The AI-augmented underwriter - an unsupervised learning approach towards transparent, fair predictive underwriting

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Abstract

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Declaration

I herewith declare that I have produced this paper without the prohibited assistance of third parties and without making use of aids other than those specified; notions taken over directly or indirectly from other sources have been identified as such. This paper has not previously been presented in identical or similar form to any other Irish or foreign examination board.

The thesis work was conducted from 2023 to 2024 under the supervision of Dr. Martin Cunneen at University of Limerick.

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Introduction

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1.1 Modern Insurance Underwriting

First, we introduce to the field of life insurance underwriting and comment on the state of automation in underwriting decision-making today.

TODAY, life insurance underwriting best practice typically blends automated rule-based engines with referrals to traditional underwriting for more complex applications (Wang, 2021). The observation of the author having seven years of experience working within the Reinsurance sector is that the job of maintaining and managing rules governing automation becomes more difficult as the number and complexity of product offerings increase. As shown in this research, in recent years research has emerged demonstrating the potential of machine learning techniques to instead directly predict underwriting decisions, with a number of these models being successfully deployed commercially by major insurance carriers such as MassMutual (Maier et al., 2019). While the level of precision that such approaches enable at individual level provide opportunities to drive efficiencies and profitability we examine here the implications this introduces as as potential threat to social solidarity one of the key original purposes of insurance. This research examines the potential of approaches that can address this issue still availing of the benefits of modern techniques AI automated or underwriter-augmented decision making that keeping human-in-the loop oversight in critical decision making also prioritising interpretability of models as a means towards the transparency that forms a prerequisite to a more ethical and fair automated underwriting decision making.

1.2 Thesis Structure

The remaining chapters of this dissertation are as follows:

Chapter Two provides a comprehensive review of the literature concerning the intersection of insurance and its social functions, particularly mutualisation. It explores the methodologies by which underwriting assesses and classifies risk and investigates the implications of increasing automation in underwriting processes. The review examines contemporary research on predictive techniques using supervised machine learning, examining their impact on mutualisation. It also examines the notions of actuarial fairness, bias, and unfair discrimination. Furthermore, the chapter surveys the governance and regulatory frameworks in the United States and the European Union with respect to consumer protections.

Chapter Three introduces the data set with an Exploratory Data Analysis (EDA).

Chapter Four describes the methodology for the design and execution of the experiments using supervised and unsupervised machine learning techniques.

Chapter Five presents the results from experiments.

Chapter Six draws conclusions and evaluates the results from experiments. Finally, it suggests possible future works.

A series of documents have been included in the Appendix section of this dissertation. These are:

- *Appendix A* outlines . . .
- *Appendix B* presents . . .
- *Appendix C* includes . . .

Available with this dissertation are two Jupyter Notebook files containing the following items:

- *Notebook 1*: contains an Exploratory Data Analysis (EDA) of the Prudential data set and application of supervised machine learning techniques on this dataset to predict risk classifications.
- *Notebook 2*: contains application of various unsupervised clustering approaches to the dataset.

2

Literature Review

2.1 Introduction

Background

The purpose of this review of the literature is to introduce the central topics related to the research, including the key literature related to these topics. The review begins with a background on the insurance industry and its ongoing transformation through automation. Next, the focus is more specifically on machine learning and its adoption in insurance underwriting, and after surveying the regulatory environment with regards to AI especially in the area of decisioning, moving into literature around risks to the key insurance concept of "mutualization" from modern methods and approaches.

The context is to ensure social fairness for consumers through transparency within the context of the technological advances that machine learning offers in the field of life insurance underwriting. The research question is focused on whether modern unsupervised learning techniques can be leveraged to offer models that encourage fairness through improved levels of transparency while maintaining performance characteristics comparable with "back-box" supervised methods. As such, a critical analysis of the literature here aims to identify gaps that can justify the need for such research.

Purpose of the review

Evaluate the impacts of the wider availability of personal data and the acceleration of machine learning in the field of automated underwriting. Secondly, this review aims to evaluate the impact on fairness and the extent to which regulation and governance have mitigated any threats.

Scope of the review

The scope of the review will be insurance, focusing on life insurance in particular and spanning the insurance industry evolution from traditional manual underwriting, subsequent advancement through the adoption of technologies such as rules-based systems for increased automation and efficiency towards modern efforts to adopt machine learning methods to drive further automation of underwriting decisions. The scope of the literature will be global, but with a focus on the United States, since the largest market for life insurance is based in the United States, where there is also greater availability of personal information that may be included in underwriting decision making.

Review Methodology

The following methods were used to select and analyse the literature. First, selecting key themes for each section, various sources including Google Scholar, UL Library, semanticscholar.org, connectedpapers.com, elicit.com, litmaps.com, scite.ai were searched to identify key relevant and impactful papers both historically and from the last five years; these were downloaded and collated with Zotero before reviewing adding relevant references to the narrative discussion and critically analyses in the relevant sections. The approach is to critically analyse the literature with a view to identifying and analysing gaps that are consistent with the research question.

2.2 Origins and Ethos

Here we briefly trace the origins of insurance mutualisation and how this is preserved from a governance, regulatory, and compliance standpoint.

In 18th and 19th century Britain, insurance was viewed as a form of gambling, leading to regulatory measures like the Gambling Act of 1774 and the Annuity Act of 1777 (Tapan Biswas, 1997). Different types of insurance, such as life and fire insurance, developed different market characteristics. Life insurance, being a long-term contract and form of saving, required companies to establish reputation and trust. In contrast, fire insurance, typically short-term, demanded less trust (Tapan Biswas, 1997). The life insurance market primarily targeted the wealthy and middle class as they could afford to save and plan for their families' futures.

In fact, the development of life insurance in this period was marked by moral controversies and cultural changes. Initially condemned as sacrilegious in the US, life insurance gradually gained acceptance as a means of financial protection (V. Zelizer, 1979). In England, early life insurance societies offered mutual economic protection and promoted reforming ideals, but also faced challenges in distinguishing between prudential insurance and gambling on lives (Geoffrey Clark, 1997). The industry grappled with the assessment of both physical and moral risk, particularly with regard to certain groups such as Jews and Irish (R. Pearson, 2002).

The rise of insurance coincided with the dismantling of feudal solidarity and the emergence of individualism, reflecting a capitalist ethos (F. Ewald, 2019). As the industry evolved, it developed new moral technologies to segregate legitimate from illicit motives to protect and restrict members' proprietary rights over policies (Geoffrey Clark, 1997). This transformation shaped the culture of life insurance in England from 1695 to 1775 (T. Alborn, 2000).

We see that the insurance market underwent significant changes during the 18th and 19th centuries, reforming its image as gambling on lives to being considered as a means of mutual financial protection. In addition to the moral hazards and ethnically based discrimination pointed above and its origins according to Halpérin is that its origins are less "founded on a sense of solidarity" and "common security" than in the spirit of financial gain (F. Ewald, 2019).

2.3 Underwriting Automation (first generation - 1980 to 2010)

This section traces the origins of underwriting automation in insurance from the "first-generation" of expert decision support systems before more recent adoption of machine learning models.

With the advent of expert systems in the 1980s attempts were underway to automate and enhance decision-making processes in insurance underwriting. Early research focused on developing prototypes and examining the feasibility of applying expert systems to determine applicant insurability based on mainframe, rule-based systems and utilising LISP and PROLOG at an unamed Midwestern insurer (Gary A. Wicklund and R. Roth, 1987). Subsequent studies went beyond rule-based systems to explore various nascent artificial intelligence techniques, including fuzzy logic, evolutionary algorithms, and even neural network techniques. Risk classification and claim cost prediction was implemented using k-means clustering and heuristic methods to group policy holders (A. C. Yeo et al., 2003); (K. Aggour et al., 2005); (K. Aggour et al., 2005).

These systems showed promise in automating underwriting tasks, with one implementation at Genworth achieving a significant automation rate close to 20% on LTC product applications at Genworth (K. Aggour et al., 2005). Researchers were also investigating the workflow side with the integration of web services and alerts to enhance workflow automation and exception handling in underwriting processes (Raymond C. M. Lee et al., 2007); indeed, having actively participated in such programmes during the past seven years, the author can speak to such workflow automation and optimisation efforts ongoing in major insurers to this day. Later, neural network models also emerged tentatively being proposed as support tools for determining premium rates in property and casualty insurance to address limitations of traditional interpolation methods (Chaohsin Lin, 2009).

Although relatively sparse during this period, the research reflects a focus on researching rule-based and fuzzy systems for underwriting decision-making. However, based on our observation of the state of automation in large insurers globally in the past decade, the reality is more likely that industry adoption of such emerging technologies would have significantly lagged transformations in financial domains such as banking which underwent dramatic transformation during this era. More likely, this period was still very much marked by traditional manual underwriting methods, with automation being introduced more around process automation to support the manual underwriter, digitisation of documentation, etc. with relatively little automated decisioning.

2.4 Evidence-based risk assessment

In this section, we trace the evolution and emphasise the importance of medical and other evidential data in modern insurance underwriting.

Underwriting has evolved from data collection at a population level or ad hoc at an individual level to a much more systematic gathering of the critical medical and other related data that underpins individual life underwriting decisions. Milano (2001) proposed a comprehensive, rule-based risk assessment framework that moved toward implementing a much more systematic, personalised, evidence-based risk assessment than traditional empirical methods and reliance on generic population data, thus improving the quality and consistency of risk selection. This represented an evolution of insurance underwriting towards a more evidence-based, systematic, and competitive approach compared to traditional empirical methods.

Milano (2001) noted at that time the limited availability of good quality evidential data and the need for training and interpretation of such data. Of course availability of data has become much less of an issue with increased access to digitized personal health records as provided by third-party data vendors to insurers especially in US including the more recent availability of personal Electronic Health Records (EHR) and uptake by insurer wanting to leverage these as part of risk assessment.

Klein (2013) details the multiple data sources that supplement the typical application risk assessment in US begineeing with the tele-interview questionaire now generally evolved to an online format. Additional evidences range from reports and data on fluids (blood and urine and oral) to MIB check for any existing conflicting applications (Medical Information Bureau), doctor APS reports (Attending Physician Statement), MVR (Motor Vehicle Record) reports and data from state DMVs, Pharamceutical prescription records (Rx) in addition to other medical reports such as EKG, Chest x-rays etc.

Some of these evidences may be requested by default on application initiation, and others may be requested depending on the disclosures made by the application during the interview. The insurer decides the circumstances in which evidence data are requested. These may be ordered automatically or manually depending on the specific characteristics of an application and the overall level of automation implemented in the underwriting workflow.

2.5 Risk Classification

Here, we outline the reasons for the critical role of classification in risk assessment and the central role played by the underwriter in evaluating and classifying risks to preserve the health of the insurer portfolio.

Underwriters analyse information on insurance applications to determine whether a risk is acceptable and will not result in an early claim using underwriting guidelines and typically working with medical doctors and other specialists to assess the risks. Risks are divided into different classes (standard, substandard, preferred, etc.) based on the likelihood of a claim that allows the insurer to charge appropriate premium rates (Macedo, 2009).

The underwriter must evaluate and select risks to maintain a homogeneous portfolio of risks for the insurer. As Macedo (2009) points out, this is based fundamentally on the Central Limit Theorem principle that a large enough number of similar risks will exhibit a normal (Gaussian) distribution. Therefore, risks should have a high degree of correlation to behave in a predictable manner. However, different insurance companies may accept different risk profiles across their product lines. In these cases, the underwriter may accept the risks under different conditions (terms), such as charging an extra premium (loading), applying exclusions, or imposing waiting periods.

However, the goal is to maintain the necessary homogeneity of risks required by the insurer in the overall portfolio. As Macedo (2009) identifies, this is crucial because insurance companies can only create value by reducing the volatility of claims if their portfolio consists of homogeneous risks. arguing that this involves understanding not just the biophysical risk characteristics of the insured but the "moral risk" including applicant's reputation, financial position, etc. The latter point begins to move away from what are considered traditional data sources mentioned in the section on *Evidence-based risk assessment* and toward more newer data sources, which are more controversial including criminal and credit records in addition to those shared from the world of personal electronic devices either with express consent (personal fitness trackers) or not (social media networks).

2.6 Predictive Underwriting

Leaving behind traditional rule-based expert systems, this section explores the emergence of machine learning models leveraging the dramatic increases in availability of personal data, compute and advances in AI and machine learning techniques. Ultimately, we would like to identify what formats and contexts have these been most successfully deployed for life insurance underwriting decision making.

2.6.1 Earlier Developments

Predictive underwriting is not only a phenomenon that arises in the context of recent advances in AI. In the early 1990s Nikolopoulos and Duvendack (1994) described the application of machine learning to life insurance decision making, first comparing and then combining evolutionary learning with classification tree techniques to build a knowledge base of rules for an expert system to determine the expiration of life insurance policies.

In the early 2000s, data mining and knowledge discovery techniques were emerging to produce tools for decision support and risk assessment reminiscent of the modern machine learning of today (Apté et al., 2002). These were aimed at using large volumes of high-dimensional data to develop automated, scalable analytics that could supplement or replace traditional human-expert approaches. Predictive models were used to set competitive premiums while managing risk, avoiding overcharging low-risk policyholders and undercharging high-risk ones (Apté et al., 2002).

2.6.2 Modern Predictive Underwriting

This section traces the rise of predictive models in underwriting decision automation during more recent times arising from dramatically increased access to personal data and advances in AI and machine learning techniques.

Recent research has explored the application of machine learning techniques to automate and enhance risk assessment in life insurance underwriting. Here, we outline the aims, techniques, and results from key studies relating to application of machine learning to underwriting decision support.

Boodhun and Jayabalan (2018) aimed to enhance risk assessment comparing multiple algorithms, including Multiple Linear Regression, Artificial Neural Network, REPTree, and Random Tree classifiers, to predict applicant risk levels. Using the publicly Prudential Dataset, they found that REPTree performed best with Correlation-Based Feature Selection producing a lowest mean absolute error (MAE) of 1.5285 and root-mean-squared error (RMSE) of 2.027, while Multiple Linear Regression excelled when combined with Principal Components Analysis for dimensionality reduction with the lowest MAE of 1.6396 and RMSE of 2.0659.

Biddle et al. (2018) similarly implemented and evaluated classical techniques this time to predict the application of exclusions using a dataset provided by a leading Australian life insurer covering an 8-year period from 2009 and 60,000 thousand individual applications. The researchers noted challenges with the data exhibiting sparsity in the questionnaire responses due to the conditional-branching structure, as well as extreme class imbalance in the application of exclusions, with over 1,000 different exclusions present. Implementing and evaluating techiques including Logistic Regression, XGBoost, and Recursive Feature Elimination. The study found that both Logistic Regression with L1 regularization and XGBoost performed well in predicting exclusions, with XGBoost using significantly fewer features to achieve similar accuracy, suggesting it as the better model for the task.

Levantesi and Pizzorusso (2019) aimed to investigate the ability of machine learning techniques to improve the accuracy of some standard stochastic mortality models in the estimation and forecasting of mortality rates. This study used tree-based machine learning techniques (decision tree, random forest, and gradient boosting) to calibrate the machine learning estimator parameter that was then applied to standard mortality models. The study showed that the implementation of these machine learning techniques, based on features such as age, sex, calendar year, and birth cohort, leads to a better fit of the historical data compared to the original standard mortality models. The key novelty of the paper was that machine learning was used as a complement to standard stochastic mortality models, rather than as a substitute, in order to both improve model fit and forecasting, while also trying to create a bridge between the data-driven machine learning approach and the theoretical mortality modelling.

(Maier et al., 2019) aimed to use a large historical dataset of life insurance applicant data at MassMutual to develop a mortality prediction model using machine learning techniques, designing a novel evaluation framework, this forming the core of an algorithmic underwriting system at MassMutual. The key techniques used were Survival modelling using the Cox proportional hazards model and random survival forests to predict mortality risk. The results showed that the random survival forest model outperformed traditional underwriting, yielding a 6% reduction in claims in the healthiest pool of applicants. This algorithmic underwriting system reduced the time to issue policies by 25% and increased customer acceptance by more than 30% for offers made with a light manual review, saving millions of dollars in operational efficiency while driving the decisions behind tens of billions of dollars of life insurance benefits.

The group at MassMutual Maier et al. (2020) followed a year later with an improved version of the original model the aim of developing a "high-resolution mortality and life score" to serve as a primary driver of an algorithmic underwriting systems for life insurance, that would embrace transparency in terms of methodology sufficient to build trust with consumers and regulators. The research used a comprehensive dataset of 1.5 million MassMutual records over 20 years. Random survival forest model to directly estimate the cumulative hazard function and derive a standardised life score. Similarly to the original study Maier et al. (2019), a random survival forest model was used to directly estimate the cumulative hazard function and derive a standardised life score. Although the results were comparable with the original study, this study had more focus on transparency by implementing a SHAP framework to generate additive feature contributions to explain individual life score predictions. MassMutual also developed a consumer-facing transparency tool called MyLifeScore to demonstrate how various factors drive individual risk.

Hutagaol and Mauritsius (2020) also aiming to examine how machine learning can help life companies determine the risk level of prospective applicants, implemented classical machine-learning techniques of Support Vector Machine (SVM) using different linear and non-linear kernels), Random Forest and Naive Bayes, implementing on the Prudential dataset. Results found Random Forest achieving the highest precision (0.85) over SVM (0.72) and Naive Bayes (0.49).

Wang (2021) constructed predictive machine learning models to predict underwriting decisions for life and health insurance applications using reinsurer real-world dataset of 29k records covering a 3-year period from 2017. Uniquely, the solution included machine learning techniques such as natural language processing and clustering analysis to process data including free-text descriptions of impairments and occupations.

Models were trained comparing the performance of various machine learning algorithms including Random Forests, Decision Tree, Gradient Boosting, Extreme Gradient Boosting, Bagging, AdaBoost, Support Vector Machine, Stochastic Gradient Descent, K Nearest Neighbors, and Ordinal Logistic Regression. The best performing algorithm was Extreme Gradient Boosting (XGB), achieving 94% accuracy on the training set and 71% accuracy on the test set. It was noted that this was a significant improvement over rules-based engines that can only process about a third of applications. In terms of explainability, feature importance ranking from XGB provided underwriting insights, such as BMI being a key predictor. Overall, the study concluded the potential of predictive modelling to handle complex cases over rules-based engines.

Sahai et al. (2022) also focused on Machine Learning (ML) techniques in underwriting decision making have saved time and improved operational efficiencies user-friendly cause-and-effect explanation of model's predictions. The research compared performances between tree-based classifiers including Decision Tree, Random Forest and XGBoost. The XGBoost classifier performed best with an AUC value (0.86) and F1-score (above (0.56) on the validation data, followed by Random Forest with AUC value (0.84) and f1 score (0.53). The research also focused on interpretability of these techniques applying SHAP to the more complex (bck-box) models XGBoost and neural networks and 'Feature Importance' to models including Logistic Regression and tree-based models such as Decision Tree and Random Forest. (Dataset details not available at time of writing)

Recently, Varadarajan and Kakumanu (2024) surveyed the work of researchers attempting to determine the optimum machine learning model to enhance the accuracy of predicted policy issue decisions and to determine the strategies used to arrive at individual risk predictions. The findings were that the XGBoost model was the most effective and has the advantage of immunity to missing values according to the research. A notable omission is Maiers work on the MassMutual dataset, which speaks to a predictive model implemented in an underwriting system at a major US insurer. Varadarajan and Kakumanu (2024) proposes an increased focus on class-balancing, cross-validation and hyperparameter optimisation on the customer dataset, as not having received much attention in prior literature. However, since these are normally taken as standard it seems more likely that these activities have been included to some extent but perhaps have not explicitly mentioned.

2.6.2.1 Analysis

First, we will summarise some of the most pertinent aspects of the studies outlined in the previous section.

The increasing availability of data and advances in machine learning now means that underwriting automation can significantly speed up the processing of applications Boodhun and Jayabalan (2018). A common theme in the research is the use of supervised machine learning techniques to create predictive models from a publicly available dataset such as that published by Prudential (2016) and used by Boodhun and Jayabalan (2018) and Hutagaol and Mauritsius (2020) or proprietary historical underwriting datasets such as those used by MassMutual (Maier et al., 2019). Data sets include biophysical, occupational, insurance history and medical characteristics; however, Maier et al. (2019) refers to the increasing availability of nontraditional sources such as financial, public records and even wearables but does not include any of these in the data set. In addition, traditional sources such as drug prescriptions (Rx) and motor vehicle records (MVR), which Maier et al. (2019) acknowledge would improve accuracy, are also omitted from this study. On the other hand, Boodhun and Jayabalan (2018) state that the Prudential dataset has almost sixty thousand applications with 128 attributes, however, it is unclear whether all of the expected traditional sources are included since values are normalised and field names anonymised e.g. `Medical_History_41`. We can conclude that all models examined may be incomplete to a significant degree in terms of missing some of the fundamental data sources typically utilised as part of the life underwriting process by insurance carriers in the North America region in the author's experience.

Commentary

A common theme in the literature is the research, comparison, and in some cases ultimately the adoption of machine learning techniques as a core element of the underwriting decision. The studies can be categorised into distinct groups based on what they predict;

- Predict the outcomes of the risk classification decisions in the underwriting application.
- Predict outcomes of underwriting application decisions other than risk classification, such as risk such as loadings, exclusions, and other terms.
- Predict mortality to provide a life risk score.
- Predict other aspects of the policy lifecycle, such as policy termination.

In the experience of the author with respect to the third item above, such risk scoring models can relate to, for example, smoking risk or overall mortality that typically serve as input to the underwriting evaluation (automated or manual). While such scores are useful, the authors observation is that insurer evaluations typically include risk score models when available as an input factor as part of a holistic view of evidences evaluated from multiple sources including biophysical, medical, and avocational to make a comprehensive assessment of an applicant's risk. The implications of a trend towards risk-based scoring in terms of transparency and fairness are discussed separately later.

Sahai et al. (2022) notes the desire for explainability as a "user-friendly cause-and-effect explanation of model's predictions" being useful to stakeholders, financial institutions and regulators.

Ultimately, the aim, regardless of technique, is by such adoption to save time and improved operational efficiencies in the underwriting process, as achieved at MassMutual. However, Maier et al. (2020) also speaks to the "technical and business challenges" to get to full implementation in a production environment.

2.6.3 Industry adoption

Today, best practice in life insurance underwriting typically blends automated rule-based engines with referrals to traditional underwriting for more complex applications (Wang, 2021). The observation of the author having seven years of experience working within the reinsurance sector is that the job of maintaining and managing rules governing automation becomes more onerous for carriers as the number and complexity of product offerings increases. In recent years, research has emerged showing the potential of machine learning techniques to directly predict underwriting decisions, with a number of these models successfully being commercially deployed by major insurance carriers such as MassMutual (Maier et al., 2019). However, the authors experience is that the field continues to be dominated more by rules and model hybrids with a primary rules mechanism governing underwriting decisions while incorporating model results as an element of that decision making.

2.6.4 Risks to Mutualisation

The insurance industry relies from a commercial perspective on customer segmentation while simultaneously fulfilling the social function of mutualisation. As Charpentier et al. (2015) details, traditionally insurance relies on mutualising risks among policyholders, creating the need for homogeneous risk pools. Segmentation helps insurers achieve homogeneity by using proxy variables such as age and location to classify risk levels. The challenge is to balance segmentation and mutualisation in a competitive market as more fine-grained segmentation risks introducing increasing variability and potential risk of market exit to the insurer.

Algorithmic prediction and big data are potentially "disruptive" to the traditional insurance model, promising to allow highly personalised insurance policies and premiums based on individual behaviour and risk profiles, rather than pooled risk (Cevolini and Esposito, 2020). Charpentier et al. (2015) concurs pointing out that this increased capacity for personalised data analysis enabled by modern machine learning and AI threatens to disrupt the traditional insurance model as insurers embrace the ability to predict individual risk more accurately and price accordingly. Cevolini and Esposito (2022) indicates use of telematics and behavioural data in motor insurance as an example of the industry moving from an actuarial valuation model to a more individualised behavioural model that allows insurance companies to better predict individual risk exposure, rather than relying on proxy variables such as gender, age, etc. This enables personalised pricing, potentially reducing cross-subsidisation between different risk groups.

The demise of risk pooling with increased focus on individualisation, which according to Cevolini and Esposito (2020) risks an end to mutualisation, might ironically be accelerated by consumer demand for personalised pricing. This risks introducing a new form of discrimination and exclusion as insurers refuse to cover higher-risk individuals, which conflicts with the social solidarity function Cevolini and Esposito (2020).

Actuaries should have a responsibility to balance technical with social considerations in risk pricing. Cevolini and Esposito (2020) argues that the shift from pooled risk to individualised prediction in insurance could fundamentally transform the social function and meaning of insurance, with wide-ranging consequences still largely unexplored. The advent of InsurTech and the availability of detailed personalised behavioural data creates asymmetry, as the insurer knows more about the policyholder than they might know about themselves raising privacy concerns despite the benefits. (Cevolini and Esposito, 2020).

Cevolini and Esposito (2022) speaks about the evolution in such an environment of "behavioral tribes" where risks are no longer pooled but rather individualized raising concerns about fairness and discrimination. Cevolini and Esposito

(2022) references the ongoing debate around whether this is more or less fair than traditional actuarial approaches. The use of behavioral data also provides opportunities for a changing more proactive role for insurance companies with policyholders perhaps a "coaching" role in trying to improve policyholder behavior and reduce risk, rather than just reacting to claims, potentially transforming the traditional business model and relationship between insurers and policyholders Cevolini and Esposito (2022)

2.6.5 Regulation and Compliance

This section describe key legal regulation relating to AI, specifically around predictive models and algorithmic decision making focused on EU and US as it relates to insurance and underwriting. A primary focus is to determine how current machine learning predictive models align with the transparency requirements set by various legislations.

2.6.5.1 United States

US Federal

At the federal level, the Health Insurance Portability and Accountability Act (HIPAA) Rights (OCR) intersects with regulations around algorithmic and automated decision making, particularly in the context of protecting patient personal health information (PHI) and ensuring that fair practices in healthcare algorithms and automated systems must comply with stringent standards. HIPAA through granting patients rights over access to their health information implies that there must be transparency in how patient data is used in algorithmic decision-making. HIPAA further intersects with efforts to regulate algorithmic fairness as system must not discriminate based on protected health characteristics (Rights , OCR).

In the authors experience, HIPAA compliance is already well embedded as part of the life insurance application and underwriting lifecycle with U.S. insurers during which the applicant is typically requested to consent to the terms of HIPAA to release access to applicant medical data.

The American AI Initiative Act (AII) Sen. Cantwell (2024) provides a comprehensive approach to regulating algorithmic and automated decision making. By establishing standards, promoting transparency, ensuring fairness, and encouraging human oversight, the Act claims to aim to foster trustworthy and ethical AI systems that protect individual rights and promote innovation while preventing algorithmic discrimination Sen. Cantwell (2024). The Act also includes establishment of an Artificial Intelligence Safety Institute and tasking tasked (NIST) with developing a voluntary risk management framework to ensure AI systems are trustworthy.

The Act requires proactive and continuous efforts to ensure that AI systems do not produce biased outcomes based on protected characteristics although focus on development of voluntary standards and metrics. The Act includes provision for human alternatives and oversight in AI systems ensuring mechanisms for human intervention in automated decision-making. This is an aspect that is a focus on in this research as we define a process that involves the underwriter oversight as an inherent part of the process.

US States

The Colorado State Department of Insurance adopted regulation *Notice of Adoption - New Regulation 10-1-1 Governance and Risk Management Framework Requirements for Life Insurers' Use of External Consumer Data and Information Sources, Algorithms, and Predictive Models — DORA Division of Insurance* (n.d.) requiring insurers to remediate any unfair discrimination detected when using external consumer data and information sources (ECDIS) and any associated algorithms/models. The regulation requires from insurers a framework comprised of a gap analysis, compliance roadmap and risk assessment rubric to prioritize high-risk use cases of ECDIS. The insurer must further establish a cross-functional governance group to oversee the operation of the model as well as document policies, processes and procedures related to the full lifecycle of ECDIS from design, development and testing through to operation. Noteably specific documentation is required around racial bias testing. As noted by *The Final Colorado AI Insurance Regulations: What's New and How to Prepare* (n.d.) the requirement to remediate detected discrimination could raise concerns about unintended consequences.

This is significant legislation in being the first to specifically address predictive models in insurance imposing specific governance and risk management requirements on insurers, and frameworks to prevent and remediate algorithmic discrimination in addition to regular auditing of their AI models. This includes documenting policies and procedures, ensuring senior management accountability, and addressing consumer complaints about AI system usage.

Colorado's AI legislation sets a precedent in the US for comprehensive regulation of high-risk AI systems, strengthens consumer protection, and fair practices in consequential decision-making processes.

Other States

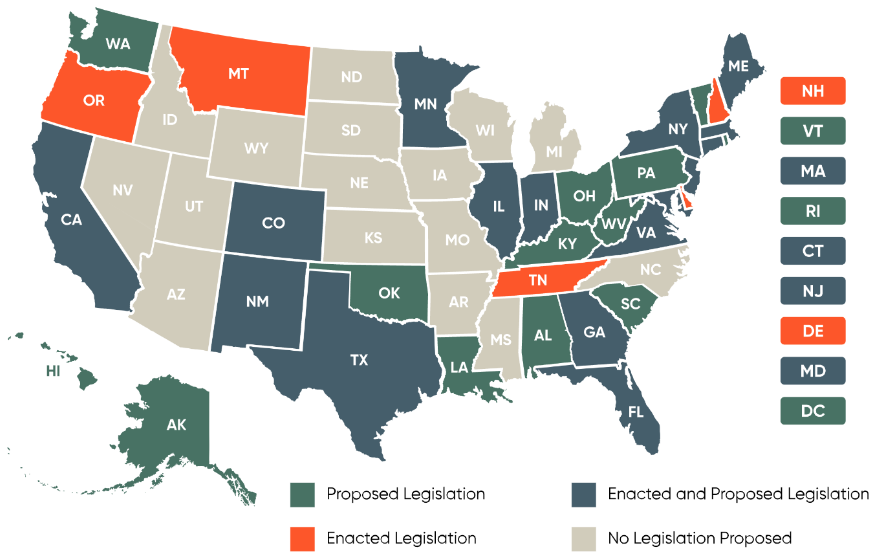

Figure 2.1: US State AI legislation status.Paisner (2024)

2.6.5.2 Europe

GDPR Article 22: Automated Individual Decision-Making

The General Data Protection Regulation (GDPR) *Art. 22 GDPR – Automated Individual Decision-Making, Including Profiling* (n.d.), implemented by the European Union in May 2018, is one of the most comprehensive data protection regulations globally. Article 22 of the GDPR specifically addresses automated individual decision-making, including profiling. It covers data subjects right not to be subject to automated decisions or "decisions made solely on automated processing", including profiling, without express consent, with non-compliance having potential for large fines (*Art. 22 GDPR – Automated Individual Decision-Making, Including Profiling*, n.d.).

EU Artificial Intelligence Act (AIA)

The European Union is also working on the Artificial Intelligence Act (AIA) *High-Level Summary of the AI Act — EU Artificial Intelligence Act* (n.d.), aiming to create a legal framework to regulate AI classifies AI systems into four risk categories. High-risk AI systems, such as those used in critical infrastructure, including transportation, energy), law enforcement, and healthcare (*High-Level Summary of the AI Act — EU Artificial Intelligence Act*, n.d.).

Insurance underwriting falls under the category of "Access to and Enjoyment of Essential Private Services and Public Services." AI systems used in insurance underwriting assess the risk profiles of individuals and determine the terms and pricing of insurance policies. Given the significant impact these decisions can have on individuals' financial stability and access to essential services, they are likely to be classified as high-risk under the EU AIA. High-risk systems must adhere to strict requirements, around transparency, accountability, bias mitigation, human oversight, and robustness. For this research in addition to performance we will evaluate the model under these criteria.

[paragraph from INS5103 work commented out - review and integrate]

2.6.5.3 International

The OECD Principles on AI call for AI systems to be transparent and accountable European Parliament. Directorate General for Parliamentary Research Services. (2019)and The Council of Europe is drafting a legal framework to ensure the development and use of AI respects human rights, democracy and the rule of law *ECHR - Homepage of the European Court of Human Rights - ECHR - ECHR / CEDH* (n.d.).

2.6.5.4 Analysis

Considering the rapid acceleration in the sophistication of machine learning models, we find that balancing the benefits of precise risk assessment with the social goals of insurance becomes more complex.

In general, while there is growing awareness of the need for algorithmic accountability and transparency, comprehensive legislation is still emerging. Existing laws provide some protections; for example, The US Equality Act 2010 Tobin (2024) prohibits discrimination in the provision of services, which could apply to algorithmic systems. However, more targeted regulation may be required to fully address the challenges posed by algorithmic decision-making systems.

For example, in addition to ensuring that individuals are not subject to bias or unfair discrimination, the Colorado State Dept of Insurance legislation *Notice of Adoption - New Regulation 10-1-1 Governance and Risk Management Framework Requirements for Life Insurers' Use of External Consumer Data and Information Sources, Algorithms, and Predictive Models — DORA Division of Insurance* (n.d.) requires insurers to prove and monitor this on an ongoing basis and to take remedial action where it might occur.

In some regions, regulations are more permissive of using certain types of individual data that can end up being used in the underwriting decision. However, this varies greatly by jurisdiction (e.g., stricter in EU with GDPR). In the US, in the experience of the authors that insurers have direct access to a wide range of medical and behavioural data on the individual from third-party data vendors, a survey of these "traditional" data types is provided in **?**. This is provided subject to the applicant's consent to the terms of the HIPAA, typically provided as part of the application process.

It could be argued that regulators should also intervene to ensure fair access to insurance. This is pertinent in the context of the trend towards individualisation and the potential for individuals to lose out based on an apparent trend away from social solidarity of risk pooling towards more precise individual risk scoring.

2.7 Research Gap

Introduction

The life insurance industry has generally been considered a laggard in terms of technology adoption. Today, life insurance underwriting blends rule-based inference engines with referral to manual underwriting processes for complex and high-value cases. Fully automated application decision rates, also known as straight-through processing (STP), vary widely among insurers depending on client base profile, face amount, maturity of the rules base but typically vary between 30% to 80%.

Availability of large historical underwriting data sets at insurers, a competitive environment, and the desire to increase STP rates means a high level of interest in the potential of predictive models to improve STP rates. However, as adoption has been slow, this research contends that two significant contributing factors are lack of sufficient transparency in such models and their potential to undermine rather than augment the role of the underwriter.

Current State of Research

Contemporary literature in relation to insurance is relatively sparse, presumably relating to commercial sensitivities. A common theme in the research is the use of supervised machine learning techniques to create predictive models from the publicly available Prudential data set (2016) such as the research published by Boodhun and Jayabalan (2018) and Hutagaol and Mauritsius (2020) or more rarely, the results are published based on insurer proprietary underwriting datasets such as those published by MassMutual (Maier et al., 2019).

(@Note: will probably omit this paragraph as duplication or review and integrated..)

Maier (2019) asserts that "it is imperative that analysts and underwriters can effectively explain why an individual applicant received a given offer". This can be viewed in the context of Maier (2019) further observing that "machine learning models [have] become increasingly opaque" with even simpler linear models being challenging to interpret. Boodhun and Jayabalan (2018) and Wang (2021) employ SHAP and LIME techniques to provide a degree of interpretability to model predictions. Indeed Maier et al. (2019) also adopted an approach based on the same techniques to identify the relative contribution of each feature to a decision. However, it should be noted that these techniques do not provide a complete understanding of how the model arrived at its decision can be difficult to interpret for non-technical users amongst other limitations (citation needed)

A significant study was MassMutual training data that spanned 15 years to implement a mortality model and develop a life score metric with which to evaluate applications, reporting an increase of 30% in appliant uptake using the automated system and continuing to implement it fully, resulting in savings of millions of dollars over two years Maier et al. (2019). Wang (2021) at Lloyds of London is a researcher in this space notable for a focus on XAI. Wang trained a series of supervised models on reinsurer data with the best result from XGBoost with a test accuracy of 0.81 and using SHAP and LIME to explain decisions. Varadarajan and Kakumanu (2024) recently surveyed the work of nine researchers attempting to determine the optimum machine learning model to enhance the accuracy of predicted policy issue decisions and to determine the strategies used to arrive at individual risk predictions. All but one used the same Prudential data set with majority finding that either RandomForest or XGBoost being the most effective model, with a notable absence of focus on explanability result from the research. The origins of insurance are rooted in mutualisation of risk after reforming an initial more negative image associated with ”gambling on lives” in the 18th and 19thC (F. Ewald, 2019) being replaced with the principles of social solidarity and common security. The initial adoption of automation did not disrupt that focus on rules-based systems and decision support systems that support the manual underwriter. However, contemporary research focused on individual risk scoring models threatens this principle.

Identification of Gaps

It is recognised by Maier et al. (2019) that "topics related to fairness and transparency of complex models are equally crucial to study" However, explainability appears to be somewhat of an afterthought in much of the literature. Maier et al. (2019) admits the weakness of feature importance techniques such as SHAP that while "these quantitative contributions can serve as an explanation, ..these methods may not directly generate actionable explanations".

Contemporary research focused on individual risk scoring models threatens the traditional principle of risk mutualisation but is not much discussed in the contemporary technical literature, which appears instead to strive towards greater model accuracy. The reality is that insurers are unlikely to adopt such models in the decision making systems unless interpretability and explainability are also sufficient.

The limitation of previous studies is the lack of publicly available data sets, with the Prudential data set being used in the majority of studies, obfuscated to the extent that it is unclear to properly evaluate performance results. There is a clear gap in literature in the application of unsupervised techniques to this dataset, either to identify new features that may augment the performance of existing supervised techniques but more particularly in the context of building a potentially inherently interpretable visualisable model that is more explainable in terms of the reasoning behind individual decisions.

The dangers of the trend to individual risk score based to mutualisation is exposed in Cevolini and Esposito (2020) but no research endeavours to actually address this question in the related research studies.

Relevance of Identified Gaps

The gap that exists in relation to transparency relate to an emphasis on performance metric such as accuracy at the expense of interpretability and explainability.

The gap that exists in relation to a drift away from mutualisation towards a more profit-driven model that may ultimately undermine insurance markets and

disenfranchise more vulnerable consumers who are no longer able to avail of insurance, being squeezed out by insurer models that target them as no less profitable as individuals. An approach that reaffirms the notion of risk categorisations in predictive underwriting models while aiming to achieve comparable performance with typical supervised models can speak to Responsible AI.
The gaps that exist in underwriter decision support as opposed to underwriting automation can also speak to Responsible AI by retaining the pivotal oversight role of the underwriter remaining the key decision maker by being able to visualise and confirm the risk categories within the data before assigning risk assessments to the categories. This paradigm is more likely to be adopted than the former, which appears to trend towards greadually replacing the underwriter function. The visualisation capability should rather empower the underwriter, allowing potential discovery in the data.
The lack of data sets presents a challenge for any new research. Running the standard supervised techniques on a new proprietary data set would contribute significant value to the research. If this is not possible then running the standard.....

Research Focus

This research intends to explore the application of contemporary unsupervised learning techniques on the Prudential data set having the aim of providing a means for underwriters to visually fine-tune the identification of clusters so that they can closely align with predefined risk categories. The research will evaluate how closely the results from the use of such cluster identification can match the results from the supervised methods. The research will evaluate how risk classification predictions on unseen applications can be interpreted and explained in a user-friendly way that is potentially useful to underwriters and customer. Further, the research will evaluate how this application of advanced clustering algorithms can be used to explain predictions in a robust mathematical way that can withstand regulatory and legal scrutiny. The research will apply supervised methods as a reference for evaluation in comparison with unsupervised methods.

A key hypothesis is that application of unsupervised learning techniques for underwriting risk classification can provide models suitable for development into tooling for use by underwriters to augment understanding of the data, reviewing and applying risk categorisations for use by automated decisioning system. Another hypothesis is that these models are inherently more interpretable from the perspective of being visualisable and explainable from the perspective of having known mathematical techniques underpinning the definition of the clusters. This contrasts with the supervised approaches, which are effectively black-boxes in terms of and so rely on post hoc explainability techniques which lack sufficient mathematical rigour in explaining decision rationale.

Conclusion

The research community has explored different methods to enhance the interpretability and explainability of AI systems, ranging from formal definitions of interpretability to visual explanations and strategies to improve task performance based on generated explanations. However, the literature also highlights a gap in focus on the explainability of machine learning models decisions, indicating the need for further research to develop new strategies tailored to specific fields of application (Gunning et al., 2019, p. 3). This research aims to contribute to this gap by developing a novel strategy aimed at enhancing explainability AI systems in the domain of life insurance.

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Additional sections for Literature Review or Analytical Background section..

2.7.1 Fairness in Predictive Models

2.7.1.1 Definition and Importance of Fairness

2.7.1.2 Common Biases in Predictive Models

2.7.1.3 Techniques to Ensure Fairness

2.7.2 Interpretability and Explainability in AI Models

2.7.2.1 Definition and Importance

2.7.2.2 Existing Frameworks and Techniques

2.7.2.3 Challenges and Solutions

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3

Analytical Background

The Experiments and Results section will contain a detailed account of the experiments conducted and the results obtained.

3.1 Theoretical Framework or Models

3.1.1 Methodological Approaches

3.1.1.1 Data Preprocessing

Both Boodhun and Jayabalan (2018) and Hutagaol and Mauritsius (2020) studies preprocess the Prudential dataset using Missing At Random (MAR) and multiple imputation methods to replace missing values, omitting features with greater than 30% missing values. Boodhun and Jayabalan (2018) tested CFS and PCA dimensionality reduction techniques eventually reducing the number of attributes to twenty using PCA. Hutagaol and Mauritsius (2020) essentially follow the Boodhun and Jayabalan (2018) study also combining medical keywords into a single attribute. In regard to preprocessing there is no significant variation in Boodhun's approach. On the other hand, Wang (2021) applies natural language processing and unsupervised techniques (k-means clustering) to those fields containing free-text descriptions of medical conditions and occupations prior to applying mutual information and recursive feature elimination (RFE) techniques for feature selection. In contrast with such automated feature selection approaches, Maier et al. (2019) instead bases selection on the advice of medical and actuarial experts, performing machine learning techniques to help validate and support the process.

3.1.1.2 Modelling

Boodhun and Jayabalan (2018) implemented basic algorithms on the Prudential dataset to build predictive models using Multiple Linear Regression, REPTree, Random Tree and Multilayer Perceptron (MLP) algorithms. Next, Hutagaol and Mauritsius (2020) working with the same dataset implemented further machine learning algorithms namely Support Vector Machine (SVM) with various kernels, Random Forest and Naive Bayes determining the best model through analysis of resulting metrics including accuracy, precision, and recall metrics. Later, Wang (2021) employed ensemble methods of XGBoost (eXtreme Gradient Boosting), Random Forest, and Bagging with the aim of further improving underwriting decision predictive performance. While these studies focus largely on optimising well-known machine learning algorithms Maier et al. (2020) took a more nuanced approach focus modeling on the Random Survival Forest (RSF), discovering superior results to those from Cox statistical survival risk model and deep neural networks.

Discuss any theories or models that your research is based upon or influenced by.

3.2 Supervised Learning

3.3 Unsupervised Learning

3.4 Explainable AI (XAI)

Approaches...

3.4.0.1 Post-hoc

3.5 Interpretable AI

Approaches...

4

Methodology

The Methodology section will contain a detailed explanation of the research design methods and data analysis techniques used to conduct the research.

5

Experiments

The Experiments and Results section will contain a detailed account of the experiments conducted and the results obtained.

5.1 Datasets and Metrics

5.2 Implementation Details

5.3 Datasets and Metrics

5.4 Results on the ...

6

Conclusions and Future Directions

The Conclusion will summarise the main finding of the research and its implications for the field. It will also highlight the limitations and suggest directions for future research.

6.1 Summary

6.2 Conclusions

6.3 Contributions

6.4 Future Work

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