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# Artificial Intelligence and Machine Learning for Real-Time Risk Assessment in Group Insurance and Retirement Investments

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**Abstract**
This body of work details a sophisticated investment evaluation service for retirement savings, Roth, SEP, and traditional IRAs, as well as for employees in group 401(k) plans and pension, profit-sharing, and thrift plans. The service utilizes AI and machine learning to forecast the trajectory and risk of returns from the stock and bond markets, while simultaneously projecting the contribution of portfolio performance to participants' retirement wealth and estate value. This predictive power enables focused analysis of investments subject to correlations with the performance of broad-based market indices and testing of the capability of 401(k) options and an adviser/manager using the forward-looking evaluation of stock/bond probabilities to monitor/adjust recommended and selected portfolios responsibly. The analysis is particularly useful for identifying high-growth low-risk equity investments and both equity and bond alternatives for socially responsible and theme investment portfolios.
Forecasts are generated using a proprietary one-factor ARMA family time series model using machine-learning-enhanced estimation/extrapolation techniques called every-nth-point modeling. The extrapolation technique offers a tractable model with few parameters to estimate that can contain sharp local bumps, runs, and notable declines. The model has been used to forecast a wide variety of economic and financial series—money supply growth, inflation rates, short- and long-rate Treasury yields, stock returns, gold prices, and exchange rates—as well as volatility of individual stocks and stock indices, and interest rates from the term structure.

**Keywords** : Artificial Intelligence, Machine Learning, Real-Time Risk Assessment, Group Insurance, Retirement Investments, Predictive Analytics, Data Governance, Agentic AI, Financial Risk Modeling, Proactive Compliance, Decision Support Systems, Actuarial Intelligence, Insurance Technology, Investment Optimization, Automated Underwriting, Intelligent Systems, Data-Driven Insights, RegTech, InsurTech, Financial Innovation.

## 1. Introduction

Avandom efforts to democratize insurance products, the industry is undergoing a massive transformation propelled by strategic technologies such as Artificial Intelligence and Machine Learning. As a result, Customer Experience has made the leap to become a primary source of differentiation for organizations in mature markets at the same time that new product lines are also emerging as the digital technology space continues to evolve. Group Insurance and Pension sector are an integral part of the financial services ecosystem. There has been a great deal of interest in recent years on how these organizations have chosen to respond to the challenges posed by customers who have become accustomed to high levels of personalisation, security, value add services and convenience from service interactions. Risk Managers with their ability to take decisions really quickly are pivotal in ensuring the survival of these businesses. They are expected to contrive and administer the most optimal group insurance plans while at the same time appropriately monitoring the returns involved over the entire investment period. Having set the product strategy, a pivotal component to the success of these product lines is pricing. The pricing structures have to be competitively positioned and appropriate for the amount of risk assumed by the organization while additively providing a level of surplus that will furnish an appropriate return on equity and free surplus. Untimely predictions of risk exposure are not only financially catastrophic, but they could endanger public trust and perception of an organization. To this end the actuarial models, particularly the ones predicting excess events such as rare catastrophe events and mortality modeling despite years of effort to curtail the extensive usage of assumptions or vast amount of consulting work, have still not outlived their partial blind spots and the "curse of dimensionality". In addition, with the widespread acceptance of generalised linear models as the go to statistical models for excess predictability, the product pricing within actuary work has become highly standardised.

## 2. Background and Literature Review

The concept of risk assessment has been explored for centuries, if not millennia, dating back to ancient measures of probability and practical risk assessment methods. An early attempt to quantify risk was conducted by an Indian mathematician and astronomer in 476 CE, where he measured the risk of loss, and thereby prospect theory, in gambling games. A mathematician is credited with formalizing concepts of probability from his gambling observations in the 1500s though neither risk-reward was measured precisely nor loss prediction was connected clearly with odds calculation. His contemporaries built upon these concepts in the 1600s to foundationally connect expected value to risk assessment, creating further developments in applied mathematics. In the late 1600s, these mathematical probabilities were used to connect gambling games with finite prospect theory. Nearly 200 years later, in the mid-1800s, modern development in risk assessment began with a mathematician funding the theoretical foundations of probability, complemented 20 years later by another mathematician. Approximately 100 years after these concepts emerged, with the realization of the Great Depression in the 1930s, risk assessment gained renewed attention, publishing public assessments of the cost of different risks to assist with financial planning.


**Fig 1 : AI in Wealth Management: Use Cases, Benefits and Implementation**

Group insurance is a relatively nascent development in the history of risk and retirement assessment, emphasizing collective prospective computations to reduce and redistribute the risks associated with having few or no near-term non-negative current capital assets. After the founding of mutual life insurance companies to offer policies on groups of insurers in the mid-1800s, the origins of group life insurance dates back to the construction of the Great Wall 2,000 years ago to combat worker attrition. By pooling resources during their working years, the ancient society attempted to redistribute the effects of workers dying while they were still providing for their dependents. The modern development of group health insurance closely follows the timeline of group life insurance in America, growing much earlier than other group-insured costs, such as disability and retirement, becoming preferred employer services during World War II.

### 2.1. Historical Context of Risk Assessment

There are several historical precedents related to the assessment of risks using statistical methods. For instance, risk assessments have been common in the use of fire insurance during the 1880's, where fire histories for certain cities were compiled as part of the fire insurance underwriting process. The expansion of underwriting guides, along with premium rates that were based on historical experiences, fostered the growth of mathematicians who consulted in the study of these fire insurance risks. After extensive study of these historical fire losses, these mathematicians proposed a law of errors to approximate the distribution of fire loss above a certain threshold, along with a suggestion that the square root of the fire loss be independent for fires occurring within the same city on the same day for nearby cities.

In 1892, a method to test the independence of two associated statistical distributions was developed. In 1901, the first edition of a significant work on statistics was published. The contents proved to be quite successful that it was reprinted several times in the following years. These early developments laid the groundwork for the widespread use of statistical methods, and data, for risk assessments. However, the use of pure statistical models to assess risks and develop risk factors suffered from several problems. These problems related to the availability of large databases on which to fit statistical models, but more importantly, these databases typically contained historical experiences where the statistical relationships were changing over time. The first issue has been addressed, because of the availability of significantly larger databases, and the decline in the cost and ease of computerized statistical analyses. The key question now is whether the second issue is critical enough that the predictive ability of these statistical models should be disregarded in favor of using advanced econometric models.

### 2.2. Overview of Group Insurance

Group insurance is a relatively new phenomenon in the history of insurance, and its development has taken place simultaneously with the expansion of business activities in the modern world. This insurance, applied to a specified group defined by law or by the employer, is different from individual insurance in its nature and principles. Unlike individual insurance, which is based on the voluntary insurance of individuals according to their own self-interest, group insurance is created and contributed to by an employer or other organizing body in the interests of individuals which also serve the interest of the organizer. Hence, group insurance is a risk dispersion process by virtue of which a loss sustained by one member is met from the fund which has been formed from contributions by other members of the group. The underlying principle is protection of a member of the group against a calamity suffered through the fact that he is a member of that group.

Life insurance products for the group market differ in several aspects from those for the individual market. First, the underwriting of the risks is, actually, performed at the group level; if the group fails to qualify regarding size and financial health of its sponsor, the product will not be offered or sold. Second, the premiums are usually calculated according to common mortality tables: the whole group of insured is paying premiums that mirror the costs associated with the mortality experience of the entire group. Third, single lives are not underwritten, which means that inclusion is generally guaranteed to defined benefit members; this is usually the case for employees and retirees, but also for their dependants.

### 2.3. Fundamentals of Retirement Investments

Retirement investments are designed for the longer term as opposed to regular insurance contracts, and because they are for a longer-term horizon, they allow for riskier underlying general account investments and are therefore the riskier part of the guaranteed investment options provided to clients. However, because they are guaranteed forms of investments, they must also be priced prudently for their unique risks, and there are already many complexities that come into play in creating these investment streams, some for short-term horizons and some for longer-term, that need to be taken into account in managing these, which is of significant importance to the guaranteed investment market. Some of these complexities will be explored in this context for the guaranteed investment contracts offered, pricing, reporting, asset liability management, internal modeling, and regulatory capital.

Retirement investments involve many risks, the most significant of which may be interest rate risks but that also include equity risks, credit risks, liquidity risks over multiple, varying time horizons, that require the existing business and regulatory capital for covering the complexities involved in guaranteed investment contracts with the underlying dynamics in determining the market-bearing rates and shapes of the investment guarantees, the GPV of streams of investments, and potential LR shocks in doing so. Several valuation and internal modeling approaches have been used for assessing the IA benefits, but they are not immune to the fundamental problems that the practitioners in other areas of actuarial practice may face. Improvement of the existing actuarial investment models so that they allow for more accurate accounting and more powerful internal models becomes, thus, a focal point of the research trade-off between ease of use and accuracy, especially, since such improvements will also benefit the other areas of actuarial practice.

**2.4. Advancements in AI and Machine Learning**

Machine Learning (ML) is a method to achieve artificial intelligence. ML provides data modeling techniques to detect patterns in the historical data and to use these patterns to make decisions about the unknown or future data. In contrast, Artificial Intelligence is a broader concept to build intelligent systems. AI could use ML to accomplish an intelligent task, but not necessarily. AI refers to building intelligent systems that can experience the world via sensors, act via effectors, perform intelligent behavior, and use knowledge to perform intelligent tasks and solve problems.

ML has gained popularity over the last decade due to various reasons. The aforementioned advances in technology available for Internet, network bandwidth, and storage capacity have enabled many different application domains of ML. The growth of the web revolutionized the availability of data across domains. Data availability is critical for building ML models. The exploration of methods and algorithms developed within statistics, computer science, and control theory has also contributed to the recent boom in ML. The success of ML in applications such as automated speech recognition, computer vision, bioinformatics, robotics, and text processing has also ensured its popularity.

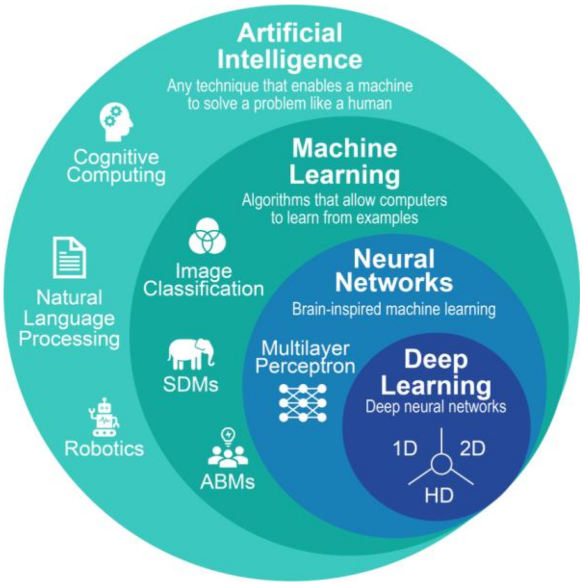


**Fig 2 : The nested hierarchy of artificial intelligence (AI), machine learning**

The earliest ML algorithms were based on linear statistical regression or classification models to estimate, predict, or classify outcomes based on features. In particular, linear regression was proposed as far back as 1822 by the French mathematician Pierre-Simon Laplace to model the relationship between the sample outputs and features as a linear combination with unknown-model parameters. Similarly, the statistical learning theory, which attempted to unify ideas from statistics, optimization, and theoretical computer science, was developed to make rigorous the practical success of earlier approaches such as empirical risk minimization.

**3. Theoretical Framework**

This section illustrates the theoretical foundations of the proposed model that enables carrying out real-time risk assessment of an insurance or pension client's portfolio. It discusses the theoretical framework of models that enable predicting the probability of an adverse event occurrence, algorithms that can be used in these models, data sources that can be utilized to build the models and discuss the issues regarding data quality.

Risk assessment can be defined as the process of determining the chances of an adverse event occurrence in a defined time period. The practical formulation of risk assessment is usually probability prediction, where the predicted probability indicates the chances of an adverse event occurrence. Risk assessment has been an important research area in the insurance and pension sector. In property and casualty insurance and retirement investments, risk assessment is utilized to estimate the probability that a policyholder will file an insurance claim or face bankruptcy in a certain time period, which helps in making decisions related to pricing, underwriting, or claims management.

In the modern business environment, risk assessment is primarily carried out using traditional statistical techniques such as regression analysis, decision trees, neural networks, and machine learning algorithms. Machine learning algorithms such as support vector machines, random forests, gradient boosting, deep learning, and extreme gradient boosting have gained growing attention. According to the big data theory, model performance should improve with the amount of training data. Due to the large number of individuals, historical events, and risk factors available, the amount of training data is very large in the insurance and pension sectors.

Publicly-available company sources enable us to collect the necessary data. To implement the proposed model, the following data sources may be utilized: Public Financial Statement Databases: Insurance and pension organizations are required by law to regularly publish comprehensive financial statements such as balance sheets, income statements, and cash flow statements.

### 3.1. Risk Assessment Models

In light of the design of effective and informative insurance products, risk assessment models are very relevant for insurers. Pricing adequately collaborative risks is especially essential, and assessing risks is a vital activity for insurance companies, since they are called to divide a manageable part of the risk, charging the clients a premium, and to ensure a coverage of the whole risk, for the case that the negative impact occur. Model building becomes, hence, an interesting area to explore for actuaries, statisticians, and anyone dealing with risk assessment in financial services, although some traditional challenges can be debated. The problem of capital allocation to a portfolio of collaborative risks, for example, is usually made on the basis of expected utility theory, and an interesting discussion regarding the difficulties of calibrating its parameters in order to reproduce market behaviors, arises. Another interesting debate consists of model uncertainty; while, in most of traditional risk management approaches, a maximum likelihood estimate is the solution preferred, several alternatives to account for model uncertainty risk have been proposed. Next chapters describe and discuss some common risk assessment models applied in general areas of quantile regression estimation, and machine learning, and in some specific insurance areas and retirement investment areas with the aim of presenting a portfolio of possible techniques that can be used in risk modeling. The terms "risk modeling" and "risk assessment model", and their relative derivatives, are usually used in the text without specific meanings and distinctions, since they are treated as synonyms in most of the literature. Nonetheless, it is possible to put forward some guidelines that can help to bound the general meaning and use of both terms.

**Equation 1 : Risk Score Calculation using Logistic Regression**

$$P(\text{Risk}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)}}$$

- **Where:**
  - $P(\text{Risk})$: Probability that a customer is high-risk
  - $x_1, x_2, \ldots, x_n$: Customer features (e.g., age, health indicators, income level)
  - $\beta_0, \beta_1, \ldots, \beta_n$: Learned coefficients from training data

### 3.2. Machine Learning Algorithms

The most widely used algorithm across the various models presented in this research are the Multi-Layer Perceptron and Random Forest, both in the development of Predictive Models for other evaluation criteria mainly in Credit Modeling, for example. Thus, it is worth delving into these algorithms. The Multi-Layer Perceptron is a neural network with a topology developed in at least three layers: an input layer, one or more hidden layers, and an output layer. Each layer has several interconnected neurons that apply the summation functions and a non-linear function to the weighted sum of the inputs. The interconnection of neurons between layers is one of its features. Neurons within the same layer are not interconnected. Random Forest is an extension of the Bagging algorithm, which aims to reduce the variance of classifier models. It is based on the ensemble concept, where multiple base models are trained using random subsets of the training dataset and the corresponding classes are predicted for the combining process. Bagging can be used with any model that, in isolation, has a high variance, such as Decision Trees, because bagging is a meta-algorithm that aims to reduce this variance. The key concept of Random Forest is to insert randomness into the Decision Tree learning process by introducing randomness in the feature selection process. In its training phase, Random Forest builds a forest of Decision Trees, where each tree is learned with a specific random set of samples and another random subset of features. In its prediction process, Random Forest averages the predictions of all trees that make up the forest.

### 3.3. Data Sources and Quality

Machine learning models are data-hungry systems. They need a considerable amount of the right kind of data to work properly. But these data are often difficult to acquire or missing due mainly to the relatively small size of the groups involved. We are looking at a kind of segmented data that account for only a small fraction of all possible group business transactions. The data we do have may suffer from reliability issues driven by problems surrounding fraud detection and financial advice quality. The data are complex, both internally and regarding their interactions with external factors such as labor market status. With these caveats in mind, we present the research developed during the last decade and a half on understanding data requirements for machine learning models to support real-time risk recognition and evaluation as well as fraud detection and evaluation in group life and retirement funding business. We focus on three questions: What data types? What data sources? What data quality? Data types. Machine learning models are data-hungry systems. They need a considerable amount of the right kind of data to work properly. But these data are often difficult to acquire or missing due to, primarily, the relatively small size of the groups involved. We are looking at a kind of segmented data that account for only a small fraction of all possible group business transactions. The data we do have may suffer from reliability issues driven by problems surrounding fraud detection.

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**4. Methodology**

This study investigates Artificial Intelligence and Machine Learning (AI-ML) techniques to allow the Group Insurance and Retirement Investment (GIRI) business functions to improve their ability to assess risks in real-time. Through an exploratory analysis of various stakeholders, a base set of design requirements was developed. A conceptual framework and model for the capabilities and workflow of real-time risk assessment in GIRI was then created informed by a concurrent literature review in the domains of GIRI, AI-ML, financial services, digital/isomorphic innovation diffusion, and industrial organization. The framework was adapted using Generalized Design Science Research to create six predictive models for risk attributes of various classes of insurance products. The empirical predictive model predictions were compared to the practices currently used by GIRI practitioners. The models were further validated and evaluated for their feasibility through in-depth interviews with GIRI practitioners. Finally, support tools were developed to facilitate data collection and model exposure.

To facilitate external validation of this research and to drive the cross-domain knowledge contribution and to share the cost of model development with business stakeholders, existing, large and publicly accessible model training/open data sets were leveraged. For the insurance industry, publicly accessible datasets were used to predict risk attributes for mortgage default, which are related to life insurance underwriting; and travel delay and cancellation probabilities which are related to travel insurance underwriting. For the retirement investment industry, publicly accessible datasets were leveraged to predict risk attributes related to stock index return probabilities, which are related to equity investment product risk assessments. These empirical model predictions are intended to address the operational needs and research problem described and evaluated previously.

**4.1. Data Collection Techniques**

In the realm of financial services, where schemas routinely interact with clients and generate massive volumes of data, the collection of valuable and appropriate data from the available client databases acts as the foundation for successful model development, whether for credit rating, complaint risk prediction, or other use cases. Different degrees of automation and speed in data collection are required, based on whether domain experts can be relied on or not. In our studies, domain experts can be relied upon to choose variables, as most models deal with relatively small subsets of the variables available in the Client's databases, targeted to specific geographies, segments, or clients, for explanations as well as schematic-driven calculations. This aids and speeds up proper indexing. Variable transformations generally are not complex, and we present some of the techniques used. For example, probability of occurrence, impact, and severity variables usually are log-transformed as the resultant distributions normalize fairly well on standard on the natural logarithm base. Further, as most of the models our samples develop are meant to run in production under tight turnaround times, speed of input data extraction is a consideration, which requires thorough testing of various data extraction methods. Future model versions, running such models in the post-market environment or on supercomputers, could have great potential to use the preprocessing methods, have the flexibility to adopt change on even more complicated data transformation methods for highly accurate targeting, while absorbing unforeseen input data latencies. We describe data extraction solutions in our work, to illustrate the nature of input data proposed to run these analytical models, and these preprocessing solutions are applicable to other use cases in the Client's portfolio as well. Continuous inputs usually measure statistical or economic time series in the outside environment, where these models are run, obtained from central banks or associated institutions.

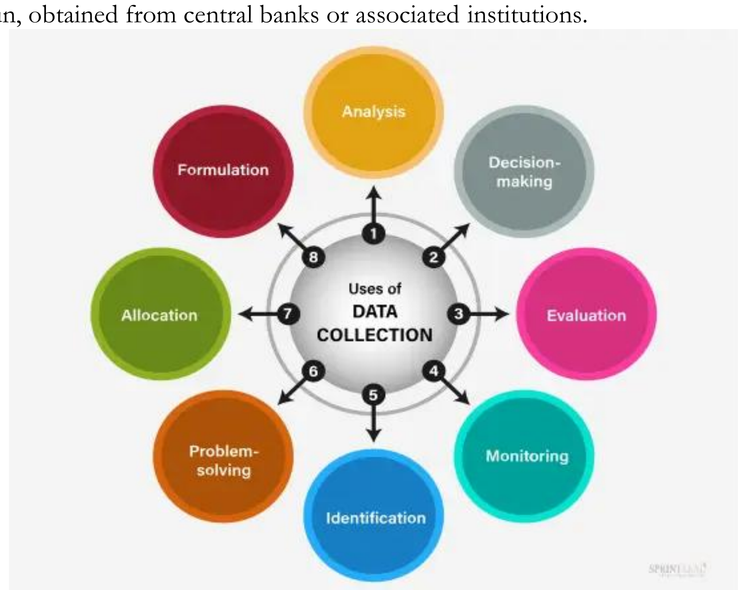


**Fig 3 : Data Collection Methods Explained**

### 4.2. Model Development Process

The goal of this study was to develop predictive models that provide probabilities of SSA death, SRI withdrawal, and SRC plan termination, all conditional on the start of the relevant time intervals, and all having a common set of predictors. One competing prediction model is a standard survival time model, fitted by maximum partial likelihood estimation. The backbone of standard survival time analysis is the Cox proportional hazards model. Such models are commonly used for modeling group insurance claims. However, there currently is, to the best of my knowledge, no example in the literature of its use in conjunction with a group retirement system for predicting the occurrence of all three major event types used in this paper. Furthermore, most of the models used for the consideration of these three major event types have not been survival time models, but parametric prediction models.

Survival time models have long been used not only in economics but are more prevalent in health research. The primary reason is the computational burdens required for estimating the parameters of survival time models. However, recent advances in high power computing now provide the necessary minimal costs needed for the use of survival time models in econometrics. The survival time models used in this study are well-formed, flexible, and parsimonious extensions of the Cox proportional hazards model tailored to prediction. They were chosen legally and consistently, in estimation, selection of predictors, and variable transformations. Categorical variables were modeled with $K - 1$ dummy predictors for each variable having K distinct values. Continuous predictors were transformed as necessary into a form conducive to modeling, and real modeled intervals were recorded. In contrast to plausible assumptions regarding the distribution of Y which may not hold, SRI and SRC termination prediction modeling may provide accurate predictions on only the RSON2 interval, and SAS and SRC termination prediction modeling may provide accurate predictions on the RSON1 interval.

### 4.3. Evaluation Metrics

Choosing the right evaluation metric is crucial in elucidating the model's performance. As classification tasks involved multiple classes and imbalanced data regarding underwriting share per cluster, it entailed using multiple classification-related metrics to understand the predictions in detail. These metrics are utilized for both consumer classification lists, which aid in decision-making for portfolio insurance or selection of an optimal insurance scheme with minimum possible risk, based on the distance metric, which decides placement in a consumer cluster, and consumer sample clusters for which models have been developed. For model reconfirmation, the standard classification metrics such as accuracy, F1 score, precision, recall, ROC/AUC value are sufficient for quantifying model performance across all models. For quantifying model performance across all models, the average balanced accuracy for all samples under each consumer category cluster per hundred rows is calculated. However, since consumer sample clusters contain clustered samples according to some features of the target variable, for such considerations, these metrics may not be enough. For establishing model interpretability and understanding their performances on cluster levels, we also use these metrics for the consumer category share/groups across the cluster decision on stratified sampling of the model data, later split according to total distance factor between data from various clusters, and finally update samples according to the selected traffic.

## 5. Application of AI in Risk Assessment

Influential leaders of global corporations and many other senior executives increasingly influence machine learning and artificial intelligence research and development. They have identified realistic applications that can enhance their products and services, and have advocated for the concentrated application of talent and funds to solve interesting and challenging problems. One area that is being transformed by such applications is Insurance and Retirement. For the condition that can lead to your "life's savings" being wiped away, with little or no hope of recapture or repair, the need is for policies that provide for equitable and adequate payouts when a need arrives. In this paper, we highlight only one of the major levels in Insurance and Retirement, Risk Assessment. An "Uber-like" transformational introduction is an efficient assessment of the risks associated with large numbers of potential policyholders, not just the few that traditional methods service today. Today, policyholders identified as very low-risk through financial measures, may subsequently suffer financial tragedies stemming from risks not considered during the application phase. Insurance companies suffer when offering such low premiums that only small, inadequate payouts are available. Having much better information on more risks much earlier allows action to be taken. With preventive action at the very earliest stage, pre-emptive thought must be given to restructuring insurance costs and operating procedures.

Predictive analytics in insurance has moved beyond conventional multivariate regression-based modeling, to complex pattern recognition. The business intelligence applications that have emerged from data warehousing and reporting, have moved beyond being enterprise analytical tools, to business unit decision support mechanisms. Automated decision systems based on discovered patterns, have been implemented at all levels in all lines of insurance business. Data processing engines have been expanded beyond corporate centers, so that data from diverse sources can be accessed for localized and specialized customer segments, and be immediately acted upon. Patterns discovered by data mining are being included in claim processing and development support, claims detection, medical data evaluation, market targeting, customer acquisition and retention, and premium and commissions optimization. Once the cost of applying an identification algorithm is lowered to a fraction of the cost of using an intelligent data mining process, either could be used for screening. Why not use the more complex intelligent model? For the risky populations that are segmented, the more complex model provides improved identification even at greater cost.

**5.1. Predictive Analytics in Insurance**

Big Data technologies are continually applied to numerous domains. For example, in some companies, predictions are developed in-house and this is one of their core competencies while decision-making is based on third parties' predictions. Predictive database models can yield revenue of 5-35 times of the investment made.

Predictive analytics is one of the most used Big Data use cases. This term refers to technologies that use machine learning and predictive modeling to analyze current and historical facts in order to make predictions about future events. This capability is crucial for organizations that assess risks in order to prevent losses and maximize outcomes. Predictive analytics forecast key decision variables, thus enabling various functions of the organization to act upon actual and expected outcomes, given certain parameters that the organizations cannot or don't want to change.

Within the predictive analytics domain, three major difficulties are identified. First, unlike other predictive use cases, within this domain the accuracy of the predictions is far more important than any other criterion. Second, statistically significant predictive power, used to create predictive relationships, is often absent, resulting in the difficulty of justifying the decisions made. Third, the predicted values may not match the original ranges to which the predicted values belong, creating errors of interpretation at decision-time. Reputation-concern-based prediction may overcome this issue due to its consideration of the function happening on the predicted variables. Logic-based predictive relationships are currently the only way to address the above-mentioned difficulties

**Equation 2 : Expected Retirement Investment Return using Time-Weighted Rate of Return (TWR)**

$$\mathrm{TWR} = \prod_{i=1}^{n} (1 + R_i) - 1$$

- **Where:**
  - $R_i$: Return during period $i$
  - $n$: Total number of time periods
  - Used in AI/ML models to predict investment performance over time.

**5.2. Real-Time Data Processing**

The world is becoming increasingly connected through the Internet of Things, with numerous devices, appliances, and systems being enabled to share data among themselves. Such developments have enabled an instant flow of information between consumers and businesses. The data produced from sensors embedded in every object can create new models for risk assessment and have much richer information for underwriting than that stored in the databases of insurance companies. New generations of consumers demand experiences that are built from data and critical events in their financial lives now trigger a response and immediate action. They expect recommendations to reflect current prices and the risk implications of their behavior. For companies embracing the changes brought by globalization, mobility, big data, and new technologies, speed is essential. Real-time analytics can provide them with the insights they need to identify and act on the most relevant business opportunities in the moment, maintaining competitive advantage in an ever-changing marketplace. Assessing risks in real-time, and taking appropriate action immediately, can have a massive impact on the financial health of organizations and individuals. Using only predictive analytics to develop risk assessments is no longer sufficient. Instead, analytics must be performed at the point in time when events occur to minimize the impact of contributing risk factors. Predictive analytics improves the speed and accuracy of risk intervention by eliminating guesswork based on stale data or intuition based on incomplete data. A predictive modeling score can decorate policies, insurance applicants, or transactions so that risks can be identified as events occur. The objective of real-time risk processing is to help the policyholder and the organization mitigate the consequences of something disastrous happening; for example, a dangerous person or vehicle with a high probability of causing accidents and losses.

**5.3. Case Studies of Successful Implementations**

AI implementation is conducted by grouping interested corporate identities into an association. Associations happen to be led by a few sound institutions but they are able to soften the load on individual companies by sharing AI infrastructure costs such as cloud computing and consultation, management of the team of experts that implement and maintain the AI capability. Such advanced AI capabilities for real-time data sensing, monitoring and evaluation are not available to any company until a new technology democratizes it. So it will take time and investment for AI in insurance industries to achieve its full potential. This section reviews some already implemented examples of insurance corporations and consulting firms who are at the forefront of utilizing AI.

Sensing Ecosystems identified three companies that have started to implement predictive analytics techniques to sense accidents quicker and trust for the safety of passengers using their service on-demand. Uber's location-based Accident Detection can trigger the detection of an accident based on the pattern of movement of the passenger or the Uber transportation vehicle if one ceases for a benchmark time. Lyft's SOS Button enables passengers to contact emergency services. FF & W Uber's Move it program tracks accident patterns based on user demand and in accordance with Uber's funding of self-reports about accidents by Uber drivers or vehicles involved to identify black-box trucks. The intent is to highlight areas of problematic road construction or traffic flow hot spots for local authorities to arrest.

**6. Challenges and Limitations**

In this work, we have proposed a framework for using Artificial Intelligence and Machine Learning to automate risk assessment in 5's Group insurance and 5's Retirement Plans with greater precision and speed than current rules-based methods. And although the resulting system will be able to provide incremental business value early-on, have a robust design to allow scaling and extension to additional products, and support embedding core business knowledge into the model, will recommend changes to business processes, and increase business process transparency; there are numerous challenges and limitations in using AI and ML specifically to 5's group insurance and retirement investment business systems, and in this section, we discuss a few.

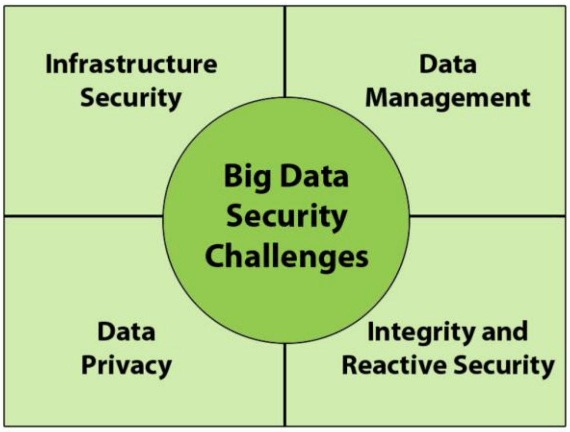


**Fig 4 : Main Issues in Big Data Security**

The first challenge concerns data privacy and security issues. Software systems supporting the 5's group insurance and retirement investment domains were developed when privacy laws were quite permissive, and prior to the establishment of regulations governing the collection and analysis of personally identifying information, sensitive personally identifying information, private health information, etc. Data privacy laws prohibit the use of personally identifying information in new products and services without the expressed consent of the owner. This presents a significant hurdle when using ML for 5's insurance and retirement planning innovation in that much of the risk assessment data at the heart of the operations of these businesses are extremely sensitive. Further, recent advances in AI privacy preserving machine learning, or what is referred to as fairness, accountability, and transparency machine learning, prevents such systems from being used based on personally identifying information data.

**6.1. Data Privacy and Security Issues**

The extensive use of Artificial Intelligence (AI) and Machine Learning (ML) techniques, to facilitate real-time risk assessment and decision-making in group insurance and retirement investment activities poses several challenges and raises certain serious concerns. Only comprehensively tackling the ensuing challenges guarantees that the benefits of applying the innovative techniques can be achieved and that the associated risks or adverse repercussions can be identified, used to create a robust framework, and avoided. Chief among the challenges is the issue of protecting and preserving the data privacy and security, integrity and quality, and confidentiality of sensitive and confidential personal and financial information, and related data-related concerns. The problems are exacerbated in group insurance and retirement investments contexts, as these involve the monitoring and tracking of the daily financial transactions of the employees of a multitude of organizations.

Secure access to data used in AI and ML model training and their testing and validation is of the utmost importance. Group insurance and retirement accounts contain an employer's significant financial investment and usually consist of a large member pool since the funds are collected from employees. Risk controls must be in place to ensure confidential data is not exposed to unauthorized individuals. Remote access systems often compromise data security and breach detection controls. It is thus not unusual for unauthorized individual(s) to access the stored data and alter or corrupt sensitive data records. Advances in access control technologies and biometric data, such as retina scans, fingerprints, and palm patterns, to successfully authenticate users, are being relied upon to minimize data protection breaches. Additionally, the technologies can be further strengthened through data anonymization, the process of deliberately altering the original data records to prevent users from gaining access to the original files as well as regular auditing.

**6.2. Algorithmic Bias and Fairness**

In addition to privacy and security, there are important ethical issues associated with AI and ML algorithmic solutions. The most important moral question that is characteristic of AI is algorithmic bias; that is, algorithmic decisions favor some consumer groups while they discriminate against other consumer groups in a non-equal process concerning the same group of input variables. However, if a particular algorithmic decision-making process, even if it is biased at some level, is known to all affected parties and is justified, such a situation would not be seen as unethical. However, while the rules determining the algorithmic bias result are known to the parties making the decision, this is usually not the case for the individuals affected by a biased decision. Unfortunately, many AI and ML algorithmic solutions do not have any associated explainability and interpretability, which results in making it impossible for affected parties to be aware of the fact that the solution is biased. This is particularly true for ML solutions. Therefore, any AI and ML algorithmic solution applied to real-life data in practice needs to be checked for the presence of bias to not produce unintended and unwanted results. This is true for both predictive processes as well as decision-making ones.

A particular issue in validating algorithmic fairness is whether the fairness notion being used in a particular situation is truly warranted by the social context. Perhaps, the most important of these notions is demographic parity. This states that the result of the algorithmic action be not dependent on membership of a group of individuals, also referred to as a sensitive attribute;

for example, that decisions made concerning loans should not depend on the race of the potential borrower. This property applies equally to the results of predictive processes or actions for the same input values. However, there are other important property notions that are being used such as individual fairness, conditional demographic parity, and within-group impact, which is typically used in the analysis of the presence of disparity in outcomes. These more relaxed measures would state that some kind of tolerance level would be imposed on the decisions affecting specific demographic or other consumers who possess similar input variables or risk factors associated with the algorithmic decision-making process. However, such tolerant notions would not apply to strictly point-wise foolproofing of the algorithmic or probability scoring output space resulting in the absence of bias.

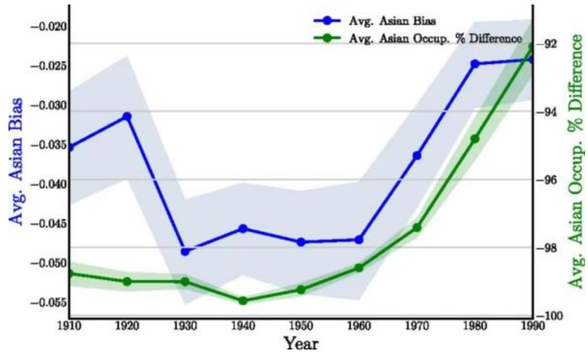


**Fig : AI Researchers Answer the Five Big Questions About Fairness**

**6.3. Regulatory and Compliance Challenges**

Innovation in machine learning is a disruptive force in almost every industry, and financial services is no exception. Machine learning is transformative because it helps perform tasks that were previously not possible or so costly that it was not economic to employ them. In the past few years, we have seen various organizations adopt machine learning tools to support business growth. Nevertheless, for financial services firms, the journey may prove to be complicated for the multiple regulatory, risk, governance, and compliance considerations that create friction as financial services explore machine learning.

At least five primary factors contribute to this friction. First, there is a regulatory requirement that management demonstrate effective management of machine learning as a process, including model governance and controls, similar to other risk and regulatory obligations. While this could be seen as just another layer of governance on the top of the existing governance framework of financial services, it does require substantive development work. The deepening of the model governance function is especially challenging when different machine learning use cases have been developed across various business use cases. Each machine learning use case has its own unique characteristics that need to be taken into account, and it becomes bureaucratic if each element of the machine learning process is run in a silo. Secondly, machine learning comes with powerful tools. The automation of data preparation is becoming machine-based, and there are various tools for building machine learning models. The availability of multiple development tools allows employees who are not entirely proficient to misapply machine learning tools. Over time this has increased the pressure on second-line validation functions to assess the efficacy of such tools.

**7. Future Directions**

Despite the advanced capabilities of chat-based AI utilisation of knowledge databases, programmable APIs, and customisation, there remains considerable innovation in how artificial intelligence technologies can adapt to and enhance risk management, directly, in the near future. Considering the convergence of knowledge embedded in language model intelligences and financial services, companies may elect to incorporate unique plan design and other strategic modelling techniques into creative and knowledge-valuable guidelines and instructions for employees recuperating efficiency expended on those efforts. In addition, future improvements in the specificity required to design novel plan buildings may lead to the discovery or optimization of unique provision structures that clarify tax liability and depreciation management in a manner that has been previously unjustified or unreliable.

Integration with increasingly intelligent corporate financial management technologies and the environment disclosures that accompany the relevant leveraging of risk-bearing resources may support the internal decision-making processes of companies against larger macroeconomic shocks on recruitment and retention of a key workforce that drives profitable operations. Emerging speciality insurtech and regulatory technology service infrastructures often already service the aggregation, structuring, and guidance continuum. Presume that those enabling infrastructures efficiently disclose that, at a target treasury discounting rate of return, deferred compensatory distributions to employees prepare the workforce for more efficient, tightly-coupled, on-time follow-through service levels on stakeholders exposed to ongoing market uncertainty, as a disincentive to explore a competing firm's alternative equitable exposures of long-term career incentives.

The combination of unique language modelled knowledge partners that are explicable and capable of building relationships through corporate disclosed partnerships with the enhanced intelligence involved in unique block-chained, trusted and validated, autonomous decision-making mechanisms provides a pipeline into a multi-respondent, predicted, optimally-designed, internal decision-making process blueprint. In addition to stakeholder incentives, employee behaviours associated with risk-bearing disincentives could include triggers for employer-provided insurance operationally incorporated into automatic savings with recognised investment portfolios that are also responsive to employer interest.

### 7.1. Innovations in AI Technology

Artificial intelligence (AI) technology is advancing rapidly, and has already improved almost every aspect of the field. As is the case with any software, the AI that constructs the models of the future is evolving rapidly. A specific goal of this work is to create fast, flexible predictive models that vary with time due to changing databases, and which can be ported easily to make real-time anticipatory predictions about a variety of financial events, and then be used in risk calculations for group insurance or retirement investments. As outlined below, the expansion of modeling technique options enables exploration and growth in the types of models that evaluate risk, enabling faster and better risk prediction, model speed improvements, and model clarity, all leading to better, more responsive implementations of AI model in predicting risk for group insurance or retirement investments.

In 2020, an important extension of reinforcement learning was produced by combining it with concepts taken from graph neural networks, called a deep, directional graph architecture. Graphs are important for modeling a huge number of real-life systems, and improving the predictive capabilities of reinforcement learning will lend itself to studies in a lot of important real-world domains outside finance and insurance. Other innovations involved incorporating previous neural networks – specifically convolutional neural networks – into quickly training other neural networks via attention chasing, where previously trained concept extractors were used to create an artificial neural network that was trainable hundreds of times faster than if it were not initialized in such a manner. These innovations in the speed and capabilities of AI behavior prediction will naturally flow into better risk prediction for actuarial science.

**Equation 3 : Real-Time Risk Score Aggregation (Weighted AI Model Output)**

$$\text{Total Risk Score} = \sum_{i=1}^{k} w_i \cdot f_i(x)$$

Where:

- $f_i(x)$: Risk prediction output from the $i^{th}$ model (e.g., decision tree, neural net)
- $w_i$: Weight or confidence of model $i$
- $k$: Total number of models in ensemble
- This is common in ensemble learning (e.g., stacking or boosting) for more accurate predictions.

### 7.2. Integration with Financial Technologies

AI is fortuitous in integration with key financial technologies already developed and used in the provision of investment and retirement planning advice. This technology is shaping and reshaping the investment and retirement planning industry. Interactive platform models that integrate the use of AI technology into the traditional coproduction of advice by advisors or planners for their clientele at account set-up, account maintenance and during financial emergencies can combine cost advantage, ease of use, low investor knowledge level or sophistication requirements, and quality of advice close to allocative and production efficiency of human advisors. AI can also be integrated with other tools that address particular user needs in investment, savings and retirement activities, features that are currently underserved by existing human planners and advisors in the investment and retirement advice space.

These emerging combinations of Fintech and related AI advice engines share some common characteristics. They either assist the user in their investment, saving and retirement planning decisions or automate parts or all of these decisions, or offer users to interact with them to varying degrees. They operate in real time or close to real time and use algorithms and rules that are data driven or heuristic-based. These technologies have the potential to deliver fast, user-friendly interfaces that residents of developed economies can increasingly access via smartphone-based services essentially free of charge or at very low cost with ease. AI is expected to replicate the patterns of high service, low cost, highly sophisticated services delivered in traditional advisory and planning markets for affluent Canadians and their retirement portfolios using traditional financial artifacts and instruments.

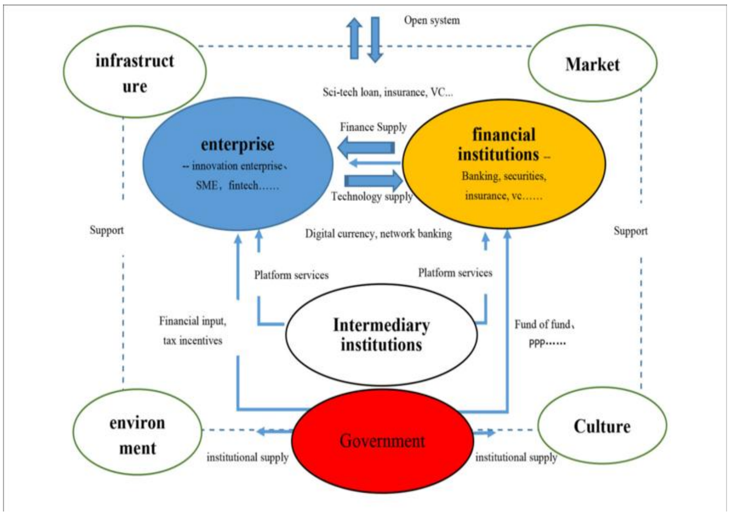


**Fig 5 : Schematic diagram of the sci-tech financial ecosystem**

### 7.3. Potential for Enhanced Predictive Models

The degree of uncertainty about the future is a crucial input in any process that affects future cash flows in group insurance and retirement investments. In our analysis, we have used uncertainty that results from the amount of unexplained variance in predictive models for the number of future claims for insurance policies, the number of years remaining to retirement for pension plans and the value of pension fund investments at the time of retirement. Advanced techniques have the potential to develop predictive models which are more accurate than the traditional techniques used in the case studies and our more general use of predictive functions because of the greater ability of neural networks and similar techniques to discover complex nonlinear relationships in large amounts of structured and unstructured data. Technology has also been used with great success in the field of risk assessment in personalized insurance products.

Improved predictive models for the events that impact the pension as well as the retirement insurance flow can enable insurance and pension fund companies to develop more dynamic and accurate business planning systems. Actuaries have a slightly different perspective than technology providers. Actuarial modelling techniques need to identify, explain and quantify the factors which modify the risk assumed by the insurance company or the pension and retirement fund. There is a need for models which are interpretable in this manner. Studies have also found that the performance improvement gained by applying more flexible models diminishes when considering actuarially relevant product levels of analysis. The two approaches have different objectives, and the future will likely see a merger of the two schools, where the performance many times obtained by models can be obtained and enhanced by models.

**8. Conclusion**

In this essay, we presented our research work on computational frameworks that integrate real-time data analytics, risk assessment and evaluation of fund management services and retirement investment products. We showcased how financial services organizations in the group insurance and retirement investments space can develop and augment their processes related to project management, product development, enterprise risk assessments, data science, and fund management with the help of AI, ML and computing platforms. Our work discusses a few key projects where we applied AI and ML to use case problems shared by our industry collaborators. These pre-commercial prototype solutions operating in a controlled, virtualized decision support environment have been provided as illustrative examples of the expected values of enhanced internal funds management evaluation and monitoring functions. Given the uniquely complex, non-linear, multi-dimensional and time-sensitive nature of performance evaluation and risk assessment associated with real-time updates, we couple investment expression type based evaluation methodologies with cognitive, unsupervised deep learning architectures.

As a conclusion, we assert that financial services institutions, in particular, group insurance and retirement organizations looking to adopt AI and high-performance, interactive computing for risk assessment and improved project performance monitoring and management should take note and build an internal smart innovation engine, which helps solve existing industry business needs. Well-designed internal needs-driven customized solutions will urge the evaluation and selection committees for services selection to look into these intelligent tools. Organizations can then put their skilled resources into higher-end decision making for the outcome of their product lines funded for the longer-term investment horizon. The more established graduate or business schools, by forging partnerships with firms, can mentor problem-driven applied research. Flexible student engagement mechanisms involving internships can support a common framework for joint client participation. The academic partners can further aid fund management in applied research.

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