre-processing steps. This includes data cleansing, performing feature selection, extraction and engineering (i.e., finding and potentially building the most relevant features). Those steps are crucial in the training process and usually take most of the time of data scientists.

Another dimension to consider in the life analytics development is **ethics** and regulation, which are becoming increasingly important topics, to a point where big companies now have AI ethics researchers and dedicated governance. The literature about ethics in AI has started to proliferate recently, in conjunction with the rise of AI, so different frameworks and recommendations started to appear. As noted in the paper on the ethical use of AI and analytics,[1] there has been a convergence to several core principles, in particular, transparency, fairness, accountability, explainability, data privacy and security. Around the world, different regulatory frameworks have started to emerge for the use of data and AI.

Interpretability is also a significant area of focus for companies and was an obstacle to implementing machine learning as opposed to more traditional actuarial techniques.[2]

Data and analytics are only enablers which should lead to **business impacts**. The transition from a business need to a production-ready solution can be challenging.

Usually, to deploy a data analytics solution, different steps from data manipulation and modelling to deployment are involved. A good framework for AI and predictive analytics should notably generally address the following aspects: **tracking, automation and DevOps, monitoring and observability, and reliability**. Moreover, having reliable and centralised data is important in order to to fully take advantage of AI and analytics and create business opportunities. The progress in data storage and processing is what has enabled innovation across all industries during the last decades and remains a key lever for understanding customers, anticipating market changes and staying ahead of the competition. It is why data management systems are a key component for enabling transformation.

In this research paper, we present **life insurance data analytics use cases** that have proven their ability to generate **business value** in a broad scope of business applications, some of which have been developed by Milliman teams.

[1] (Milliman, Artificial Intelligence: The ethical use of AI in the life insurance sector, 2020)

[2] (Milliman, Interpretable Machine Learning for Insurance)

Regarding **risk management**, one field of application is the estimation of future mortality rates, which plays a central role for life insurers in pricing their products and managing longevity risk, especially given the evolution of mortality over the last century. The usage of **neural networks** models together with accessibility of public data base have opened new modelling opportunities. The life insurance industry dedicated efforts over the past years to leverage these techniques with direct implications in the improvement of the mortality risk assessment, risk management and pricing.

Another example of concrete application of data analytics in life insurance modelling is cash-flow projections used notably for risk management and regulatory capital or accounting. This can be a very computationally intensive, and data analytics techniques can be used to optimise input compression, thus minimizing the deterioration of the projection quality.

Data analytics and AI are also strong enablers to improve **underwriting process**. Taking out a life insurance policy can be a relatively tedious and lengthy process. Machine learning methods help to improve the speed and accuracy of risk assessment in underwriting. And even when the underwriting process is not fully automated, AI can be used in some parts of the process to facilitate underwriters' work. One of the challenges of insurance underwriting is that the files to be analysed by the underwriter are relatively large and include several kinds of data files (images, emails, call center data, and documents). To speed up this process, it is possible to use artificial intelligence techniques to automatically process the data: NLP and OCR methods for text data, computer vision methods for images.

One of Milliman's insurtech practices, **IntelliScript,** has developed sophisticated data aggregation and interpretation tools and predictive models to help life insurers instantly process vast amounts of electronic records. These data-driven solutions enable underwriters to assess and select risks quickly and accurately. We provide details on the applications of the solution in this research paper.

There are also many examples where AI and data analytics can be used in pricing. We provide in this paper a few examples, as for the calibration of pricing assumptions referring to the estimation of past biometric and behaviour parameters (e.g., mortality, surrenders) and their projection in the future. Machine learning methods can derive these pricing assumptions from the data. The advantage of using machine learning methods compared to more classical statistical approaches lies notably in the possibility of considering complex cross-effects between different variables and defining models on a more significant number of variables.

Data analytics and AI also find much application in **product design**. Products offering usage-based insurance or real-time pricing are entering the insurance market. Similarly, life insurers now may offer insurance products where the premium paid by the insured depends on the lifestyle of their customer.

Moreover, increased digitisation in all industries has created a demand for fast access products with fewer touch points. Historically, life insurance services were the ones with the lowest customer satisfaction rate due to their difficulty of use. So digitisation is essential for increasing customer satisfaction but also for gaining operational efficiency and reducing acquisition and contract management costs. In this context, digitalisation tools, IT systems and artificial intelligence could enhance the following aspects: accelerate sales and contract management processes, reduce or even eliminate the underwriting process, provide instant advice and answers to customer questions, and accelerate claims processing. As an illustration, recent progress in artificial intelligence has made it possible to automate more and more human administrative tasks: document reading and face recognition via computer vision methods (OCR, image segmentation, and classification) or automated assistance via chatbots and NLP methods (e.g., text generation, question answering, semantic search). These technologies can also be coupled or directly integrated into robotic process automation (RPA) tools, thus providing immediate benefits for both the insurer and the insured.

However, the gains through the digitalisation of services must be qualified because the decrease in social interactions, particularly with agents, can decrease customer retention. When implemented, insurers may also take full advantage of these services by collecting user data to predict possible policy cancellations and perform strategic retention campaigns. These retentions campaigns can then be optimised using predictive analytics and machine learning. This paper presents a large number of use cases and applications in **marketing,** with different objectives such as predicting policyholders with a higher risk of redemption considering customer value concepts, development of product recommendation systems fitting customers' needs, building relevant segments and set-up campaigns adapted to each segment, usage of policyholder in force data combined with external datasets to identify clusters of customers that behave similarly in regard to their insurance policies, and robo-advisors aiming at automating the process of guiding potential policyholders, ensuring 24/7 availability.

Another important process along the life insurance value chain is **claims management,** for which a significant portion of the work can be automated to gain operational efficiency—for example, by extracting relevant information from textual data. Life insurance claims often contain unstructured data which needs to be processed using OCR and NLP to gain efficiency. We present in this research paper a Milliman use case in which the objective was to enhance the straight-through processing and the decision-making process of invoices using different analytics techniques.

In addition to claims management automation, AI is widely used for **fraud detection** and **identity verification**. We provide references of interesting articles in this research paper.

Regarding **investments**, financial institutions increasingly use AI and analytics to increase returns, generate alpha and reduce risk. We present in this report examples of key applications.

Finally, the emergence of **data science** tools and **advanced analytics** and the generalization of their application are bringing new perspectives for **controlling and finance** units which relied on information from different legacy systems. Therefore, ensuring the data quality and reconciliation of data in controlling departments would be labor-intensive, resulting in high costs for the company. New techniques can provide quicker, deeper insights at scale.

In the final section of this paper, we summarise three interviews with data leaders in the life insurance and reinsurance industry. We discuss how AI and analytics are used, the main strategic investments and the key challenges.

- We interviewed the Head of Data Science from a large life reinsurer. Reinsurers have the ambition to provide risk assessment services to their clients, powered by their strong risk expertise across all types of life risks. In line with this strategy, the Data Science team from this reinsurance company develops solutions to help clients assess risk and gain efficiency. In the meantime, the team is also developing solutions that enable operational efficiency improvements through AI. Life insurance risks are particularly subject to long time frames, low frequencies and high intensities, making models and studies particularly sensitive to the assumptions and models used. This temporality also poses data availability challenges: working with contracts and data that are more than 30 years old and only available as scans. In this case, the use of NLP and OCR is inevitable. As always, the integration of analytics and data skills poses some challenges (understanding the issues, setting up user-friendly services for business services). To address these issues, the Data Science team is composed of complementary profiles that work together on each project: data value creator, data engineer, and data scientist.
- In the pension market, the same dynamics in the use of AI are in play. One of the largest pension providers in the Netherlands has assigned AI as a strategic priority for the company, according to its director of innovation. With its AI program, the company aims to develop AI as a strategic competence. This program has a company-wide perspective and is not just about technology. For instance, it also aims to increase the AI knowledge of the organization and build a more data-driven culture. A use-case-centered approach has been deployed which covers customer contract, process digitalisation, asset management and new business models.
- We also interviewed the head of research of a major French life Insurer. The company operates in a different area of the world (notably Europe and South America). From the beginning of its data lab development, the company has focused on a practical and pragmatic vision. There was a prioritization of topics to put more emphasis on feasible and cost-effective projects. This focus was made possible by the background and skills of the individuals behind the teams, who had several years of experience in life insurance in addition to their academic skills. Today, the successful implementation of specific use cases has led to the creation of a new subsidiary which operates as a startup specialised in the use of data and advanced analytics for life insurance.

3. Artificial intelligence and analytics

3.1 WHAT ARE AI AND ANALYTICS?

3.1.1 What is AI?

Artificial intelligence has grown considerably in recent years and is now part of the everyday life of many companies, from sales to steering functions.

However, to fully understand this phenomenon, it is first necessary to recall “What is artificial intelligence?" Indeed, many definitions have surfaced since the introduction of this idea in Alan Turing’s fundamental work “Computing Machinery and Intelligence,” published in 1950. In this paper, Turing proposes to focus on the question “Can machines think?” To answer it, he suggests a test, better known as the Turing test, where the goal is to test a machine’s ability to imitate human behaviour.

Although the scientific community questioned the relevance of this test for various reasons, it remains the starting point of the reflection and research around artificial intelligence. Thus in 1995 was published *Artificial Intelligence: A Modern Approach*, which remains one of the reference books in the field and gathers the different definitions of “artificial intelligence” into four groups, based on the notions of rationality, thought, and action:

- The human approach
  - A system that thinks like a human (Haugeland, 1985), (Bellman, 1978)
  - A system that acts like a human (Kurzweil, 1990), (Rich, 1991)
- The rational or ideal approach
  - A system that thinks rationally (Charniak, 1985), (Winston, 1992)
  - A system that acts rationally (Poole, 1998) (Nilsson, 1981)

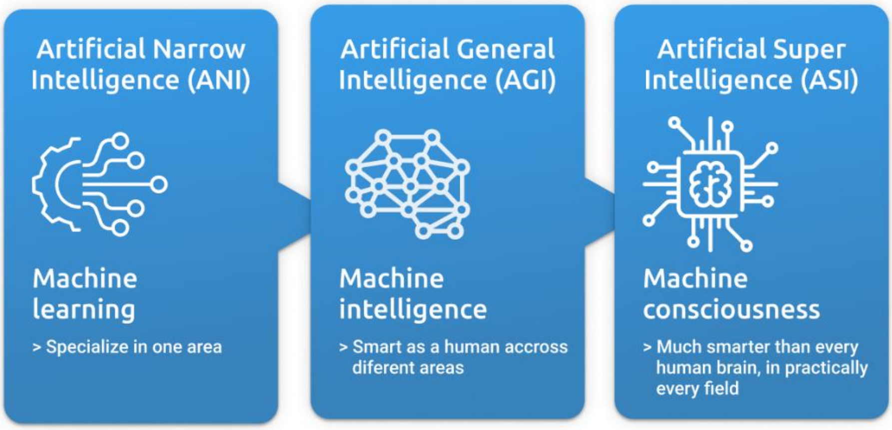
Beyond this grouping, the scientific literature on artificial intelligence also distinguishes two types of artificial intelligence: weak (or narrow) intelligence and strong intelligence.

3.1.2 Strong versus weak AI

Strong intelligence corresponds to artificial general intelligence (AGI) and artificial superIntelligence (ASI). This is a theoretical form in which artificial general intelligence would be comparable to human capabilities, whereas artificial superIntelligence would be an intelligence exceeding human capabilities in almost all areas by a significant order of magnitude.

Weak (or narrow) intelligence (ANI) refers to the most widespread form of artificial intelligence: machines or systems specialised in specific tasks (e.g., voice recognition, image recognition). Tools such as Amazon Alexa, Google or Tesla Autopilot are examples of weak intelligence systems. These weak models may be, by their ability to process more data, better than humans at these specific tasks.

FIGURE 1. ANI, AGI AND ASI.



On the technical side, ANI is mainly based on statistical learning methods such as machine learning and deep learning; these concepts are covered in more detail in section 3.4.2. In this paper, and almost every time nowadays, the concept of artificial intelligence generally refers to the weak (or narrow) version.

Thus, this report focuses on the following applications of artificial intelligence (not exhaustive):

- Machine learning on structured data: Detection of patterns in the data (e.g., classification of policyholders by risk level, scoring of policyholders most likely to terminate their policy)
- Computer vision: See and understand images to extract information (e.g., image classification, face recognition, object detection)
- Natural language processing: Read and understand text data to extract information (e.g., sentiment analysis, named entity recognition, topic classification), but also generate text data (chatbots)
- Speech recognition: Understand speech data and convert it to textual data (text to speech)

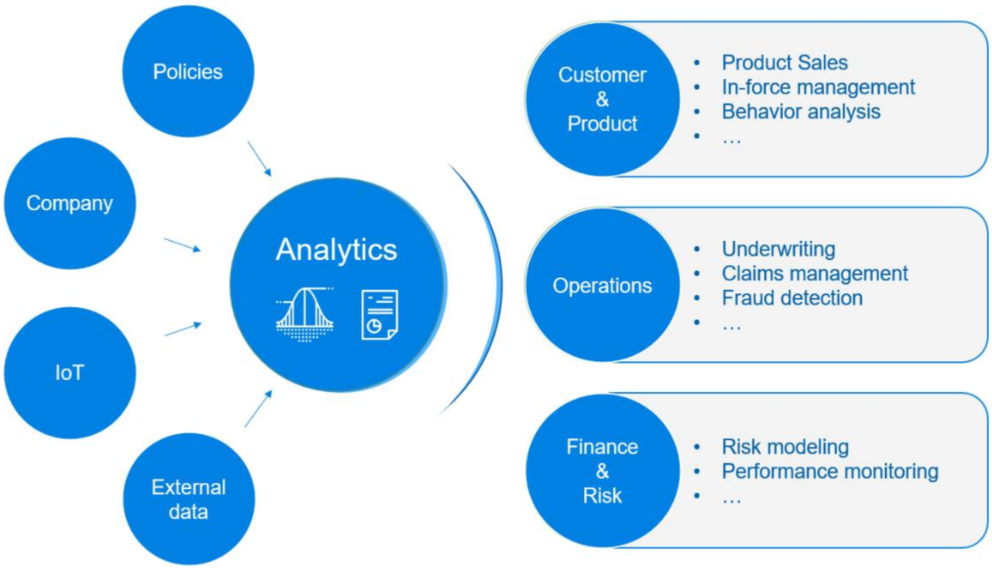
3.2 PREDICTIVE ANALYTICS

Predictive analytics refers to analysing and interpreting data in a given context, using visualization tools, statistical methods and machine learning. Its goal is to provide insights into the collected data to deduce management decisions (e.g., marketing campaigns, portfolio analysis, performance and monitoring indicators, risk management).

In recent years, analytics has become particularly crucial for P&C insurers to remain competitive (e.g., enhance the pricing framework through the use of better modelling habits or even telematics information). Although there are still disparities, life insurers also increasingly use analytics and AI. Indeed, in the context of economic uncertainty and rising costs, life insurers need to define acquisition strategies focused on the most profitable customers. However, identifying and keeping the most profitable customers requires a robust and reliable strategy. Analytics is, therefore, an essential tool to provide insights and to define these marketing strategies effectively.

For life insurers, analytics can help the company with customer management (underwriting, cross-selling, lapse), operational efficiency, product development to manage and optimise the portfolio's profitability. The access to new set of data and development of new modelling techniques is also bringing new opportunities for their risk management and pricing. Section 4 details these different use cases of analytics and AI.

FIGURE 2. ANALYTICS AND AI USAGE.



If analytics has experienced a particular turn in recent years, it is mainly due to the explosion of the amount of data collected by companies and technology which brings new tools to collect, store, analyse and process these data. In all fields, companies have realised the potential of data in the different business functions. They are therefore constantly looking to improve their data acquisition strategies and their internal data management to gain a competitive advantage. Life insurance is progressively undergoing the same transformation, notably due to the increase in connected devices. So the following decades represent a turning point for which life insurers need to be ready.

3.3 DATA

A model without proper input data does not supply any useful insights. What is more, the performance of a model increases along with data quality and its amount. Every day more than 2.5 quintillion bytes of data is created, and that pace is only accelerating along with the growth of Internet of Things (IoT) and usage of 5G. The Google data centre is one of the world's largest buildings, with more than 2 million square feet (about twice the area of Chicago's Millennium Park) of usable space. Vast columns of numbers are describing the world around us, starting with national statistics and worldwide financials through our personal data, pictures of our neighbourhood, our activity on the internet and even our inner world gathered by devices embedded under our skin. Such information will never be enough to perfectly forecast the future, assuming we are not living in a Matrix and there exists such thing as a free will. On the other hand, big data combined with the increased usage of machine learning algorithms allow to model surrounding world much better than in the past and therefore to understand more in detail underwriting risks.

3.3.1 Data sources

The data to be used in AI models may come from various sources. Traditional models use mostly data points provided by policyholders, such as age, sex, marital status, addictions, health and drugs history or medical results. In addition, other data is also collected by the insurer but often not used, such as contact details, history of interactions with a client (via email, chat box, telephone or by agent) and information gathered while selling other products. Modern data mining techniques allow the extraction of value from such variables that could improve models or at least knowledge. Thanks to methods such as natural language processing and deep learning it is possible to analyse unstructured data such as text, images, audio, or videos and to better understand underlying risks, relationships, behaviours, etc. Additionally, machine learning algorithms are not so vulnerable with regard to enormous size of datasets (in terms of number of observations, but also in terms of number of variables or features) compared to standard actuarial techniques such as the generalised linear model.

Especially in case of life insurance, data quality matters a lot, and data never will be perfect. Based on some limited information, we need to take underwriting decisions which will be in force even for the next 30 years. Here is where the external data come in. A first application of external data sources is to validate currently possessed information, starting from basic client information (e.g., accuracy of home address) to crucial information about the clients' health history (e.g., using the Medical Information Bureau in the United States to confirm correctness of supplied answers). The value is added twice: We improve data quality and there is also a possibility to recognise and identify people who are less committed to be honest.

Another application is even more obvious. As we do not want to ask too many questions and we want to speed up underwriting processes or to improve the performance of models, we might want to obtain more information about the client automatically. To do so, we can reach out for external data sources such as:

- Credit scoring of a person
- Value, attributes, and pictures of the clients' home
- Historical addresses
- Vehicle driving history
- Data gathered by IoT devices, like smart watches or medical devices (used in risk prevention models)
- Tracking of activity on the internet
- Social media presence
- Conversion rates based on the information from web aggregators
- Financial data like buyer confidence, inflation rates, house price indices, unemployment rates or asset performance (helpful mostly for retention models)
- Geographical statistics like average time to reach a patient by ambulance, weather conditions, level of pollution, delinquency, education, purchasing power, number of hospitals in the neighbourhood, etc.

Of course, during the next 30 years of a contract, input variables will change over time, and that is true not only for age or vehicle driving history but also for geographical statistics. However, it does not mean we should not use them, but rather we should treat such data carefully and not draw excessive conclusions based on it. What is more, it is necessary to make sure that all interested parties (including customers, regulators, and data owners) do not have any objections for the usage of such data. If you would like to learn more details about potential data sources for the purpose of life insurance modelling, we encourage you to reach out for an upcoming Milliman whitepaper on data sources for life insurance AI modelling.

3.4 MODELS: DESCRIPTION OF THE MODELS AND THEIR APPLICATIONS IN INSURANCE

3.4.1 Learning frameworks

Artificial intelligence and advanced analytics rely on the training and use of statistical and machine learning models. These models are generally classified into three main categories:

- Supervised learning: The model is trained on a labelled data set, meaning that the dataset contains records with input features often denoted as X (e.g, tabular data, image, text) and output data denoted as y (e.g., probability to lapse). The model is then supposed to learn to a function that map X to y: $y = F(X)$. If we take for example, a dataset of emails and labels representing if each email is spam or not, the trained model would then be able to predict (with some accuracy) if an email is spam or not. Supervised learning comprises ensemble learning methods (e.g., random forest, gradient boosting), which prove to be particularly efficient, as they take advantage of multiple predictors for their final predictions.
- Unsupervised learning: In this framework, the model is trained on unlabeled data, meaning that only the input feature is available X and the model is supposed to learn patterns in the data (e.g., clustering, PCA, autoencoders). For example, this kind of learning algorithms could be useful to detect new fraudulent schemes by identifying abnormal patterns in the data.
- Reinforcement and online learning: The two approaches above (supervised and supervised learning), are generally performed in an offline setting: Data is acquired, stored and processed before training the model. Reinforcement and online learning are frameworks where data is acquired during training; the output of the model is influencing the data the model sees during training and vice versa. This framework is notably used for training recommendations and online ad targeting and systems.

These categories help classify models and learning frameworks, but they are not perfectly distinct and some approaches can be at the intersection of different categories: semi-supervised learning, online unsupervised learning, etc.

Machine learning approaches range from simple linear regression to deep neural networks models containing hundreds of layers and multiple gigabytes of parameters. Hopefully, when working with large neural networks, we don't need to train the entire model and fit all the parameters each time we take advantage of deep learning. Indeed, transfer learning allows us to reuse the parameters fitted on similar datasets and simplify the training of machine learning models on non-structured data such as text or images.

3.4.2 Machine learning in insurance

The ability of machine learning models to automatically interpret patterns in the data and use them to make predictions has unlocked new use cases and opportunities for companies across all sectors. However, building good models that perform well is not a straightforward process.

On the technical side, training ML models requires to undergo a number of preprocessing steps. This includes data cleansing (e.g., testing the data quality, removing potential unwanted data), performing feature selection and engineering (i.e., finding and potentially building the most relevant features). Those steps are crucial in the training process and usually take most of the time of data scientists. We often mention that "80% of a data scientist job is about data preparation."

Besides, the feature selection process outlines a weakness of traditional ML models, which deep learning models try to tackle by automatically learning features from the data. However, deep learning models also have their drawbacks, as they have many hyperparameters; fitting and interpreting the model can be more challenging, leading the data scientist to try many different sets of hyperparameters. Section 3.6.2 goes into more detail in how to operate those kinds of tasks in a production-ready environment.

In the end, the choice of the ML model will depend on the use case and the underlying data. At first it may not be obvious what would be the best model for the task, and the process of model engineering might involve an iterative process of training, testing and validating as described in the specific section on ML engineering workflow. Some common ML models are listed in Table 1.

TABLE 1: ALGORITHMS APPLICATIONS. SOURCE: (MILLIMAN, ARTIFICIAL INTELLIGENCE: THE ETHICAL USE OF AI IN THE LIFE INSURANCE SECTOR, 2020)

LEARNING ALGORITHM FAMILY	LEARNING ALGORITHM EXAMPLES	TYPES OF LEARNING	TYPES OF PROBLEM SOLVED	TYPES OF DATA FAMILY	COMMON APPLICATIONS
Regression models	- Linear - Polynomial - Logistic - Piecewise - Splines - Regularised	Supervised	Both regression and classification	Structured	Forecasting, prediction
Decision trees	- Iterative Dichotomiser 3 (ID3) - C4.5 - CART - MARS	Supervised	Both regression and classification	Structured	Prediction, data manipulation, variable selection
Bagging (Ensemble Method)	- Random forest	Supervised (most common) or unsupervised.	Both regression and classification	Structured	Prediction, variable selection
Support vector machine (SVM)	- Radial kernel - Linear kernel - Polynomial kernel	Supervised (unsupervised if dealing with unstructured data)	Both regression and classification	Structured (an extension of SVM can be used for unstructured data)	Prediction, image, text classification
Neural Networks	- Multi-layered perceptron - Recurrent Neural Networks, LSTM and Attention Networks - Convolutional neural networks	Can be supervised (most common), unsupervised or used in reinforcement learning	Both regression and classification	Unstructured and semi-structured	Patter recognition, image identification, system identification, data mining and visualisation machine translation filtering, medical diagnoses, finance
K-nearest neighbour	N/A	Supervised	Both regression and classification	Structured	Forecasting, recommendation engines, fraud detection
Boosting (Ensemble method)	- Adaptive Boosting - GBM - XGBoost - LightGBM - CatBoost	Supervised	Both regression and classification	Structured	Prediction
Naïve Bayes	N/A	Supervised	Classification	Structured	Prediction, classification
Clustering	- Naïve K-means clustering - K-means ++ - Jenks natural breaks optimization - Hierarchical (dendograms) - Fuzzy - Density Based	Unsupervised	Clustering	Structured or unstructured	Feature learning, image segmentation, customer segmentation, pattern recognition, recommendation engines

3.4.3 Deep learning techniques used in insurance

3.4.3.1 NLP

Natural language processing (NLP) and natural language generation (NLG) are the tasks of processing, understanding and generating text data through learning algorithms, generally deep learning algorithms. The usage of NLP is now democratised: it is a powerful tool to improve processes and increase operational efficiency in insurance. The interpretation of text data from contracts, underwriting information, emails, clients requests and feedbacks, and internal or external reports allow the automation of a large number of tasks in the insurance processes—for example, in claims management, underwriting or policy management.

NLP and NLG can be subdivided into the following subtasks (not exhaustive):

- Classification: Text classification can be used, for example, to automatically classify emails between regular emails and spam or customer messages, and automatically address them to the appropriate team or for sentiment analysis.
- Named entity recognition (NER): This task consists of automatically extracting specific information from a text, such as dates, places or names. For example, this could be useful to automatically extract relevant information from contracts or medical data submitted by life insurance applicants.
- Question answering/semantic search: This task consists of automatically answering questions on a specific text by quoting the section of the text which is the most relevant regarding the question asked. This can be useful for improving the overall operational efficiency across different business teams.
- Text generation: Text generation can be used by some chatbots and in text summarization tasks.

Nowadays, the most popular models for NLP tasks are based on deep learning models with an attention mechanism.[3] Those models can be used and fine-tuned using tools such as the “transformer” library in Python. Recent activities around NLP are linked to Google (BERT), OpenAI (GPT), Microsoft (MT-NLG), etc.

3.4.3.2 Computer vision

Computer vision is attracting more and more attention among insurers for many reasons, including its successful application in P&C for automating claims management (e.g., tractable insurtech for motor claims). Computer vision more broadly encompasses the tasks of understanding and extracting information from images. This task is generally based on a convolutional neural network (CNN), which automatically extracts features from images and can be used for a wide variety of tasks, such as the following:

- Image classification: Classifying claims images can be used in general insurance to help automated damage analysis.
- Facial recognition: This task is notably used to automatically verify documents (ID, passport) and ensure compliance with KYC (know your customer) while lowering operational cost.
- Image segmentation and object detection: This aims to automatically detect specific elements in an image. It can be useful, for example, in automatically extracting tables from scanned documents and also to interpret medical images and detect potential diseases.
- Optical character recognition: Automatically recognizing text from scanned documents is essential in life insurance, as risks are more long-term than in P&C. Utilizing stored paper documents may require making use of scanned documents.

3.5 INTERPRETABILITY, REGULATION AND ETHICAL USE OF THE MODELS

3.5.1 Regulation and ethical use of the models

3.5.1.1 Why care about ethics?

In the following sections, we dive into the ethics, regulation and interpretability of AI. This topic is becoming increasingly important, to a point where big companies now have AI ethics researchers and dedicated governance. Even though we try to give an overview of this topic, the reader can refer to other papers which deal more extensively of this topic (Artificial Intelligence: The ethical use of AI in the life insurance sector, 2020).

[3] (Vaswani & al., 2017)

During the last decade, preoccupations around AI have accompanied its significant growth. Big tech firms are using it more and more extensively and many scandals came to light:

- One of the most famous was Cambridge Analytica, which showed how Facebook had indirectly influenced American elections through their data and their targeted marketing service.
- Data usage and transparency: Some scandals have raised interest in how data is used once it is online. For example, in the IBM photo-scraping scandal, IBM released a database with 1 million pictures of faces intended to help develop face recognition algorithms.
- Model fairness: Researchers found racial discrimination in Uber and Lyft's pricing algorithms (The Sun, 2018).

As a result, public opinion is increasingly worried about how big companies use their data and AI models. Gaining public trust in the context of AI is even more critical for the insurance sector due to its policyholders' natural defiance and long-standing public trust issue. While AI could help expand the life insurance industry into cultural markets, technology is also a double-edged sword: AI underwriting systems could exacerbate adverse societal outcomes, even when insurers intend to achieve financial inclusion. In 2018, 32% of policyholders said they would trust insurance companies with their data (much below banks [57%] and healthcare providers [64%]) (Open Data Institute, 2018).

Following the Cambridge Analytica scandal, around 26% (The Atlantic, 2018) of people changed their behaviour on other social media platforms. Following these scandals, customers care increasingly about ethics and consider it when making their usage and buying choices.

Ethics could also be an opportunity for companies to distinguish themselves and improve their brand. Therefore, ethics could help a company gain a competitive advantage. Platforms such as Ethical Consumer[4] or The Good Shopping Guide[5] already have rankings for ethical insurers according to their tax and investment strategy. If the concerns around ethics continue to grow and the public becomes more educated about the use of AI in insurance, they may choose life insurance from companies that show an ethical use of AI.

Finally, it is crucial to frame the growth of AI so that customers are inclined to share data and insurers can improve their services. In the end, the use of AI could be beneficial for both the insurer and the customers: e.g., improving risk segmentation, detection of frauds and building more personalised products.

3.5.1.2 What ethical framework?

The literature about ethics in AI has started to proliferate recently, in conjunction with the rise of AI and XAI (explainable AI). Different frameworks and recommendations started to appear. As noted in some papers on the ethical use of AI and analytics,[6] there has been a convergence to several core principles. In particular, there is a focus on the following core principles: transparency, fairness, accountability, explainability, data privacy and security (data and prevention of harm and misuse).

3.5.1.3 What guidelines are given by the regulation?

Data regulation

Around the world, different regulatory frameworks have started to emerge for the use of data and AI. In Europe, the primary regulation applied is currently the **General Data Protection Regulation (GDPR)**. This regulatory framework is based on the following principles:

- Lawfulness, fairness and transparency in the processing of the data subject
- Purpose limitation of the data subject when data is collected
- Data minimization: We should collect only as much data as needed
- Accuracy of the personal data, which should be kept up to date
- Storage limitation: Personal data should only be stored for as long as needed for the specified purpose
- Integrity and confidentiality should be ensured when processing and storing data (e.g., with encryption)
- Accountability: The data controller is responsible for being able to demonstrate GDPR compliance with all of these principles

[4] Ethical Consumer: the alternative consumer organisation (https://www.ethicalconsumer.org/)

[5] Ethical Shopping - The Good Shopping Guide (https://thegoodshoppingguide.com/)

[6] (Milliman, Artificial Intelligence: The ethical use of AI in the life insurance sector, 2020).

Generally, the different regulatory frameworks that govern data manipulation worldwide (e.g., CCPA, Digital Charter Implementation Act) emphasize at least the following principles: transparency, accountability, integrity and confidentiality.

3.5.1.4 AI regulation

We see that regulation about the use and management of AI systems is progressively being structured. The European Parliament proposed in April 2021 the first draft[7] for harmonised rules on AI, and the EIOPA published a report in late June[8] on the artificial intelligence governance principles.

Although those documents are not in-force regulations yet, they indicate what could come next and give insights into how companies can deal with AI-related issues. The European Union (EU) proposed draft is supposed to complement the GDPR, so companies subject to GDPR would also have to comply with the regulation rules on AI. One of the critical components is the introduction of a framework based on the risk the AI system poses:

TABLE 2. EXAMPLES OF LIMITED, HIGH AND UNACCEPTABLE-RISKS AI SYSTEMS.

Limited and minimal risk	High-risk	Unacceptable-risk
Systems that don't fall in high or unacceptable risk categories Examples: Assistance chatbots, spam filters, customer and market segmentation systems	Biometric identification and categorization of a natural person Management of critical infrastructure (e.g., gas, water) Access to specific services: credit scoring (private service) and public services	Systems that are in opposition with the EU values (e.g., violating fundamental rights) Subliminal, manipulative causing harm Biometric identification in public spaces All form of social scoring

Depending on the level of risk, companies would be subject to different requirements. Systems in the unacceptable level of risk would no longer be permitted in the EU. Systems falling in the high-risk level would have to provide elements showing transparency, security, data quality and monitoring, and human oversight.

The human oversight should notably include assessment regarding the data (e.g., biases), and how system outputs are designed and monitored. It should also ensure that systems are explainable and interpretable.

The EIOPA paper on the governance of AI systems, which is summarised in some papers,[9] emphasizes principles that are similar to the draft AI regulation:

- Proportionality: Similarly to the risk-based approach of the European Parliament draft proposition, the EIOPA emphasizes a proportionality principle, meaning that measures should be proportional to the risk of the AI system. However, the EIOPA doesn't specify the risk framework that insurers should use, taking into account that currently, all AI use cases in insurance should fall into the "limited or minimal risk."
- Fairness and non-discrimination: Insurance should adhere to these principles, notably by keeping records and monitoring the outputs of models to ensure fairness and non-discrimination, mitigating biases, and working on the interpretability of the models. This may be challenging to address, as sensitive variables may not be stored, and thus it may be difficult to detect bias.
- Transparency and explainability: Insurers should deploy explainability solutions with AI models, and explanations should be meaningful for the different stakeholders. Moreover, the user should be aware of the data used by the AI system, and the insurer should communicate it transparently.

[7] (European Parliament, April 2021)

[8] (EIOPA, Artificial intelligence governance principles: towards ethical and trustworthy artificial intelligence in the european insurance sector, June 2021)

[9] (Artificial Intelligence governance principles. A summary of the report by EIOPA's Consultative Expert Group, 2021)

- Human oversight: Roles and organizational structure of the people involved in AI systems should be clearly documented in the governance system. Employees involved in AI should be provided with training adequate to their implications.
- Data governance and record-keeping: The principles defined in the GDPR should be the basis for data related to AI systems. Insurers should ensure that the data is accurate, complete and appropriate (including for external data).
- Robustness and performance: AI systems (whether internal or from third parties) should be robust, especially considering their criticality and potential to cause harm. The calibration, validation and reproducibility of AI systems must be done in a sound manner to ensure that the AI systems' outcomes are stable.

We also note that according to the EIOPA paper, "Insurance-related activities are currently not included among the high-risk AI applications that will need to comply with the requirements of the legislative proposal, which now needs to be deliberated by the European Parliament and the Council."

Most of the key points expected from regulators rely on setting up reliable and sound practices and defining roles. However, the interpretability and explainability of the models are key points that raise technical challenges. We discuss these issues and the potential solutions in more detail in the following section.

3.5.2 A key but challenging consideration: Interpretability and explainability of the models

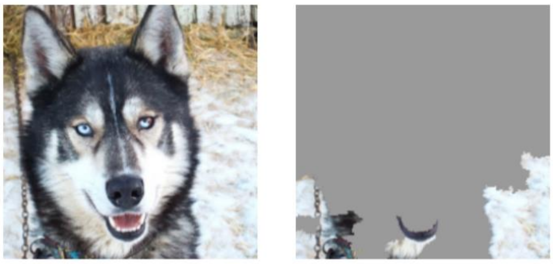
Interpretability and explainability of the models can be considered to be technical issues, as they are still active research fields. They are also often closely related, and the distinctions between the two are thin:

- Interpretability is the capacity to understand how a change in the inputs induces a change in the results.
- Explainability is the task of describing the decision mechanism behind an AI model in human terms.

Understanding how the AI models make predictions is helpful to provide explanations to the stakeholders (e.g., an underwriter). It can help to understand if the output is accurate or if the model might have learned spurious correlations between the inputs. The latter was put in evidence in (Ribeiro, Singh, & Guestrin, 2016) in the case of a computer vision model where the authors trained a model to distinguish between huskies and wolves on an intentionally biased dataset. All the wolves' pictures contained snow, while pictures of huskies did not. Consequently, the model predicted if the picture was of a wolf or a husky based only on the presence or absence of snow.

FIGURE 3 - PREDICTION VS. EXPLANATION.

The prediction is only based on the snow and not the Husky aspect or pose. Source: LIME ("Why Should I Trust You?": Explaining the Predictions of Any Classifier, 2016)



(a) Husky classified as wolf (b) Explanation

It is critical that companies debug and improve their AI models and better assess the potential risks of spurious correlation and predictions. Explainability is also helpful for deriving decision rules. For example, if an output explanation doesn't seem intuitive, it may draw attention to the need for additional manual review.

3.5.2.1 Interpretability methods – Technical overview

On the technical side, the scientific literature generally differentiates interpretability approaches that aim to interpret one specific prediction (**local methods**) and approaches that aim to explain how predictions are made globally on the dataset (**global methods**). Some approaches are only made for some **specific models**, whereas others are **model-agnostic**. Depending on the use case and the goal behind interpretability, the approach may vary. Below is a brief overview of some of the classical methods.

The interested reader could also refer to (Molnar) and (Interpretable Machine Learning for Insurance), which describe interpretability methods in detail from a general and actuarial perspective. We list below some traditional interpretability methods:

3.5.2.2 Global model-agnostic

- Partial dependence plot (PDP): The PDP shows how the prediction varies according to one coordinate by calculating the expected value of the marginal distribution of each variable. It can show, for example, if the relationship between the output and the feature is linear, monotonic or more complex.
- Marginal plots (M-Plot) and accumulated local effects (ALE): As PDP is based on marginal distributions, it is not well suited to interpret the model accurately when we have strong correlations between features. The M-Plots and ALE aim to remedy this problem using conditional and partial derivatives distributions, respectively.
- Global surrogate: A global surrogate model is an interpretable model trained to approximate a black-box model's predictions. This approach, however, is only relevant if the surrogate model approximates the black-box model well.

3.5.2.3 Local model-agnostic

- Individual conditional expectation (ICE): The ICE is similar to the PDP, except that instead of plotting the average over the whole dataset, it plots a line for each instance of the dataset.
- Local surrogate: Local interpretable model-agnostic explanations (LIME). The idea is to approximate the predictions of the black-box model on a neighbourhood of the point that we want to explain. LIME has become popular, as it is one of the few methods that works for different kinds of data (tabular, text, images).
- SHapley Additive exPlainations (SHAP): SHAP is based on the Shapley value. In cooperative game theory, the Shapley value defines the optimal allocation for the contributions of different players for a coalition game. The idea is to consider our model's feature as the players of a coalition game where the outcome is the model's prediction.

3.5.2.4 Model-specific

- Computer vision (CNN[10]) – Feature visualization: Different interpretability methods have been implemented in computer vision. One of the most commons is a feature visualization technique which relies on optimizing a unit activation in the neural network.

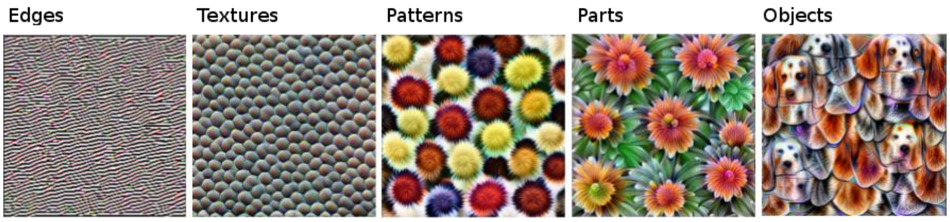


FIGURE 4 - FEATURES LEARNED BY A CNN (INCEPTION V1) TRAINED ON THE IMAGENET DATA. *Lower layers seem to learn simple features (left), whereas higher layers learn more abstract features (right). Source: Olah, et al. 2017 (CC-BY 4.0)*

- Neural network – Disentanglement: Another recent approach for neural network interpretability is to embed some interpretability features directly in the model through what is called model disentanglement. To understand disentanglement, we must first recall that neural networks automatically extract features and learn representations of complex input data. However, this learning task is known to produce representations where the axes of the embedded space are not disentangled, making it more challenging to interpret the representation learned by the neural network. So recently the scientific community has been focused on building neural networks that learn disentangled embedded space, making it easier to interpret the model.

[10] Convolutional Neural Networks

3.6 TO GENERATE BUSINESS IMPACTS, HOW TO MOVE FROM PROOF OF CONCEPT TO PRODUCTION AND INDUSTRIALISATION

3.6.1 Enabling innovation and business impact through analytics and AI

Data and analytics are only enablers which should lead to business impacts. The transition from a business need to a production-ready solution can be challenging, especially in structures that have been in place for several decades. This is why, according to Gartner Research, only 15% of use cases by 2022 exploiting AI techniques such as machine learning, deep neural networks, and the Internet of Things will be successful. Indeed, we can mention several key success factors for these projects which could be challenging to achieve.

- Strong and continuous interactions between the business and the tech team in charge of developing the innovative solution. Because the tech team is generally not familiar with the business need and challenges, communication with business experts is crucial. A lack of it can impede the construction of relevant solutions for the business team. Moreover, if the business team's project plan is hindered by data or technical limitations, it is possible that workarounds and alternative solutions can be found. Some companies have dedicated teams to bridge the gap between the two worlds.
- Lack of interpretability of the model can create friction for its use among business teams. As an example, the analytics team might develop a churn model ranking the people with the highest propensity to lapse but may not provide explanations to the predictions. In that case, the sales team might not feel not empowered enough as to how they should reach and interact with the client, leading to a loss of efficiency and opportunity.

Identifying these limitations is not always obvious upstream because they depend on the application and the approach used to operate the digital transformation.

3.6.1.1 Internal versus external analytics solutions

The following approaches (internal versus external) can be complementary for effecting digital transformation. There is no “one size fits all,” as each decision depends on the business context.

- External solution: The company can choose to drive innovation through the integration of solutions (as SAAS or PAAS) built by external providers (e.g., software editor, insurtech). For example, AKUR8, an insurtech specialising in pricing (health and P&C), provides state-of-the-art pricing and interpretability software as a service. Milliman also provides external solutions many insurers use, such as those developed and offered by IntelliScript, which enhances underwriting speed and accuracy. More detail is provided in the next section.
- Proprietary solution: Some insurers also invest in homemade solutions developed by internal teams dedicated to innovation, sometimes referred to as data lab or innovation lab. These teams are generally made up of a mix of technical profiles (e.g., data scientist, developer, data engineer) and profiles that bridge the gap with business teams. The construction of such teams, comprised of employees from across the company, allows for the development of customised proprietary solutions and the application of AI and analytics to sensitive subjects (e.g., pricing, strategic management).

The choice between an internal or external solution depends on the use case considered, the company’s objectives, and the level of internal maturity in using AI and analytics. Regarding the development of internal solutions, it is not only about developing and industrialising the internal solution but also about having the capacity to operate the solution moving forward and to carry out the maintenance over time. In the following section, we focus on the different building blocks for implementing internal solutions (skills, workflow, tools).

3.6.2 How to put use cases in production

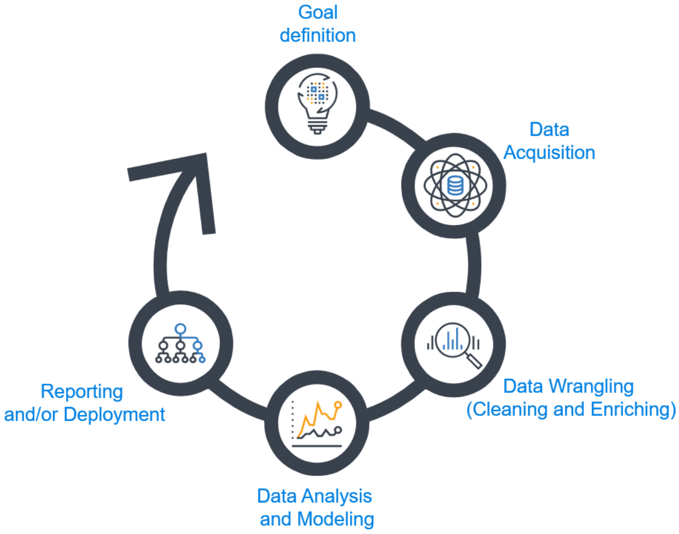
3.6.2.1 Workflow

Currently, there are no standard methods for managing ML or AI-based projects as seen in IT development (SCRUM, Kanban), even if adaptations of these methods exist. However, predictive analytics and AI projects generally seem to follow the workflow described below:

- Goal definition: This first step consists of identifying and framing the problem with the technical and business teams to ensure the project’s feasibility. Since the people in charge of developing AI and analytics systems do not necessarily have business expertise, this step is essential. It ensures that the various parties involved have the same understanding of the need.

- Data acquisition: This step is significant because the bigger the data, the greater the chance to extract insights and value. This data can be acquired in different ways: internal data, open data, API.
- Data cleaning and enriching: This is an essential step that can typically take up to 80% of the data scientist's time. In this step, the data scientist tries to understand the data and perform extensive checks for the dataset's quality.
- Data analysis and modelling: The analysis and visualization stage is particularly decisive, as it is the last step before deployment. The goal is to identify the relationships between the variables and choose the most relevant model and visualizations.
- Reporting and or deployment: This step involves using the right framework (e.g., API, dashboard, web app) so that the business teams can fully take advantage of the solution.
- Iteration: Once the solution is deployed, it is necessary to iterate on the previous steps because problems are rarely static: Data can change (in fraud cases, fraudsters usually end up adapting to detection techniques to go under the radar), and needs can also evolve. According to O'Reilly,[11] one of the primary mistakes people make with machine learning is to believe that once the model is built and available in production, it will continue to work indefinitely. Instead, models degrade over time if they are not continually updated and improved with new data.

FIGURE 5. ANALYTICS AND AI PROJECT WORKFLOW



3.6.2.2 ML frameworks

The workflow described in the previous section involves different steps from data manipulation and modelling to deployment. If these processes are carried out manually without tracking, they can jeopardise the reproducibility of the results. However, this reproducibility is essential in an iterative process such as this one, especially when the end goal is to deploy in production. The different steps of the process must be easy to reproduce and automated (if necessary) to gain efficiency and time during the different iterations and to ensure the traceability of the treatments. It is essential because traceability is becoming more and more critical in the context of AI regulation (see section 3.5).

A good framework for AI and predictive analytics should generally address the following aspects: tracking, automation and DevOps, monitoring and observability, and reliability.

[11] Lessons learned turning machine learning models into real products and services – O'Reilly (2018)

3.6.2.3 Tracking

Tracking or versioning creates a mechanism for model and data governance. When a model is not performing as expected, teams must quickly determine how and when the given model was created. Model versioning provides structure to the model creation process and makes it easy to rework old models. As described in the previous section, ML model development is experimental and iterative in nature, and reproducibility can be a major asset.

Furthermore, many models are trained on sensitive data, which are destroyed after some time. Should the data be deleted, it may still be necessary to have access to the model and version history. In addition, regulations increasingly require traceability and transparency in models (see section 3.5.2 for more details on these regulatory aspects). In particular, the European GDPR law requires a “right to explanation” for automated decisions, so tracking the model history and knowing exactly which model is in production is crucial.

It is necessary to use a model registry and a features store system to ensure a good model versioning process. Platforms such as ML Flow, Neptune.ai, Domino Data Lab or Dataiku provide these kinds of services.

3.6.2.4 Automation and DevOps

Automation is vital because the ML and analytics process is iterative. Any manual mistake can introduce errors in the final result, and these errors are often not easy to detect. Automation helps to prevent this, as well as to save time and money and to speed up the innovation process. Moreover, it helps engineers spend less time on manual tasks (deployment, data cleaning, and preparation) and more on challenging problems with strong stakes.

In traditional software development, automation is performed through what is called CI/CD (continuous integration and continuous delivery). It is a process and a workflow in which every iteration of the code (i.e., commit) goes through a pipeline (or DAG).[12] In software development this framework typically defines three stages: build, test (including unit tests) and deploy.

In the case of ML and analytics, this framework can be used to:

- Automatically train the model on new data. The training of the model could be seen as a build step. Then, following the training, we expect the pipeline to automatically perform tests on the model and display the results in automatically generated reports. Tools like Airflow, Luigi or MLFlow can help to automate the ML pipelines.
- Automate the reporting: Analytics and ML generally involve visualizing the data and some specific results through charts and tables. The production of such reports can be automated (e.g., Jupyter notebooks)
- Package models and efficiently distribute them: Depending on the use case, there are different ways to distribute the trained model:
  - Embedded model: This is a case where the application is packaged with the application consuming it.
  - Model deployed as a service: The model is constantly available as a service that can be used for training or inference. As long as the input format to the model stays the same, the model can be updated without redeploying it.
  - Models published as data: In this approach, the model is an *artifact* of the build stage. It can then be deployed in production through classical deployment approaches (e.g., canary deployment).

Of course, manual validation steps should be included independently of the deployment strategy before putting models into production. This can easily be achieved with solutions such as Jenkins; it is possible to automatically receive model evaluation reports and have an approval prompt through mails. Once approved, the model can then be deployed in production (or lower levels: e.g., A/B testing, staging).

[12] Directed Acyclic Graph

3.6.2.5 Monitoring and observability

In software development, monitoring is now part of a whole new field called "observability engineering." This ranges from monitoring to managing and improving business-critical systems. We will not provide further details here, but we list some fundamental aspects to monitor when deploying ML solutions:

- Monitor availability and reliability: If the ML application is available through some type of real-time service, it is essential to test the availability of the ML service with periodic requests and measure latency and uptime. Latency can be the first indicator to give an alert if the service encounters high traffic. If the service fails to respond, it is essential to log when it fails in order to identify the potential reason and automatically alert.
- Monitor the model and the data: Since ML application depends on data, it is crucial to have a way to log the data, and to help understand system failures and potential drifts in performance. So good monitoring should include a way to log the model ID (linking to a version of the model registry), request and prediction; this should be logged into a database, preferably.
- Monitor potential drifts: ML models are trained and evaluated on specific datasets. As long as these datasets reflect the real data, the model should perform as expected. However, as soon as the data changes for external reasons, the model performance could deteriorate, so potential drifts could occur and should be monitored.

  The monitoring for drifts can either be achieved directly through the input data or the predictions. In the first case, automated reports with descriptive statistics can help detect potential drifts. In the latter case, predictions need to be labelled to assess the model performance; this can be facilitated with third-party labelling services such as Amazon Sagemaker Ground Truth and Labelbox.

3.6.2.6 Data management systems

Having reliable and centralised data is important in order to fully take advantage of AI and analytics and create business opportunities. The progress in data storage and processing is actually what has enabled innovation across all industries during the last decades, and it remains a key lever to understanding clients, anticipating market changes and staying ahead of the competition. It is why data management systems are a key component for enabling transformation.

Traditionally, data management systems (DBMS) mainly consisted of relational database management systems, which organise data in tables composed of rows and columns containing database records. Relational databases were often built around the SQL programming language and a rigid data model best suited to structured transaction data. As a consequence, other types of DBMS emerged later, categorised as **NoSQL** databases, which don't impose rigid requirements on data models and database schemas.

NoSQL databases are often used in **big data management** because they allow storing and managing various types of data structure. **Big data** environments are also generally built on open-source technology such as **Hadoop,** which allows for the distributed processing of large data sets across clusters of computers, generally used in combination with **Spark** for processing batches of data and **Kafka, Flink** and **Storm** for streams of data.

Three alternative repositories for managing analytics data are data warehouses, data lakes and data lakehouses. **Data warehousing** is the more traditional approach: A data warehouse is typically based on a relational database, and it stores structured data from different operational systems ready for analysis. The primary use cases of data warehouses are business intelligence and traditional analytics. **Data lakes**, on the other hand, store pools of big data containing unstructured data, and are more fitted to predictive modelling, machine learning and other advanced analytics applications. However, data lakes are subject to some technical limitations (lack of ACID transactions and data quality enforcement). Due to those limitations, **Data lakehouses** started to emerge in recent years; they are intended to incorporate the best of both worlds (data warehouse and data lake) in a unique ecosystem.

4. Data analytics and AI application in life insurance

In this section, we present life insurance data analytics use cases that have proven their ability to generate business value in a broad scope of business applications, some of which were developed by Milliman teams.

4.1 RISK MANAGEMENT AND ACTUARIAL MODELLING

4.1.1 Use case 1: Mortality modelling

The estimation of future mortality rates plays a central role for life insurers in pricing their products and managing longevity risk, especially given the evolution of mortality over the last century. The usage of **neural networks** models together with accessibility of public data base have opened new modelling opportunities. The life insurance industry has made dedicated efforts in recent years to leverage these techniques, with direct implications in the improvement of mortality risk assessment, risk management and pricing. We illustrate in this section advanced applications developed over the past years on **usage of analytics** and **multiple data sources** to improve the mortality/longevity risk modelling.

It is well known that mortality has decreased at all ages, leading to a rapid increase in life expectancy. Consequently, mortality prediction models have taken a relatively important place in the scientific actuarial literature. Numerous models have been proposed since Gompertz published his law of mortality in 1825. Among the most popular is the Lee-Carter model (1992), which remains one of the most widely used in the world today, notably for its robustness. The model initially proposed explains the evolution of mortality over time by two parameters: an age-related static life-table component and a time-related index component. The prospective calculation of mortality is then done by projecting the temporal component following a random walk.

4.1.1.1 Mortality data

The models used to derive mortality forecasting are based on mortality tables, some of the most famous being those from the Human Mortality Database (HMD). Mortality tables are essential inputs for forecasting future mortality scenarios, and so ensuring their reliability is crucial.

In the past, mortality data have been known to include so-called “cohort’s effects.” Renshaw & Haberman (2006) notably added a cohort effect to the LC model to capture different mortality of different cohorts of lives. However, it has been shown in more recent work that these cohort effects are actually errors caused by a sudden change in fertility patterns.[13,14] Boumezoued[15] notably underlined the universal nature of these false cohort effects, which were present in most period tables in Version 5 of the HMD. These effects were then corrected in Version 6 of the HMD using monthly fertility data. However, in the case of the absence of fertility data, the bias remains in the HMD. Further mathematical developments were then proposed by Boumezoued et al. (2018, 2019), who provided improved estimators and a related theory for death-rate inference.

In one of the latest works from Boumezoued & Elfassihi (2020), the authors have taken advantage of neural networks to correct the cohort effect in the absence of monthly fertility data.

Use case: Mortality data correction in the absence of monthly fertility records (Boumezoued & Elfassihi, 2020)

In the latest version of the HMD Methods Protocol (Wilmoth et al., 2019), collected birth-by-month data are now used to more accurately estimate population exposures. However, these methods do not apply to countries for which birth-by-month data are not available. Until now, most studies dedicated to stochastic mortality modelling, including a cohort component, reproduced what is known now to be data anomalies and false cohort effects.

The purpose of the Milliman work was to produce corrected mortality tables for countries for which fertility data is not available.

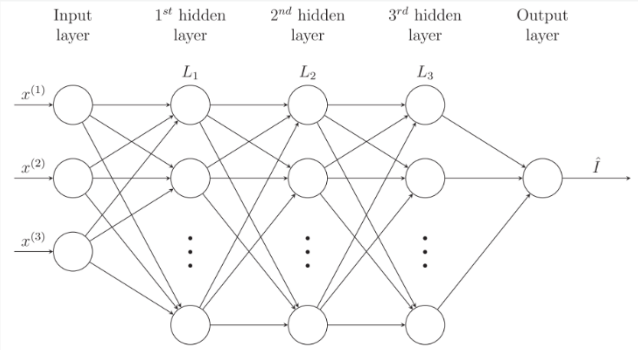
[13] The cohort effects that never were (Milliman, 2020)

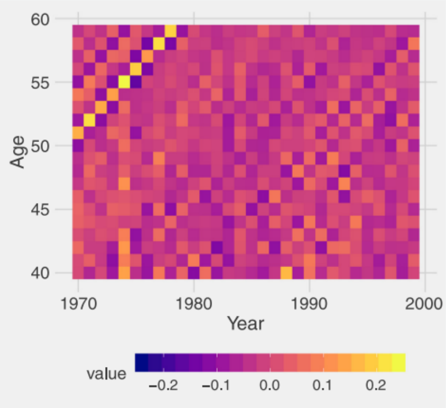
[14] Reliability issues in the construction of national mortality tables (MIlliman, 2017)

[15] (Improving HMD mortality estimates with HFD fertility data. North American Actuarial Journal., 2016)

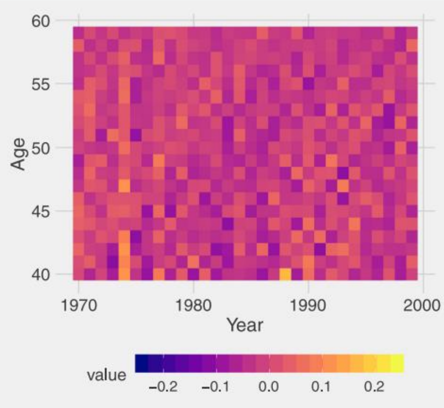
Different models were tested, including a linear model and a feed-forward neural network with ReLu activation function for the three hidden layers and dropout layers to avoid overfitting and get better generalization of the neural network.

The baseline linear regression showed good results in average prediction MSE error, and the neural network approach improved the results, which includes age as an additional covariate.





Mortality improvement rates – West Germany raw data



Mortality improvement rates – West Germany corrected data by the neural network method

Beyond global mortality forecasting at a country level, a process of refining the mortality data to a more granular level has been initiated. The Society of Actuaries (SOA) supported the HMD to expand the database by including cause of death information for a set of countries. This refining of the mortality data would allow actuaries to have finer modelling and forecasting of the mortality; these perspectives were studied by a Milliman research team.[16]

4.1.1.2 Mortality forecasting

Recent approaches on mortality modelling notably tried to enhance the classical Lee-Carter model. Bouhns et al. (2002) embedded the Lee-Carter model into a Poisson regression framework using GLM. Renshaw & Haberman (2006) utilised alternatives methodologies to fit their extensions of the LC model. Currie (2017) shows how generalised linear and nonlinear models can be used to fit both the LC model and other popular mortality models. Shang (2019) extends the classical LC model based on a static PCA to a dynamic PCA regression to model temporal dependence.

More recent approaches suggested the use of **neural networks** to **forecast mortality and extend the Lee-Carter model**. Richman & Wüthrich (2019) proposed a multiple population version of the Lee-Carter model based on a neural network; the study showed that the **deep neural network** implemented successfully learns the relationships between the input and mortality rate and projects mortality for all countries in the HMD with a high degree of accuracy.

[16] (Boumezoued, Klein, Louvet, & Titon, 2021)

4.1.2 Lapse and policy behaviour actuarial modelling

In the literature, lapse often denotes both termination of policy accompanied by the payout of a surrender value to the policyholder and termination without any payment. Lapses can impact life insurers in many different ways:

- A massive lapse can threaten the liquidity of the insurer and force the selling of assets.
- Lapses often lead to the loss of future profits, especially early lapses for which acquisition costs are not fully amortised.
- Lapses might diminish the effect of risk pooling and deteriorate the profitability of the in force.
- Finally, lapses can hurt the insurer's reputation, leading to even more lapses.

Lapse behaviour is one of the significant risk drivers for life insurers. Lapses' assumptions can impact the company risk assessment, so modelling lapses and policyholder behaviour (fund switching, partial withdrawal) should be done with great attention.

Different approaches have emerged for modelling lapse behaviour. Most of them fall in a framework where lapses are either estimated as a whole or distinguished between structural (or deterministic) lapses (depending on policy characteristics) and dynamic lapses (depending on the economic context). The modelling of structural lapses is usually done by measuring lapses on historical data and assuming that the lapse probabilities would remain constant in the future. In contrast, the modelling of dynamic lapses can be more complex, as it depends on the evolution of dynamic factors such as the economic context (e.g., interest rates, stocks, unemployment rates).

The modelling of dynamic lapses is a vast research topic with different approaches, including microeconomics concepts for modelling the policyholder's utility function and decisions. We cover in the table below some recent approaches that focus on **using machine learning methods** for **modelling lapse behaviour**.

TABLE 3. EXAMPLE TARGET COMPRESSION RATES

Reference	Algorithm
(Modeling surrender risk in life insurance: theoretical and experimental insight, 2021)	GLM, XGBoost, Random Forrest, Neral Network
(A spatial machine learning model for analysingcustomers' lapse behaviour in life insurance., 2020)	GLM (on spatial data)
(Deep Learning Applications: Policyholder Behavior Modeling and Beyond., 2018)	GLM, GBM, Neural Network

Despite the performance of some **machine learning algorithms**, we note that some of these articles conclude that classical methods may be acceptable and that the complexity of models such as **neural networks** may not always be worthwhile. Moreover, depending on the regulator, the modelling choices may be restricted; for example, in France, the dynamic lapses on savings products are expected to fall in a specific ensemble of functions (see national guidelines from the French regulator regarding the implementation of Solvency II).[17] However, machine learning can also be used as a complement to traditional approaches to improving risk management.

[17] Orientations Nationales Complémentaires. ACPR

4.1.3 Use case 2: Clustering policy data

One of the key elements in modelling in life insurance is cash-flow projection used notably for risk management and regulatory capital or accounting. It typically consists of individual policy level calculations to generate accurate liability cash flows and ALM calculations on portfolio level to incorporate the impacts of market movements, strategic asset allocation and management decisions. This can be very computationally intensive, especially in case when an ALM model links dynamically period by period with the liability projections. Therefore, grouping algorithms can be applied to the individual policy data to reduce the number of data lines (model points) that need to be processed. That way, more time can be spent exploring different scenarios or alternative management decision rules, or more focus can simply be placed on analysing and understanding the results. However, a balance needs to be found between the input compression and deterioration of the projection quality. A naïve grouping approach would create bins across input variables and put policies with similar values in the same bin, increasing the count of policies in a given bin. This can be done for most variables with many possible values, such as policyholder age, guaranteed interest rate, policy term, etc.

This simple approach often pays no regard to the model outcomes, however. Policies with seemingly similar inputs in the space of the characteristics will end up in the same bins, but might in fact be generating different cash-flow patterns, which will deteriorate the post-grouping results. Additionally, the grouping criteria have to be prescribed a priori (or as an iterative process) and are usually arbitrary. To solve these problems, we offered our clients a more sophisticated approach using **non-supervised machine learning methods** of **k-means clustering**.

In the clustering approach, the policy data variables are split into clustering and segmentation variables and enriched with selected model results. Segmentation variables are the variables for which different values should not end up in the same cluster, such as different types of products or IFRS17 cohorts, while clustering variables are the dimensions along which similar points will be grouped. Some model results, such as key (discounted) cash flows, mathematical reserves, best estimate liabilities or present value of future profits can be added to the clustering variables. As a result, this approach will create sets of clusters based on combinations of the segmentation variables and identify the best groupings of policy data lines, while optimizing the model results, potentially across several scenarios.

The k-means clustering creates a predefined number of clusters from the input data. This can be subject to an optimisation routine to identify the optimal compression rate (number of clustered data points/number of original data points) and the compression quality, defined as deviation of the clustered model results from the original model results on selected metrics. In practice, it is good to vary the desired compression rate with the size of the original portfolio per segment, targeting higher compression rates for segments with a higher number of input data points.

TABLE 4. EXAMPLE TARGET COMPRESSION RATES

Number of input data lines	Target compression ratio
>= 0	100.00%
>= 100	50.00%
>= 1000	10.00%
>= 5000	3.00%
>= 10000	1.00%
>= 30000	0.75%
>= 50000	0.50%

In a representative example on a portfolio combining some traditional and some universal life products, the total compression rate achieved by an (optimised) k-means clustering was approximately 0.5% (five data lines left for each 1,000 lines in the original input). At the same time, the average error in the discounted cash flows did not exceed 0.1% for the vast majority of the metrics used and did not exceed 0.4% for any of them.

TABLE 5. MODEL QUALITY: CLUSTERED VERSUS REFERENCE

Quality metric	Error in NPV terms	Max yearly error
Total cashflow	0.00%	1.55%
Statutory reserves	0.09%	0.20%
Gross profit	-0.08%	1.19%

Compared to the naïve grouping, clustering policy data resulted in both a significantly better compression rate and a smaller error in the cash-flow patterns, which was consistent across the base and shock scenarios. With virtually no loss in quality, the cash-flow projection model observed almost a hundredfold performance improvement.

4.1.4 Approximation of complex stochastic models

Most traditional life insurance products (e.g., term life) can be calculated using simple, straightforward calculations. However, the calculation may be computationally intensive for some cases, and performance may be a real issue. That is notably the case when:

- Products contain with-profits clauses with guarantees and options (e.g., variable annuities). In that case, the calculation may require running many stochastic scenarios to estimate the expected value of future cash flows.
- Nested simulations are required to calculate certain risk measures required by the regulator (e.g., SCR[18] in the EU).
- Decision makers want to calculate more frequently the solvency ratio and other KPI due to economic changes.

In those cases, the insurer might use proxy modelling techniques to simplify the calculation, and so AI and machine learning can help in this regard. Milliman consultants have a deep knowledge of proxy modelling approaches and have published multiple white papers related to its practical implementation. See for example (Leitschkis, 2012), (Murray & Phelan, 2013), (Cherchali, Chaudhry, Leitschkis, & Vedani, 2021).

Today, many insurers use LSMC to perform proxy modelling. However, the LSMC approach relies on linear models, whereas the underlying structure modelled is non-linear. As a consequence, some insurers have started to explore the use of machine learning approaches. The scientific literature regarding this topic describes ML alternatives (including random forest, neural networks and SVR). [19,20]

However, it is worth noting that the use of machine learning comes with challenges, as AI models create a black-box effect on the proxy model. The interpretability of the model results might be challenging, especially if the model is applied on thousands of different scenarios.

[18] Solvency Capital Requirement

[19] (Kopczyk, 2018)

[20] (Castellani & al., 2018)

4.2 UNDERWRITING

Taking out a life insurance policy can be a relatively tedious and lengthy process. It is, for example, sometimes necessary to perform medical examinations, which the underwriter then analyses. The entire process can take six to eight weeks for a term life insurance policy. This is a clear pain point in life insurance today, any many successful life insurtech companies are trying to tackle this issue.

4.2.1 Algorithmic underwriting

Machine learning and artificial intelligence methods allow for the automatic processing of large amounts of data, thus automating the underwriting process. Some life insurers have implemented machine learning algorithms to automate underwriting and reduce the need for medical information.[21]

Haven Life Insurance (a MassMutual subsidiary) applies machine learning to MassMutual's internal data and third-party data such as medical prescription histories, driving records and credit histories (see section 4.5.1). This allows the company to increase the accuracy of pricing models and to offer algorithmic underwriting services in real time (through their InstantTerm process), allowing customers to purchase life insurance online in just minutes without needing a medical exam.

Other companies offer similar services with algorithmic underwriting, such as Bestow[22] (with policies issued by the North American Company for Life and Health Insurance), Ethos[23] and Ladder Life.[24]

4.2.2 Augmented underwriting

Even when the underwriting process is not fully automated, AI can be used in some parts of the process to facilitate underwriters' work. Indeed, one of the main challenges of insurance underwriting is that the files to be analysed by the underwriter are relatively large and include several kinds of data files (images, emails, call centre data, and documents).

The underwriter has to go through these different documents to highlight the ones that could be relevant in decision-making. To speed up this process, it is possible to use artificial intelligence techniques to automatically process the data: NLP and OCR methods for text data, computer vision methods for images.

4.2.3 Use case 3: Milliman IntelliScript

4.2.3.1 US life insurance applicant data is regulated and protected

US regulators recognise that life insurers must have complete and accurate data to effectively assess mortality risk and make responsible policy decisions. They also recognise that the privacy of each life insurance applicant's personal information must be safeguarded and stringently controlled. To satisfy the balance of both needs, regulators look to two major laws that permit and govern the collection, transmission and use of personal data: the Health Insurance Portability and Accountability Act (HIPAA) and the Fair Credit Reporting Act (FCRA).

Life insurers have become increasingly reliant on electronic health and consumer data for risk assessment. The data is more widely available and quicker to access, allowing them to render policy decisions in a matter of days or hours, whereas traditional methods often take months. The use of electronic personal data has led to much greater efficiencies in life insurance underwriting, but it has also called for greater awareness of security and privacy. HIPAA and FCRA rules are applied to help achieve those critical safeguards.

4.2.3.2 HIPAA requires a life insurance applicant's signed authorization for data access

- HIPAA establishes standards for the privacy and security of protected health information (PHI), creating a non-negotiable imperative for healthcare providers and their partners and contractors. HIPAA requires organizations and people that handle PHI to follow detailed protocols to protect PHI, whether it is stored electronically or on paper. The privacy aspect of HIPAA addresses PHI in any format, while the security rules regulate how electronic PHI is protected in during storage, aggregation and transmission.

[21] Validating Algorithmic Underwriting Models – Expert Panel Report (soa.org)

[22] What is algorithmic underwriting? (bestow.com)

[23] Life Insurance Underwriting And Why You Should Care (ethoslife.com)

[24] What's unique about Ladder's approach? – Ladder Life Insurance

- HIPAA gives consumers control of their PHI, including who may access and use it. When an individual applies for life insurance, they sign a HIPAA authorization that allows the insurance company and its contractors to access the individual's PHI. Without a signed authorization, a carrier cannot gather an applicant's PHI for use in the underwriting process, so an individual declining to authorise the release of their PHI to a carrier may hamper the application process.

4.2.3.3 FCRA ensures consumers can review and correct their information

There are many reasons that organizations check consumer reports, including issuing loans, conducting employee background checks and selling insurance. FCRA dictates how consumer reporting agencies can collect and share information about individual consumers and how such information may be used. It also allows consumers the right to access, review, and contest and correct their own information. Adherence to FCRA requirements related to collection, disclosure and use of information about individual consumers allows life insurers to use it in making adverse action determinations (i.e., declining an applicant or issuing a less favourable policy).

4.2.3.4 Patient data is carefully accessed in real time via the US private health care system

Life insurance carriers ask applicants to provide health and pharmaceutical histories on their application forms, but medical information is complex, drugs are hard to remember, and most people simply do not recall the finer details of their healthcare. Life insurers look to prescription and provider records to fill in the blanks and get a more complete and accurate assessment of an applicant's risk.

Most private healthcare providers keep electronic patient records and adhere to common medical coding classifications. When a patient sees a provider for care, the provider bills a health insurer for the treatment. Similarly, when a patient fills a prescription, the pharmacies retain the drug and dosage information. With the help of a data aggregator and interpreter like Milliman, the billing and diagnosis codes contained in the medical and pharmacy claims can give an insurer a more complete picture of the patient's health history than the application information alone.

Milliman contracts with various and multiple private healthcare sources to access this data in real time. A redundancy of data from many sources provides greater depth and accuracy. With the applicant's signed HIPAA authorization, the insurer initiates a system-to-system call with Milliman. Milliman instantly retrieves the data and interprets it using a rules engine developed with deep clinical and actuarial consultation. The actuarially relevant, intelligent interpretation is rendered back to the insurer in seconds, providing an applicant risk profile that may lead to a fast policy decision or further applicant review.

4.2.3.5 Data analytics, predictive modelling, and machine learning are advancing life underwriting

Prescription data is widely used by life insurers for underwriting and risk selection. Most rely on machine-assisted interpretation of fills, dosages, combinations, interactions and other drug factors to accurately determine health conditions and their severity.

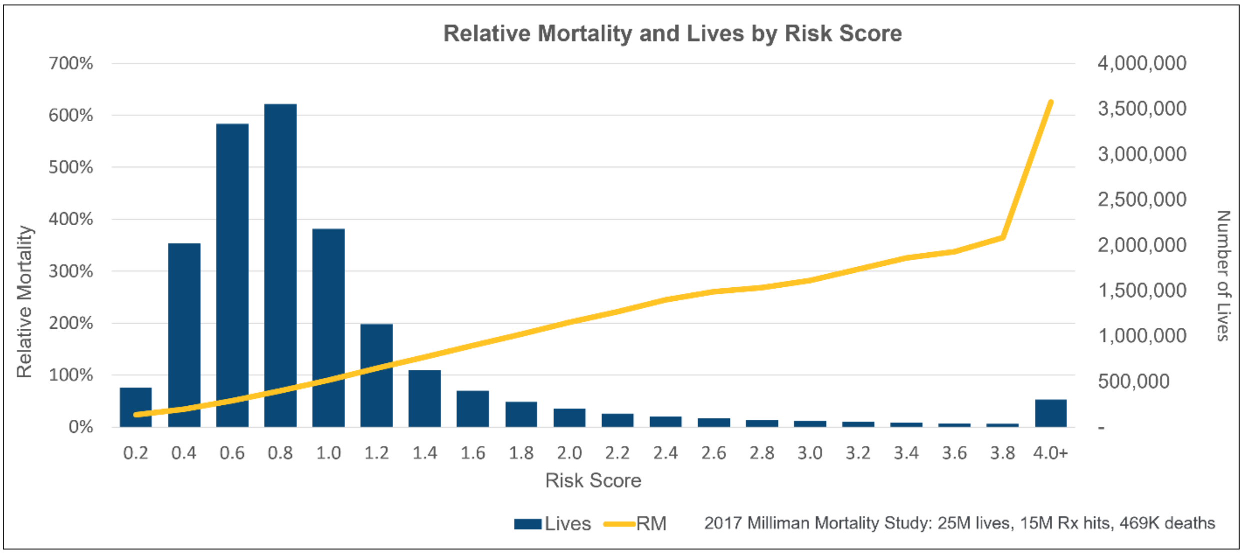
But Milliman's predictive modellers, actuaries and clinicians have further advanced the use of prescription histories to offer a multivariate, holistic view of mortality, condensed into a single risk metric. Milliman currently has two FCRA-compliant modelling tools that render a life insurance applicant's relative mortality score: **Irix® – Risk Score** and **Irix® – Risk Score with Credit Data**. Both predictive models stratify risks with far greater precision and speed than traditional underwriting methods possibly can.

- Irix – Risk Score

  Risk Score draws on the data of a Milliman mortality study of 469,000 death and 104 million exposure years. (This will soon be updated to Milliman's 2021 mortality study of 1.7 million deaths and 238 million exposure years.) Risk Score uses machine learning and the clinical interpretation of seven years of an applicant's prescription history, along with age and gender factors, to issue a score that signifies the individual's expected relative mortality.

  Because the Risk Score model is trained to predict actual mortality, not to mimic underwriting decisions, it more rapidly but accurately identifies risks with a holistic, multivariate analysis. Risk Score also stratifies risks within a given medical condition, such as diabetes, to allow for a much finer degree of risk selection.

  Risk Score's effectiveness in stratifying risk is demonstrated via relative mortality plots which show that as the score of an applicant increases above 1.0, relative mortality worsens; conversely, applicants with scores below 1.0 have better relative mortality.



This chart shows that Risk Score effectively predicts mortality. A score of 1.0 indicates a relative mortality of 100%, 1.2 indicates 120%, and so on. Milliman took lives from a proprietary large-scale, retrospective mortality study and scored them, grouped them by risk score, and calculated the relative mortality of each group of lives. The X axis is the centre of each Risk Score range. The right Y axis is the number of lives; the blue bars use that scale. The left Y axis is the relative mortality; the yellow line uses that scale.

With the power of machine learning applied to large datasets, Risk Score picks up on complex relationships in the applicant's prescription profiles and assesses the risk appropriately. Within a specific medical condition, Risk Score can determine which applicants have significantly higher or lower relative mortality than would be expected based on knowing the condition alone. This allows carriers to accept good risks that could be missed by traditional approaches.

- Irix – Risk Score with Credit Data

  Risk Score with Credit Data incorporates the applicant's credit attributes into the prescription data to issue a single, combined score. Examples of credit attributes are number of accounts, open accounts, installment accounts, third-party collections and inquiries.

  While the interpretation is the same as in the Risk Score model, the addition of credit data offers heightened risk stratification. The prescription and credit attributes are modelled holistically within a unified framework that can identify interactions between the two types of data and determine their joint influence on mortality. Consequently, Risk Score with Credit Data delivers a more predictive score than either type of data could alone.

4.3 PRODUCT DESIGN

4.3.1 Beyond traditional insurance: Ecosystems

We live in a world where technology reshapes customer experience and allows multiple services to coordinate seamlessly to serve the customer as best as possible. This paradigm has allowed the emergence of "ecosystems" across various industries, from financial services to retail to healthcare. Ecosystems are interconnected sets of services in a single integrated experience. They are not limited to a single sector; they can transcend multiple sectors.

Life insurers' profits have been challenged during the last decade in the context of low-interest rates. To find new revenue sources and increase customers' engagement, life insurers (and reinsurers) are rethinking their traditional goals and moving to adopt an ecosystem mindset. This process implies a shift from a business focused on providing financial services and claims payments to a business focused on broader services, notably including well-being, prevention, support for recoveries, etc. Ecosystems can have multiple positive impacts on the company: increasing customer retention and engagement, improving the company's reputation and diversifying the source of revenues.

4.3.2 More personalised products

Products offering usage-based insurance or real-time pricing are entering the insurance market. The demand for these products has particularly developed following the COVID-19 crisis and periods of confinement over the last two years—for example, where people have had to pay insurance for vehicles they used little or not at all.

Similarly, life insurers now offer insurance products where the premium paid by the insured depends on the lifestyle of their customer. These insurers can actively track and collect data on the policyholder's health and lifestyle habits via connected devices such as smart watches, or via activity tracking applications (e.g., Google Fitness, Apple Fit). These data allow life insurers to propose to the policyholders offers fitting their lifestyle or their needs.

The analysis of the collected data can be carried out via machine learning algorithms in order to predict an individual's risk profile in light of their lifestyle. For example, several studies have looked at the classification of policyholders from telematics data for P&C insurance: Gao & Wüthrich (2019) and Dong, et al. (2016). Similarly in life insurance, Jankovic, Savic, Novicic, & Popovic (2018) provide insight into how deep learning methods applied to wearable data could be applied to the identification and classification of various health problems, behaviours, or physical characteristics.

Insurance products using this kind of data are still in the early stages of their development and, therefore, any reductions serve more as a customer and data acquisition strategy than as a truly personalised pricing approach at the moment. However, the collection of these data may allow for more accurate and granular pricing approaches in future years.

Examples of pay-as-you-live products in the UK life insurance market include:

- Vitality: Life insurance premiums are reduced immediately for policyholders who have undergone a health examination and commit to monitoring their activity, and reductions are calculated continuously from year to year, depending on the policyholder's health and lifestyle. The continuously calculated discounts are based on the number of Vitality points earned by the insured. These points can be earned by participating in sporting events, by performing health tests or based on the activity tracked by a compatible smartwatch (Withings, Samsung, Apple Watch, Fitbit etc.):

TABLE 6 – VITALITY ACTIVITY POINTS – REGULAR ACTIVITIES (SOURCE: *FITNESS TRACKER OFFERS | ACTIVITY TRACKING | VITALITY*)

8 Vitality activity points	5 Vitality activity points	3 Vitality activity points
12,500 steps tracked in a day	10,000 steps tracked in a day	7,000 steps tracked in a day
30 minutes at 70% maximum heart rate	Partner gym visit	
60 minutes at 60% maximum heart rate	30 - 59 minutes at 60% maximum heart rate	
30+ minutes at 600kcal burned per hour (300kcal)	30 - 59 minutes at 300 kcals burned per hour (150kcal)	
60+ minutes at 300kcal burned per hour (300kcal)	parkrun volunteer	
parkrun		

- Reviti (underwritten by Scottish Friendly): Reviti offers different insurance products for smokers, depending on their type of consumption and their goals (smoking cessation, e-cigarettes, etc.). In partnership with the SideKick Health app, Reviti collects data on the lifestyle and well-being of policyholders. It offers reductions in insured premiums if they stop smoking or use alternatives such as heated tobacco or e-cigarettes.
- YuLife (underwritten by AIG Life Ltd.): Provides group life insurance, critical illness insurance and income protection to businesses with rewards that encourage employees and their families to adopt healthy habits. Employees are rewarded with YuCoins when their fitness tracker or apps show that they have reached a high number of steps or practiced mindfulness.

4.3.2.1 Challenges with the use of wearables

It is important to underline, however, that the use of wearables raises certain challenges, vis-à-vis the data collected. First, insurance is based on solidarity and mutualisation, and with these techniques, even if the ultimate goal is to help people to be actively involved in improving their health, you may move away from these principles.

These devices are not necessarily medical devices, so the biological measurements obtained depend in particular on the technology used and the way in which the device is worn. Second, the way data is collected can eventually lead to anti-selection behaviours. Indeed, there is an important difference between data collected by a person who has chosen to wear an "additional" tracking device for a clear purpose, such as a pedometer to track steps, and data from a mobile phone, which will be collected transparently. In the first case, the risk of anti-selection is always present because users can exercise a choice about the nature and timing of data collection. If users know the purpose of the device and how the data is likely to be used, they are able to "play" the system.

The ideal would be to collect data in a transparent way so that it is more representative of the insured. Data retrieved via a smartphone can be considered relatively reliable since we are not used to entrusting our smartphone to other people (with the idea of achieving better results) and we are relatively dependent on these devices.

However, collecting data in a transparent manner potentially presupposes setting up data disclosure agreements with partners. The implementation of such robust agreements should therefore be done in a manner consistent with data protection legislation, allowing customers to consent to the sharing of their smartphone data with their insurer. Data regulation is discussed in more detail in Section 3.5.

On the other hand, although the use of trackers and rewards may encourage policyholders to monitor their behaviour and thus live longer, it can be noted that this incentive to adopt a healthier lifestyle would mainly benefit products that are highly exposed to the risk of mortality or morbidity (for example, term insurance).

4.3.3 Reducing the number of touchpoints

This section differentiates sales models with a high intensity of touchpoints—involving multiple interactions focused on the human link in sales and customer service—and sales models with few touchpoints. Companies seeking to develop a close relationship with their customers (e.g, luxury) are generally interested in emphasizing this kind of customer interaction. However, this is at the expense of speed and efficiency.

Increased digitization in all industries has created a demand for fast-access products with fewer touchpoints. In particular, the recent pandemic environment and containment measures have highlighted the need to be able to provide services as frictionlessly as possible to customers. However, at the same time, life insurance services were also the ones with the lowest customer satisfaction rate due to their difficulty of use. So digitization is essential to increase customer satisfaction but also to gain operational efficiency and reduce acquisition and contract management costs.

In this context, digitalization tools, IT systems and artificial intelligence could enhance the following aspects:

- Accelerate sales and contract management processes: For example, using face recognition to allow users to confirm their identity using a photo taken on their smartphone or to review supporting documents (e.g., proof of address, drivers' licence) using character recognition (OCR) and natural language processing.
- Reduce or even eliminate the underwriting process: This would involve automating the manual processes behind the pricing and underwriting of policies via machine learning and artificial intelligence methods. Milliman has developed with IntelliScript turnkey solutions for insurers wishing to simplify underwriting and refine their pricing accuracy. The

- Pricing and *Underwriting* sections go into more detail on this.
- Provide instant advice and answers to customer questions: This can be achieved through virtual assistants (chatbots) to facilitate access to assistance (24/7). Section 4.3.4 goes into more detail on this part and gives examples of use cases.
- Accelerated claims processing: By automating, for example, the processing of documents related to claims files (e.g., using natural language processing to review documents), but also by implementing fraud detection methods via the use of external data and analytics for the discovery of new fraudulent patterns. See the *Claims automation* section for more details.

However, it is crucial to keep in mind that this reduction of touchpoints should be done strategically and would predominantly benefit simple products (e.g., term insurance or critical illness), for which pronounced touchpoints are not necessarily valuable. Whereas for the most advanced products where people seek guidance, agents and analytics should work hand in hand to satisfy the customer as best as possible. Especially because a reduction in social interaction with agents can lead to lower customer retention, so a reduction in the number of touchpoints should be accompanied by solid analytics to know when and how to reach the customers.

4.3.4 Self-serviced customer service

As described in the previous section, consumers increasingly place the ability to access their services on a self-service basis as a criterion for choice. However, insurance companies traditionally manage contracts via agents by mobilizing staff physically present in agencies or by telephone in call centres. This mode of operation poses both a cost issue for the insurer and an availability problem for the policyholders. Certain services are generally unavailable during specific periods, and access to an advisor by phone is sometimes subject to a significant waiting time.

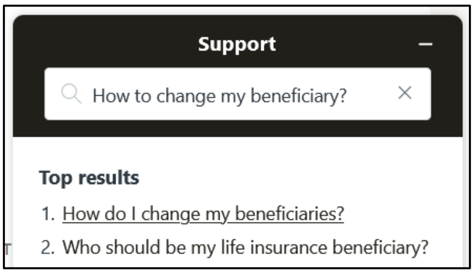
Fortunately, recent progress in artificial intelligence has made it possible to automate more and more human administrative tasks: document reading and face recognition via computer vision methods (OCR, image segmentation, and classification) or automated assistance via chatbots and NLP methods (e.g., text generation, question answering, semantic search). These technologies can also be coupled or directly integrated into robotic process automation (RPA) tools, thus providing immediate benefits for both the insurer and the insured.

Some insurers have started to implement self-service assistance through chatbot and advanced UX:

Aviva offers assistance on their platform MyAviva through an AI chatbot. The company also deployed an assistant through Amazon Alexa, which helps customers demystify insurance terms and understand insurance products.

Haven Life also has a chatbot that helps customer access their services and navigate through their platform. The chatbot can give short Q&A that answer the customers' needs.

FIGURE 6. EXAMPLE OF SUPPORT FROM HAVEN LIFE ASSISTANT (SOURCE: HAVENLIFE.COM)



However, the gains described above through the digitalization of services must be qualified because the decrease in social interactions, particularly with agents, can decrease customer retention. When implemented, insurers need to take full advantage of these services by collecting user data to predict possible policy cancellations and perform strategic retention campaigns. These retentions campaigns can then be optimised through the use of predictive analytics and machine learning.

4.4 SALES AND MARKETING

4.4.1 Policyholder behaviour and retention

Analytics and AI can detect policyholders most at risk of terminating their contracts or exercising specific options available in their insurance contracts (e.g., conversions, purchase of a guaranteed annuity option, surrenders, lapses). In particular, as seen in the risk management use cases' section, surrender behaviour is critical.

Accurately predicting policyholders with a higher risk of redemption makes it possible to target these individuals efficiently and save marketing costs. Traditionally, predictive models are focused on the detection of possible terminations and aim at detecting the customers with the highest propensity to lapse. These approaches are often completed with a customer value concept that aims at not only detecting customers with the highest propensity to lapse but also customers that have the highest customer value, including the costs which would have to be considered to reach the targeted customer.

Indeed, more economic measures take into account the costs of reaching customers and the costs of incentives offered to them to directly optimise the value of the retaining campaign.[25] Most of these values are based on the notion of customer lifetime value,[26]

$$CLV_i = \sum_{t=1}^{T} \frac{r_{i,t} \cdot CF_{i,t}}{(1+r)^t}$$

where $r_{i,t}$ is the retention probability and $CF_{i,t}$ is the cash flow generated by the customer i if they have not churned.

Then Loisel et al. (2021) try to optimise the retention gain (RG), which is defined as the difference between the customer value, with retention campaign (lapse managed portfolio value, LPMV), versus without retention campaign (reference portfolio value, RPV):

$$RG = LMPV - RPV$$

Table 7 sums up the results from different papers:

TABLE 7. LITERATURE ON LAPSE MODELING USING ML

Authors	Approach studied
Applying economic measures to lapse risk management with machine learning approaches **(Loisel et al., 2021)**	XGBoost, SVM, LR, CART
Modelling surrender risk in life insurance: Theoretical and experimental insight **(Kiermayer, 2021)**	GLM, XGBoost, Random Forrest, Neural Network
Surrender triggers in life Insurance: What main features affect the surrender behaviour in a classical economic context **(Milhaud, Loisel, & Maume-Deschamps, 2019)**	CART, Random Forrest
Analysing customer churn in insurance data: A case study **(Morik & Köpcke, 2004)**	SVM, Decision Trees

Finally, we note that the approaches described here rely mainly on internal data (policyholder and contract characteristics). However, it would be possible to consider approaches based on more external data (e.g., analysis of company sentiment from social networks) to detect possible trends that could influence terminations.

[25] (Fridrich, 2018)

[26] (Gupta et al., 2006)

4.4.2 Existing customers: Cross-selling and upselling

4.4.2.1 Targeted marketing

The use of AI and analytics for targeted marketing campaigns is not new. Almost all industries are now using it, from local restaurants to international corporations, and internet giants such as Google or Facebook benefit from it as well, generating tens of billions of dollars through the selling of targeted marketing.

However, to fully benefit from targeted marketing, it is important to understand how and when to reach customers. In life insurance, the issue is unique due to the structure of the underwritten products. Products that are suitable for an individual depend on their situation and are likely to evolve. Studies have shown that the occurrence of certain life events, like the birth of a child, can significantly impact the behaviour of policyholders (Liebenberg, Carson, & Dumm, 2012). Therefore, it would be useful to collect data during the life of the insured to detect possible changes in their situation. That information could be collected via external (e.g., open data) or internal data sources (e.g., update of postal address); the acquisition of this kind of data is explored in more detail in an upcoming Milliman research report on data sources for life insurance AI modelling.

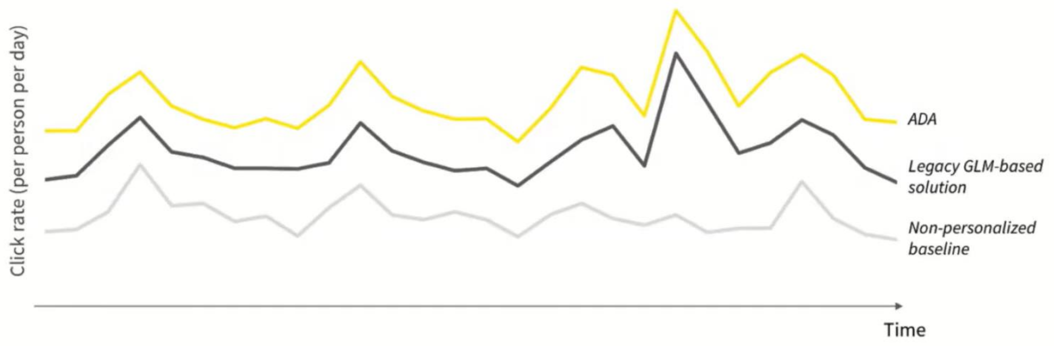
4.4.2.2 Recommendation systems

Finally, we note that recommendation engines also find their application in the life insurance sector. Well-known platforms such as Netflix or Spotify are already using them extensively. Recommendation algorithms are in charge of proposing recommendations (e.g., movies, video, music) in line with consumers' tastes.

The following paper presents the application of product recommendation systems to demonstrate how these techniques commonly used by digital retailers can also assist insurers: (Life Insurance Sales Recommender System, 2020).

In the case of Aviva Life Insurance, a multi-faceted algorithmic decision agent (ADA) was built using the Dataiku data science platform. The decision agent is based on a recommendation algorithm that is used to determine which products Aviva consumers are most likely to purchase based on their personal data (Dataiku, 2019).

FIGURE 7. PERFORMANCE OF AVIVA'S CURRENT ALGORITHM (ADA) VS. PREVIOUS APPROACHES



4.4.3 Acquiring new customers

The challenge in converting prospects into new customers lies in building strategies that are capable of converting effectively. For this purpose, it is necessary to build relevant segments and set up campaigns adapted to each segment. Then the goal is to optimise when and how to reach these different segments.

Analytics and artificial intelligence methods are state-of-the-art answers to these problems. Machine learning algorithms allow for processing large amounts of data of different natures (e.g., buying behaviour, mobile application usage and responses to previous marketing campaigns) and using them to segment according to specific patterns automatically. Section 3.4 deals in more detail with machine learning algorithms and their applications. Of course, the segmentations and strategies adopted must be coherent with the business visions, which eventually requires the involvement and communication between the different teams (data, underwriting, actuaries).

It should also be highlighted that data analytics projects aimed at acquiring new customers may be harder, for instance, than the ones aimed at reducing churn because you will have access to less data to train models for new clients than for existing clients.

In life insurance, we can observe that some specific mass-market segments, for example, mainly focus on their current career and are sensitive to new technologies; these segments are sensitive to digital distribution channels and robo-advisors. On the other hand, some other mass-market segments are more sensitive to the long-term stability of their financial situation and are more in search of advice with a face-to-face interaction with an individual.

There are opportunities for cross-selling to existing customers as well. Policyholder in-force data when combined with external datasets such as demographic, financial behaviour, purchasing habits etc. can be used to identify clusters of customers that behave similarly in regard to their insurance policies. These clusters can then be used as look-alike models in order to identify custom audiences for marketing campaigns or other offline distribution channels.

4.4.3.1 Targeted marketing

In the previous section on increasing sales on existing customers, we saw that, at the individual level, demand for life insurance products is mainly driven by lifecycle events. Online marketing tools like the Facebook targeting platform can help to reach new customers based on very specific criteria which can cover lifecycle events (e.g., place of residence, marital status, children).

The targeting of customers should be managed using advanced analytics to optimise the targeting campaigns and ensure that the return on investment in advertisement is worthwhile.

4.4.3.2 Recent shift to online sales and digital tools

Historically, for the distribution of life insurance products, the focus was primarily on in-person sales. As a result of the pandemic and the containment environment, agents found it difficult to conduct in-person conversation by May 2020. Mainly due to the pandemic, we could expect a significant acceleration of digitalization and an evolution in the distribution channel mix.

The pandemic context has greatly increased the demand for products offering online underwriting and assistance. Some insurtechs are taking advantage of this shift to online sales by offering streamlined underwriting in just a few clicks:

- Bestow offers all their term life products without medical exams, with coverage from $50,000 to $1.5 million for people aged 18 to 60. The underwriting process is 100% online and the customer can get quotes in minutes.
- Haven Life offers streamlined life insurance products (term life, annuities); when required, medical exams can be performed offline. The company also has a term life product (Haven Simple) without medical exams for coverage ranging from $25,000 to $500,000.
- Ladder Life offers products ranging from $100,000 to $8 million in coverage for people aged 20 to 60, with an underwriting process that takes just a few minutes to get coverage.

4.4.3.3 Robo-advisor emergence

Robo-advisors aim to automate the process of guiding potential policyholders, recommending the most appropriate product options (policy type, guarantees, and benefits) while considering the policyholder’s details and needs (family, home, income, and finances). They are an opportunity to automate some or all financial advisors’ work, thereby reducing costs while ensuring 24/7 availability.

In life insurance, robo-advisors are particularly well suited to the underwriting of relatively simple insurance products (e.g., term insurance, critical illness, and income protection). Some insurtechs are offering this kind of solution, such as PolicyGenius or Anorak. However, we note that robo-advisors are currently encountering more resistance from customers of complex insurance products or those that have a particular impact on the client’s lifestyle (e.g., retirement options). As mentioned before, this is partly because the segment demanding digitalised interactions is not the main one looking for this kind of decisive insurance product. In these cases, the presence and experience of a physical advisor are particularly appreciated and allow for better conversion than advice given by an AI.

4.5 PRICING

4.5.1 Speed and accuracy

Machine learning methods help to improve the speed and accuracy of risk assessment in underwriting. For example, MassMutual (a large US life insurance company) implemented an ML algorithm approach that proved to be more efficient on some specific products than the initial pricing in place. The authors explain that this gain results from ML algorithms allowing for better segmentation of risk profiles. On the healthiest risk group, a 6% reduction in deaths after 15 years was seen compared to the legacy pricing model.[27] This model is used in production for all MassMutual life products and is used to evaluate 90% of “low risk” cases, providing the benefit of reduced response times on individual cases as well as better modelling. In addition, MassMutual teams have developed a consumer tool that uses model interpretability methods to provide transparency in the mortality risk score.

Similarly, Prudential Financial has explored the use of predictive models for underwriting risk assessment, using machine learning models (multiple linear regression models, decision trees, random forests and artificial neural networks); see (Boodhun & Jayabalan, 2018).

4.5.2 Individualised/granularity of risk assessment in pricing

Life insurance underwriting is the process of evaluating the health and financial situation of a potential insured to determine if they are eligible for life insurance coverage and, if so, to estimate the fair price for that coverage. A fair analysis of the insured risk profile is critical in order to stay competitive and ensure the company’s prosperity. This process is particularly crucial when the insurance contract contains mortality or morbidity coverage.

Underwriting is mainly based on an analysis of medical data to determine the health status of the potential insured. This medical data can represent tens of pages from which the underwriter extracts pieces of information relevant for the risk assessment. In legacy pricing systems, each characteristic then leads to a reduction or increase in risk, but the correlations and cross-effects between multiple characteristics are not always considered.

However, machine learning and deep learning algorithms make it possible to consider complex cross-effects between these different variables, thus allowing the creation of more refined risk groups. Moreover, the increased amount of data collected, especially with IoT and wearables, potentially opens up access to a more refined vision of the individuals to be insured.

For example, MetLife announced in 2017 a partnership with Digital Fineprint, an insurtech whose technology aims to allow insurers (with policyholders’ permission to analyze data posted on their social networks (Facebook and Instagram) to identify potential risk factors.

Finally, a granular approach is all the more desirable to meet the needs of consumers who are looking for more personalization, as described in section 4.3.2.

4.5.3 Updating pricing assumptions

The calibration of pricing assumptions refers to the estimation of past biometric and behaviour parameters (e.g., mortality, surrenders) and their projection in the future. This estimation is particularly sensitive in the context of life insurance, given the duration of coverage of some specific risks.

Machine learning methods can derive these pricing assumptions from the data. The advantage of using machine learning methods compared to more classical statistical approaches lies notably in the possibility of considering complex cross-effects between different variables and defining models on a more significant number of variables.

One of the most documented examples regarding the use of machine learning models concerns the prediction of mortality assumptions; (Richman & Wüthrich, 2019) and (Boumezoued & Elfassihi, 2020) for example, used machine learning to correct mortality data and predict future mortality. We cover these approaches in more detail in section 4.1.1.

[27] (Transforming Underwriting in the Life Insurance Industry, 2019)

4.6 CLAIMS MANAGEMENT

4.6.1 Claims automation

Claims management is an expense item for which a significant portion of the work can be automated to gain operational efficiency. In non-life insurance, claims automation is already part of the everyday life of many insurers. For example, Tractable is an AI-based insurtech used extensively in auto claims to give instant estimates with pictures taken by the customer; the insurtech has notably partnered with Geico, the United States' second-largest motor insurer, and Covea in France.

Claims automation can of course also be used in life insurance to process claims faster—for example, by extracting relevant information from textual data. Life insurance claims often contain unstructured data which needs to be processed using OCR and NLP to gain efficiency. For example, the US insurer MetLife partnered with a startup specializing in automation and document processing (IndicoData) to automatically read and extract current and past claims. Being able to have structured data allows MetLife to unlock new possibilities (see the

Pricing section.).

In France, life insurers have also used AI to analyse claims for which the beneficiary or the insured are lost. Following a regulatory constraint,[28] insurers had to demonstrate the deployment of processes to find unclaimed claims. Some companies have put advanced modelling techniques in place.

4.6.2 Use case 4: NLP classification in insurance claim emails

In the light of progressing digitalization and automation, a client was interested in enhancing the straight-through processing and the decision-making process of invoices. The invoice office was outsourced to a branch in a different country to process standard structured invoices.

In the era of digital communication, invoices that are sent by email are typically accompanied by additional text messages. These messages are not relevant for the business cases in most of the situations. However, every now and then they contain an important explanation or a question from the client. Such atypical messages have to be handled individually and require a separate administration process. Failing to capture such messages in a proper and timely way yields a client-relation risk and in the worst cases may also have legal consequences. Therefore, the outsourced invoice office was instructed to return to the origin office every atypical message. In reality, it caused a great overhead of returned emails which in fact did not contain any relevant text that required an individual response.

The objective of our task was to construct a model to reduce the amount of emails sent back to the origin office (quantity measure) but keep the false negative rate as low as possible (quality measure). We started off of a situation of 45% quantity measure and unknown quality measure, whereas the expected true quantitative measure was estimated to be around 14%.

After initial tokenization, we removed a set of stop-words or stop-patterns. These were necessarily all personal information, like bank account numbers, names and addresses, but also other irrelevant frequently occurring words, for example, present in the signatures of the emails. Next, we applied stemming, which not only limits the number of words but also introduces better meaning separation. It is particularly important for the next step of the Latent Dirichlet Allocation algorithm. This technique helps in dimensionality reduction without much loss of information. Using LDA, the terms are divided into topics, which greatly reduces the number of variables for the classification task. Although the number of topics is important in terms of interpretation, increasing the number of topics results in more information retention at the cost of independence between these topics.

Next to the topics, we added several other features to the model. We extracted four from the body (Internal, Confidential, Question, Document size) and two from the subject line (Forward, Reply). The last feature, Number of Attachments, was extracted from the attachment line in the email’s header.

[28] Eckert law (June 13, 2014)

For model-selection purposes, we compared performance of several classification models:

- Support Vector Machine (SVM)
- K-Nearest Neighbor (KNN)
- eXtreme Gradient Boosting (XGBoost)
- Multi-Layer Perceptron (MLP)
  - With one hidden layer
  - With two hidden layers

Due to the different characteristics of these models, they either benefited from a larger independence between variables or from a larger information retention. Parameters from the LDA needed to be adjusted to reflect these characteristics, ensuring the optimal performance of each of the considered classification models. Therefore, we considered a hybrid model setup, where the LDA and a classification model work in sequence as a combined machine learning model. For each of the classification models, the hyperparameters of the model in question and the number of topics of the LDA model were considered the tunable parameters. We used Bayesian optimization for hyperparameter tuning, as it greatly reduces the computation time as opposed to greedier search algorithms such as random or grid searches. Each parameter set was evaluated using five-fold cross validation on an 85/15 train-test split.

Determining the most optimal models was done using a custom performance measure based on two metrics of quantity and quality. Both of the scoring metrics also had prescribed minimal target levels, which imposed hard constraints on the model selection process.

The best performing model was found among the XGBoost classifiers and realised 16.4% quantitative and 0.9% qualitative metrics.

In conclusion, implementing a hybrid NLP model to support the decision process can add significant business value by reducing the unnecessary workload and leaving more time to answer relevant questions, thereby increasing customer satisfaction.

4.6.3 Fraud detection

In addition to claims management automation, AI is widely used for fraud detection. Life insurance fraud can manifest itself in different ways. The most concerning types of fraud include the use of false medical claims, fraud conducted through agents, and criminal (e.g., money laundering).

According to an RGA study (RGA, 2016), the cost of life insurance fraud could be between $10 billion and $20 billion each year. The impact of fraud is not only reflected in premiums that are ultimately more expensive for policyholders, but it also restricts insurers' capacity to innovate. Indeed, according to the same study (RGA, 2016), 87.5% of insurers believe that fraud reduces their ability to innovate, especially on products with simplified underwriting. The insurers then tend to limit the face amount of the simplified underwriting products to limit the cost of potential frauds.

Therefore, detecting fraud in an efficient and automated way is a significant challenge for life insurers in order to facilitate the development of their offer and remain competitive. Insurers are implementing fraud detection methods based on **machine learning** and **analytics** to gain efficiency and try to detect fraud in the best possible way.

Besides, frauds in life insurance can relate to customers submitting false documents at the underwriting process with misrepresentation on health, family history or occupation. In this context, the use of external data could also help to identify potential frauds. For example, using claimants' personal details such as names, emails and birthdays, the insurer can look at the claimant's web presence on the internet, which might show whether they lied on their policy application (e.g., about smoking or drug use).

TABLE 8. LITERATURE ON FRADULENT CLAIMS DETECTION

Author	Approach
(Ekin, Frigau, & Conversano, 2021)	Random Forest, Neural Networks, KNN, and other methods. Various methods for imbalanced data (RU, SMOTE, MWMO)
(Johnson & Khoshgoftaar, 2019)	Random Forest, Gradient Boosting, MLP (Multilayer Perceptron)
(Richard, Bauder, & Khoshgoftaar, 2017)	Logistic Regression, Random Forest, Gradient Boosting

4.6.3.1 Identity verification

Within the last 24 months, there has been an uptick in account takeover (ATO) fraud attacks in the retirement services and life insurance space in the United States. ATO occurs when fraudsters access existing customer accounts with stolen personally identifiable information (PII) and credentials to take out loans against, withdraw from or surrender a policy before the actual customer or insurer notices. In the past, the banking industry, which also faces similar risks, has deployed third-party identity verification solutions to identify patterns of abnormal user behaviour and suspicious activity. Using third-party data for user demographics and past activity also opens up the use case for using advanced machine learning methods to find signals of abnormal behaviour. For example, any fraud consortium data which contains actual instances of fraud incidences can be used to train an anomaly detection model to identify suspicious agents. Other techniques such as Isolation forests and semi-supervised anomaly detection models have also been used. In the past, Milliman has worked on a solution that combines third-party identity verification data along with advanced analytic models that helps companies identify normal instances of activity, thereby reducing the operational burden on the insurer's fraud operations team, which end up having more bandwidth and capacity for investigating probable fraud instances.

4.7 INVESTMENT

Many life insurers either have internal investment teams, outsourced investment activities, or wealth and asset management subsidiaries. Having strong investment returns is challenging in the current economic context of low interest rates. It is, however, crucial to attract new customers with competitive bonuses on with-profit contracts and at the same time to remain profitable and to generate capital returns for the shareholders of the company.

Financial institutions and hedge funds increasingly use AI and analytics to increase returns, generate alpha and reduce risk. The key applications include the following:

- Extract new insights and signals: Extracting information from textual data or images can provide valuable insights. With the use of AI and analytics, the extraction of information from these unstructured data sources can be automated, allowing quicker investment decisions. This competitive advantage is crucial, as having a fast reaction time and staying one step ahead of the market is essential for investment teams. For example, satellite images can be analysed through **computer vision** to predict future crop harvest and economic activity (Katona, Painter, Patatoukas, & Zeng, 2018). Textual data, including news articles, central bank minutes and online posts, can also be processed using NLP to understand future changes in the financial market.[29] Textual information extracted using **NLP** has been shown to make better predictions of market crashes[30] and macroeconomic outcomes.[31] As an example of a real-world use case, ManAHL, the world's largest traded hedge fund, has also used **Bayesian machine learning** to extract predictive signals from broker recommendations.[32]

[29] (Groth & Muntermann, 2011)

[30] (Manela & Moreira, 2016)

[31] (Cong, Liang, & Zhang, 2019)

[32] The Rise of Machine Learning at Man AHL | Man Institute | Man Group

- Create new investment strategies: Generating alpha is usually a labour-intensive process that requires experimenting and backtesting many different strategies to find the ones with the best risk-return profile. **Machine learning** can help to automatically identify patterns on high dimensional data (macro feature, fundamentals) to find statistical arbitrage strategies that indicate when and how much to buy or sell. ML models can also be used to predict regime switching, and **advanced analytics** can help to find arbitrage strategies automatically on high-dimensional data.
- Support decision making of fund managers through external data: NLP, Computer Vision and analytics can help fund managers get new investment insights from **external data**. For example, a paper[33] showed that the results of the 2016 European Union referendum vote could have been predicted through the use of sentiment analysis on tweets. These signals would allow investment managers to adapt their portfolios and hedge themselves against brutal market changes.

4.8 FINANCE AND STEERING

Better, faster product-development decisions have never been more critical. Hopefully, the emergence of **data science** tools and **advanced analytics** and the generalization of their application are bringing new perspectives. Previously, controlling and finance units relied on information from different legacy systems. As a consequence, ensuring the data quality and reconciliation of data and building smart and dynamic reporting for the management in controlling departments would be labour-intensive, resulting in high costs for the company.

New techniques can provide quicker, deeper insights at scale (cloud storage, data warehouses and data lakes). The exponential increase in the volume of data that can be processed (searched, shared, stored, analysed and presented) and the increase in computing power offered by the evolution of information technology are unlocking new capabilities, including the following:

- Visualization and insights: Companies can provide advanced analytics and better understand business opportunities with streamlined and uniform access to data, leading to more optimised steering of the company.
  - Data quality: Current technologies make data querying and searching easier, offering the possibility to automate data quality, testing and validation. Open data can allow the improvement of data quality by enriching existing data.
  - Dashboards: Analytics allow for more sophisticated reporting and visualizations than ever before, with user-friendly tools (e.g., PowerBI, Tableau, Dataiku) that can be easily adopted by all business teams.
- Real-time: New technologies offer real-time capabilities, making it possible to react to market changes instantaneously and implement new strategies quickly. On the technical side, it makes use of the following aspects:
  - Automation: The emergence of open-source software, API and microservices allows the systems used by the different teams to interact seamlessly, which results in opportunities for more automation (reporting automation, interactive dashboarding, automatic alerts).
  - Reliability: Having all KPI and insights calculated in the same centralised source of truth with data warehouses (or lakehouses) ensures the reliability of the information.

[33] Emerging risk analytics, Milliman

5. Market feedback

In this section, we summarise interviews with data leaders in the life insurance/reinsurance industry. We discuss how AI and analytics are used, the main strategic investments and the key challenges.

5.1 FEEDBACK 1: PERSPECTIVES FROM A LIFE REINSURANCE MARKET PLAYER ON THE USAGE OF DATA ANALYTICS AND AI IN ITS BUSINESS

5.1.1 Context

This section presents insights shared by the Head of Data Science from a large life reinsurer. Reinsurers have the ambition to provide risk assessment services to their clients, powered by their strong risk expertise across all types of life risks. In line with this strategy, the Data Science team from the reinsurance company we interviewed develops solutions to help clients assess risk and gain efficiency. In the meantime, the team is also developing solutions that enable operational efficiency improvements through AI.

Life insurance risks are particularly subject to long time frames, low frequencies and high intensities, making models and studies particularly sensitive to the calibrated assumptions and models used. This temporality also poses data availability challenges: working with underwriting data (e.g., contracts and data, etc.) that are usually dating back to dozen of years ago when it comes to analysing life insurance events (mortality, longevity, etc.) that could currently occur. In this case, the use of algorithms such as NLP and OCR is inevitable. Temporality thus poses additional challenges to the application of AI and analytics compared to non-life insurance.

5.1.2 Use cases

5.1.2.1 Underwriting

With digitalization sped up by the COVID-19 crisis, underwriting is one of the priorities of the company.

The life insurance underwriting process is generally a relatively long one involving back and forth between the insurer and health institutions. Depending on the products underwritten and the insured's characteristics, the insurer may ask for medical tests and examinations to determine the insured's risk profile. Once the insurer has received all the information, it can take several weeks to process and reply (accepted with an estimate of the premium to be paid or refused). This process is long and relatively expensive due to the medical examinations to be carried out and the time required by the insurer to process the application.

Therefore, it is necessary to adapt the processes to gain operational efficiency and enhance the applicant experience. So the Data Science team is working on automating and simplifying the underwriting process. This includes:

- Improving risk assessment and pricing models
- Improving application data processing to accelerate the underwriting process

<u>Risk assessment and pricing</u>

The analytics team works on the accuracy and relevance of the underwriting algorithms. Traditional underwriting tends to over-penalise risk factors that might be correlated. Use of the new generation of algorithms helps to identify correlations and provide a more accurate risk understanding for underwriting.

The granularity varies according to the regions of the world: In the United States, the data collected by insurers with consents from applicants are relatively significant (medical data, car insurance scoring, etc.) and can help to better assess risk. In addition, ML models (like XGBoost) can help in assessing correlation with this context of larger databases that traditional statistical models struggle with.

However, taking into account the complex correlations and cross-effects poses some challenges regarding the interpretation of the results and coefficients. The organization is working in partnership with doctors from the AP-HP to ensure the relevance of the models developed.

To simplify the underwriting process, the company also uses external data (e.g., credit scores provided by vendors like Milliman IntelliScript—section 4.2.3 describes the possibilities offered by Milliman IntelliScript in greater detail).

Application data processing and underwriting

In some cases, applicants must undergo several medical examinations. The medical records sent by patients can contain several hundred pages that a medical underwriter must study to extract only the information relevant to the risk assessment, a process of one to two hours. But with the use of OCR and NLP algorithms, the process can be significantly improved by automatically extracting the relevant information in a few minutes. The return on investment of this work is then immediate.

From a technical point of view, the automatic processing of these data poses certain difficulties. For privacy reasons, the data must be anonymised at certain stages of the process. This step is also automated through NLP and more precisely through NER tasks, which help to hide names and personal information.

5.1.2.2 Back office

Certain tasks performed in the back office can be relatively time-consuming and make in-force management analyses relatively complicated. Typically, reinsurance treaties contain several parameters that are sometimes entered manually in the systems. Work is currently being done on the automatic retrieval of these parameters to gain efficiency and unlock new analytical possibilities.

Information extracted from a document can be used either to populate a system automatically or to provide augmented data to better advise or collect structured insights on a risk. On the technical side, these use cases are mainly based on NLP, OCR and, more generally, computer vision. However, most of the algorithms associated with these methods have been trained on fairly generic data that is not directly related to the vocabulary and issues specific to insurance. This is why the company's Data Science team has put a particular emphasis on adapting these models to the insurance industry.

5.1.3 Organization

The integration of analytics and data skills poses some challenges (understanding the issues, setting up user-friendly services for business services), and an organization should be structured to have the ability to address business opportunities. The Data Science team is composed of complementary profiles that work together on each project:

- Data value creator: Generally with a background in actuarial science and analytics, the data value creator facilitates the bridge between the business functions and the more technical profiles (data engineer and data scientist).
- Data engineer: The data engineer is in charge of DevOps and IT architecture and is expected to have excellent software development skills.
- Data scientist: Data scientists are in charge of processing data, building models and visualization tools.

In addition, the teams attend training sessions on an ongoing basis. Knowledge sharing and learning is key in data science as it is a "young" discipline constantly evolving in a moving technical environment. A particular emphasis is placed on IT excellence and being able to develop production-ready solutions from A to Z.

In the short and medium term, the problems of OCR and computer vision in the broad sense remain relatively crucial for processing the available data. The temporality of life insurance requires processing data that is several decades old, so computer vision is inevitable to leverage on traditional paper data which is much richer than data recorded in traditional legacy systems. This difficulty will probably be overcome in a few decades once the history of digitised data is sufficient, but for the time being it remains a challenge and a significant issue to unlock the potential of AI and analytics in life insurance.

5.2 FEEDBACK 2: PERSPECTIVE ON THE AI PROGRAM ORGANISATION OF A LARGE PENSION PROVIDER

5.2.1 Context

In the pension market, the same dynamics in the use of AI are in play. One of the largest pension providers in the Netherlands has assigned AI as a strategic priority for the company, according to its Director of Innovation.

With their AI program, the company aims to develop AI as a strategic competence. This program has a companywide perspective and is not just about technology. It, for instance, it also aims to increase the AI knowledge of the organization and build a more data-driven culture. By education of its current workforce, together with recruiting new talent, the company is growing its data science competence. The main areas of knowledge it invests in are data engineering, data science and business translation.

5.2.2 Use cases

To create momentum within the organization around AI adoption, the company has decided to deploy a use-case-centred approach. Its roadmap of AI applications, so-called “moonshots,” must ensure that the organization starts generating business value early on in the program and that momentum is created in the organization. These moonshots also help it compete more effectively in recruiting the hard-to-find talent, as most data specialists are attracted to working on interesting use cases.

Four strategic areas have been defined, for which the use of AI can bring the company a competitive advantage:

1. **Customer contact**

   The company uses AI to improve the relevance of its customer contact, both for its corporate customers (business-to-business) as well as the participants in the various pension schemes (retail). Leveraging its data in combination with AI, for instance, helps the company to educate the participants about their retirement planning and to take the right decisions by providing a digital retirement coach. This initiative is expected to increase customer satisfaction while at the same time lower the costs of these services by making them more scalable.

2. **Process digitization**

   To improve the consistency of its processes and to reduce costs, the company is investing heavily in digitization. Training AI algorithms with data from these digital processes allows the company to develop more algorithmic decision making and smart automation.

3. **Asset management**

   In its asset management organization, the company continuously investigates the use of alternative data sources in combination with AI techniques to find an edge in its investment decisions. Using these data in combination with AI models can help the organization to achieve higher returns on its investments and incorporating specific ESG criteria in decision making.

4. **New business models**

   Leveraging its data, combined with AI techniques, also provides pension providers and life insurers with the opportunity to offer new scalable products and services. This will drive innovation in the sector and increase customer satisfaction by providing data-driven services to clients. This will have a profound impact on the industry, according to the Director of Innovation.

5.3 FEEDBACK 3: PERSPECTIVE ON THE USE OF DATA ANALYTICS WITH A KEY LIFE INSURER IN EUROPE

5.3.1 Context

We interviewed the Head of Research of a major French life Insurer. The company operates in different areas of the world.

From the beginning of its Data Lab development, the company has focused on a practical and pragmatic vision, according to its Head of Research. There was a prioritization of topics to put more emphasis on feasible and cost-effective projects. This focus was made possible by the background and skills of the individuals behind the teams, who had several years of experience in life insurance in addition to their academic skills. Today, the successful implementation of specific use cases has led to the creation of a new subsidiary which operates as a startup specialised in the use of data and advanced analytics for life insurance.

5.3.2 Use cases

5.3.2.1 Unclaimed claims

Following a new regulation enforced by the French regulator, insurance companies had to demonstrate the deployment of processes to find unclaimed claims. If the process were judged insufficient by the regulator, companies would be fined. One of the challenges regarding this topic was to deal with homonyms and potential mistakes in the data. To answer this issue, the organization developed a solution based on NLP and external data. This final solution based on AI proved itself to detect more unclaimed claims than basic methods based on simple query, but it also allowed for greater efficiency by limiting the number of cases that needed a manual inspection.

5.3.2.2 Underwriting and cross-selling

AI also plays an increasingly important role in better, faster underwriting. NLP and computer vision allow for faster underwriting by automatically reading and extracting information from documents, but also by helping to detect potential fraudulous documents. ML techniques are also more frequently used in client segmentation and pricing, as they allow for a finer modelling that considers potential interactions.

5.3.3 Challenges and solutions

Communication between the Business and Data teams is essential for prioritising the most relevant topics and delivering as much ROI as possible. Consequently, interpretability of the models is also a key component of data science projects. It can intervene at different steps of the process, in the development as well as in the final product delivered.

The transversality of the skills of the collaborator is also key. The current team of the Data Lab is composed of around 15 people with backgrounds in general data science and data engineering as well as backgrounds in actuarial science. The team is also in close collaboration with IT departments in work to scale ML algorithms and identify potential pain points at the beginning of the process.

The organization also invests in R&D by setting up an academic chair with one of the leading actuarial research laboratories in France. The chair is organised around a multidisciplinary team composed of researchers and an operational team. The goals of the project are to explore the use of AI and ML for actuarial topics, mainly:

- Study and manage the notion of customer value in a new context of digitalization of the insurance sector
- Improve the management and assessment processes of technical risk in life and non-life insurance
- Anticipate future societal needs, with in-depth studies and the development of a prospective vision related to environmental risks and the extension of human life expectancy

6. Conclusion

Life insurance data analytics and predictive modelling developments combined with significant new data sources offer massive opportunities for life insurance business on the entire value chain. Indeed, as outlined in this research paper, business processes (claims, underwriting and sales) which could be costly and time-consuming for life insurance can be considerably improved. All the possibilities offered by data and analytics will also help life insurers to better understand the customer, improve quality of touchpoints and provide better experiences and outcomes. Last but not least, life insurance risk management with its specificities (policyholders' behaviour risks, mortality/longevity risks, sensitivity to market risk) also benefit from new data sources and modelling capabilities which are complementing existing actuarial and modelling approaches.

While life insurers have definitely started the journey, as clearly demonstrated with the interviews from insurers and reinsurers presented in this research paper, this industry did not fully integrate predictive modelling at the same level as the P&C business. With the effects of the COVID-19 pandemic, there is a clear willingness from the companies to accelerate their digital transformation and the usage of data and analytics as a key strategy which can be now leveraged.

After having presented the technical foundations and key principles of data analytics techniques, this research paper outlines use cases by life insurers or reinsurers or by insurtech partnering with the life insurance industry. It is our hope that it stimulates further thinking on how life insurers can leverage data analytics to support their future business ambitions.

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