Open University of Cyprus

Faculty of Pure and Applied Sciences

Postgraduate (Master's) Programme of Study *Cognitive Systems*

Postgraduate (Master's) Dissertation

The Role of Cognitive Assistants in Medical Insurance Underwriting

Antonios Apergis

Supervisor

Loizos Michael

December 2023

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The present Postgraduate (Master's) Dissertation was submitted in partial fulfilment of the requirements for the postgraduate degree in Cognitive Systems.
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Summary

The prominence of Cognitive Digital Assistants in the domain of Medical Insurance Underwriting has experienced considerable expansion as the insurance sector further explores the advancements of the fourth industrial revolution. These sophisticated solutions, which are equipped with innovative algorithms, not only enhance the efficiency of the underwriting process but also prioritise a customer-centric approach. The Cognitive Digital Underwriting Assistant is not only a tool, but rather a transformational entity that leverages advanced artificial intelligence technology. The present learning system exhibits a constant drive for improvement, relying on human contact as a means to boost its capabilities.

One critical element of this endeavour is the dual-training mechanism. The system has been carefully crafted to facilitate the education of junior underwriters by offering them up-to-date information, analyses, and assistance with decision-making. This guarantees a swift adaptation to the complexities inherent in the underwriting process. Simultaneously, senior underwriters perform an essential function in refining the capabilities of the cognitive assistant. By means of machine coaching, these seasoned experts are able to readjust and enhance the AI's repository of knowledge, guaranteeing that its suggestions closely correspond to optimal methodologies within the industry and the unique intricacies of the organisation.

When machine learning is combined with arguments, a symbiotic relationship is created between the AI and its human consumers. The foundation of this interaction between humans and machines is mutual comprehension, which enables the ongoing adjustment of data. The reasoning mechanism integrated into the system not only provides health insurance applicants with risk classification recommendations but does so in a transparent manner, elucidating its justification in an informative and persuasive fashion.

The Cognitive Digital Underwriting Assistant aims to enhance the collaboration between junior and senior underwriters and enable seamless interaction between humans and machines. This advancement holds the potential to revolutionise policy issuance and management by combining technology and human expertise, resulting in unparalleled efficiency and precision.

Περίληψη

Η σημασία των Γνωστικών Ψηφιακών Βοηθών στην Ανάληψη Ρίσκου Νοσοκομειακών Ασφαλίσεων έχει ενισχυθεί αισθητά με την ανάπτυξη της τέταρτης βιομηχανικής επανάστασης. Οι προηγμένες λύσεις, εξοπλισμένες με προηγμένους αλγόριθμους, ενισχύουν όχι μόνο την αποδοτικότητα της διαδικασίας ανάληψης ρίσκου αλλά επίσης προκρίνουν μια πελατοκεντρική προσέγγιση. Ο Γνωστικός Ψηφιακός Βοηθός δεν αποτελεί μόνο ένα εργαλείο, αλλά μια μετασχηματιστική οντότητα που αξιοποιεί την προηγμένη τεχνολογία της ΤΝ. Το παρόν σύστημα μάθησης εκδηλώνει τη συνεχή προσπάθεια για βελτίωση, βασιζόμενο στην ανθρώπινη επαφή ως μέσο ενίσχυσης των δυνατοτήτων του.

Ένα κρίσιμο στοιχείο του μηχανισμού είναι ο μηχανισμός διττής εκπαίδευσης. Το σύστημα έχει διαμορφωθεί ώστε να διευκολύνει την εκπαίδευση των αρχάριων underwriters παρέχοντάς τους ενημερωμένες πληροφορίες, αναλύσεις και βοήθεια στη λήψη αποφάσεων. Αυτό εγγυάται γρήγορη προσαρμογή στις προκλήσεις που είναι χαρακτηριστικές στη διαδικασία ανάληψης ρίσκου. Ταυτόχρονα, οι έμπειροι underwriters συμβάλλουν στην εξέλιξη των δυνατοτήτων του γνωστικού βοηθού. Μέσω της μηχανικής καθοδήγησης, είναι σε θέση να προσαρμόσουν και να ενισχύσουν το αποθεματικό γνώσης της ΤΝ, εξασφαλίζοντας ότι οι προτάσεις της συμφωνούν στενά με τις βέλτιστες μεθοδολογίες εντός του κλάδου και τις ειδικές απαιτήσεις του οργανισμού.

Όταν η μηχανική μάθηση συνδυάζεται με επιχειρήματα, δημιουργείται μια συμβιωτική σχέση μεταξύ της ΤΝ και των χρηστών της. Η βάση αυτής της αλληλεπίδρασης μεταξύ ανθρώπων και μηχανών είναι η αμοιβαία κατανόηση, η οποία επιτρέπει τη συνεχή προσαρμογή των δεδομένων. Ο ενσωματωμένος μηχανισμός λογικής του συστήματος όχι μόνο παρέχει συστάσεις ταξινόμησης κινδύνου, αλλά το κάνει με διαφάνεια, επεξηγώντας τις αποφάσεις του με σαφήνεια και πειστικότητα.

Ο Γνωστικός Ψηφιακός Βοηθός Ανάληψης Ρίσκου ενισχύει τη συνεργασία μεταξύ underwriters και διευκολύνει την αλληλεπίδραση ανθρώπων-μηχανών, προσφέροντας τη δυνατότητα για επαναστατική αλλαγή στην έκδοση και διαχείριση ασφαλιστηρίων συμβολαίων με ασύγκριτη αποδοτικότητα και ακρίβεια.

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Chapter 1

Introduction

The insurance business, like several other industries, has experienced substantial changes, notably due to the emergence of modern technology and processes. The primary objective of this Master's dissertation is to thoroughly examine the complexities associated with these transformations, with a particular focus on the field of medical underwriting. The landscape of risk assessment and policy decision-making has undergone significant changes, ranging from the integration of rules and ontologies in the Semantic Web (Antoniou & Bikakis, 2007) to the emergence of machine learning in the non-life insurance sector (Grize, Fischer, & Lützelschwab, 2020). The significance of cognitive systems, which possess the capacity to connect human and automated thinking (Kakas & Michael, 2016), has grown crucial. Furthermore, the advent of Insurance 4.0 is characterised by the integration of conventional procedures with state-of-the-art technology, hence influencing the trajectory of the insurance sector (Nicoletti, 2021).

1.1 Background of the Study

Every industry has been impacted by the worldwide shift towards the fourth industrial revolution, and the insurance sector has been particularly proactive in its response and adjustment. Particularly profound is this transformation when viewed in the context of Greece. Digitalization and innovation are driving a paradigm shift in the Greek insurance market, which is characterised by its illustrious past and the country's distinctive economic challenges.

Throughout its history, the Greek insurance market has successfully navigated a multitude of economic disruptions, regulatory modifications, and evolving consumer inclinations. The nationwide economic crisis had extensive ramifications across various sectors, including the insurance industry. In the face of these obstacles, the sector exhibited fortitude by progressively adopting technological innovations to restructure its operational frameworks and approaches to consumer interaction. Greece's implementation of Insurance 4.0 is distinctive among all nations, as it combines internationally recognised standards with regional intricacies.

Digital technology adoption in Greece's insurance industry is a planned development adapted to the country's unique requirements rather than just following a worldwide trend. The Greek insurance market, which has always been based on interpersonal connections and conventional business procedures, is currently confronted with the task of fusing these age-old customs with the digitalized, networked frameworks that international standards need. There are several obstacles to this integration, such as guaranteeing cybersecurity, bridging the technology divide, and modifying legal frameworks to accommodate new business models.

As the Greek insurance industry commences this paradigm shift, it is critical to comprehend the intricacies of this transition, encompassing both the obstacles and the prospects that lie ahead. Insurance 4.0 in Greece entails a cultural shift in organisations towards data-driven decision-making and customer-centric services, in addition to the deployment of new technologies. The shift from conventional supply-chain models to digital, interconnected value network systems is a strategic imperative, not merely a technological one. Nicoletti (2021) provides valuable perspectives on the evolution of the Greek market through the lens of the worldwide shift towards Insurance 4.0, with a particular emphasis on the contributions of technology, data, and collaboration to industry expansion.

This dissertation aims to conduct an in-depth analysis of the insurance sector's transformation during a critical juncture. It will specifically concentrate on the influence of intelligent systems, real-time data exchange, and digital integration on the sector's future course.

1.2 Objectives of the Research

An important strategic shift towards automation and data-driven decision-making is demonstrated by the introduction of intelligent systems, which will bring about a major transformation in the insurance sector. This dissertation's main goal is to find out how these cutting-edge tools and the algorithms that go with them are modernising insurance procedures. Intelligent systems exhibit remarkable skills, frequently outperforming conventional computing programs, in their capacity to learn from data, adjust to novel situations, and carry out intricate tasks. Insurance firms can use artificial intelligence and machine learning to improve customer experiences and increase productivity by integrating these systems and streamlining procedures.

1.2.1 Enhancing Health Underwriting

Accelerating the underwriting process has been a key development in the modernization of insurance operations. Underwriting, the foundation of the insurance business, is the process of carefully evaluating the risks involved in providing coverage for people and property as well as carefully deciding on the parameters of the policy and the amount of the premium. These duties have historically been typified by labor-intensive and prone to error manual methods, which have resulted in lengthy processing times and inconsistent conclusions that cast doubt on the accuracy of underwriting results.

By integrating cognitive intelligence into these systems, cognitive digital assistants can bring a paradigm shift in underwriting by greatly expediting the decision-making process. With the help of sophisticated data analytics and pattern recognition, these cutting-edge tools can quickly go through and analyse massive amounts of data in order to identify possible risks and improve underwriting choices.

The underwriting process is made more accurate and efficient by utilising the powers of cognitive digital assistants. By ensuring consistent application of policy norms and adherence to risk thresholds, this automation helps to reduce the unpredictability that frequently results from human judgement. This technical leap is best illustrated by the launch of the Digital Assistant for Health Underwriters, which exerts the company at the forefront of industry innovation targeted at managing and demystifying the complexity inherent in health underwriting.

Underwriters play a crucial role in the insurance industry. They are entrusted with the difficult duty of analysing health risks, which requires them to navigate through large amounts of data in order to identify trends and derive useful insights. By giving underwriters access to advanced analytical tools that improve their capacity to make well-informed judgements about policyholder coverage and premium calculations, cognitive digital assistants supplement this process.

Therefore, the Digital Assistant for Health Underwriters is a revolutionary step in the industry's digitization process. It represents the fusion of knowledge and technology, giving underwriters a strong ally in their quest to deliver customised, fair, and financially sound insurance solutions. The future of insurance operations promises to be one in which underwriting speed, accuracy, and efficiency are not just aspirational but rather realised standards, thanks to the integration of such intelligent technology.

1.2.2 The Role of Cognitive Digital Assistant

The underwriting process is accelerating, which is a crucial development for the modern insurance industry and a key component in its modernization efforts. The foundation of the insurance industry, underwriting, necessitates a thorough evaluation of the risks involved in providing assets and individual coverage as well as in determining the parameters and cost of policies. Traditionally, underwriting has struggled with long processing times and erratic decision-making due to manual labour and human error. On the other hand, the cognitively intelligent digital assistants of today provide a new era for this complex process.

These cognitive algorithms quickly traverse through large databases by using sophisticated data analytics and pattern recognition. Their expertise is in identifying possible hazards and creating the best underwriting choices, which helps to accelerate and improve the accuracy of the underwriting procedure. Automation of this kind maintains risk thresholds with unmatched accuracy and upholds strict policy requirements, acting as a beacon of consistency.

The Digital Assistant for Health Underwriters has been meticulously designed to enhance the effectiveness, precision, and uniformity of the underwriting function in response to the request for innovation. This innovative tool explores large datasets in great detail to find patterns and abnormalities that are invisible to the human eye. By deploying it, the risk of human error and the unpredictability resulting from subjective decision-making are reduced. Through algorithmic precision, the Cognitive Digital Assistant makes sure that underwriting judgements are firmly based on data-driven insights, eliminating any layers of bias or intuition that may have previously obscured judgement.

The industry's dedication to changing and adapting is demonstrated by the rise of these digital assistants, which guarantee underwriting decisions are made more quickly and with a level of accuracy that was previously impossible. Underwriting is destined to evolve from being merely an administrative duty to a strategic asset that is essential to creating just, inclusive, and financially sustainable insurance solutions as we embrace this technology innovation.

1.2.3 Implications of Transitioning to Insurance 4.0

After incorporating the Cognitive Digital Assistant into their process, underwriters have the oppurtunity to enter a revolutionary age. This advanced instrument not only expedites the decision-making process but also imbues it with an unparalleled degree of accuracy. The insurance sector will probably experience a paradigm shift as a result, moving towards a more transparent environment where underwriting decisions are made based on individual risk profiles rather than general demographic trends and take into consideration a variety of elements that specifically define an individual's risk profile.

With the launch of the Cognitive Digital Assistant, health underwriting will increasingly take a data-driven, open, and equitable approach. These tools are becoming essential for the insurance industry to successfully traverse the increasingly complex world of healthcare in this day and age. This change is essential for insurers to maintain their social responsibilities and increase commercial efficiency.

Insurance 4.0, a response to the fourth industrial revolution, is forcing the sector to integrate a number of emerging technologies, such as big data analytics, IoT, and AI. Through the use of intelligent systems and automated methods for processing applications, this shift promises to completely alter customer service by providing a more efficient and personalised experience. By offering self-service options and prompt responses, these advances boost consumer happiness and loyalty.

But this development comes with its own set of difficulties, as insurers have to deal with the complexities of data security, privacy issues, and legal compliance. Furthermore, it's still a pressing issue how to combine automated procedures with human knowledge. Intelligent systems can be useful, but human underwriters' knowledge and judgement are still valuable, especially in complex instances.

To sum up, this dissertation intends to shed light on the significant influence that intelligent systems have on the insurance sector, clarify the benefits of using cognitive intelligence to improve underwriting procedures, and investigate the broader ramifications of shifting to a more networked, data-driven, and customer-oriented business model. The results will give insurers a strategic road map for navigating Insurance 4.0, highlighting opportunities to increase productivity and profitability as well as tactics to overcome the inherent difficulties of this significant shift.

1.3 Statement of the Problem

Historically, the insurance industry has been seen as conservative and reluctant to adopt new ideas. The foundation of its traditional business strategy, which has endured for generations, is the development of dependable, trust-based client relationships. Strong entrance obstacles like strict rules, the size required to create diversified risk portfolios, the time needed to develop client trust, and a sizable amount of customer inertia have all contributed to this resistance to change.

In spite of this, the rate of change has accelerated in recent years and poses a danger to established business norms. Technology has raised customer expectations for better, more individualised service across all channels. Customers now expect providers to know and anticipate their specific wants and preferences. Innovation is becoming more and more necessary for insurance companys in this changing environment, going beyond being a "nice-to-have." In order to improve efficiency, insurers must embrace innovation in order to enhance their skills, optimise their operations, and reinvent their roles. Customers stand to benefit from more advanced goods and services through innovation, which might completely transform their experience.

The insurance sector is currently facing three major challenges: the hazards posed by newly developed automated systems, the inefficiencies of traditional underwriting procedures, and the ongoing discussion about how best to balance algorithmic precision with human judgement. Every facet offers unique obstacles to overcome and chances to take advantage of. This is a critical juncture where automated technology have the power to completely change the direction of the industry while also casting doubt on long-standing practices.

Although automated technologies reduce the inefficiencies of traditional underwriting, they also bring with them a new set of difficulties. An over-reliance on these tools may result in a loss of human interaction and the possible ignoring of consumers' complex needs. Furthermore, it becomes challenging to track down the reasoning behind specific results due to the opaque nature of AI "black box" decision-making processes, which raises questions about accountability and transparency. In addition, there is a serious risk that algorithms will incorporate systemic biases, which could, if left unchecked, result in unfair or discriminatory practices. Another critical concern is data security, since these systems frequently handle sensitive data that is open to online attacks.

The selling of a promise is the foundation upon which the insurance industry is based, and agents have historically represented this trust. But with the introduction of digital virtual assistants and cognitive systems, which greatly improve the quantity and calibre of assistance available, this fundamental component is under threat. Although deploying cognitive systems as advisory tools might initially be advantageous for intermediaries, these systems are becoming more and more sophisticated to the point where they can function as independent insurance experts, which will lessen the need for human agents.

Potential downsides of automation include decreased human involvement in customer service, algorithmic prejudice, and heightened susceptibility to cyber threats. These offset the potential advantages of automation, such as enhanced efficiency and precision. This dissertation aims to explore the delicate balance between the efficiencies offered by automation and the trusted human touch that has long defined the insurance industry. It will be set against the robust regulatory and ethical frameworks that characterise the Greek insurance market.

1.4 Significance of the Study

In the insurance business, the traditional underwriting processes, which mainly depend on the manual gathering, combining, and assessment of supporting documents, present serious difficulties. Due to the overwhelming amount of work involved in this labor-intensive process, past performance and experiences are frequently overlooked. As a result, the creation of policies can take several days. But underwriting is about to change. It is anticipated that underwriters will work together more efficiently all along the way, which will help them make decisions about policy quickly, precisely, and affordably.

An intelligent underwriting assistant such as the Cognitive Underwriting Assistant offers significant business value in the context of digital transformation for insurance-related businesses. With the use of big data analytics and a digital platform, this cognitive solution seeks to modernise the underwriting process while improving decision-making and productivity. It uses real-time analysis to pinpoint risk factors and has the potential to expedite the delivery of policies to clients.

This solution helps businesses create and assess risk profiles and set premiums by using Cognitive and Predictive Engines. The Engine expedites the underwriting process by utilising data from multiple external sources. In order to quickly produce policies, it uses cognitive computing to identify meaningful signals and "cause and effect" relationships in risk indicators. In addition to speeding up the creation of policies, this data-driven methodology frees up human experts to work on more complex aspects of risk assessment, costing, and product development.

Moreover, the Cognitive Digital Underwriting Assistant greatly improves the accuracy of pricing and risk assessment decisions. It quickly adjusts to new trends and recognises operational problems or opportunities as they arise. Better decision-making and more efficient application procedures characterise this redesigned underwriting strategy, which eventually results in better customer service, more output, and more earnings.

The study examines how important Cognitive Underwriting Assistants are to streamlining the underwriting procedure, highlighting both their effectiveness and their contribution to a customer-centric mindset. The dissertation explores the ways in which these systems enhance performance and adjust to the changing demands of the sector. Cognitive Underwriting Assistants are not just tools; rather, they are revolutionary forces that are redefining the underwriting market. The dual-training mechanism of Cognitive Underwriting Assistants guarantees that AI recommendations are in line with both organisational nuances and international best practices by allowing senior underwriters to fine-tune the system's intelligence while allowing junior underwriters to quickly adapt to industry standards.

The study emphasises the benefits of combining human reasoning and machine learning to create more intelligent, transparent, and sophisticated risk assessments. This is achieved by looking at how Cognitive Underwriting Assistants and human underwriters can collaborate together. This cooperation is essential to striking a balance between automated efficiency and human judgement.

Finally, by showcasing the strategic importance of Cognitive Underwriting Assistants in the medical insurance underwriting procedure, this study may establish new benchmarks for the sector. A new era of accuracy and efficiency in policy management and underwriting is promised by the integration of state-of-the-art AI with human expertise through intelligent systems, signalling a revolutionary shift in the industry.

Chapter 2

Literature Review

The global economy of the modern era has entered the fourth industrial revolution. Insurance 4.0 is defined by advanced digitalization and the industry's ongoing transformation. This chapter explores the concept of Insurance 4.0, characterized by its advanced digitalization and ongoing transformation, pivoting from a traditional supply chain model to a dynamic value network model. Intelligent devices and systems communicate with one another via interconnected functions, enabling organizations to use and share real-time data. Intelligent systems and associated algorithms are critical components in assisting insurers in streamlining their processes, enhancing their knowledge, and optimizing the performance of business decisions. Cognitive intelligent solutions accelerate the overall underwriting process by automating decision-making and reducing time-to-market.

2.1 Overview of Underwriting

Underwriting is a critical function in insurance, involving risk evaluation to determine policy issuance. Insurance underwriters evaluate risk in insurance proposals to determine whether a policy should be issued or if modifications are necessary based on the applicant's risk profile. Based on a risk category, the underwriter determines whether the applicant should be approved for coverage. Underestimating the risk would entail the applicant paying insufficient premium to cover the financial risk associated with insuring that individual. Overestimating the risk would result in an uncompetitive premium and, ultimately, customer loss. The risk category is determined by risk factors such as the insured person's age, gender, and occupation. Within insurance portfolios, risk profiles vary. As a result, the underwriters classify the portfolio into homogeneous risk classes, or groups of policyholders who share similar risk factors (Denuit, Hainaut, & Trufin, 2019). However, when policies are tailored to individual needs, such as health insurance policies, it is clear that each policyholder becomes unique, even for large portfolios. To conduct risk assessments, linked policy and claim information at the individual risk level is required. The data used to perform risk classification is condensed into a set of features. Each characteristic may take on a variety of formats, including categorical (male and female), discrete (number of children), and continuous (number of children) (age). According to the corresponding retail life underwriting report from Generali Hellas Insurance Company S.A., the end-to-end process for generating a life insurance policy can take up to twenty or thirty working days. The underwriter must make a decision quickly, accurately, and economically. It is necessary to be assisted in this transformation by intelligent systems that provide new underwriting insights that improve application process flow and risk estimation, ultimately resulting in improved customer service and profitability. This section examines how intelligent systems are reshaping this process, facilitating quicker and more accurate decision-making, thereby enhancing customer service and profitability.

2.1.1 Evolution of Underwriting

Management of uncertainty and cost sharing are mutual benefits of insurance. An insurance policy is essentially a contract in which the insurer agrees to pay a policyholder's premiums in exchange for covering specific losses up to predetermined limits. The insurance industry's main pillars are its clear, transparent processes and stable economy. The industry includes a range of insurance products, including life, property, and liability, as well as those mandated by legislation. These values of openness and justice are enforced in the insurance industry by European regulators, which support general financial stability.

Drawing from Nicoletti (2021), insurance has its origins in prehistoric customs, such as the practice of prehistoric humans stockpiling food for the hard winter months. The insurance market has changed over time due to changes in society, technological advancements, and individual demands. From Insurance 1.0 to the current period of Insurance 4.0, the market has seen multiple significant eras of evolution. The first industrial revolution began with the invention of the steam engine, which replaced human labor with machinery and laid the groundwork for contemporary mass manufacturing and infrastructure. Transportation also advanced throughout this time, with the growth of railroads, aircraft, and naval transport being the most notable examples.

Companies like the Railway Passengers Assurance Company introduced innovative products like disaster insurance in 1848, marking the beginning of the first industrial revolution. The telegraph, electrification, and new work procedures brought about by the next revolution improved transportation and communication even more. During this period, governments started implementing national health and retirement insurance programs, which signaled the beginning of an increasingly international approach to insurance management.

The advent of computers marked the beginning of the third revolution, sometimes known as the digital revolution. The separation of hardware and software as a result of this technological advance allowed for greater flexibility and creative problem-solving. Desktop automation systems were first used by independent insurance agents as a way to cut expenses and increase productivity. The standards-setting body Acord created standards like AL3, XML, OLife, and ObjX that facilitated international communication within the industry and streamlined operations. The industry has saved a significant amount of money by avoiding the creation of thousands of proprietary forms thanks to the Acord forms.

The fourth industrial revolution, known as Industry 4.0, is currently underway, fusing information and communication technologies with industrial practices. The smart insurance system, which combines internet technologies with intelligent items, is being made possible by this integration. Insurance 4.0 integrates several technologies to reimagine conventional processes, continuing the disruptive path set by its forebears. Organisations must rearrange responsibilities and ties to create what is referred to as a "value constellation"—an interconnected ecosystem—in order to flourish in this new climate. Systems need to be able to leverage automation and the internet of things to their full potential in order to keep up to date with Insurance 4.0.

2.2 The Emergence of Machine Learning

The insurance sector has undergone a paradigm shift with the advent of machine learning, especially in the areas of risk assessment and underwriting. This section delves into how insurers leverage machine learning to analyze vast datasets, thereby simplifying processes and achieving more accurate risk assessments. It also demonstrates the challenges and complexities involved in adopting these technologies. Insurers may now improve their decision-making processes by using advanced analytical models to derive meaningful insights from vast datasets. The incorporation of machine learning into insurance analytics is still in its early stages, but it has the potential to totally transform the insurance business through data-driven, intelligent decision-making and even in the face of obstacles like model complexity and the requirement for transparent interpretability.

2.2.1 Cognitive Mapping Techniques

Cognitive mapping approaches have shown to be a valuable tool for the complex task of insurance risk assessment. These techniques enable methodical study and graphical representation of the decision-making landscape. To further improve the process of identifying and prioritising risk indicators, Fernandes and Ferreira (2020) have creatively combined cognitive mapping with the MACBETH (Measuring Attractiveness by a Categorical Based Evaluation Technique) approach. The evaluation framework is guided and shaped by the in-depth knowledge of insurance industry professionals, whose nuanced observations are included in this hybrid technique.

Since big data entered the health insurance market, insurers have gathered enormous amounts of health-related data. When combined with cutting-edge analytics, this abundance of data has completely changed insurers' capacity to process, evaluate, and extract insightful knowledge that guides risk assessment. When cognitive mapping and the MACBETH approach are used together, decision-making becomes more organised and well-informed, allowing for the quantification of experts' subjective assessments and more accurate navigation of the complex world of risk.

In an era of plentiful data, insurers face difficulty in effectively managing and interpreting this data to facilitate smart decision-making. In this endeavour, methods like cognitive mapping and MACBETH are essential tools because they guarantee that expert knowledge is recorded and methodically used to evaluate risk, which in turn produces more fair and informed insurance decisions.

2.2.2 Machine Learning Algorithms

Machine learning is already enhancing the life insurance industry significantly. Actuaries and underwriters can recognize and classify patterns using machine learning technologies. As a result, underwriters are better informed, and they can make faster decisions about new policies and renewals, because they are presented with real-time visual representations of internal and external risks. Grize et al. (2020) emphasized the importance of relevant data and their use in developing machine learning algorithms to address the problem of policy retention and the implementation of a model for dynamic pricing in online motor insurance in their study.

Algorithms for machine learning (ML) are improving analytical problem solving in the insurance industry. ML algorithms include deep learning, extreme gradient boosting (XGB), algorithmic approaches, and conventional multivariate statistical modelling. They perform better than traditional modelling, manage large amounts of data efficiently, and can be automated to expedite installation. Many machine learning models lack interpretability, which could restrict their use. The challenges faced by nonlife insurance ML applications are IT infrastructure, trust, premium volatility, ethical data ownership, and data preparation. Machine learning (ML) is used in nonlife insurance to analyse data. This includes traditional multivariate statistical modelling, algorithmic techniques like CART, NNs, and more recent methods like XGB and deep learning. ML is valuable because to its new and better algorithms as well as its innovative modelling techniques. New techniques fit several models with many parameters fast by utilising massive computational resources. Time and money can be saved by automating feature analysis and hyperparameter estimation. Pricing, claims, marketing, and prevention are examples of actuarial or analytical insurance problems that ML technologies excel at solving.

Machine learning is used in private/commercial predictive maintenance and household insurance retention models.

Analytics aid in the underwriting process by ensuring that the appropriate premiums are charged for the appropriate risk, thereby avoiding adverse selection. Traditional risk classification methods, which group insured persons according to their estimated level of risk, are extremely time consuming. Boodhun and Jayabalan (2018) investigated predictive modeling using a variety of different learning algorithms, including Multiple Linear Regression, Artificial Neural Network, REPTree, and Random Tree. The findings indicated that machine learning algorithms are capable of accurately predicting an insurance applicant's risk level. Predictive analytics is used in the study to precisely categorise application risk levels, which enhances underwriting. This will simplify the procedure and maintain insurers' competitiveness. Supervised learning techniques such as Random Tree, Multiple Linear Regression, and Multilayer Perceptron are used in predictive models. While Random Tree and REPTree are good classification trees, artificial neural networks can make better predictions by learning from neurons that are connected to one another. By exposing data structure, these techniques aid researchers in refining predictive models.

2.3 Rise of Cognitive Systems

This section discusses the role of cognitive systems in streamlining insurance processes. These systems enhance business decision-making and optimize performance. However, challenges exist, such as ensuring transparency and the necessity for human expert involvement in complex decision-making contexts.

Intelligent systems and associated algorithms are critical components in assisting insurers in streamlining their processes, enhancing their knowledge, and optimizing the performance of business decisions. Cognitive intelligent solutions accelerate the overall underwriting process by automating decision-making and reducing time-to-market. A common challenge is the difficulty of ensuring the transparency of a relevant assessment, particularly when there is a lack of relevant historical data to quantify the models used in decision and risk analysis. Hence, while machine learning-based methods are used to assess risk in many fields of decision and risk analysis, the inclusion of human experts is still necessary, particularly in adversarial contexts (Werner and Ismail, 2021). As Kakas and Michael (2016) stated, users, who are also known as collaborators, expect the system to use common sense to fill in any critical details left unclear by the user and to continue learning about the application's domain and the user's personal interests and beliefs through their interaction.

2.3.1 AI in Insurance

The insurance sector is undergoing a major transformation thanks to artificial intelligence, which is improving underwriting, fraud detection, and customer service, among other areas. According to Ikonomi et al. (2022) Insurance businesses can now use artificial intelligence and machine learning technology to automate procedures and extract data using Natural Language Understanding (NLU) from a variety of sources, including social media, SEC filings, and online reviews. This development lowers errors, enhances communication between insurers and insured parties, and results in more precise risk assessments and pricing strategies.

Because AI can analyse data and documents, it can make more accurate predictions and thus lessen the need for human specialists, which helps to prevent fraudulent activity. Deep learning, open-source data ecosystems, AI-enabled apps, and intelligent personal assistants are all examples of how technology is developing. These technologies increase productivity in the industry by handling both routine and complicated documentation duties. By identifying savings for clients and helping with home chores, AI-enabled personal assistants and algorithms are predicted to further transform the sector by 2030. AI-powered cognitive models will provide bindable offers, which will help insurance businesses expand and engage with their customers on a deeper level.

Companies like AXA and Fukoku Life Insurance, which employ Google TensorFlow and IBM Watson Explorer, respectively, for policy optimisation and claim processing automation, are prime examples of how AI is being used practically in the insurance industry (Kumar, Srivastava, & Bisht, 2019). The application of H2O.ai machine learning by Transamerica is a prime example of developments in marketing and consumer intelligence. In order to improve customer service, revenue, and innovation in the insurance industry, artificial intelligence (AI) technologies including machine learning, smart robotics, object identification, and predictive analytics are being used.

AI is also used in context awareness, virtual assistants, recommendation engines, natural language processing (NLP), and predictive analytics APIs. These tools enable context-aware proposals for policies, comprehension of the complexities of human language, and improved engagement. In addition, they provide customer insights, sales and marketing optimisation, and future event and behaviour forecasting.

There has been a notable increase in investments in artificial intelligence (AI) aimed at achieving several objectives, including the enhancement of risk pricing, automation of claims processing, and improvement of client experiences. While artificial intelligence's use in underwriting and fraud detection improves processes and fights fraud, its function in natural language processing helps clients in a variety of interactions. Artificial Intelligence has the potential to be used in risk prevention and underwriting, as seen by the emergence of new forms of cyber insurance coverage and cooperation with major insurers in autonomous vehicle initiatives like Oxbotica's DRIVEN. In general, artificial intelligence is a major factor changing the insurance sector by increasing profitability, efficiency, and client pleasure.

2.3.2 Benefits and Challenges

Artificial intelligence is revolutionizing the way computers learn and think like humans. Cognitive science suggests that moving beyond technological trends in terms of what and how computers learn can help explain how quickly human minds absorb information from their surroundings. Intuitive psychology, which involves understanding objects and agents, is a critical component in designing a Cognitive System. Human-like learning and reasoning are shaped by early experiences in ways that are not possible with modern machine learning. Deep neural networks can foresee the stability of three-dimensional structures without explicitly modeling causal interactions in three dimensions. This allows for efficient learning from others, particularly in educational settings where knowledge is communicated through immersive experiences like Frostbite and Google's DeepMind artificial intelligence project.

Compositionality is another significant consideration in designing a Cognitive System. Domain information is used to build learning models, such as image and caption-generative models of images, which tackle pattern recognition problems using vast data sets and little topic expertise. Compositionality has inspired AI and cognitive science concepts of object recognition, mental representation, and language. Causality is a key third component in designing a Cognitive System. Deep neural networks are tasked with inferring causal models from instances, which may be used for Frostbite and Characters assignments but may not yet pass the visual Turing tests.

The capacity to infer is a fourth critical factor in designing a Cognitive System. Deep neural networks can act as bottom-up proposers to facilitate probabilistic inference or as causal general models. When old and new models share characteristics, learning-to-learn can occur. The speed of cognition is the fifth key component in the design of a Cognitive System. As abilities become habitualized, the control paradigm shifts from model-based to model-free. If neural networks are pre-trained on the same experience, they can do as well as humans at learning new tasks. Neuroscience can serve as a source of inspiration for artificial intelligence and cognitive models. Language is necessary for the development of machines capable of learning and thinking, improving compositionality and learning-to-learn capabilities.

Cognitive architectures are intended to make it easier to execute generic intelligent behavior. We can ascertain an architecture's generality by building intelligent systems capable of performing a number of tasks and operating in a variety of environments. The more instances in which the design supports intelligent behavior, the broader it is. Adaptability is related to the generality and task capability of a cognitive architecture. The less effort required to generate intelligent behavior across a variety of circumstances, the more adaptable an architecture is.

By examining the relationship between the framework's objectives, knowledge, and behaviors, we can ascertain its logic. Cognitive architectures must be capable of accomplishing tasks within constraints in terms of time and space. Efficiency can be quantified by assessing how work complexity, environmental unpredictability, operating time, and other complicated elements affect it. The less impact these aspects have on the efficiency of an architecture, the more scalable it is. The responsiveness of an architecture is defined as its ability to respond rapidly to unforeseen events or occurrences. Additionally, it is the probability of responding inside a particular recognize-act cycle. While it may appear that reactivity and persistence are mutually exclusive at first glance, they are not. A design that is constantly responding to minor environmental changes risks losing sight of its long-term objectives. The capacity of an architecture to learn can be quantified in terms of its capacity to accomplish previously unachievable objectives. The rate at which performance improves as a function of programmer time can be quantified. Due to the fact that different types of learning focus on unique types of information, we should not expect that a single procedure can improve behavior universally. We want learning to encompass more than simply recalling specific occurrences. We can determine an agent's degree of generalization and transfer by exposing it to environments and activities that are notably different from those encountered previously. The architecture must be robust enough to enable both autonomous and extended operation.

Argumentation is a common-sense science that can be used to construct novel cognitive systems. The psychological and computational perspectives on argument and cognition are discussed. Thus, communication is a shared responsibility between the user and the device. Computational argumentation may provide a more direct link between human and machine thinking than the traditional logic base on which automated systems are developed. It is a scenario model that demonstrates reasoning about premises based on their intended interpretation. The primary function of human reasoning is to elaborate on these inferences and develop rational arguments in favor of the final conclusion. Human beings strengthen their arguments by identifying counter-arguments to objections.

This technique is well-suited for developing cognitive systems such as personal assistants. Since the 1980s, a subfield of artificial intelligence known as argumentation has arisen, fueled by both the quest for intelligent systems with human-like reasoning abilities and the study of dialectic reasoning in a variety of domains of human cognition. Numerous AI challenges require agents to be autonomous and adaptable in ways similar to humans. It is a development of classical logic that is well-suited for thinking in both artificial intelligence and non-AI fields such as economics and politics. Computational argumentation may address the capabilities of human thinking.

Utilizing a dialectical acceptability definition, argumentation enables "on demand" reasoning. It is easily adaptable to human prejudices and assumptions. Cognitive assistants are a significant category of cognitive systems that aid in decision-making. Cognitive assistants make decisions on behalf of their users. By encoding user-specific preferences and biases, it enables natural solutions for representation, decision-making, and persuasion.

Users expect the assistant to use common-sense to fill in any critical information left unspecified by the user and to continue learning about the application's domain and the user's personal preferences and beliefs through their interaction in order to comprehend and supplement a system's reasoning. Belief arguments integrate knowledge about omitted data, causation of actions, and time. Humans reason in a way that prioritizes preferences above beliefs in order to form a coherent knowledge of a situation. This mode of thought is intimately connected with narrative comprehension. Cognitive assistants should share their users' capacity for cognition.

Additionally, the logical basis for human decision-making could be extended to tale comprehension. Consider it an internal judge of the results and preferences of a cognitive helper. After then, the cognitive assistant can begin supervising online learning. According to user feedback, the reasons for a conclusion are unacceptable, and the user's preferences for particular arguments must be revised. Argumentation is a natural complement to the process of learning.

Learned knowledge may transmit only conventional and logical connections between concepts, the strength of which varies according to the application domain environment. Cognitive systems exemplify a modern recognition of the importance of reconnecting with the fundamental basis of artificial intelligence while pursuing successful systems engineering. Within an argumentative framework, stimulating and inhibiting links may comprise defenses and assaults.

In conclusion, the integration of AI and machine learning into the insurance sector marks a significant turning point. While challenges remain, the potential for improved efficiency, customer satisfaction, and profitability is immense. As we continue to navigate through the era of Insurance 4.0, it's crucial for industry players to adapt and innovate, leveraging these technological advancements for continued growth and success.

Chapter 3

Ethical Dilemmas

Growing ethical dilemmas are a consequence of the increasing complexity of AI systems. Erroneous results may occur from bad data and methodological errors. AI has the potential to influence cyber-attacks in a way that enhances their effectiveness, accuracy, and evasion. Massive Turing tests involving Microsoft's Xiaoice and Tay chatbots demonstrate how the data-driven and objective nature of AI can introduce bias into input data. In an effort to prevent unintended harm caused by AI systems, the European Union has issued guidelines for the development of trustworthy artificial intelligence. If human liberty, freedom, and the rule of law are protected, then all will benefit from the advancements of AI. Human brains and computing machines will soon converge in a manner that surpasses the capabilities of information-handling machines of the present. This convergence will enable AI to surpass its current limitations.

3.1 The Ethical Imperative

Artificial Intelligence is a fast-moving set of technologies, while new discoveries, methodologies and tools are released every day. The Computational Intelligence area evolves with respect to human problems and questions evolution, creating room for further research on providing more efficient, stable and theoretically established algorithms in the CI field. AI technologies are already saving lives and transforming societies. If used wisely, AI can be used to tackle many of the world's greatest challenges. Used unwisely, however, AI can unintentionally amplify many of humanity's worst traits. If we are to trust multipurpose machines operating untethered from their designers or owners, we must be confident that their behavior satisfies appropriate norms. The challenge of ensuring that robotic systems will act morally has held a fascination ever since Asimov's three laws appeared in "I, Robot" (Anderson & Anderson, 2011). The European Union published guidelines for the development of Trustworthy Artificial Intelligence. The guidelines are intended to provide a foundation for faith in artificial intelligence systems. They seek to ensure that, even though AI systems have the best of motives, they do not inadvertently inflict damage. The rewards of AI will be reaped by everyone if human freedom, liberty, and the rule of law are respected.

3.1.1 Emerging Ethical Dilemmas in AI

The complexity of AI systems is increasing, leading to a corresponding expansion of ethical dilemmas. A plethora of machine learning systems are currently exerting influence on various aspects of our daily decision-making processes. Erroneous results may arise due to the presence of flawed data and methodological errors. In the state of California (Yao, Zhou, & Jia, 2018), the system recommended the release of a man that had previously multiple previous probation violations due to wrong input of the days that he had already spent in jail. This same man shot a local photographer five days after. Furthermore, the impact of AI on cyber-attacks can be substantial as it enhances the effectiveness, accuracy, and ability to avoid detection in these malicious activities. The integration of artificial intelligence (AI) into various technologies such as wearables, standard computing devices, and the Internet of Things (IoT) has become pervasive in our daily lives. However, this widespread adoption of AI also introduces potential security risks, particularly in instances where malicious actors exploit AI for nefarious purposes.

Although artificial intelligence (AI) is inherently objective and driven by data, any biases present in the input data used to train an AI system can persist and potentially be amplified. For instance, empirical studies have demonstrated that the sensors employed in autonomous vehicles exhibit a higher degree of accuracy in detecting lighter skin tones compared to darker ones. In addition, it came to the attention of Amazon customers that the option of same-day delivery was unavailable in areas where mainly black people are living.

AI is a fast-moving set of technologies, while new discoveries, methodologies and tools are released every day. Artificial intelligence technologies are already saving lives and transforming societies. If used wisely, AI intelligence can be used to tackle many of the world's greatest challenges. Used unwisely, however, AI can unintentionally amplify many of humanity's worst traits. It is critical to consider the manner in which we employ technology and ensure that its benefits extend beyond a select few individuals. As AI continues to transform our world, we must continue to ask difficult questions regarding accountability and how to ensure everyone's safety.

3.1.2 Formulating Ethical Guidelines

The establishment of an AI and ethical framework for the European insurance market has been undertaken by the European Insurance and Occupational Pensions Authority (EIOPA). The primary objective of this framework is to examine and tackle ethical concerns and contextual factors pertaining to the utilisation of big data analytics, artificial intelligence (AI), and machine learning within the insurance sector. The incorporation of Artificial Intelligence (AI) within the insurance sector is fundamentally transforming conventional methods by capitalising on the plethora of data in the era of digitalization and powerful data-processing technologies. The insurance industry, being inherently focused on data, can greatly benefit from the predictive accuracy, automation characteristics, and cost-saving efficiencies offered by AI.

The utilisation of AI was already widespread in 31% of European insurance companies, according to EIOPA's 2018 findings; furthermore, 24% were investigating the potential of AI; this trend was accelerated by the pandemic. This digital transformation enables the development of IoT-powered, custom-tailored products, including health monitors and vehicle telematics, which contribute to more precise risk assessments and pricing models.

Nevertheless, the proliferation of AI applications gives rise to ethical quandaries, predominantly concerning the customization of insurance policies. The growing customization of insurance policies carries the potential peril of compromising the mutualization principle, which could result in the exclusion of high-risk individuals from accessing affordable coverage. Additionally, extensive personal data reliance raises concerns regarding privacy and poses the risk of unfair treatment.

Regulatory entities encounter the intricate challenge of simultaneously fostering innovation and safeguarding digital ethics, non-discrimination, and equity amidst the ongoing digital revolution. International organisations, such as the OECD and EU, have endorsed principles of AI governance that prioritise accountability, transparency, and the protection of human dignity and autonomy.

The primary objective of this ethical framework is to strike a balance between the economic advantages of artificial intelligence in the insurance sector and the well-being of society and consumers. With the continuous evolution of the industry, insurers are obligated to incorporate these principles into their AI strategies, thereby recognising their ethical duty to utilise technology in a fair and considerate manner. Hence, in the realm of insurance, the emerging AI environment demands a strategic approach that reconciles market advancement with ethical obligations and regulatory oversight.

Holland, Mullins, and Cunneen (2021) investigate the relationship between big data and the insurance industry, scrutinize the ethical issues stemming from this interaction, and highlight the urgent need for new governance frameworks that address the inherent risks. Furthermore, this observation underscores the significance of ethical supervision within the insurance sector, given that the implementation of AI technology may result in biassed outcomes, information imbalances, and potential negative ramifications for the industry.

The amalgamation of ethical and governmental principles within the realm of insurance has prompted scholarly debates surrounding notions of equity, discrimination, and detrimental consequences. The implementation, for example, of telematics in motor insurance has the potential to mitigate gender-based variables, although it also gives rise to apprehensions regarding surveillance, autonomy, and privacy. The field of data ethics within the insurance industry encompasses the ethical considerations surrounding the processes of data collection, exclusion, and the preservation of human autonomy.

Model transparency and process transparency are two distinct concepts recognised by the Financial Conduct Authority (FCA). The incorporation of explainable artificial intelligence (AI) is of utmost importance in ensuring the ethical utilisation of big data and AI within the insurance industry. The EIOPA Expert Group on Digital Ethics emphasises the need for inclusive approaches that go beyond conventional thinking, and the best course of action is a strategic governance framework that combines several governance tools. This might entail encouraging stakeholders to make better-informed decisions when creating and providing insurance products and services to clients, with an emphasis on openness and explicability when it comes to machine decision-making, automation, risk assessment, and customer data when determining prices and providing insurance goods and services.

3.2 Bias in Automated Underwriting Systems

The ethical landscape surrounding automated decision-making systems is coming under more and more scrutiny, especially in delicate areas like medical insurance underwriting. Even though improving efficiency and objectivity is artificial intelligence's (AI) main goal, biases often surface in these systems. Empirical evidence has demonstrated that automated systems have the potential to perpetuate deeply rooted biases in society, taking these issues beyond the purview of theory.

While AI has significantly impacted the insurance industry, biases in its training data could still exist. Leying Zou and Warut Khern-Am-Nuai's empirical study from 2022 provides insight into the persistence of ethnic bias in previous mortgage approvals and how it becomes more pronounced when AI models are used without human oversight.

This issue is common in many industries, including health insurance underwriting. The research calls for a comprehensive analysis of fair machine-learning algorithms because of the unintended consequences that may arise from their implementation, which can impact all parties. Because discrimination is a morally and legally problematic use of AI systems, using AI in underwriting requires careful balance between using data to inform decisions and making sure those decisions don't infringe on people's rights. The research suggests a fair strategy that combines artificial intelligence's predictive powers with human experts' highly developed judgement. This approach seeks to lessen biases without sacrificing the dependability and integrity of underwriting processes. Ethical recommendations for the use of AI in underwriting may include transparent AI systems with integrated accountability measures, regular bias audits, and human checks to prevent discriminatory outcomes.

Bias that exists during the underwriting procedure can have serious repercussions. If historical data used to train machine learning models keeps reproducing discriminatory practices from the past, biases may continue to exist. Given AI's propensity to reinforce bias, a significant ethical conundrum emerges: how can we maximise automated systems' efficiency while maintaining the values of fairness and impartiality?

The ethical obligation becomes even clearer when one considers the possibility that these prejudices could result in unfair treatment of people based on their gender, race, or other legally protected characteristics. In addition to being a commercial concern, these biases may show up as higher premiums or the denial of coverage to specific groups. These actions also raise ethical and legal questions.

According to recent research, biases can be reduced by using algorithms that are intended to promote fairness. However, attaining equity in algorithmic decision-making requires a careful assessment of the trade-offs that must be made with respect to other performance metrics, like accuracy and predictive reliability. The difficult part is finding a balance between these frequently at odds interests.

Given the effects biassed AI has had on the insurance industry, strict ethical guidelines for its application are imperative. This is accomplished by putting in place transparent algorithmic procedures, conducting frequent bias audits, and incorporating human judgement to supervise and contextualise AI decisions. An ethical checkpoint system that not only identifies bias but also offers doable remedies to lessen its impacts ought to be established.

This dissertation explores the best practises for integrating AI to lessen bias in underwriting processes. Moreover, it will highlight how important it is to take a multidisciplinary approach that combines knowledge from data science, ethics, and law to guarantee that the use of AI in underwriting complies with social norms and values. The goal is to offer a strategic framework for the creation of AI systems that uphold social and ethical responsibility and demonstrate extraordinary technical skill.

In conclusion, there are advantages and disadvantages to using AI for medical insurance underwriting. It could increase efficiency and objectivity, but it also has the potential to foster prejudices. In order to ensure that the benefits of artificial intelligence (AI) are realised while maintaining the values of justice and equity, thoughtful analysis and action that tackles the complex and varied ethical issues surrounding this issue are necessary.

3.3 The Role of Transparency and Accountability

The integration of AI in life insurance underwriting has elevated transparency and accountability from mere regulatory obligations to critical pillars of client confidence. Sophisticated mortality models utilise considerable health data in order to compute life scores. Thus, ethical decision-making and transparent communication are imperative. Adherence to these principles ensures that advancements in predictive modelling provide equitable benefits for all stakeholders. The life insurance industry can foster an atmosphere of trust and patronage through the use of AI integration, which is facilitated by accountability and transparency.

3.3.1 Improving Accuracy and Transparency

For numerous households, life insurance is an essential source of financial security that helps lessen the financial blow of unexpected death. The goal of traditional underwriting techniques has been to strike a balance between risk assessment accuracy and cost effectiveness. However, there is a rare chance for artificial intelligence to revolutionise underwriting in the life insurance industry due to the introduction of new data streams and large historical datasets.

MassMutual (Maier et al., 2020) is at the forefront of this cutting-edge field and has created an advanced mortality model. Using artificial intelligence (AI), this model provides a personalised mortality risk score faster and more precisely than it can using traditional techniques. Notably, this enhanced approach has been demonstrated to reduce claims by nine percent among the group of healthiest candidates. These developments have the potential to improve customer trust through increased transparency, a wider range of options for acquiring life insurance, and easier access to individualised health and wellness initiatives.

Studies in this area have produced models that not only directly and precisely assess mortality risk, but also optimise some aspects of the underwriting procedure and imitate past underwriting judgements. Adopting a universal life score might increase customer portfolio diversification, encourage insurers to engage customers in wellness programmes, and democratise access to life insurance.

Maintaining industry and consumer trust through clear approaches and cutting-edge precision in long-term mortality risk forecasts is essential if the life insurance sector is to adopt such a life score.

The Mortality Model developed by MassMutual is an example of how cutting-edge research and medically validated inputs may be applied. It is based on about sixty factors that are obtained via biophysical measurements, blood and urine tests, and health history questionnaires. The main focus of this investigation is how artificial intelligence (AI) might improve risk selection in life insurance by creating an algorithmically driven model-assigned book of business.

These AI systems must be routinely assessed for accuracy and fairness in order to bring this model into compliance with moral principles and correct any potential biases. The insurance business can guarantee that the advantages of AI are realised without sustaining historical prejudices by implementing a human-in-the-loop strategy, in which knowledgeable underwriters evaluate and contextualise AI-generated scores. By maintaining the moral application of AI, this procedure guarantees that underwriting advances are fair and reasonable for all applicants.

3.3.2 Balancing Automation and Human Decision

Machine morality and the moral dilemmas posed by artificial intelligence, it is clear that, even as technology advances, it will remain crucial to strike a balance between human judgement and automation. With the advent of artificial intelligence (AI), a new paradigm has emerged in which computers act not just as tools but also as essentially autonomous entities. This has caused us to reconsider how human supervision and technical control intersect.

In the underwriting industry, the relationship between AI's analytical prowess and human judgement is very important. Even while AI can analyse vast amounts of data at unequalled speeds and with unparalleled precision, it is human moral judgement and contextual knowledge that ensures decisions are made with a sense of moral responsibility. AI's cognitive powers must be complemented by human purpose and morality, especially when making decisions that might have a significant impact on people's rights and the norms that society respects.

While we advance with the integration of AI into critical decision-making procedures, we also need to set up mechanisms that guarantee the continuous involvement of people at critical points. Artificial intelligence might increase objectivity and efficiency with this hybrid approach, but human oversight would provide the required checks and balances to guard against any ethical risks that could arise from automated systems. AI operations should be aligned with human values and interests; it is imperative to prevent AI activities from undermining societal cohesion.

The debate over moral agency is becoming more and more relevant as we anticipate how artificial intelligence technology will advance from its current level of weak AI to a likely future state of strong AI. Although AI is theoretically capable of having moral agency and free will, its current capabilities are still far from exhibiting such qualities. But the fact is rooted in the skills that AI has at this point. Therefore, it remains entirely the responsibility of humans to make moral judgements.

Artificial intelligence (AI) is given a moral responsibility that is reflected in the human values and ethical considerations included into its programming and operational design. Using this lens, we can make sure that artificial intelligence (AI) plays a positive role in the advancement of human civilization. This progress encompasses not only the political and economic domains but also our ethical customs and the pursuit of artistic aspirations. It is not only a technological issue; finding a solution that balances human judgement with automation is also morally required. This will guarantee that we don't stray from the moral principles that form the cornerstone of human civilization as we advance towards more autonomous AI systems.

3.3.3 Machine Coaching Shapes Ethically Sound Machines

A novel method for integrating moral thinking into AI systems is suggested by Michael in his 2020 paper, Machine Ethics through Machine Coaching. This paradigm shifts machine learning from being data-driven to becoming a participatory, iterative process where human feedback helps AI improve its decisions. The fundamental idea is that people can actually coach machines to make morally sound decisions in real life. In this method, human instructors assess the machine's reasoning as moral inspectors. When the computer is unable to provide an explanation, they provide refutations and contextual information. Through repeated interactions, machines acquire knowledge and adjust, aligning their decision-making with human morality.

This approach is comparable to legal reasoning, in which the context and purpose of a decision are crucial. Understanding the "why" behind decisions is just as important in self-driving cars as the decisions themselves. Legal systems and non-specialists equally cannot be made to understand such reasoning by current AI. Consequently, Machine Ethics via Machine Coaching addresses a critical gap in AI development. It guarantees that robots grow and change in accordance with human morality, enabling a never-ending learning process that mimics human morality. This tactic holds human coaches morally responsible and increases the transparency of AI decision-making.

Michael's research and the moral dilemma around AI are closely related. The Machine Coaching paradigm places a strong focus on moral concerns related to automated systems, namely human oversight and striking a balance between AI autonomy and human judgement. This paradigm provides a workable method for implementing moral oversight and ongoing education to ensure AI systems act morally towards human society.

According to the Machine Coaching paradigm, AI ought to be moral when trained to emulate the moral standards of its human coaches. It also brings up interesting questions about AI's accountability by drawing parallels with child ethics and parental duty. This work subtly supports a sophisticated theory of ethical development in AI that recognises the complexity of moral learning and the need of intentionality in moral action.

Chapter 4

Machine Coaching

This chapter examines the creation and possibilities of a cutting-edge underwriting assistant intended to transform the underwriting procedure for life insurance. The main goal of this research is to determine whether it is feasible to build an assistant that is able to make well-informed decisions and then defend them by developing persuasive and tenable arguments. It is anticipated that this assistant will greatly benefit life insurance underwriters by improving the efficiency of case screening, increasing the accuracy of assessments, and promoting informed decision-making.

The assistant's position is meant to be an addition to a traditional underwriter's. It seeks to enhance the underwriting procedure by raising the standard of counsel given and the information's accessibility. This will be accomplished by providing users with solid justifications for the ultimate decision-making process, thus addressing the crucial concerns of openness and user involvement in underwriting.

4.1 Overview of Machine Coaching

A common challenge is the difficulty of ensuring the transparency of a relevant risk assessment, particularly when there is a lack of relevant historical data to quantify the models used in decision and risk analysis. Hence, while machine learning-based methods are used to assess risk in many fields of decision and risk analysis, the inclusion of human experts is still necessary, particularly in adversarial contexts (Werner and Ismail, 2021). Experts in the underwriting process can overcome expert systems' limitations caused by a lack of relevant historical data and provide the necessary argumentation for the decision made. As Kakas and Michael (2016) stated, users, who are also known as collaborators, expect the system to use common sense to fill in any critical details left unclear by the user and to continue learning about the application's domain and the user's personal interests and beliefs through their interaction.

This paper will examine how to develop an underwriting assistant capable of making decisions and justifying them incrementally through the construction of acceptable arguments. The risk management systems that we studied was focused with codifying the underwriting process's guidelines. Due to the complexity of the decision-making mechanisms involved in the underwriting phase, accountability and decision reasoning are important for all stakeholders. The assistant that we want to introduce can assist life insurance underwriters in screening cases more efficiently, evaluating them more precisely, and making informed decisions. Insurance is a product built on the foundation of trust. Underwriters must be able to justify the risk assessment process's conclusion. Additionally, customers are demanding greater convenience and transparency when insurers decide to apply exceptions to final terms and conditions, such as an additional surcharge on the initial calculated premium or waiting periods for certain diseases. Insurance companies effectively sell a promise, with personal sales channels serving as the public face of this relationship of trust. Medical questionnaires are used to elicit pertinent information about the insured person's medical history and lifestyle.

Medical questionnaires are a requirement for insured people, and they are an essential tool for underwriters to use when assessing the risks at hand. This data, which includes a person's lifestyle and medical history, serves as the foundation for the risk assessment procedure that takes place before a life insurance policy is issued. Using this information, underwriters can determine the finer points of the insurance policy, such as the inclusion of exclusions, the imposition of premium surcharges, or the imposition of waiting periods for specific medical conditions. Under this situation, assistant underwriters play a critical role in improving advice quality and accessibility and adding another level of transparency to the decision-making process.

Underwriters' traditional roles are about to be redefined by the Cognitive Underwriter Assistant model that is being envisioned. This system is intended to enhance and supplement their capabilities during the risk assessment process, not to replace them. The assistant seeks to contribute to a more transparent and rational decision-making process by offering a nuanced understanding of the risks involved.

In the past, the goal of developing underwriting support systems was to generate impartial decisions. However, because this method only provided two options—accept or reject the decisions made by the system—it frequently reduced user engagement. Kontogiannis and Kossiavelou (1999) have observed that user resistance towards these systems may have been influenced by these limitations. Furthermore, there was frequently a disconnect between user expertise and system capabilities because these systems did not change with their users.

The goal of this cutting-edge approach to AI and underwriting is to close the knowledge gap between traditional support systems' static nature and human underwriters' dynamic expertise. With its promise of a more interactive, flexible, and cooperative approach to decision-making in the insurance underwriting process, machine coaching marks a substantial advancement in the development of support systems.

4.1.1 Description of Machine Coaching

According to Michael (2019), machine coaching is an interactive type of machine learning that places an emphasis on a cooperative partnership between people and machines. Machine coaching is an essential tool for improving decision-making in the insurance underwriting domain, especially when utilising the Cognitive Digital Underwriting Assistant.

Fundamentally, machine coaching is about information adaptation and mutual understanding between human and machine intelligence. It is predicated on externalising internal thought processes in a way that is understandable to both sides. This method, which promotes the creation of machine coaching paradigms that combine machine learning with human-machine interaction, is based on psychological theories of human reasoning and technical work.

Machine coaching has the potential to significantly increase the Underwriter Assistant's capabilities in the underwriting context. It permits the assistant to gradually develop arguments and explanations for the choices they have made. When evaluating risks using medical questionnaires and historical data, this interaction is especially important for addressing the issues of transparency and user engagement.

In machine coaching, the argumentation framework plays a crucial role in helping humans and machines come to mutual understanding. This procedure expands on the conventional underwriting knowledge by utilising cognitive computing to extract relevant risk indicators. Through the use of arguments in the decision-making process, machine coaching helps the Underwriter Assistant make decisions that are clearer and more logical.

Machine coaching creates a more dynamic interaction between users, going beyond traditional support systems. Machine coaching enables a deeper level of user involvement where users can refine and influence the assistant's policy, in contrast to previous systems that restricted user involvement to accepting or rejecting decisions. This strategy is in line with the bottom-up, data-driven approach to knowledge recommended by the McKinsey Global Institute.

Machine coaching tackles a range of organisational issues, including aversion to risk and mistrust of machines. It gradually cultivates confidence in the machine's performance by creating systems that can both explain and be explained to. The advice provided is guaranteed to be cognitively consistent with human reasoning thanks to this bilateral communication between the learner (the machine) and the target (the human advisor).

Finally, machine coaching is a major development in the field of cognitive digital underwriting. It offers a framework in which artificial intelligence (AI) systems are guided and improved by human expertise in addition to learning on their own. This results in underwriting procedures that are more dependable, open, and effective. The foundation for a more thorough examination of how machine coaching might transform the insurance industry's underwriting procedure is laid out in this section of the dissertation.

4.1.2 Argumentation Framework

Implementing a robust rule-based language for creating actionable decisions is a crucial part of the development of the Cognitive Digital Underwriting Assistant. The argumentation-based language Prudens (Markos and Michael, 2022) is used by the system to facilitate effective deduction and offer justifications for its conclusions. This language is essential to the process of gaining information since it follows the guidelines of machine coaching to guarantee that the knowledge is likely to be approximately correct when compared to a predetermined target policy.

One of Prudens' unique selling points is its sophisticated feature set, which makes it easier to create and implement underwriting guidelines. It permits bespoke rule prioritisation, either explicitly in each rule's declaration or programmatically via a prioritisation function. Beyond simple rule syntax, the language has procedural predicates, unification predicates, on-the-fly mathematical operations, and partially grounded contexts. Predicate definitions using broad Boolean functions and effective numerical comparisons are made possible by these functionalities.

Importantly, Prudens works with machine coaching approaches that follow the semantics of Probably Approximately Correctness (PAC). Prudens may be successfully incorporated into a human-in-the-loop machine learning architecture thanks to its compatibility, which enables a human coach to provide strategic guidance to the machine during its learning process. The Cognitive Underwriting Assistant is being trained in the subtleties of underwriting decision-making thanks in large part to this methodology.

Prudens is a key component of intelligent decision-making in the context of the Cognitive Digital Underwriting Assistant, serving as more than merely a tool for representing rules. Its incorporation into the assistant's architecture enables dynamic, user-friendly encoding, processing, and modification of the intricate and subtle underwriting criteria. The industry's demand for efficiency and transparency in underwriting procedures is met by the assistant's capacity to pick things up quickly, adjust, and articulate its logic.

To sum up, the integration of Prudens into the Cognitive Digital Underwriting Assistant represents a noteworthy advancement in the application of sophisticated reasoning and rule-based systems to improve the underwriting procedure. It opens the door for the insurance sector to adopt more flexible, astute, and user-focused underwriting approaches.

4.2 Research Design

This dissertation employs a hybrid research design that investigates the topic using both quantitative and qualitative methods. Underwriters at Generali Hellas S.A. were interviewed in-depth as part of the qualitative component to learn more about their experiences with cognitive digital assistants in the past and what they hope to get out of integrating them into their workflow. The actual needs and potential problems faced by underwriters are vitally revealed by these interviews, and these insights are critical for structuring the creation of the Cognitive Digital Underwriting Assistant (CDUW Assistant).

In terms of quantitative work, the project involves developing and refining the DUW Assistant, a tool that utilises machine learning models and data analysis. This approach guarantees a thorough comprehension of the underwriting procedure and pinpoints the areas where cognitive digital assistants could enhance productivity and decision-making.

The first CDUW Assistant design is the first step in the study process. It is based on the observations and data collected during the underwriter interviews. The main goal of this phase is to develop a prototype that meets the objectives that have been specified and offers fixes for the issues with the current underwriting process.

As the system is developed, the underwriters at Generali Hellas S.A. offer frequent feedback that is integrated into the system. Using an iterative process, the CDUW Assistant is being developed using real-world insights. This makes it possible for the people who are meant to utilise the system to continue finding it relevant and helpful.

The prototype is then tested to see how well it works, how simple it is to use, and how helpful it is for the underwriting process before moving on to the next stage of the research. This phase is crucial for figuring out whether the CDUW Assistant can be used in real-world scenarios and for making any necessary improvements based on test results.

During the final phase, the CDUW Assistant will be refined in light of the testing outcomes, and Generali Hellas S.A. will start organising its incorporation into the existing workflow. The foundation for any future enhancements and extensions of the assistant's functionality is also set in this phase; these will be carried out in later stages.

Keeping an intimate working connection with the Generali Hellas S.A. underwriters has been crucial during the entire investigation. Their underwriting expertise and experience allow them to provide crucial guidance that ensures the CDUW Assistant is both practically effective and up to date with technology.

In summary, this dissertation's study design is distinguished by a synergistic strategy that combines the quantitative creation and testing of a cognitive digital assistant with qualitative inputs from specialists in the field. A synergistic approach is the outcome of this method. By addressing both the theoretical and practical elements of deploying cognitive digital assistants in insurance underwriting, this rigorous strategy ensures a thorough investigation. Additionally, this process guarantees that a comprehensive investigation is conducted.

4.2.1 Conceptual Framework and Functionality of the Assistant

The Cognitive Assistant's design places a strong emphasis on imitating basic human abilities to facilitate efficient communication between the system and its users. This strategy aligns with the viewpoints of N. Isaac and Michael (2016), who stress the importance of developing systems that can learn on their own and use prior knowledge to handle a variety of problems.

Three essential features were considered during the assistant's construction:

- *Personalization*: Each user's preferences and working style are recognised and the system adjusts accordingly.
- *Interactivity*: Getting users involved is important to make sure the assistant is a cooperative participant in the underwriting process rather than just a tool.
- *Deliberative Capacity*: Based on a wide range of facts, the assistant can carry out mental tasks, assist users in solving problems, and make well-informed decisions.

The Cognitive Assistant's capacity to have debatable conversations and mimic human logic is an essential feature. This capacity makes it possible to solve problems in a more flexible and sophisticated way. The assistant's reasoning module functions similarly to human cognitive processes by using information that has been stored in memory. Argumentation is used to allow for flexible reasoning using symbolic data, so that the current logic of the system can adjust to different situations.

The Cognitive Assistant's learning module is intended to close knowledge gaps through continued interactions and experiences. The system may efficiently chain knowledge base rules and adapt over time with the aid of this auto-learning process. For the system to provide relevant and user-aligned recommendations, it must be able to chain rules and prioritise them according to user interactions and policies.

The assistant uses a dialectical approach while interacting with users, always trying to learn about and accommodate the user's preferences and heuristics. The process of iteration guarantees that the suggestions made by the assistant are progressively in line with the user's opinions and prejudices. By streamlining the process of acquiring knowledge, this approach improves the assistant's intuitiveness and usability.

The CDUW Assistant makes decisions on the best course of action in a particular situation based on its interactions and experiences. The system is intended to draw conclusions from user input and the growing body of knowledge that are, for the most part, appropriate and rational.

The dissertation's research design is enhanced by the Cognitive Digital Underwriting Assistant's conceptual framework. It offers a thorough comprehension of the architecture and operation of the system, which is essential for creating, evaluating, and improving the aide during the research process. This framework ensures that the assistant is both technologically cutting edge and practically applicable in the real-world underwriting environment. It also resonates with the qualitative insights gathered from the underwriters at Generali Hellas S.A.

4.2.2 Underwriting Rules and Machine Coaching

The assistant's architecture is predicated on a dialectical interaction model, in which the user and the system converse back and forth. To effectively elicit user preferences and heuristics, this technique consists of multiple stages:

a. *User Interaction*: Users ask the assistant for advice in certain situations.
b. *Assistant's Response*: Drawing from its current body of knowledge, the cognitive assistant makes suggestions.
c. *Justification and Description*: The assistant provides thorough explanations in response to requests from users for justifications of the recommendations.
d. *Conflict Resolution*: When there is a disagreement, the user can present fresh reasons, which causes the assistant to revise or reorder rules in its knowledge base.

By ensuring that the assistant's advice is more in line with the user's opinions and prejudices, this iterative approach makes knowledge acquisition easier and more user-centric. The underwriting procedure calls for accuracy and regularity. Interviews with senior underwriters at Generali Hellas S.A. provided valuable insights into the crucial data and duties associated with life retail underwriting. These realisations aided in the codification of fundamental ideas into the cognitive assistant's model, guaranteeing that the system's functionality complies with real-world underwriting requirements.

Insurance businesses' capital asset management and premium generation processes were examined through the analysis of key performance metrics including the Adjusted Underwriting Profit. Examining applicants' medical histories and lifestyle choices is a crucial part of the medical underwriting process. These elements are taken into account by the CDUW Assistant when it makes decisions about things like imposing waiting periods or surcharges based on known risk indicators.

In the world of insurance, intermediaries like agents and brokers are crucial. Their impact on the underwriting procedure is recognised in the assistant's decision-making framework, especially when it comes to negotiating terms for applicants.

The main reasoning engine of the CDUW Assistant is Prudens. It is an embodiment of the Machine Coaching cycle, with the goal of closely matching the user's heuristics and theoretical knowledge. According to the theories of Machine Coaching, Prudens analyses the body of knowledge for particular tasks and settings and offers recommendations and clarifications. With the usage of this tool, the reasoning process becomes more transparent and more customised outcomes depending on user participation are possible.

Prudens was used in a number of scenarios during the research to show how useful and successful it is for real-world underwriting activities. These illustrations show how the application might improve the underwriting process's decision-making elements.

By integrating these components into the Cognitive Digital Underwriting Assistant's conceptual framework, its operational dynamics may be fully comprehended. It highlights the system's capacity for reasoning, interaction, and decision-making in a way that closely resembles human thinking and industry standards, guaranteeing its applicability and efficacy in the insurance underwriting domain.

4.3 Data Collection & Analysis

The Cognitive Digital Underwriting Assistant initiative seeks to create a cutting-edge, AI-powered instrument that will transform and expedite Generali Hellas S.A. underwriting procedure. This cutting-edge assistant is designed to assess a multitude of data produced throughout the underwriting procedure, improving the precision and efficiency of crucial tasks like generating health risk profiles (HRPs) and forecasting the likelihood that a policy will be converted. Through the utilisation of sophisticated artificial intelligence, the CDUW Assistant enhances the effectiveness of policy issuance and management by providing underwriters with well-informed insights and supporting them in making informed decisions. The goal is to change the traditional underwriting environment into a more dynamic, data-driven, and precise process. At its core is the synergy of advanced technology and human skill.

4.3.1 Initial Data Collection

The data collection and analysis process began with the collection of a comprehensive dataset encompassing various aspects of the underwriting process. An important tool in this phase was the Apriori algorithm, a machine learning method used for mining frequent itemsets and learning association rules. In this context, the Apriori algorithm helped uncover patterns and associations in underwriters' responses, allowing to identify common trends and decision-making factors in the underwriting process.

The Apriori algorithm is commonly employed for the analysis of underwriting data. More specifically, it is utilised to identify association rules between various variables within the dataset. These rules have the potential to reveal valuable observations, such as:

- The interconnections among various underwriting inquiries and their corresponding responses.
- To examine potential patterns that could serve as indicators of risk factors or predictors of policy conversion.
- Correlations that have the potential to provide valuable insights for the creation of Health Risk Profiles (HRPs).

Left_Hand_Side	Right_Hand_Side	Support	Confidence	Lift
Q23_Ch	Q29_Ch	1.94154E+16	6.02507E+15	3.05096E+16
Q3	Q33	4.47956E+15	6.22112E+15	2.1493E+16
Q23_Ch	None	1.94154E+16	6.02507E+15	3.05096E+16
Q3	None	4.47956E+15	6.22112E+15	2.15018E+16
Q13	Q4	4.42015E+15	8E+15	2.04956E+16
Q28	Q4	3.46958E+16	8.04408E+15	2.06085E+16

Table 1. Sample from Apriori Output

The utilisation of the Apriori algorithm enables the project to effectively extract significant patterns from extensive datasets, hence facilitating the generation of informed decisions within the underwriting process. This feature is especially advantageous in augmenting the CDUW Assistant's capacity to forecast policy results and customise its decision-making procedure based on identified patterns in the data.

In the context of the dissertation's data analysis phase, this part plays a crucial role by establishing a foundation for comprehending intricate linkages within the underwriting data. Furthermore, it contributes to the advancement of an enhanced and intelligent underwriting helper.

4.3.2 Data Consolidation and Process Mapping

After compiling a comprehensive dataset, the team embarked on mapping the entire process flow of underwriting. This stage was crucial in visualizing the workflow and identifying key areas where the CDUW Assistant could improve efficiency.

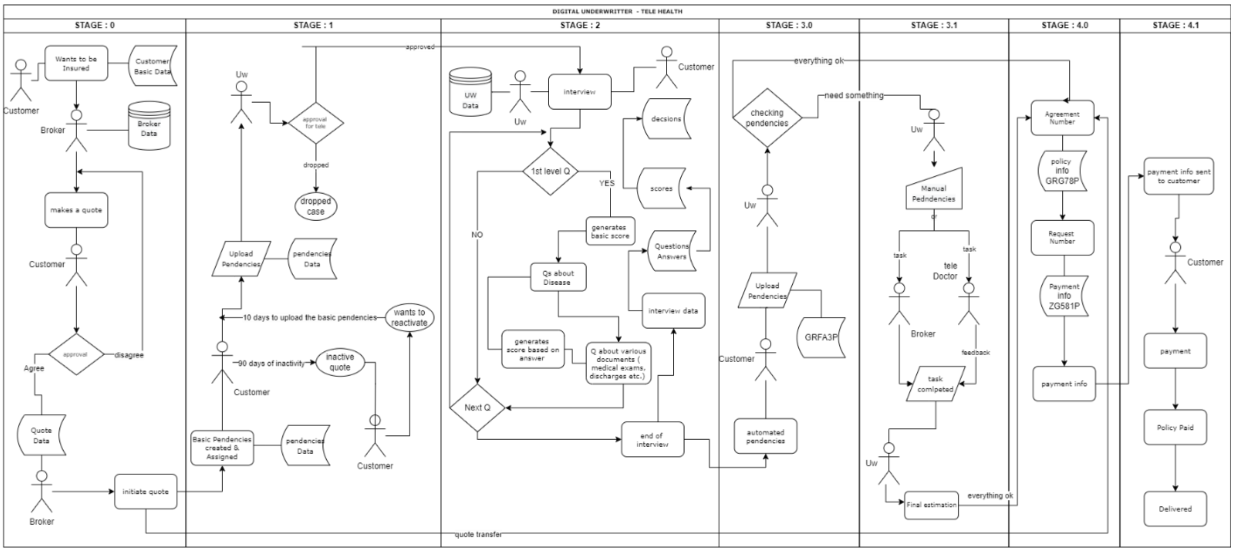


Figure 1. Process Flow

The workflow is a methodically organised procedure intended to be smoothly transitioned from the first customer interaction to the policy's ultimate delivery. There are several steps in the process, and each is essential to the overall efficacy and efficiency of underwriting.

The customer's expression of interest in acquiring insurance coverage starts the journey. A quote that reflects the conversation between the customer and the broker and specifies the insurance coverage involved is prepared in conjunction with a broker. The broker launches the quote and assigns the customer basic pendencies, like ID copies and e-signed quotes, if the customer approves of the quote and pricing. The customer and broker update the coverage information if any changes are required.

Basic pendencies are defined and assigned at this point. These chores, which involve things like e-signatures and ID copies, are necessary before the teleHealth interview. Clients who fail to finish these duties within the allotted 90 days will have their quote designated as closed. The telehealth interview is planned after a 10-day grace period for the reactivation and fulfilment of these pendencies. Additionally, quotations can sometimes be moved or skipped over this step.

The teleHealth interview is held after fundamental pendencies are finished. A dynamic questionnaire with closed-type core questions and a free-text response option for further information is included in this interview. Throughout this interview, the system actively gathers data, using the responses to produce ratings and decisions. For example, some responses may automatically initiate actions or choices, such changing or eliminating particular coverage options.

Based on the teleHealth interviewees' comments, automated tasks are created at this point. The purpose of these jobs is to gather further data that the client said they could offer. Requests for medical examinations, records of medical discharges, etc. are some examples. Here, the underwriters select the manual tasks. After the interview, UWs determine whether the broker's requirements have been satisfied and whether all information required for policy creation is accessible. If not, UWs develop manual tasks to collect the necessary data for developing insurance agreements. Quotation valuation, coverage evaluation, medical consultations, and extra exams may be part of these tasks.

All previous procedures have been completed at this advanced stage, opening the door for policy formation and agreement. Additionally, transmitted quotes from the initial stage are included in this stage, so omitting any intermediate steps. The delivery of the policy is the last phase. There are several possible states for the policy status: Pending, Reactivated and Pending, Not Delivered, Delivered and then Cancelled, and Active.

Every phase of the CDUW procedure is essential to a thorough and effective underwriting system. This procedure guarantees a customer-centric approach that adjusts to specific needs and conditions while also streamlining the formulation and administration of policies. The CDUW Assistant upholds the strict guidelines for policy management and issuance while optimising underwriting efficiency and improving the customer experience through this multi-stage procedure.

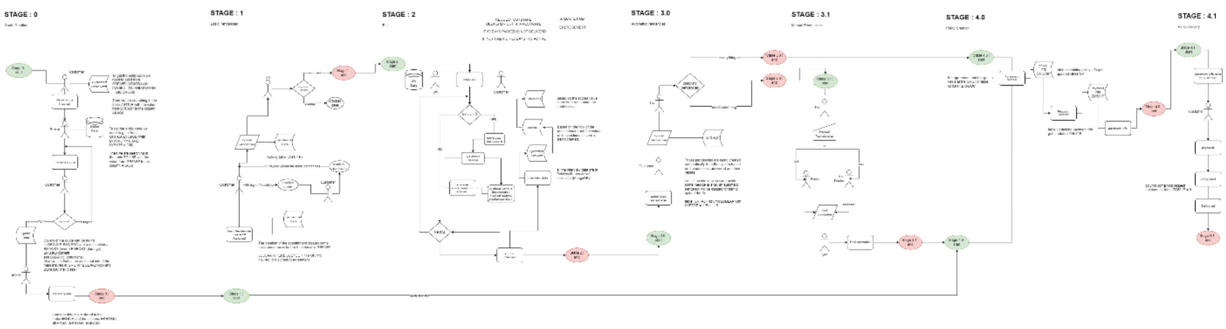


Figure 2. Stages Flow

4.3.3 In-depth Data Analysis with Machine Learning

The process-generated data underwent an extensive analysis, with a focus on policy statuses and cancellation reasons. Machine learning algorithms were employed to categorize policies and analyze cancellation trends. By applying classification algorithms, it was possible to predict policy outcomes and understand the factors contributing to policy cancellations.

Transforming non-tabular data into a structured format posed a significant challenge. Machine learning techniques, such as unsupervised learning for data clustering and pattern recognition, were instrumental in this conversion. Sankey charts, a type of flow diagram, were then used to visually represent the movement of quotes through the underwriting process.

Classification and clustering algorithms were utilized to develop Health Risk Profiles (HRPs). These machine learning techniques allowed the grouping of similar risk factors and create distinct health risk profiles, which are essential for personalized underwriting.

The clustering algorithms sorted the data into different groups, while classification algorithms helped in predicting the risk level associated with each profile.

A thorough classification of disease groups is derived, which reflects the Master's dissertation sophisticated approach to health risk assessment. These groupings are color-coded, with Green and Red representing the various risk levels and accompanying underwriting activities. The Health Risk Profiles investigation directly led to the creation of this classification scheme, which is essential in deciding the underwriting procedure for every single instance.

- Diseases classified as Green indicate no obvious danger. Green cases, which represent a base level of health risk, are handled under typical underwriting criteria. People who do not have a substantial medical history or lifestyle factors that may raise their risk of illness are usually included in this category.
- A medium level of danger is represented by the Yellow group. Particular underwriting conditions that are designed to address particular health issues noted in the individual's Health Risk Profile apply to cases in this category. Compared to the Green group, the Yellow group indicates a need for greater caution—but not to the point where extremely stringent precautions are necessary.
- Group Orange (Level of Risk 2): Cases in the Orange group are considered to be very risky. This calls for unique underwriting conditions that are more important than those for the Yellow group. One significant feature of the Orange category is the possibility of the case being withdrawn if there are several related diseases. This suggests a markedly increased risk that may not be consistent with the insurer's risk tolerance or the terms of the policy.
- Group Red (Level of Risk 3): The greatest degree of risk is represented by the Red category. Cases in this category are either closed completely or closed after a long period of inactivity, suggesting that further thought and possibly investigation are necessary. This category may also involve modifications to the policy's terms, such as increased premiums (referred to as "changing lobs to prime"). A significant health risk profile, which frequently includes complex and dangerous medical disorders, is indicated by the Red group.

This classification system plays a key role in directing underwriting choices by allowing underwriters to employ various strategies according to the evaluated risk level. It is a prime example of the system's dedication to careful, data-driven decision-making, guaranteeing that every policy is backed with a thorough comprehension of the health risk of the individual. This method not only improves the fairness and accuracy of the underwriting process, but it also supports the main goal of customising insurance plans to each customer's unique requirements and risk profile.

Although the initial chatbot prototype was not pursued to completion, the exploration involved natural language processing (NLP), a branch of machine learning. NLP algorithms were used to interpret and respond to user inquiries, a function that was later integrated into the broader CDUW Assistant system.

A rule-based approach, augmented with machine learning, was adopted to forecast conversion probability. Here, supervised learning algorithms were used to predict the likelihood of policy conversion based on historical data. This approach helped in refining the accuracy of the CDUW Assistant's decision-making process.

#	QUOTE	TASK_NO	in-progress	TRZ PREVENTION	TRZ SERVICES	TRZ HOSPITAL	participation	roomType	hasDemnd	hasChild	pInvolved	PREMIUM	AGE	POLICY
0	4038767	1	0	Basic	Standard	Premium	3000	B	0	0	1	52572	45.0	0
1	4038767	1	0	Basic	Standard	Premium	3000	B	0	0	1	52572	45.0	0
2	4038953	1	0	Premium	Standard	Flexi	1500	B	0	0	1	50044	29.0	1
3	4040026	1	0	Basic	Standard	Premium	1500	B	0	0	1	95865	54.0	0
4	4040914	1	0	Premium	Standard	Flexi	1500	A	1	0	1	155192	38.0	1
5	4040914	1	0	Premium	Standard	Flexi	1500	A	1	0	1	155192	38.0	1
6	4076944	3	0	Premium	Standard	Flexi	1500	B	1	1	2	115469	no coverage	1
7	4076944	3	0	Premium	Standard	Flexi	1500	B	1	1	2	115469	no coverage	1
8	4077227	1	0	Premium	Standard	Premium	1500	A	0	0	1	13513	55.0	1
9	4077227	1	0	Premium	Standard	Premium	1500	A	0	0	1	13513	55.0	1
10	4077998	1	0	Premium	Standard	Flexi	3000	B	0	0	1	62964	43.0	1
11	4077998	1	0	Premium	Standard	Flexi	3000	B	0	0	1	62964	43.0	1

Table 2. Conversion Ratio Analysis

Further refinement of the data for visual representation using Sankey diagrams involved both machine learning and traditional data processing techniques. The goal was to create an interactive and accessible report that highlights the efficiency of the CDUW process.

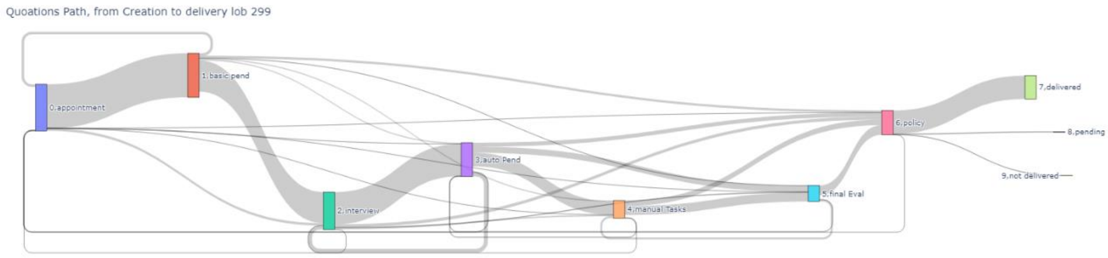


Figure 3. Sankey Diagram

4.3.4 Prudens Integration

A crucial component of the digital medical risk assessment procedure is the disease handbook. To ensure optimal utilisation of the new digital underwriting program and maximise productivity for both the underwriter and his customer, the underwriter is essentially required to implement the guidelines already provided in this manual.

The disease handbook aims to give a comprehensive overview of the regulations governing the evaluation of medical risk in hospital programs. To thoroughly cover the most typical scenarios involving potential insureds, the manual covers a large range of disorders. It includes details on how the condition is classified, what tests are required for each condition, and instructions on how to conduct the tests.

For example, the underwriter will be aware, according to the handbook, that an MRI is necessary as a supporting document to be received with the application in order to examine the disease if an insured person reports cervical disease on the Medical Questionnaire. Simultaneously, he will be cognizant of the potential outcomes that may develop throughout the evaluation, consistently with respect to all the corroborating documentation that he will have been provided. If a comparative tomography is also filed, the ailment may be automatically removed after a 1- or 3-year waiting time, depending on how severe the problem is as determined by comparing the imaging tests. In situations where an imaging test is not submitted and the issue recurs. The condition will be excluded for the next three years with the option of reevaluation, or it will be automatically removed after five years of exclusion. The application will be rejected if there is severe osteoporosis in the patient.

Based on the assistant's knowledge, the corresponding digital underwriting system will give the underwriter explanations when a health insurance application is submitted. To help the underwriter look into the matter further, the assistant will provide factors that can be attributed. The underwriter chooses how to supply the insurance coverage in the final stage or, if necessary, rejects the application. Through this iterative process of human-machine interaction, an agent can receive knowledge from an underwriter, act on that knowledge, and provide explanations in the form of arguments derived from that agent's knowledge. After the machine provides feedback, the underwriter can provide counterarguments to the agent in order to refresh their knowledge.

Prudens, a knowledge base model, leverages machine learning to enhance decision-making logic. It facilitated a more transparent reasoning process within the CDUW Assistant, aligning with the machine coaching framework. The MVP refinement stage was where the practical application of machine learning algorithms was thoroughly tested and evaluated. The algorithms' performance in real-world scenarios was scrutinized to ensure that the system's predictions and recommendations were reliable and accurate. The Prudens framework employs a set of rules that significantly enhance the decision-making process in digital underwriting. These rules allow for a nuanced evaluation of health risks, leading to more accurate and tailored insurance policy decisions (Appendix A).

- *Risk Level Assessment*: There are a set of rules that categorize quotes into various risk levels based on health risk profiles and weights. This categorization ranges from green cases (no risk) to high-risk scenarios where policies might be dropped. These rules directly influence the preliminary assessment of an application, streamlining the process for clear-cut cases.
- *Dynamic Risk Adjustment*: Other rules are designed to dynamically adjust the risk status of a quote based on new information. For instance, a quote initially classified as 'green' can be reclassified if subsequent evaluations reveal higher risks. This ensures that the underwriting process remains flexible and responsive to new data.
- *Standard and Special Underwriting Terms*: The rules facilitate the application of standard terms for low-risk cases (green quotes) and special terms for higher-risk

scenarios. This includes implementing waiting periods of varying lengths (two, five, or ten years), as determined by specific health risk weights and other factors.

- *Expert Intervention and Automated Assessments*: The framework allows for a seamless blend of automated risk assessment and expert underwriter intervention. Rules, for example, call for underwriter evaluation in specific circumstances, ensuring that human expertise complements automated risk calculations.
- *Evaluation Rights:* Some rules acknowledge the need for evaluation rights, allowing underwriters to exercise discretion in complex cases.

The integration of these rules into the digital underwriting process represents a significant leap forward in policy decision-making. By automating initial risk assessments and retaining provisions for human expertise where necessary, the Prudens framework ensures that each insurance application is processed efficiently, accurately, and with a deep understanding of the individual risk profiles. This not only enhances the speed and accuracy of the underwriting process but also ensures that policies are equitable and closely aligned with the specific needs of applicants.

4.4 Limitations

Despite all of the advantages, there are a few drawbacks and restrictions with the cognitive digital underwriting assistance that should be carefully considered. GDPR requirements require careful handling of health data, a sensitive component of the underwriting process. To preserve people's privacy and stay out of trouble with the law, it is imperative that the assistant's algorithms and data gathering techniques follow these rules.

Furthermore, when working with personal health data, ethical considerations are critical. In order to prevent biased decision-making, the assistant must be trained to identify and avoid biases present in the training set. This emphasises the significance of using data in an ethical manner and eliminating discrimination in all its forms.

The challenges of integrating the assistant into current operations are unique. Not only must the system be flexible enough to meet the unique demands of the company, but it also needs to be resource-intensive for staff training. The quantity and quality of data the assistant processes also have a major impact on its efficacy. It is important to have a consistent flow of high-quality data because incomplete or poor-quality data can result in risk evaluations that are not trustworthy. The processing of complicated human aspects in decision underwriting and expanding the system for large-scale applications without sacrificing efficiency are two more challenges brought on by technological limits.

Finally, the ever-evolving field of digital underwriting raises resource needs by requiring constant maintenance and changes to the assistant's algorithms in order to keep up with new standards and advances. Thus, even if the cognitive digital underwriting assistant represents a major development for the insurance sector, resolving these complex issues is crucial to the implementation and smooth functioning of this tool.

Chapter 5

Cognitive Digital Underwriting Assistant

Embodying a mutually beneficial partnership between artificial intelligence and human knowledge, the Cognitive Digital Underwriting Assistant (CDUW) is at the forefront of technological innovation in the insurance underwriting industry. This sophisticated tool uses complex machine learning models to do more than just analyse data; it interacts dialectically with underwriters to improve the decision-making process.

The CDUW's ability to learn and change dynamically is at its core. Junior underwriters gain from an interactive training environment that promotes quick skill development by providing them with customised assistance and explanations. Senior underwriters, on the other hand, enhance the system's intelligence by adding their experienced perspectives and reinforcing the precision of its decision-making. Human intuition and mechanical precision come together in a symbiotic environment created by this mutually beneficial interaction.

The sophisticated memory mechanism of the CDUW solidifies this dialectical link even further. It keeps track of all decisions, creating a knowledge base that is constantly updated and referred to. This advances the CDUW towards being a constantly changing, more advanced underwriting tool while also guaranteeing a strong learning environment for underwriters of all levels.

5.1 Enhancing Underwriting

The requirements and complexity of the health underwriting process are always evolving, which is why the Cognitive Digital Underwriting Assistant is created. Though effective, traditional underwriting procedures sometimes face difficulties since decisions are complex, thorough investigation is necessary, and decisions fairness and openness are becoming increasingly questioned.

In a sector where accuracy and precision are critical, the underwriting process necessitates a careful review of a variety of frequently large data sets. Underwriters are responsible for making important choices that have a big impact on policy applicants' lives and well-being in addition to the insurance provider's financial stability. Due to this dual role, a system that respects fairness and equity in addition to efficiency must be in place.

The underwriting workflow is streamlined and optimised by the integration of cutting-edge AI technology, which makes the CDUW an innovative solution. Fundamentally, the assistant uses machine learning techniques that can quickly and reliably analyse big datasets. This AI-driven method makes it possible to see trends, dangers, and abnormalities that could go unnoticed by humans. By doing this, the CDUW improves the decision-making process and allows underwriters to make choices with greater knowledge and support from data in a fraction of the time that is often needed.

In addition, the CDUW's implementation represents a major advancement in addressing the moral aspects of underwriting. Fairness in policy decisions is promoted by the AI algorithms' minimization of biases. This element plays a critical role in establishing and preserving policyholder trust by guaranteeing that underwriting choices are fair and efficient.

The CDUW not only improves decision-making but also dramatically lowers the possibility of human error. The intricacy of risk assessments and the sheer amount of data involved in health underwriting render it prone to errors and oversights. The CDUW reduces these risks by automating the preliminary phases of data analysis and pattern identification, guaranteeing a higher level of precision and consistency in underwriting results.

Additionally, the CDUW is essential to the democratisation of health insurance. The assistant helps create more equitable and competitive insurance policies by improving the accuracy and expediency of the underwriting process. By expanding their market reach, insurers gain, but end users also gain from increased accessibility and affordability of healthcare.

The Cognitive Digital Underwriting Assistant is essentially the embodiment of the fusion of human knowledge and technology. With the use of artificial intelligence (AI) and machine learning, it is a shining example of innovation in the field of health underwriting, promoting efficiency, accuracy, justice, and transparency.

5.1.1 The Workflow of Cognitive Underwriting Assistant

A data-driven underwriting system's complex process flow is depicted in the Digital Underwriting Assistant Project Flow diagram. The system starts with telehealth interviews, in which client data is gathered and saved in a MongoDB database, demonstrating the system's ability to process large amounts of data and provide real-time response.

The process of health risk profiling then involves taking the interview data and repurposing it, then using rule-based models to create unique risk profiles for each interviewee. This step of the procedure highlights the system's cognitive capacity to handle and evaluate data, converting unprocessed data into insightful knowledge that can be put to use.

The core functionality of the system is its capacity to calculate the conversion ratio, which is achieved by retrieving relevant information about event damage, coverage specifics, and other important insurance parameters. The Random Forest machine learning model, which is well-known for its effectiveness in classification tasks, is used in this procedure to determine the probability that a quote will be turned into an actual policy. In the underwriting industry, forecasting and risk management rely heavily on this predictive skill.

The Knowledge Base is the core component of the system's decision-making power; it is a dynamic database that changes with every contact. The system records the context of every instance, encompassing health risk profiles, conversion ratios, and unique interview identities, while processing data and producing recommended decisions. The system may continuously improve accuracy and relevance by tailoring its recommendations and refining its predictive models thanks to this contextual information.

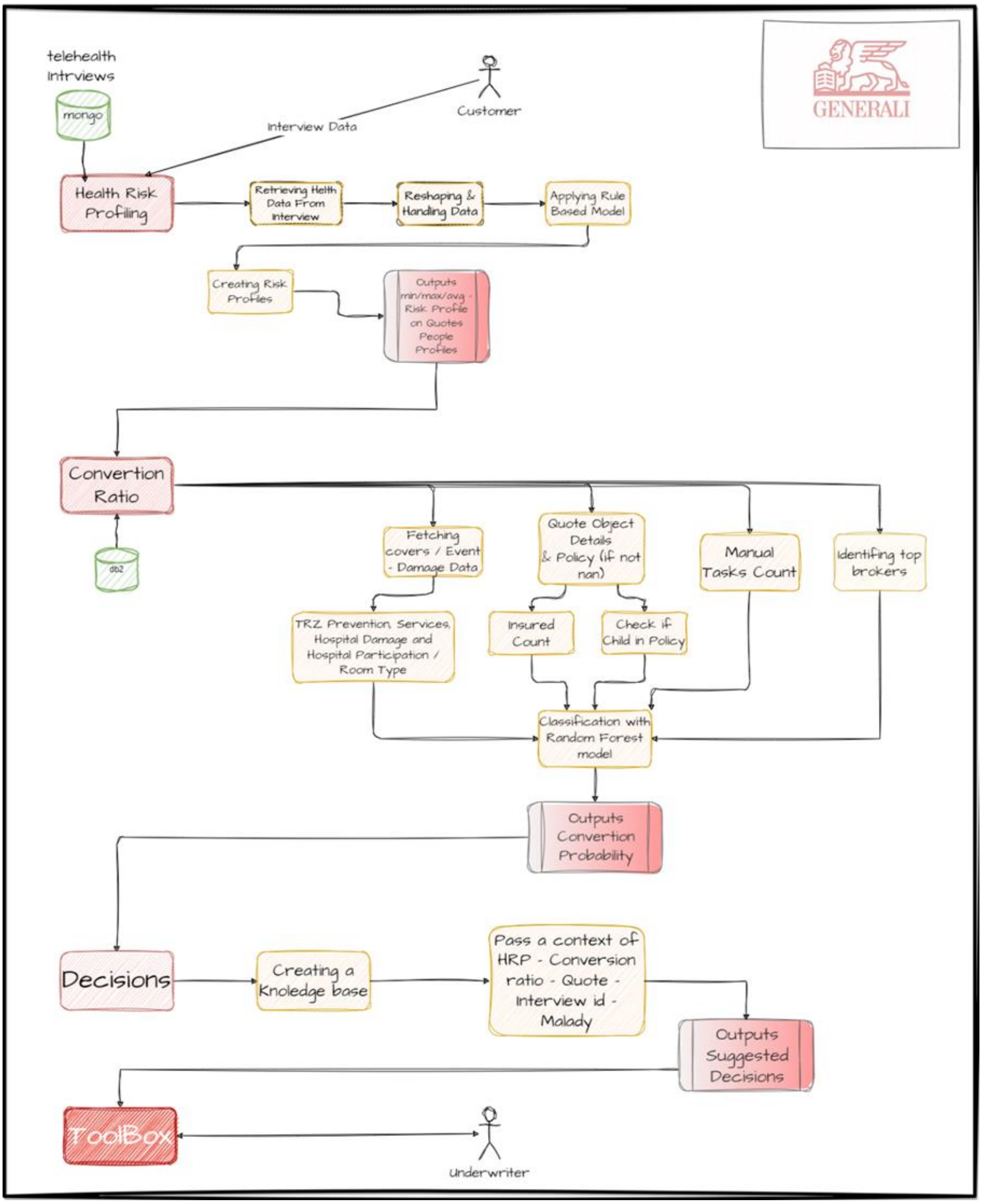


Figure 4. Flow of Cognitive Underwriting Asisstant

The final step in the CDUW system's process is to interface with the Toolbox web platfrom. Underwriters can access and engage with the system's recommendations thanks to this connection, which offers a smooth user experience. Underwriters can use the system's insights to make well-informed policy judgements by reviewing recommended actions and approving or modifying them as necessary.

The symbiotic interaction between sophisticated AI models and human expertise is captured in this process flow diagram. It presents a system that not only streamlines and automates underwriting processes but also adds human review to continuously improve its algorithms for making decisions. The end product is a strong underwriting framework that satisfies the requirements of the contemporary insurance market for accuracy, effectiveness, and flexibility.

5.1.2 Refined Workflow

A more intelligent and integrated system is highlighted by the progression of the digital underwriting process from the initial flow to the enhanced Cognitive Assistant CDUW flowchart. The new flowchart emphasises how conventional techniques may be seamlessly replaced with a more cognitive approach, combining human and artificial intelligence to optimise the insurance underwriting process.

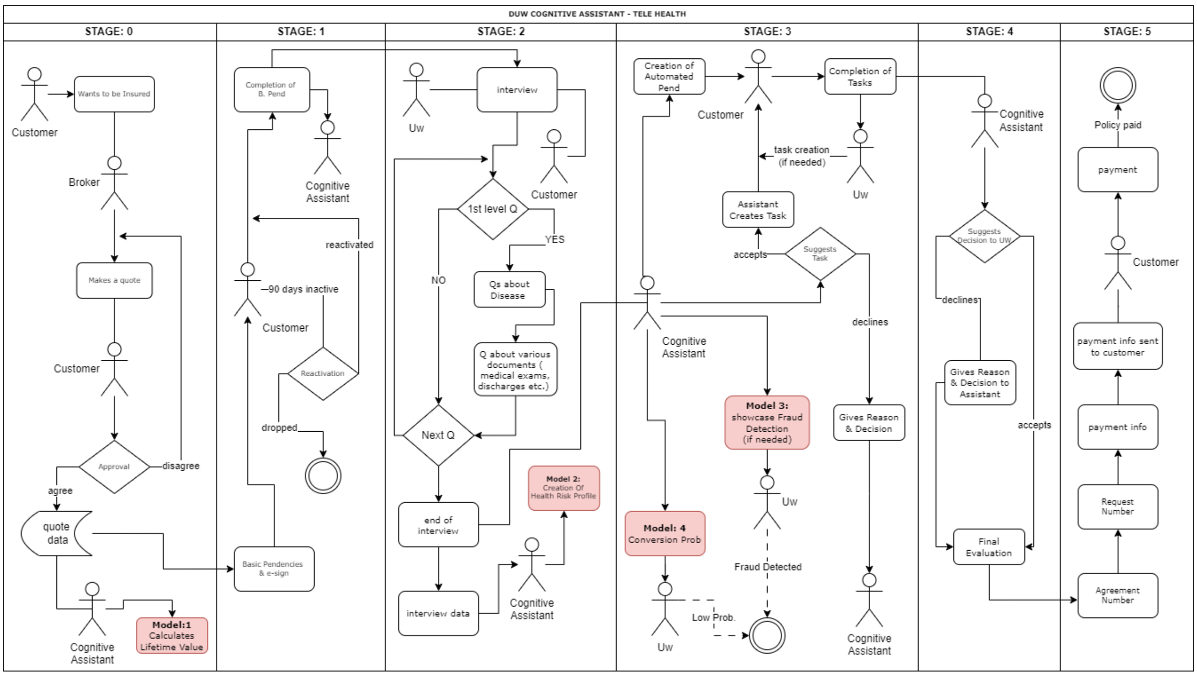


Figure 5. Evolution of the Digital Underwriting Process

At the initial phase, intermediaries enter the picture by gathering customer information and producing quotes, and prospective clients declare their desire to be insured. This phase is critical because it gathers the necessary information that flows into the cognitive system, laying the foundation for the underwriting procedure.

In order to proceed to the next Stage, the system must now handle fundamental pendencies, which include necessary user actions like submitting IDs and e-signature submissions. A dynamic interaction characterising this stage allows quotes to be discarded or reactivated based on client responsiveness, demonstrating the system's flexibility in responding to varying levels of customer participation.

In the second stage, telehealth interviews are conducted. If the initial response calls for more research, the first level questions serve as decision nodes that lead to more in-depth health-related queries. At this point, the assistant's capacity to determine when more information is needed is demonstrated, demonstrating a customised approach to risk assessment.

In the third phase, the system demonstrates its ability to generate tasks automatically and to manually intervene, generating pendencies based on interview results or underwriter judgement. This demonstrates the assistant's adaptability in managing various case complexity and underwriter knowledge in offering careful supervision.

The process comes to an end with the development and delivery of policies in late phases. Underwriters make the ultimate judgements in this case, based on suggestions from the cognitive assistant. The recommendations made by the assistant are based on a thorough assessment of the risk profile of the client, which is shaped by the data-driven insights acquired during the procedure. The system's learning agility is demonstrated by its capacity to incorporate underwriter comments and update its knowledge base.

The flowchart that shows the change from the initial system to the CDUW also shows an improved feedback loop. The cognitive assistant ensures a dynamic and ever-evolving decision-making process by soliciting and using underwriter comments in addition to offering suggestions.

In conclusion, the improved flowchart shows how the digital underwriting workflow has matured and become a more intelligent, data-driven, and adaptable system with the addition of a cognitive assistant. It offers a comprehensive and complex model that promises efficiency, accuracy, and an improved user experience, marking a substantial advancement in underwriting technology.

5.1.3 High-Level Architecture

The architecture of the Cognitive Digital Underwriting Assistant is built to facilitate efficient communication between the user and the complex back-end operations of the system. A number of interrelated services, each focused on a different aspect of the underwriting process, are the foundation of its operation.

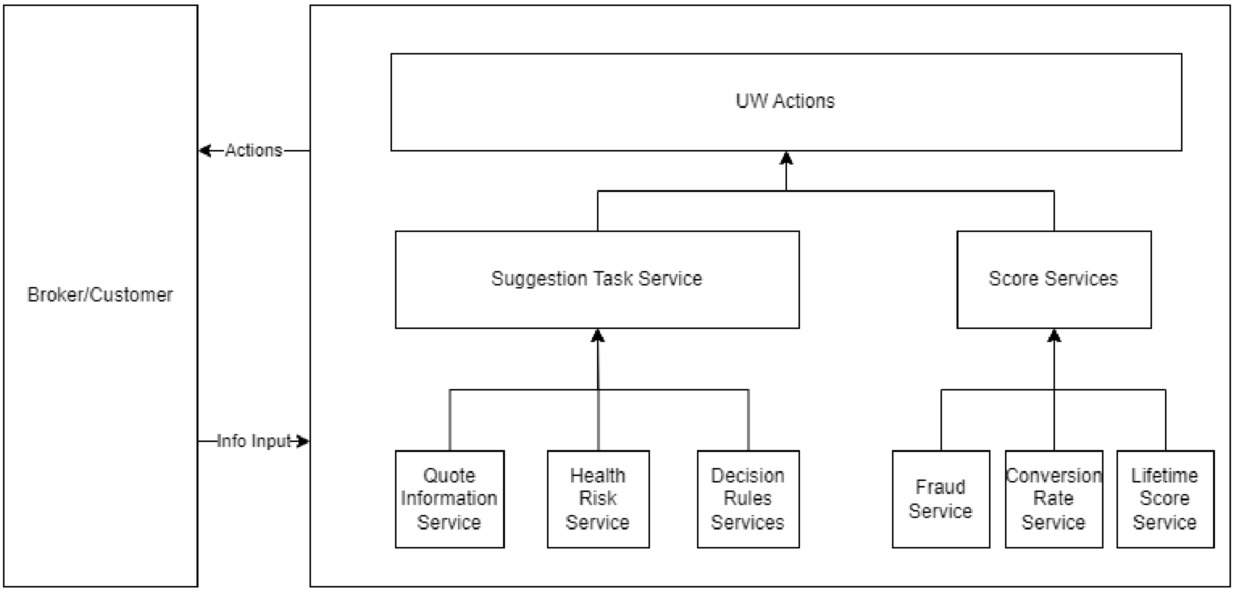


Figure 6. High-Level Architecture Diagram

- *Broker/Customer Interface*: Here is where brokers and customers enter data into the system for the first time. The user is guided through the process of inputting data required to get an insurance quote by the intuitive design of the interface.

- *Suggestion Task Service*: After receiving the initial input, the Suggestion Task Service serves as a middleman, directing the data via a number of additional services that are intended to evaluate the information and produce recommendations.
- *Quote Information Service*: All quote-related data is managed by this service. It prepares the data for additional examination by other components by processing the information supplied by the broker or customer.
- *Health Risk Service*: An essential part, the Health Risk Service assesses the client's health-related data. It uses sophisticated algorithms to evaluate risk according to the medical information entered at the beginning.
- *Decision Rules Services*: The codified business logic and underwriting rules are applied to the processed data in this crucial service. In order to make wise decisions, it considers the information obtained by the Health Risk Service.
- *Score Services*: These include a variety of scoring methods, including Lifetime Score Service and Conversion Rate Service. While the Lifetime Score Service assesses the policy's long-term value to the insurer, the Conversion Rate Service forecasts the possibility that a quote will turn into a policy.
- *Fraud Service*: Essential to the underwriting process's integrity, the Fraud Service examines the data for trends that point to fraudulent behaviour while protecting the system from possible abuses.
- *Activities of Underwriters*: The underwriters receive actionable insights at the end of the data processing process. These insights enable underwriters to make informed, data-driven decisions by providing them with a range of information, from recommendations for policy pricing to risk assessments and fraud warnings.

Each service in the system is modularly designed for easy upgrading and maintenance, and the architecture is built for efficiency and scalability. This high-level overview offers a conceptual grasp of the Cognitive Digital Underwriting Assistant's operation and a window into the intricate coordination of services that assist underwriters' decision-making processes.

A strong information flow system supports the Cognitive Digital Underwriting Assistant (CDUW), which builds on the high-level architecture by fusing user interactions and a variety of data sources to produce a smooth underwriting process.

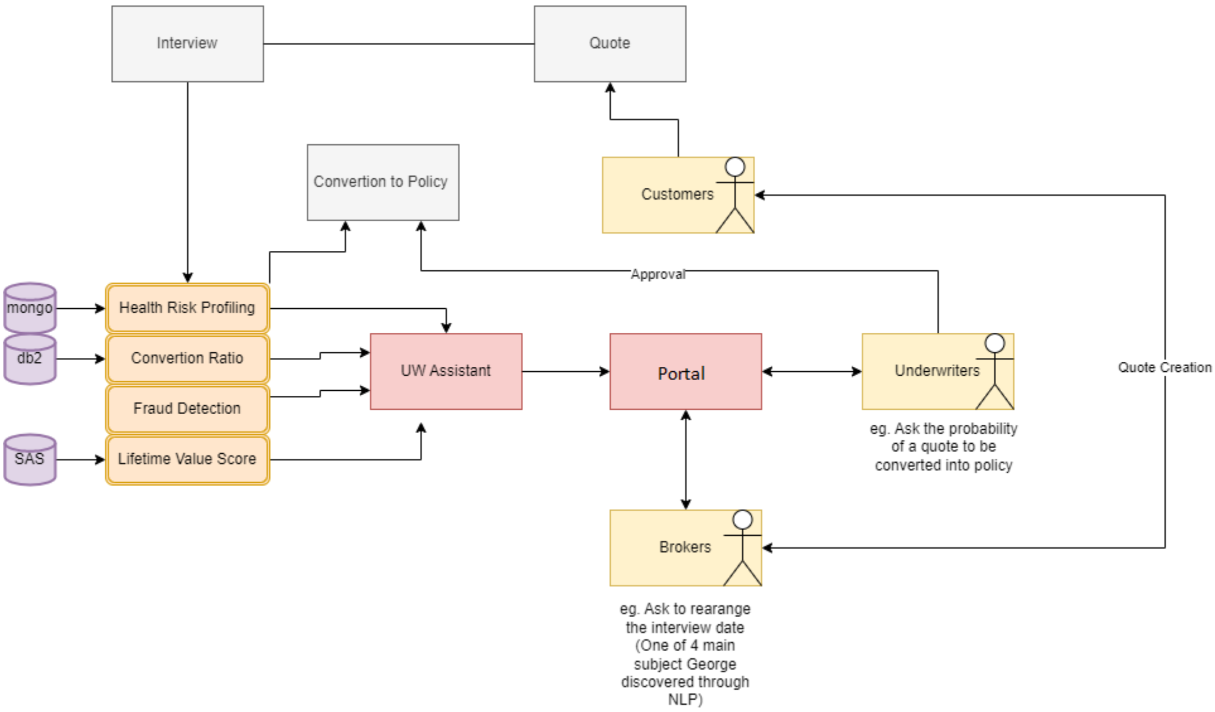


Figure 7. Information Flow Diagram

Customer data is gathered and entered into the system during the Interview phase, which kicks off the process. This data journey leads to Health Risk Profiling, a critical intersection where the customer's health risks are evaluated using data from databases. In addition, the Conversion Ratio model, which is based on SAS software's historical data analytics, forecasts the probability that a quote will be converted into a policy.

This design is centred around the UW Assistant, which receives processed data from the Lifetime Value Score, Fraud Detection, Conversion Ratio, and Health Risk Profiling services. Here, the data is combined and turned into insights that the underwriters can use. They receive a thorough analysis that includes forecasts for client lifetime value, risk assessment, and probable fraud alarms.

The Toolbox Web Portal then becomes the nexus for stakeholder interaction. Underwriters employ this portal to engage with the insights provided by the Underwriting Assistant, making informed decisions on quote validation. Customers can also interact with the

Toolbox, granting approvals and receiving updates on their quotes. Brokers utilize the portal to manage and adjust quotes based on real-time feedback and underwriter guidance.

The other essential element of this flow is the Quote, which is the result of interactions between the broker and the customer and culminates in a quote. After that, it goes through the approval process, which could involve a number of parties, such as the underwriters who make the ultimate decision and the consumers who confirm it.

The dynamic aspect of the assistant is highlighted by this information flow diagram, which shows how it combines several data sources and user inputs to streamline the underwriting procedure. In order to guarantee that the CDUW Assistant serves as a platform for communication and decision assistance in addition to being a tool for risk assessment, it highlights the system's interconnectedness and the significance of each workflow component. The CDUW Assistant operates effectively because to this extensive system architecture, which offers a sophisticated and user-friendly interface to all parties involved in the underwriting process.

5.2 Product Overview

The Assistant Underwriter system is a paradigm leap in digital underwriting, combining the accuracy of scoring mechanisms like Health Risk Profiles and Conversion Ratios with the extensive analytical powers of Prudens, a knowledge-based framework. In the field of life insurance underwriting, this integration marks the beginning of a new era of risk assessment and decision-making procedures that mimic the finer points of complex human reasoning.

After applicants have finished their medical questionnaires, the Assistant Underwriter system carefully handles their requests, using a database of medical history and lifestyle information to provide insurers with a comprehensive picture of possible hazards. The fundamental capability of this system is its capacity to deduce implicit information, emulating the nuanced cognitive processes of humans. It is based on the knowledge that already exists in the underwriting process and uses it to create a mental model that includes arguments and explanations similar to those found in human argumentation.

The identification and integration of knowledge necessary to define the various scenarios experienced in life insurance underwriting forms the foundation of the system's architecture. Taking underwriting data as input, the system uses fact-checking questions combined with prior knowledge organised as association rules that are all weighted according to their importance. This strategy is the epitome of common sense reasoning, but it necessitates complex knowledge engineering to negotiate the complexities of risk classification and the underwriting environment.

The Assistant Underwriter takes into consideration the various stakeholders that impact the underwriting process and their respective roles and interrelationships. Insurance brokers have the potential to greatly influence underwriting decisions by facilitating the purchase of policies, particularly in cases when terms differ from established practises. These processes are captured by the system in its knowledge base, which represents the many agreements between intermediaries and insurers that subsequently influence underwriting policies and judgements.

As part of its operational principles, the Assistant Underwriter creates arguments to support suggestions rather than just making them. The system is designed to argue, supporting or opposing a suggested course of action. After absorbing a customer's medical history and profile, it constructs a complex story that is placed inside the framework of the regulating underwriting guidelines and intermediary contracts.

The background knowledge of the assistant underwriter acts as a reflection of the interactions that take place between brokers, underwriting procedures, and applicants. This information is obtained mostly through knowledge engineering exercises using a knowledge-base methodology. By using straightforward yet powerful association rules, the system builds persuasive arguments that an underwriter can understand on their own. It explains the rationale behind suggestions like coverage restrictions or premium surcharges for particular applicants, converting common sense and specialised knowledge into codified, useful insights.

An empirical investigation was carried out for this master's dissertation in cooperation with Generali Hellas Insurance Company S.A.'s retail life underwriting division. The

Assistant Underwriter made choices and provided arguments to the underwriters, pushing them to follow or deviate from the suggested path of action. It emphasises how arbitrary risk assessment is, and how individual prejudices and viewpoints can tip the scales in favour of optimistic, pessimistic, or moderate assessments of the same situation.

The Assistant Underwriter system manifests a sophisticated tool that advances the underwriting process into a future where machine intelligence and human expertise combine to enhance decision accuracy and efficiency. This is achieved by integrating the Prudens framework and leveraging scores such as the Health Risk Profile and Conversion Ratio.

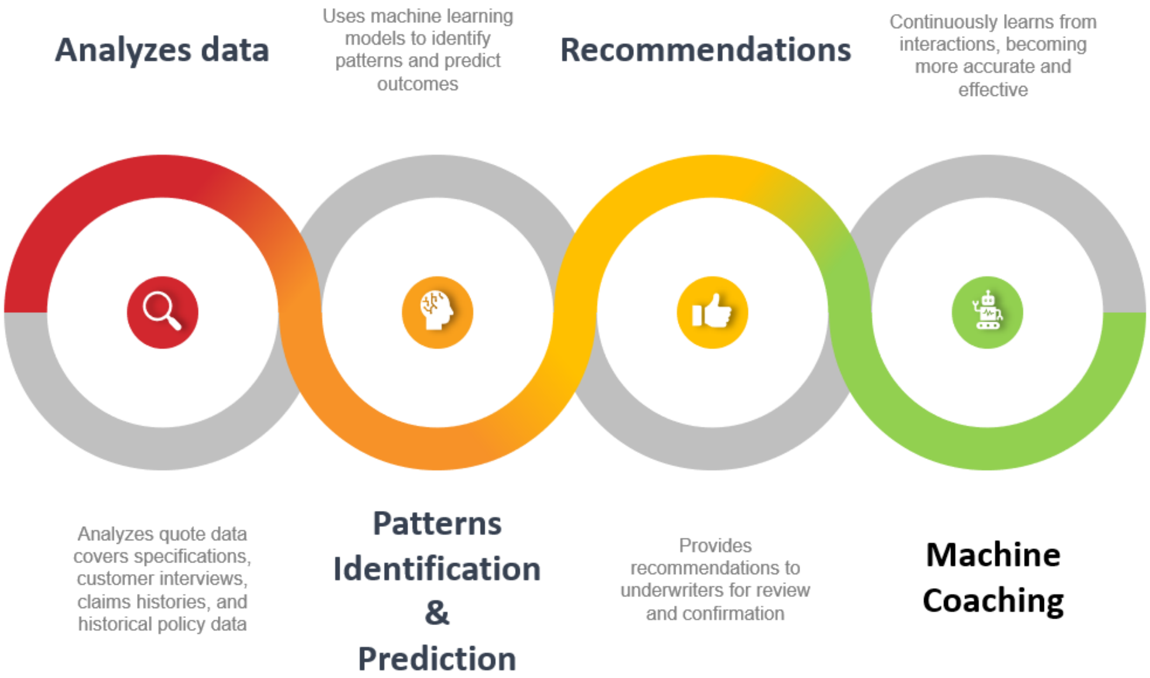


Figure 8. Product Overview

In the field of health underwriting, the Cognitive Digital Underwriting Assistant (CDUW) is a prime example of the contemporary fusion of artificial intelligence with knowledgeable human judgement. It works as a machine learning-enabled, data-centric solution that significantly enhances conventional underwriting techniques. With a background in extensive data analysis, the CDUW is able to spot complex patterns that even senior underwriters could miss, from individual quotation applications and intricate coverage details to client interviews and historical policy information.

With a wide range of advanced machine learning models at its disposal, the CDUW carefully examines data to predict results with ever-increasing precision. After being painstakingly trained to understand the nuances of insurance risk, these models iteratively interact with human underwriters to improve their prediction efficiency. The assistant can learn from and modify its algorithms through this iterative process, which guarantees that over time, its recommendations will grow more accurate and customised to the underwriting requirements.

The CDUW's real strength is found in the way it interacts with actual underwriters. It functions as both a dynamic learner and a validator of risk assessments. The assistant's suggestions can be confirmed or rejected by underwriters at their discretion, creating a dynamic where machine learning models are refined using real-world knowledge and judgement. This improves the accuracy of the assistant while also supporting and strengthening the company's established risk assessment procedures.

The CDUW now has a structured, rule-based approach that is representative of accumulated underwriting wisdom thanks to the integration with the Prudens Framework. The Assistant's decision-making process is guided by a set of dynamic and interpretable principles that are derived from the tacit knowledge of seasoned underwriters. This system may deduce meaning from data beyond what is explicitly supplied because it embodies "common sense" thinking, which is similar to human cognition.

A key component of its design is the Health Risk Profile (HRP), which uses scores such as the Conversion Ratio to estimate the likelihood that a quote will be turned into a policy. It assesses prospective insureds based on their health information and lifestyle decisions. The goal of these scoring systems, which may include a Lifetime Value Score, is to put an individual's long-term insurance risk and profitability into numerical form.

Through a sophisticated dance of human-AI cooperation, the CDUW gives underwriters a clear view into the thinking behind each of its recommendations by providing open, attributed reasoning. This clarity is essential because it allows underwriters to use their experienced judgement to validate or improve the suggestions, guaranteeing that the company's risk tolerance and underwriting standards are respected.

The CDUW improves decision-making quality by fusing the depth of human experience with the accuracy of machine learning, not only speeding up the underwriting process. The ultimate goal is a smooth integration of effectiveness with the deep, astute perception of risk that has long been the distinguishing feature of insurance underwriting. The CDUW's mission is to provide clients with fair, customised insurance solutions, carefully calibrated policies, and thorough risk evaluations.

Methods for gathering relevant data.

- Techniques for processing and interpreting data.
- Drawing meaningful insights from the data.

5.3 Comprehensive Overview

The Cognitive Digital Underwriting Assistant system is an innovative AI-driven solution meticulously designed to enhance and streamline the underwriting process within our insurance operations. This sophisticated system leverages an amalgamation of data analytics and machine learning to inform and support underwriters with actionable insights.

Data is the lifeblood of the CDUW, generated at multiple junctures throughout the underwriting process. To construct the assistant, we harnessed data from every stage, drawing from both our MongoDB, which hosts "TeleHealthInterviews," and our DB2 server, which houses a multitude of tables offering comprehensive coverage details, stakeholder information, and the state of quotes and tasks leading up to policy agreements.

We started our path towards creating the Cognitive Digital Underwriting Assistant by tackling the difficult task of data wrangling. Our key component was Python, since our DB2 and MongoDB servers could be integrated with ease thanks to the pymongo and pyodbc drivers, respectively. The task of moulding the nested documents in MongoDB into a logical structure was quite difficult. We persisted in the face of difficulties, converting the data into a binary format that opened the door to additional investigation.

The Health Risk Profile (HRP) and the Conversion Probability are two essential indicators that are at the heart of our cutting-edge underwriting assistant. Based on a scale of 0 to 4, the applicant's health profile is a gauge of their health risk. This measure compiles claims information and compares it with National Centre for Health Statistics mortality data. We determined the relative weights for each ICD10 code using a clustering approach and correlated them with claim frequency and fatality rates. It's important to remember that this model was created specifically with disease codes in mind, offering a targeted risk evaluation.

Conversion Probability shows how likely it is that a quote will develop into a policy. A categorization algorithm that processes a plethora of features—including the quote's HRP, pricing, cover details, broker influence, task completion, and demographic information—is used to determine this. A probabilistic forecast, the product of data and machine intelligence, is the end product. In order to build our model, we utilised:

- One hot encoder: This method improved the input for our algorithms by converting categorical data into a format that could be read by a machine.
- SMOTE: To ensure a fair representation of all outcomes, we enhanced the minority class to balance our dataset.
- GridSearchCV: The best parameters for our model were discovered by this cross-validation technique by combing through several parameter permutations.
- XGBClassifier: The model of choice was XGBoost, a well-known gradient boosting method that excels at handling challenging machine learning problems due to its adaptability and performance.

Among our evaluation tools were:

- Accuracy Score & Confusion Matrix: These tools measured the model's efficacy, identifying both successful and unsuccessful predictions.
- R2 Score: Based on the independent variables, this statistic showed the percentage of variance in policy conversion that our model could account for.

The Conversion Probability model relied on a wide range of essential features. From the finer points of policyholder demographics to the broker's broader sway, they encapsulated the spirit of the underwriting environment. Every variable added a verse to the predicted story, resulting in a model with an astounding accuracy rate of 82%.

The incorporation of data wrangling and machine learning has strengthened our Cognitive Digital Underwriting Assistant, as summarised above. It has also brought attention to the dissertation's theme of technological innovation in risk assessment and insurance policy issuance. We have mapped out a path towards a more knowledgeable, effective, and sophisticated approach to underwriting through painstaking data translation and sophisticated predictive modelling.

The ingenuity of the CDUW system is further amplified by integrating the Prudens framework, which infuses the assistant with dynamic decision-making capabilities through machine coaching. Users can craft and apply custom rules, which the system interprets to generate decisions, reflecting the system's adaptability and learning acumen.

For the MVP phase, we adopted the Django framework, capitalizing on its robust communication protocols. This enabled us to develop a web application that serves as the front end to demonstrate the assistant's features. Two primary models, 'Rules' and 'Decisions,' are central to the Django app, capturing the knowledge base inputs and underwriting decisions, respectively. The application's POST methods are pivotal in data retrieval and validation, ensuring the assistant's outputs are both accurate and relevant.

The CDUW is not merely a tool but a paradigm shift in underwriting, synthesizing vast data points and expert knowledge into a cohesive, intelligent system. It stands as a testament to our commitment to innovation, efficiency, and precision in the realm of insurance underwriting.

5.4 Action Recommendation

A key component of the digital underwriting application, as already stated, is the integration of the disease manual into the digital medical risk assessment process. Underwriters should use this handbook as a vital resource in order to optimise the application's capabilities and increase efficiency for the benefit of the customer and the underwriter.

The disease manual outlines the guidelines for evaluating medical hazards in hospital programmes and acts as a thorough guide. It covers a wide variety of illnesses to sufficiently address typical situations with possible policyholders. Information about condition classifications, necessary tests for each disease, and test administration instructions are all included in detail. Decisions regarding coverage, waiting periods, lifetime exemptions, reassessments, premium surcharges, and potential rejections are also covered.

For instance, the underwriter consults the handbook to determine whether an MRI is required as part of the application in order to assess the condition when processing an application in which the insured discloses cervical illness. In light of the severity determined by imaging test comparisons, the handbook offers guidance on the consequences of further provided data, such as comparative tomography, which may have an impact on the waiting period or the potential for condition exclusion.

The assistant's expertise is utilised by the digital underwriting system to give underwriters explanations for every application. It establishes causes that may be attributed, enabling the underwriter to look into each case more thoroughly. Based on a complex iterative process of human-machine interaction, the underwriter ultimately has the option to determine the insurance coverage or to reject the application. In this process, information is shared dynamically between the underwriter and the assistant, who digest it and provide well-reasoned arguments back to the underwriter. By offering further details or refutations through this feedback loop, the underwriter can expand the assistant's knowledge base and guarantee that the assistant's recommendations are up to date and well-informed.

The Cognitive Digital Underwriting Assistant now offers automatic suggestions based on data-driven insights and aligns them with accepted medical underwriting principles thanks to the integration of the illness manual's contents into the Assistant's framework. By using health risk profiles and conversion probabilities, the Assistant's recommendations are validated against the manual's criteria, guaranteeing that each advice is based on the underwriting policies of the organisation. Combining the accuracy of machine learning with the wisdom of human understanding, this synthesis of data analytics and manual guidelines provides a sophisticated approach to underwriting, where complicated decision-making is driven by a rich reservoir of knowledge.

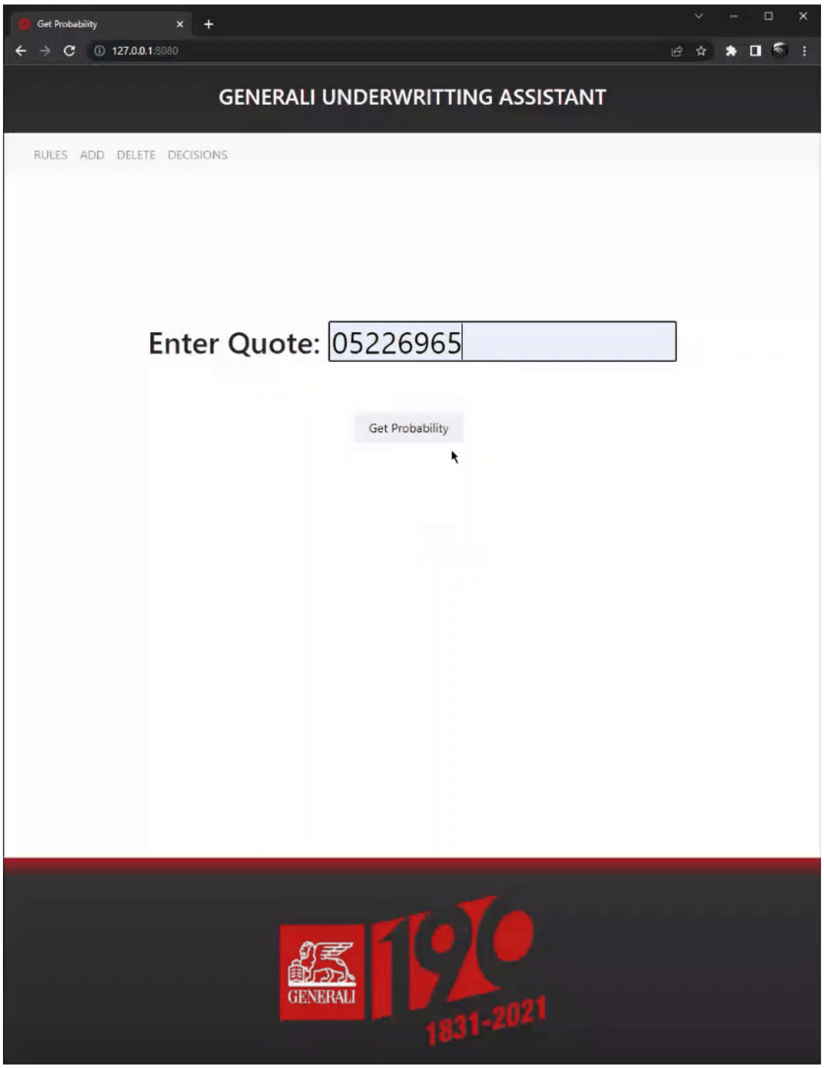


Figure 9. Pilot Project of CDUW

With its many advantages that simplify and improve the decision-making process, the Cognitive Digital Underwriting Assistant is a revolutionary step forward for the insurance underwriting industry. With the use of real-time data analysis, this creative assistant provides underwriters with deeper insights so they can make more accurate and knowledgeable selections. In a sector where identifying risk profiles is crucial, this kind of improved risk assessment is essential.

The capacity of the CDUW to reduce errors is important because it examines data for trends and results that might escape human examination. This thorough inspection supports the underwriting procedure and guarantees a better level of precision and uniformity. Moreover, the CDUW frees underwriters to focus their knowledge where it's most needed—on complex cases requiring a deep understanding—by automating basic operations. In addition to increasing productivity, this human resource optimisation lowers operating expenses.

Adopting the CDUW gives you a competitive edge from a strategic standpoint. It makes it possible to scale operations to handle a growing number of applications without sacrificing turnaround times or quality. The ability to scale is essential for business expansion and preserving a competitive advantage in the marketplace.

Smooth integration with current systems is necessary for the CDUW to fully integrate into workflows. The DB2 and MongoDB servers' data will be interfaced with via the Python-developed CDUW. It is also significant that it is integrated into the ToolBox application, where it will function as an action panel and centralise access to the assistant's skills within the underwriting platform. A specifically created API makes this connection possible and facilitates effective data interchange and communication between the CDUW and ToolBox.

Thorough testing is an essential part of the implementation process to ensure the assistant functions as expected and offers real benefits to the underwriting team. A Minimum Viable Product (MVP) has already been started in order to demonstrate the capabilities of the CDUW and adjust its features to meet the requirements of underwriters.

With this proactive strategy, the CDUW will not only meet but surpass the underwriters' and the company's overall expectations when it is fully deployed.

With the innovative artificial intelligence approach known as "machine coaching," human specialists may train and lead the system to make decisions that are consistent with the organization's complex rules and practises. Because of its interactive nature, the CDUW is guaranteed to be a dynamic system that adjusts to the constantly shifting nature of risk and insurance underwriting, rather than a static, one-size-fits-all instrument.

5.4.1 Train the Machine

Senior underwriters can train the system by programming decision-making guidelines that the CDUW can use in subsequent situations. This is made possible by their extensive knowledge and profound comprehension of the complexities involved in evaluating risk. An interface makes the process of adding rules easier to use by streamlining the difficult process of encoding expert knowledge into a digital framework.

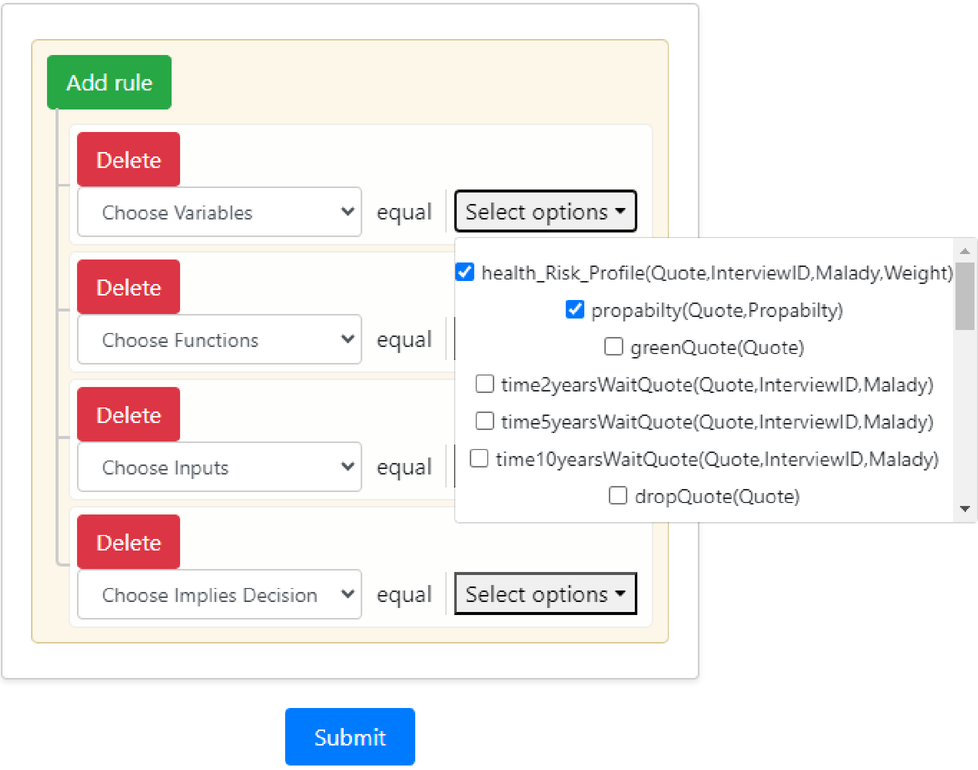


Figure 10. Rule Addition by Experts

The rule addition interface has an easy-to-understand layout that makes it possible to convert even the most complicated underwriting principles into CDUW rules that can be executed. Senior underwriters have a choice of variables to choose from, each of which represents a distinct component of the underwriting data, including policy specifications, demographic information, and health risk profiles. Underwriters can specify the functions that relate to these variables after they have been chosen. For example, they can establish thresholds for risk levels or important indicators for fraud detection. Numerical data and categorical evaluations are examples of inputs for these functions that can be easily incorporated into the decision-making process.

Underwriters can choose the conclusions or actions that the system should infer from these conditions after the variables and their matching functions are set. These choices can include endorsing a policy, recommending extra safeguards, or highlighting an instance for additional investigation. A Cognitive Assistant that is specifically designed to meet the requirements of the underwriter is the result of this approach. In order to make sure that the CDUW's recommendations are consistent with their professional judgement, each underwriter might design a set of guidelines that represent their own method of risk assessment. There are several benefits to this customised strategy. It enables underwriters to successfully increase their decision-making power throughout the company by encoding their most successful techniques into the CDUW. Because the rules supplied by many underwriters contribute to a broader, more comprehensive framework for decision-making, it also functions as a library of collective expertise.

A noteworthy characteristic of the CDUW is its ability to provide quick and adaptable re-training techniques. Underwriters can update and re-train the CDUW with new rules and variables as the insurance market changes and new risks arise, guaranteeing that the system stays at the forefront of risk assessment. Through the interface, retraining can be carried out. The system will then provide feedback on how well new rules work, based on past performance and present trends. Through constant learning and algorithmic improvement, this iterative process guarantees that the CDUW is improving its forecast accuracy.

There are numerous advantages to putting such a system in place. One benefit is that it greatly increases the underwriting process's accuracy and efficiency, cutting down on the amount of time needed for regular evaluations and lowering the possibility of mistakes. Senior underwriters can also train junior underwriters and establish a uniform approach to risk assessment by sharing their knowledge across the entire organisation. Underwriters can further guarantee that the system is in line with their organization's unique underwriting philosophy and risk appetite by customising the CDUW. This alignment guarantees the relevance, dependability, and best interests of the insured and the insurer of the recommendations and judgements rendered by the CDUW.

In summary, senior underwriters are given the ability to instill their knowledge into a cognitive system, which transforms the CDUW from a tool into a digital extension of the underwriters that can use their most successful tactics on a broader basis. This guarantees that insurance is underwritten with a level of understanding and precision that was previously impossible, in addition to improving the underwriting process.

Chapter 6

Evaluation

We started a series of practical trials inside Generali Hellas S.A.'s operational framework, working with experienced employees of the retail life underwriting team, to validate and improve our proposed Cognitive Digital Underwriting Assistant. These senior volunteers were entrusted with assessing policy applications under the prism of our novel methodology, offering a useful viewpoint on the system's effectiveness.

The necessity of a strong, uniform decision-making process throughout the underwriting stage—a crucial stage that has a substantial financial impact on the insurer and affects the client experience—served as the foundation for our examination of the system's performance. We have extensive interviews with Generali Hellas S.A.'s senior underwriters in order to obtain deeper understanding, and they provided priceless input on the features and results of the CDUW.

The SHAP value analysis has quantitatively underscored the alignment of the Cognitive Digital Underwriting Assistant's influential features with the key factors used by senior underwriters at Generali Hellas S.A. during risk assessment, validating the system's precision and reliability as a decision-support tool. This correlation shows the viability and benefits of integrating AI into the underwriting process, as it can enhance and reflect the complex judgment underwriters derive from their vast experience. Furthermore, this alignment guarantees that the cognitive assistant's recommendations are rooted in established underwriting practices and that its evolving functionality keeps pace with industry expertise.

6.1 The Key Insights Derived from the Research

As noted by Michael L. (2021), AI has changed from being primarily driven by science to comprehend human intellect to being mostly driven by engineering to create systems that address specialised and niche problems. Due to the abundance of data available, AI is now commonly used to refer to any technology that processes data in an ambiguous way and finds hidden knowledge that is embedded in it.

The vast repositories kept by insurance firms and the personal data of applicants are the two main sources of data that power these complex systems. During the application, medical questionnaire, and interview phases of the insurance coverage process, applicants divulge a multitude of information. Insurance databases also provide past policy records, claims information, and coverage specifics that, when paired with applicant information, create a full dataset ready for AI research. Explainability was a strong point of the proposed system from the start and. Explainability is a crucial component of a symbiotic relationship between humans and machines because it recognises the importance of bilateral and real-time explanations in a symbiotic relationship, going beyond the simple provision of one-way post-hoc explanations.

Explainability is a basic requirement in the field of insurance underwriting, where the stakes are high and involve sensitive personal data and important financial decisions. The creation of the Cognitive Digital Underwriting Assistant was primarily motivated by the growing importance of openness and comprehension in AI-driven systems. Explainability in AI systems, especially in this kind of setting, goes beyond just looking back and explaining the machine's decisions. It explores the creation of a two-way interactive communication channel between the machine and the human user. This is crucial for creating an environment of trust, encouraging adoption, and making sure that the users—in this example, the underwriters—can understand, trust, and make good use of the insights that the AI provides.

Explainability was a hot topic of discussion in the senior underwriter workshops throughout the CDUA's development. It became clear that comprehending the reason behind the AI's recommendations was just as important to these professionals—who are entrusted with making complex decisions that impact people's financial security—as the recommendations themselves. The underwriters stated that they required a system that presented its results as a transparent advisor whose reasoning could be assessed and comprehended, rather than as a decision that was presented as a mystery.

Working with senior professionals of the retail life underwriting team, we began a series of hands-on tests within Generali Hellas S.A.'s operational framework in order to validate and enhance our suggested Cognitive Digital Underwriting Assistant. These experienced volunteers provided a valuable perspective on the efficacy of the system by evaluating new policy proposals through the lens of our innovative methodology.

Our analysis of the system's performance was based on the requirement for a robust, consistent decision-making process throughout the underwriting stage—a critical stage that impacts the customer experience and has a significant financial impact on the insurer. To gain a deeper understanding, we had lengthy discussions with the senior underwriters at Generali Hellas S.A.; they were very helpful in providing invaluable feedback on the features and outcomes of the CDUA.

During these discussions, the underwriters gave detailed explanations of their everyday responsibilities, painting a clear picture of the complex nature of the underwriting process. They gave us a plethora of information, which we meticulously outlined in our newly developed model by dictating the essential rules that govern their decision-making processes. It was thanks to this discussion that the CDUA now closely resembles the intricate mental processes of human underwriters.

A major step towards the insurance industry's digital transformation is the integration of a cutting-edge system such as the Cognitive Digital Underwriting Assistant into the regular operations of seasoned underwriting specialists in a production setting. This shift from conventional techniques to an AI-supported strategy highlights a dedication to accuracy, effectiveness, and—above all—adaptability in decision-making processes.

Careful planning went into the introduction of the CDUA at Generali Hellas S.A., guaranteeing a smooth interface with the current underwriter's portal for application validation. The underwriters were not forced to use the system; rather, it was presented to them as an additional resource to augment their knowledge. The initial reluctance to change, which is a typical human reaction, was lessened by integrating the system into a recognisable interface, giving underwriters a safe and comfortable environment in which to examine the system's advantages.

The underwriters actively participated in the development of the CDUA, acting not only as end users but also during each iteration of its use. Their role was not that of passive recipients of the system, but rather that of critical evaluators, charged with comparing the system's suggestions to their extensive expertise and understanding of the nuances of underwriting. Every case the system handled provided an opportunity for improvement and learning, not only for the CDUA but also for the underwriters.

The input from the underwriters served as the cornerstone for further development. Every policy recommendation and recommendation made by the CDUA was scrupulously documented, as was the underwriter's evaluation of their viability. A wealth of real-world data from cases that were marked for improvement was used to recalibrate and optimise the system. Through this iterative approach, the underwriters and the CDUA were able to reevaluate mutual trust and understanding in addition to technical calibration.

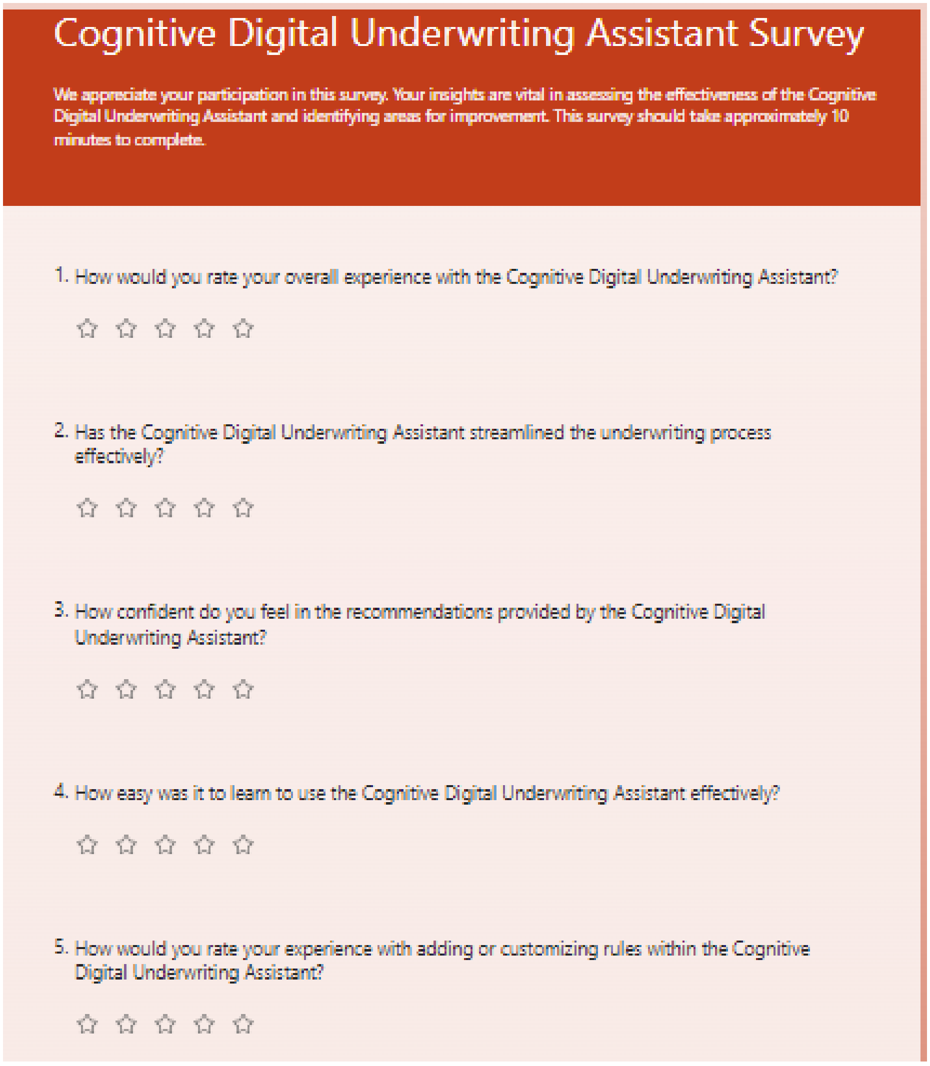
The system's robust adaptability and steep learning curve were also guaranteed by this collaborative approach. With every iteration, the CDUA improved its ability to navigate the delicate balance between risk aversion and opportunity recognition, as well as its alignment with the underwriters' thought processes and sensitivity to the subtleties of risk assessment. As a result, the underwriters improved their ability to use the system, evaluate its suggestions critically, and use its strengths to improve their own decision-making procedures.

A successful fusion of AI and human expertise is demonstrated by the integration of the CDUA into Generali Hellas S.A.'s production environment. It demonstrates how AI has the ability to complement human qualities like professionalism, knowledge, and discretion—qualities that are characteristic of seasoned underwriters—while also elevating them. This project is a positive first step towards an underwriting environment that is more perceptive, accurate, and responsive.

6.2 Expert's feedback

Through a targeted survey aimed at senior underwriters, Generali Hellas S.A. evaluated the deployment and efficacy of the Cognitive Digital Underwriting Assistant. These experienced specialists were chosen to offer a critical assessment of the CDUA's performance and its integration into their established workflow due to their broad knowledge in risk assessment and policy decision-making.

The survey was thoughtfully designed to extract in-depth input on a variety of functional aspects of the CDUA. Ten inquiries were made, each intended to delve deeper into a different area of the system, such as the precision of risk assessment or the overall user experience. The underwriters were able to provide specific feedback on their satisfaction levels by using a five-star rating system to evaluate their comments.


Cognitive Digital Underwriting Assistant Survey

We appreciate your participation in this survey. Your insights are vital in assessing the effectiveness of the Cognitive Digital Underwriting Assistant and identifying areas for improvement. This survey should take approximately 10 minutes to complete.

1. How would you rate your overall experience with the Cognitive Digital Underwriting Assistant?

2. Has the Cognitive Digital Underwriting Assistant streamlined the underwriting process effectively?

3. How confident do you feel in the recommendations provided by the Cognitive Digital Underwriting Assistant?

4. How easy was it to learn to use the Cognitive Digital Underwriting Assistant effectively?

5. How would you rate your experience with adding or customizing rules within the Cognitive Digital Underwriting Assistant?

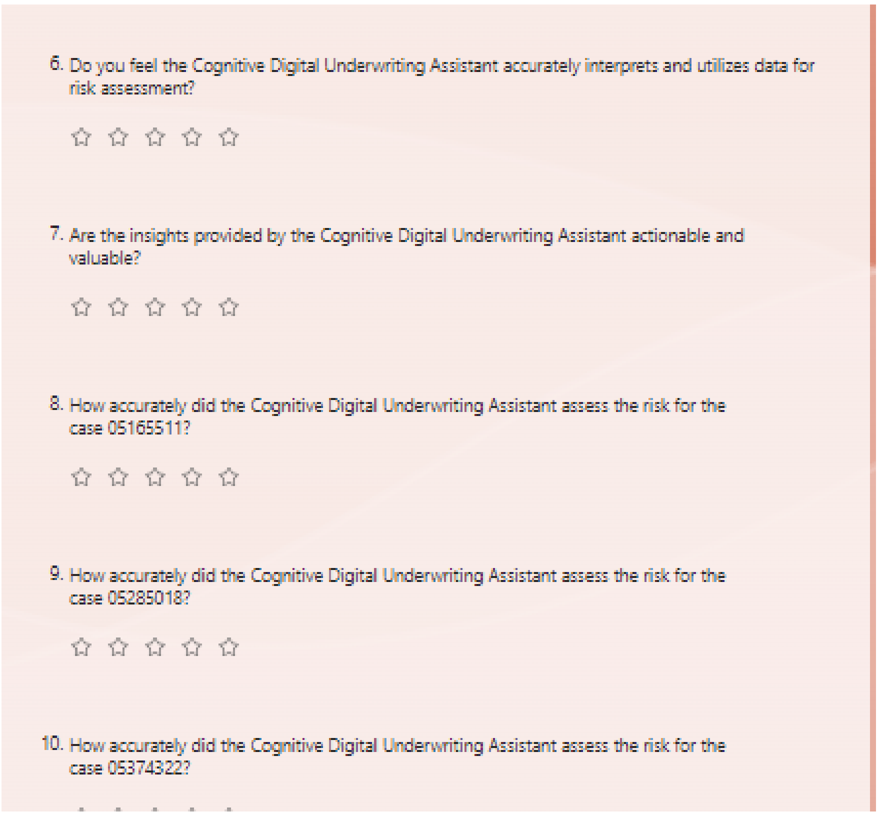


Figure 11. Survey Insights

Based on the opinions of seasoned underwriters, the survey's overall findings produced the following findings:

- Overall Experience: Senior underwriters gave the CDUA a strong average evaluation of 4.6 stars, suggesting that the system was well incorporated into their day-to-day operations, aligning seamlessly with their workflow and expectations.

Figure 12. Overall Experience Scoring

- Process Streamlining: The CDUA received an exceptional average rating of 4.3 stars, reflecting the good feedback regarding its efficacy in expediting the underwriting process. This illustrates how well the system has improved operational efficiency, thereby reducing the time and effort required for policy decision-making.

Figure 13. Process Streamlining Scoring

- Confidence in Recommendations: With an average rating of 3.8 stars, this score was slightly lower compared to other aspects. It suggests that while underwriters generally trust the system's recommendations, there remains room for increasing confidence, perhaps through enhanced accuracy or clearer rationale behind recommendations.

Figure 14. Confidence in Recommendation Scoring

- Ease of learning: The perfect score in this category underscores the user-friendly nature of the CDUA. It indicates that the system is intuitive and easy to adopt, even for underwriters who may not be deeply tech-savvy.

Figure 15. Ease of Learning Scoring

- Rule Customization: This aspect received a moderately positive response. It suggests that while the feature is useful, there may be opportunities to improve the interface or functionality for customizing rules within the system.

Figure 16. Customizing Rules Scoring

- Data Interpretation to Assess Risk: With an average rating of 4.3 stars, the CDUA's data interpretation for risk assessment was found to be correct, demonstrating the system's prowess in data analytics and its effectiveness in risk assessment, a critical component of the underwriting process.

Figure 17. Interpretation Scoring

- Actionable Insights: The actionability and utility of the CDUA's findings in the underwriting process were scored at 4.6 stars. The insights provided are highly valued by underwriters for their actionability. This score reflects the system's success in delivering relevant and practical recommendations that aid in decision-making.

Figure 18. Actionable Insights Scoring

* First Case-Specific Risk Evaluation: The high score for this case demonstrates the system's reliability in assessing standard risk scenarios, indicating that the CDUA performs well in clear-cut cases.

Figure 19. Specific Case Scoring

* Second Case-Specific Risk Evaluation: The slightly lower score for this complex case suggests that while the CDUA performs adequately, it may require further refinement to handle intricate or nuanced cases more effectively.

Figure 20. Specific Case Scoring

* Third Case-Specific Risk Evaluation The near-perfect score for this case illustrates the system's strong capability in accurately assessing risk, even in potentially challenging scenarios.

Figure 21. Specific Case Scoring

An average grade of four stars was obtained by assessing the CDUA's performance on particular situations, which demonstrated overall reliability in risk assessment. The comments also pointed up areas where the CDUA could be more closely aligned with the underwriters' expert opinions, even though the system worked well overall.

According to the survey, the CDUA is an effective addition to an experienced underwriter's toolkit. The system has garnered positive feedback for its capacity to deliver insights in real-time, enhance productivity, and make practical suggestions. The ability of the CDUA to be customised by adding new rules has also been cited as a particularly useful feature, allowing underwriters to adapt the system to their experience and the unique requirements of each case. The detailed input on each case evaluation, however, indicates that the system's interfaces and algorithms require constant improvement. It highlights how crucial it is to have a dynamic system that changes in response to the complexity of the insurance market and the underwriters' experience.

The survey's findings demonstrate a very functional and user-friendly solution that perfectly suits senior underwriters' requirements. The CDUA is exceptional at providing high levels of accuracy in risk assessment, actionable insights, and process optimisation. Although the area of rule customisation is seen favourably, it does point to a possible area for future development to improve the user experience even more. Particularly in difficult circumstances, the significantly reduced confidence in the system's suggestions suggests that further improvement and possibly more straightforward explanation procedures are required. Future generations of the CDUA will benefit greatly from this feedback, which will direct changes that will keep the system closely aligned with the complex requirements of insurance underwriting.

In conclusion, the CDUA represents a substantial development in digital underwriting that is in line with senior underwriters' expectations and areas of competence. It is a significant advancement in the fusion of human knowledge and AI-powered productivity, opening the door for increasingly complex, precise, and effective underwriting procedures in the insurance sector.

6.3 Validating System Effectiveness

The endeavour to validate and enhance the Cognitive Digital Underwriting Assistant at Generali Hellas S.A. has been marked by a rigorous integration of advanced machine learning techniques and empirical analyses. Central to this endeavour is the SHAP (SHapley Additive exPlanations) value analysis and the development of a sophisticated model to assess the conversion probability of policy quotes.

Our approach to modeling the conversion probability involved the implementation of an XGBClassifier, a potent machine learning tool known for its efficacy in classification tasks. This model was intricately designed to forecast the likelihood of transforming policy estimates into actual policies, a key indicator of the underwriting process's efficacy. To construct this model, we delved into a comprehensive range of variables comprising Health Risk Profiles, demographic particulars, and specific quote details such as price, coverage types, and broker information. The model's extensive feature set included elements like Health Risk Profiles (minimum, maximum, and average), Automated and Manual Tasks Number, Final Evaluation Task Number, various coverage types (prevention, services, and hospital), participation amounts, room types, on-Demand cover, child inclusion in quotes, the number of individuals covered, Policyholder’s age, quote’s premium, and broker details.

Employing these features, the model was developed in a bifurcated manner to address quotes at various stages of the underwriting process—before and after the manual tasks. This dual-model strategy obtained a notable accuracy rate of around 82%. Such a high degree of precision was attained through a combination of advanced data processing and machine learning techniques:

- One-hot encoding: This technique converted categorical information into a format amenable to machine learning algorithms, thereby augmenting the model's prediction accuracy.
- Up-sampling with SMOTE: To address the imbalance in class representation, we increased the number of underrepresented samples, assuring a more balanced and fair model.
- GridSearchCV: This exhaustive cross-validation approach was crucial in identifying the most effective parameters for our model, ensuring its robustness and reliability.
- XGBClassifier: The use of eXtreme Gradient Boosting, a versatile and efficient algorithm, was pivotal in solving a broad range of machine learning challenges presented in our data.

In evaluating the model's performance, we utilized tools such as the confusion matrix & accuracy score to identify and analyze model errors. This provided us with a clear picture of where the model excelled and where it required refinement. The R2 score further augmented our comprehension by illustrating the proportion of the variance in the dependent variable predictable from the independent variables.

The SHAP value analysis was integral in coupling these technical achievements to practical insights. By quantifying the impact of each feature on the model's predictions, it offered a detailed and transparent view of how the CDUA's decisions were being made. This analysis not only elucidated the 'why' behind the model's recommendations but also aligned these insights with the intuitive decision-making processes of experienced underwriters.

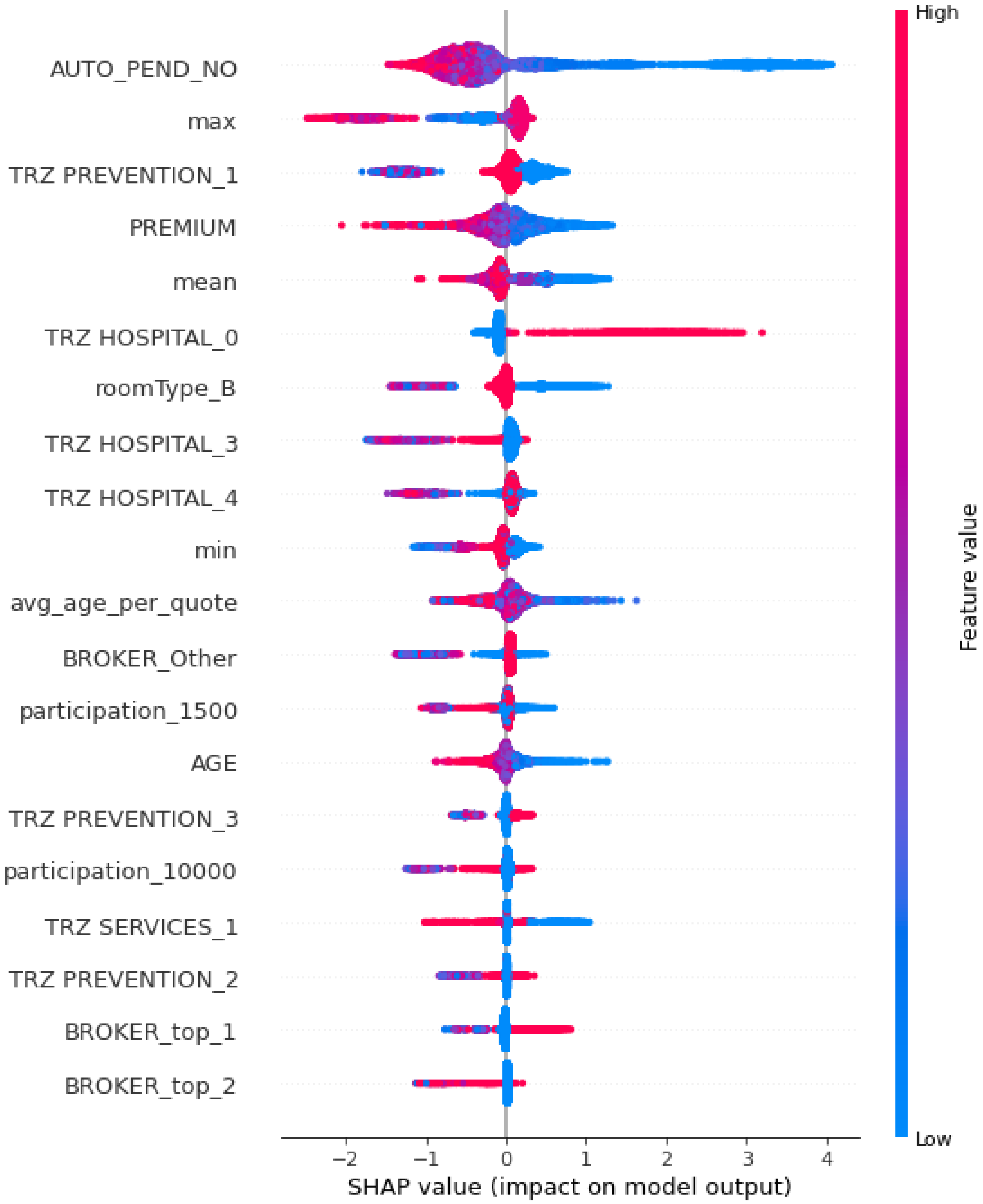


Figure 22. SHAP Value Analysis Without Tasks

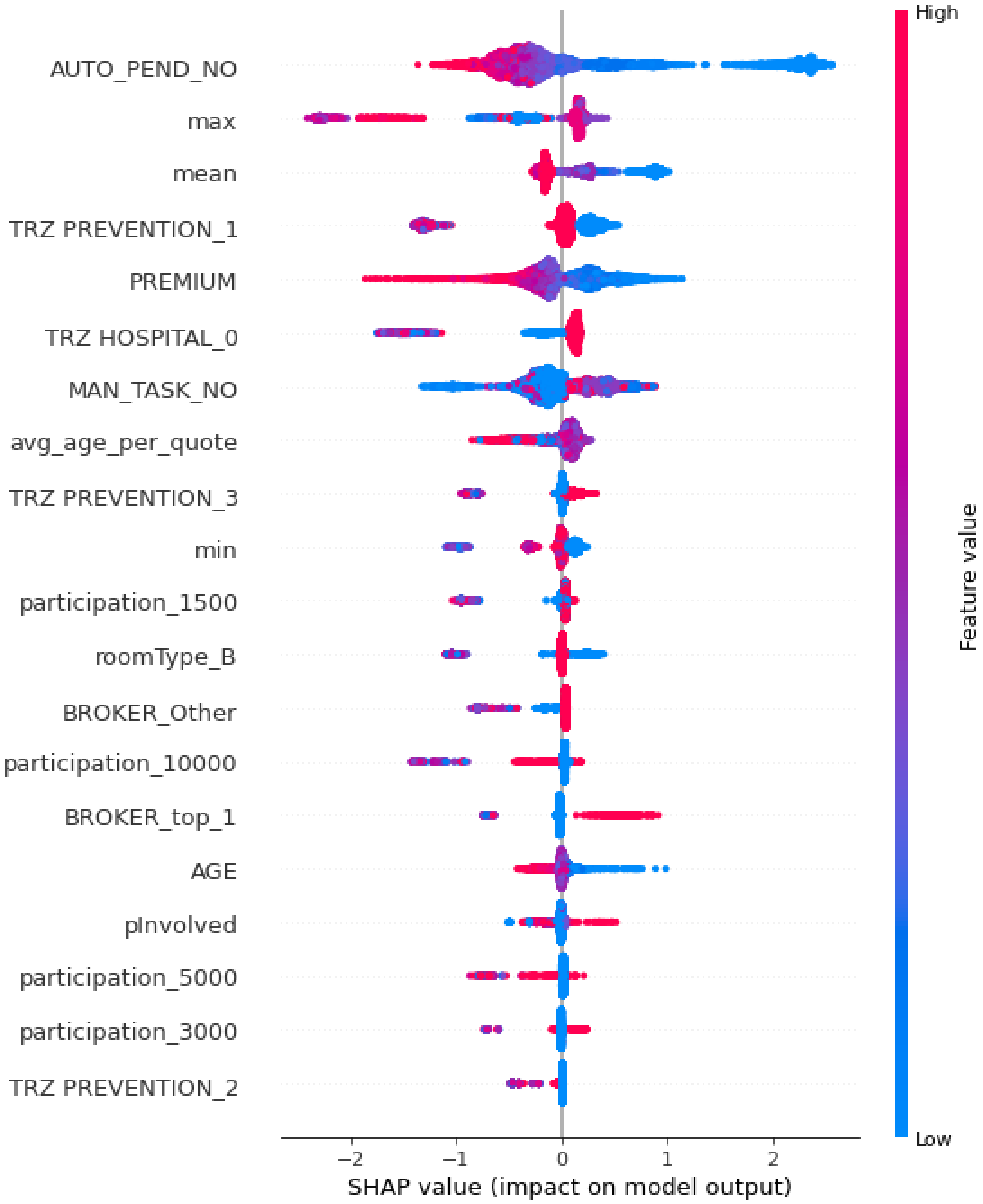


Figure 23. SHAP Value Analysis With Tasks

Furthermore, the SHAP value diagrams functioned as an effective medium for dialogue between the AI system and the underwriters. They facilitated a mutual exchange of knowledge, allowing underwriters to validate and refine the automated recommendations. This ensured that the CDUA's learning trajectory was aligned with the real-world complexities of underwriting and that its recommendations remained precise and pertinent.

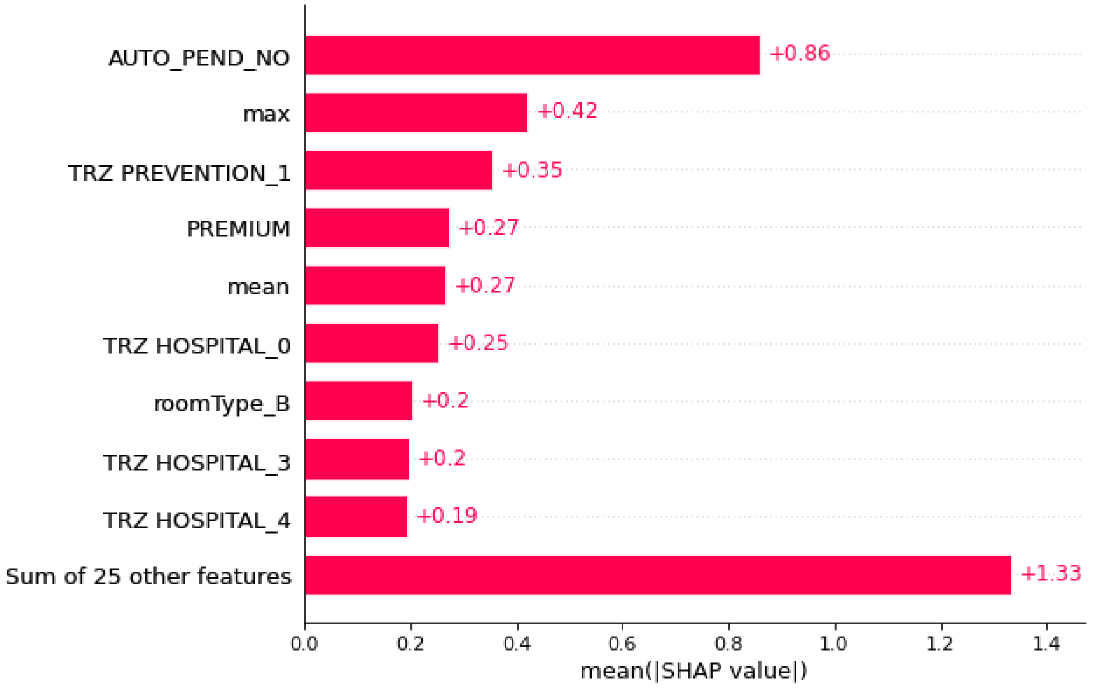


Figure 24. SHAP Mean SHAP Value Without Tasks

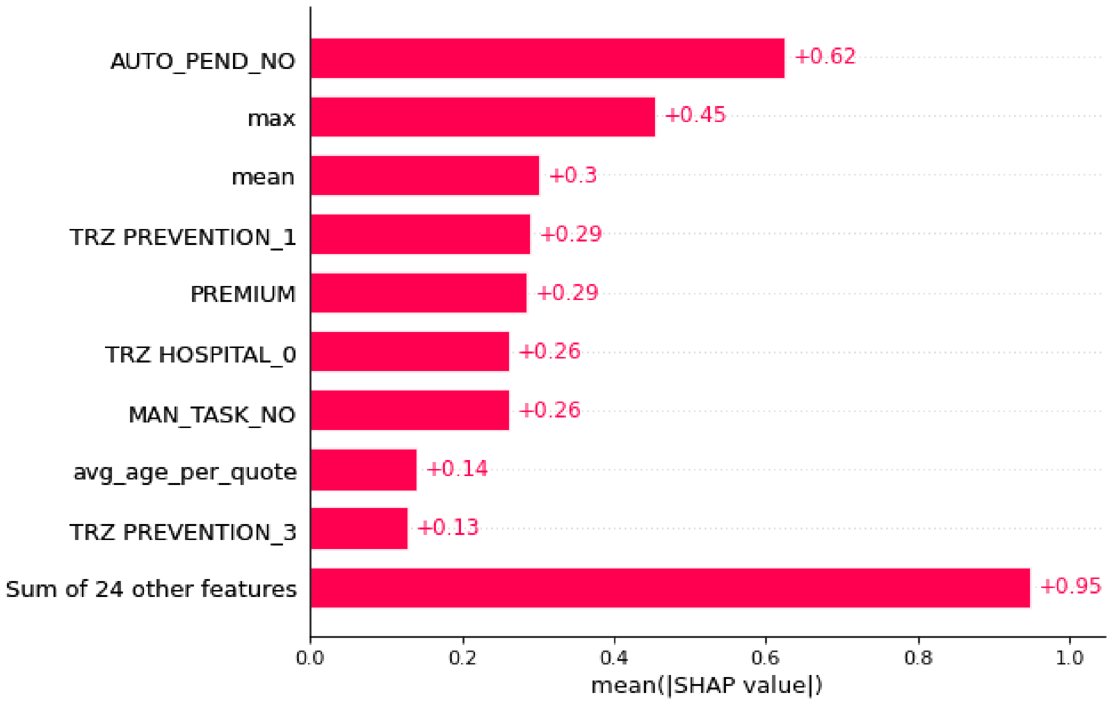


Figure 25. SHAP Mean SHAP Value With Tasks

In summary, the integration of the SHAP value analysis with the statistical rigor of the conversion probability model represents a comprehensive endeavour towards excellence in digital underwriting. It exemplifies a perfect blend of human expertise and sophisticated machine learning, where each component enriches the other. The result is a system that not only replicates human cognitive processes but also enhances them, heralding a future where underwriting is more insightful, accurate, and efficient. This meticulous validation and enhancement process positions the Cognitive Digital Underwriting Assistant as a beacon of AI-driven productivity and represents a significant step forward in the digital transformation of the insurance industry.

Chapter 7

Conclusion

In summary, the Cognitive Digital Assistant for Health Underwriters is an artificial intelligence-driven technology that aims to revolutionise the health underwriting process through the examination of data, detection of patterns, and provision of immediate insights to underwriters. The primary characteristics of the assistant encompass the capacity to provide a conversion-to-policy likelihood ratio and offer recommendations for underwriting actions based on a thorough examination of various data points.

The assistant has the capability to offer underwriters with real-time insights, enabling them to make judgements that are more informed. This, in turn, can result in improved risk assessment, decreased occurrences of errors and inconsistencies, and heightened efficiency. While there are some hurdles and restrictions to consider, the benefits of employing this technology outweigh the expenses for many firms.

This final chapter serves to consolidate the primary discoveries of this study, reflect upon their importance, and anticipate their potential ramifications for the insurance sector. In addition, we present potential areas for further investigation that have the potential to advance our comprehension and implementation of cognitive digital underwriting assistants.

7.1 Recap of Key Findings

Significant new information about the revolutionary potential of artificial intelligence in the insurance underwriting process has been gained via the investigation and deployment of a Cognitive Digital Underwriting Assistant within Generali Hellas S.A. These revelations not only reshape existing procedures but also provide direction for the sector's digital development.

The most significant effect of the CDUW has been to improve underwriters' ability to make decisions. Underwriting has always placed a great deal of reliance on the knowledge and expertise of experts to assess risks and choose the terms of policies. But with the CDUW, judgements are now informed by insights gleaned from a plethora of data sources rather than just heuristics, ushering in a data-driven paradigm. Through the use of sophisticated algorithms, the CDUW analyses historical data, current trends, and complicated risk factors to give underwriters a comprehensive knowledge of each applicant's profile. More accurate risk assessment is made possible by this all-encompassing approach, which may result in more fair pricing and policy terms that accurately represent the risk involved. The operating efficiency of the CDUW could be increased significantly in an area where time is of the essence. Underwriters can focus on more intricate and nuanced issues that call for human skill because the CDUW automates repetitive processes and streamlines the data analysis process. This workflow optimisation not only speeds up the underwriting process but also improves underwriters' job satisfaction because they are able to focus on more intellectually stimulating work instead of being bogged down by tedious administrative duties. Errors in the underwriting process could significantly be decreased as a result of the CDUW's integration. Although it is a common occurrence in all professions, human mistake in insurance underwriting can have serious consequences that result in monetary losses and harm to one's reputation. By offering a consistent and thorough risk analysis and guaranteeing that the same degree of care is given to every application, the CDUW reduces this risk. Furthermore, the system is increasingly more dependable over time because of its capacity to learn from mistakes made in the past and modify its algorithms accordingly.

One notable aspect of the CDUW is its machine learning capability, which allows for ongoing enhancements to its prediction accuracy. Every time the assistant interacts with underwriters, who examine and comment on its recommendations, it gains knowledge incrementally. The assistant's algorithms are improved by this feedback loop, which also helps to better match the insurer's underwriting guidelines and risk appetite with its risk assessment models. This eventually produces a highly developed assistant that can mimic the ability of the most seasoned underwriters to make decisions. Because the CDUW may expedite the time from application to issue, it has the ability to completely transform the customer experience. Clients gain from policies that are more tailored to their risk profiles and coverage requirements as well as more responsive services. Possessing the ability to provide effective, personalised service is obviously advantageous in a time where customer experience is of the essence.

The study also emphasises how important it is for the CDUW's algorithms to be transparent. The need for transparent and comprehensible automated decision-making systems is developing as insurers depend more and more on them. This requirement stems from a desire to uphold confidence with stakeholders and customers in addition to regulatory issues. It's critical to comprehend how underwriters and CDUWs may collaborate most effectively, as evidenced by research on human-AI interaction. The objective is to use the analytical powers of the CDUW to supplement underwriters' expertise rather than to completely replace them. Subsequent investigations may concentrate on refining these interplays to optimise the advantages of human proficiency and AI effectiveness.

The increasing integration of AI into insurance procedures necessitates strict adherence to legal guidelines, especially with data protection and ethical implications. Future studies should look into ways to adopt and construct CDUWs to satisfy these changing needs while maintaining a high level of operational benefit.

Long-term research is required to evaluate how the adoption of CDUW affects insurance companies' financial stability and consumers' pleasure. These research will offer insightful information about the long-term viability and advantages of using AI into underwriting procedures.

The Cognitive Digital Underwriting Assistant is a major advancement in the use of AI in the insurance sector. Its advantages range from more effective and efficient decision-making to better customer service and a competitive edge. Looking ahead, we see even more benefits from this technology's ongoing development and improvement, which will make insurance underwriting more accurate, efficient, and adaptable to the demands of a world that is changing quickly.

7.2 Implications for the Insurance Industry

As demonstrated by Maier et al. (2020), the insurance sector is poised for a transformation spurred by developments in artificial intelligence and machine learning. This paradigm change in the insurance industry from conventional underwriting techniques to AI-driven prediction models has significant ramifications. The accuracy with which systems forecast risks is indicative of a significant advancement in underwriting accuracy. Leveraging AI models might significantly improve the industry's ability to evaluate risks, customise policies, and maximise price efficiency—all of which increase the value proposition for the end customer.

The insurance sector needs to put more emphasis on being transparent about how consumer data is used and the advantages it offers in the age of AI underwriting. Customers are reassured of the ethical use of their personal information by this transparency, which is crucial for the acceptance of AI in insurance. The Master’s dissertation also points that insurance companies can better manage their risk pools and provide creative financial products that meet a range of customer needs by precisely identifying risks. Insurance companies now have the chance to offer their end customers individualised programs thanks to AI advancements.

The cognitive models show how well integrate with current financial and medical underwriting standards. This suggests to the industry as a whole that cognitive systems may be smoothly integrated into existing systems, providing underwriters with powerful tools without upsetting established procedures. In the AI-driven world, underwriters play a new but equally important function. Underwriters can concentrate on complex case evaluations, customer connections, and qualitative judgement while AI manages the quantitative risk analysis. A workforce of underwriters that are more skilled, adaptable, and dynamic may result from this change.

AI models that can forecast life ratings based on complex biological and demographic characteristics will enable the sector to create more sophisticated regulations. By taking into consideration individual health trajectories instead of depending just on general statistical life tables, these plans could help move insurance towards a more individualised framework. The underwriting sector needs to adjust to the use of cognitive systems, which can mean retraining employees, upgrading ethical standards, and changing legal frameworks. Insurance companies need to keep up with technology advancements in order to remain competitive and satisfy the changing demands of their customers, especially as cognitive systems become an essential component of underwriting.

An industry that is more adaptable, equitable, and efficient—one that can precisely and carefully address the sophisticated needs of the contemporary consumer—will define this sector in the future. It is crucial that insurers adopt these technologies as we enter this new era, creating a setting where technology complements human expertise and improves outcomes for all parties involved in the life insurance industry. The underwriter transforms from a data processor into a strategic thinker and relationship manager by using the insights from the system to offer individualised service and forge closer bonds with brokers and clients.

7.3 Suggestions for Future Research

A critical next phase would be to strengthen the dialectical interaction between the Cognitive Digital Underwriting Assistant and a specific underwriter, allowing for the subsequent development of trust between the two actors. The underwriters will explain their reasoning and show to the assistant how they arrived at such alternative judgments (Michael, 2019). As a consequence, the assistant must incorporate the argumentation into its system and modify resulting relative decisions and arguments appropriately. To facilitate contact and translation between the internal representations of the interlocutors, some kind of supervised natural language appears to be required.

The underwriting process as it is already stated requires high transparency and flexibility in the decision process. The underwriters will embrace the new technologies as their role will be empowered by accessing systems which models are constantly learning and adapting to the world around them. Cognitive systems in the form of digital assistants are greatly improving the quality of advice. Cognitive intelligent solutions shrink the overall

underwriting process while improving accuracy, automating the decision-making and speeding up time-to-market.
The role of the underwriter will be empowered by the Cognitive Digital Underwriting Assistant, which support their processes and enhance their capabilities in solving a wide variety of complex risk assessments. The key challenge in this project is to endow Cognitive Assistant with enough flexibility and general knowledge to handle underwriting tasks. The goal is to develop a system that can both save time for the underwriter and improve decision quality by providing the transparency through the argumentation. The underwriter then can focus on assuring that the life insurance portfolio is balanced and improve the customer's journey.

The ongoing development of the Cognitive Digital Underwriting Assistant is essential to maintaining leadership in the insurance sector, particularly given its smooth integration with Generali Hellas S.A.'s workflows. The next steps for the cognitive system entail a deliberate augmentation of its machine learning capacities through the addition of new data points that greatly increase the accuracy and utility of the system. An even more comprehensive view of the insurance market will be possible with the inclusion of broker profiles and associated variables in the CDUW. In the insurance ecosystem, brokers are vital players, and their profiles can have unnoticed clues about how policies work out. The Cognitive Digital Underwriting Assistant can provide insights with more accuracy by integrating this data, which will improve the decision-making process.

Having access to comprehensive medical exam data might transform risk assessment by identifying health risks that conventional questionnaires could miss. The cognitive assistant would be able to do more in-depth risk analysis with the incorporation of this rich data source, which would help with more informed underwriting choices and policy pricing. Analysing the financial profiles of clients and estimating their lifetime worth can greatly improve the systems's ability to predict policy conversions and retention. Financial analysis has the potential to produce more individualised insurance policies that closely match the needs and financial capabilities of policy holders.

It is essential to have a smooth integration with the internal portal. The underwriters' operating system is the portal, and with the Cognitive Digital Underwriting Assistant integrated, improved features like new rule additions and access to advanced analytics will be easily available.

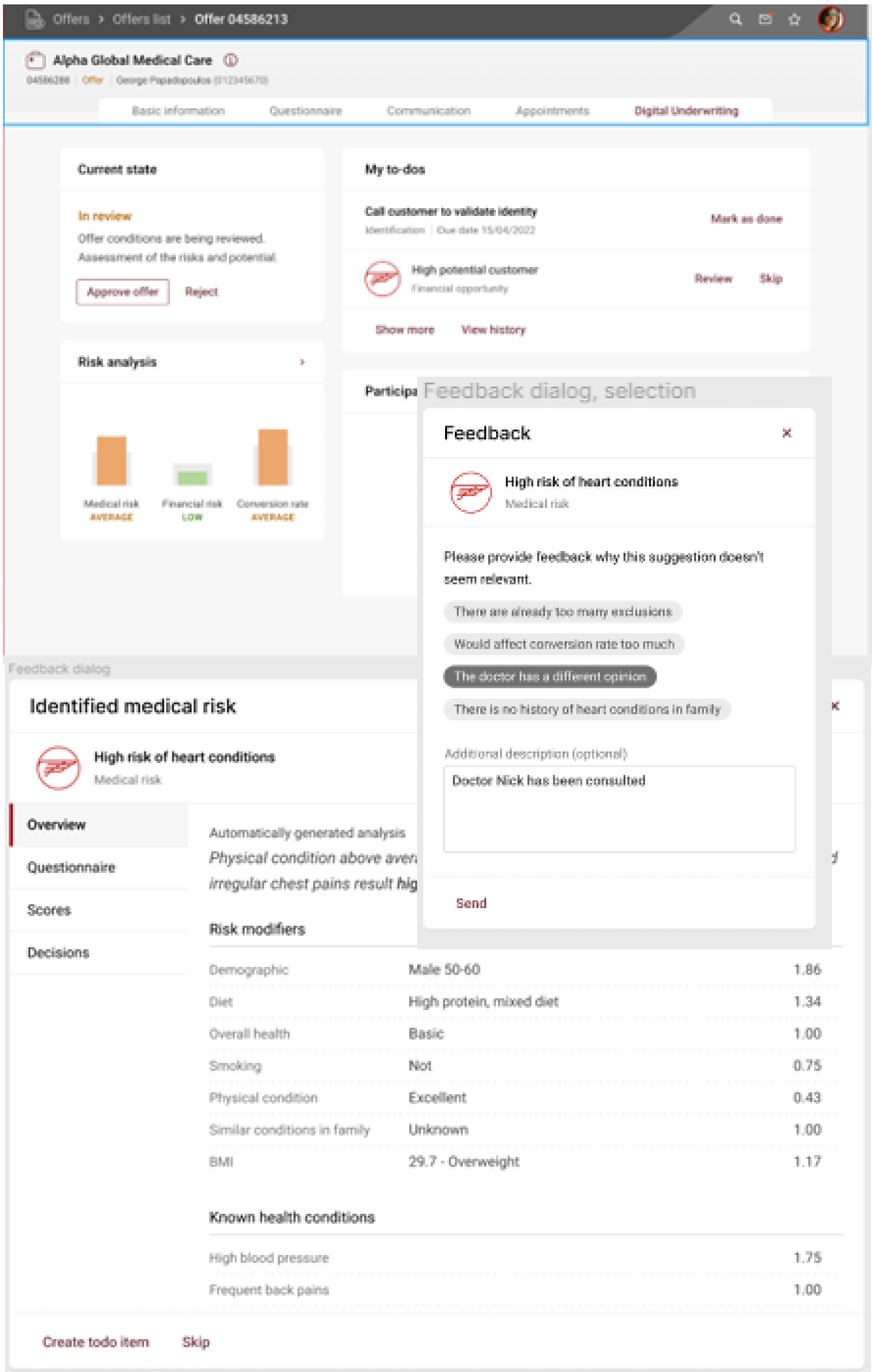


Figure 26. Assistant Integrated into the Portal

The Digital Underwriting Assistant's main interface is a simplified dashboard that uses a combination of automated insights and user interaction to manage the underwriting process. The interface of the assistant is a prime example of a well-designed digital tool; it seamlessly combines user-centered design and data-driven analytics to support the complex duties of contemporary health underwriting.

The Cognitive Digital Underwriting Assistant has a very clear roadmap: deepen its analysis, increase its transparency, and make sure its integration is easy to use and meets the requirements of the underwriters. By taking these actions, Generali Hellas S.A. can be sure that the Cognitive Digital Underwriting Assistant will always be a valuable resource, providing value through accurate, technology-driven underwriting support and insightful analysis.

Appendix A

Prudens Knowledge Base

A.1 Rules

In this section we present all the built in rules of the time the Master's dissertation was written. Each rule embodies a distinct reasoning that directs the underwriting decision-making procedure, guaranteeing that the CDUW Assistant reacts suitably to diverse risk thresholds and circumstances. By covering a wide range of situations, from straightforward risk evaluations to intricate cases needing particular consideration, the rules improve the system's capacity to make well-informed and sophisticated underwriting judgements.

Rule Name	Rule Body
R1	health_Risk_Profile(Quote,InterviewID,Malady,Weight), propabilty(Quote,Propabilty), ?=(Weight,0) implies greenQuote(Quote);
R2	health_Risk_Profile(Quote,InterviewID,Malady,Weight), propabilty(Quote,Propabilty), ?=(Weight,1) implies time2yearsWaitQuote(Quote,InterviewID,Malady) |0;
R3	health_Risk_Profile(Quote,InterviewID,Malady,Weight), propabilty(Quote,Propabilty), ?=(Weight,2), ?lowPropability(Propabilty) implies time5yearsWaitQuote(Quote,InterviewID,Malady);

Rule Name	Rule Body
R4	health_Risk_Profile(Quote,InterviewID,Malady,Weight), propabilty(Quote,Propabilty), ?=(Weight,2), -?lowPropability(Propabilty) implies time2yearsWaitQuote(Quote,InterviewID,Malady);
R5	health_Risk_Profile(Quote,InterviewID,Malady,Weight), propabilty(Quote,Propabilty), ?=(Weight,3), -?lowPropability(Propabilty) implies time10yearsWaitQuote(Quote,InterviewID,Malady) | 0;
R6	health_Risk_Profile(Quote,InterviewID,Malady,Weight), propabilty(Quote,Propabilty), ?=(Weight,3), ?lowPropability(Propabilty) implies dropQuote(Quote)| 0;
R7	greenQuote(Quote), time2yearsWaitQuote(Quote,InterviewID,Malady) implies -greenQuote(Quote);
R8	-greenQuote(Quote), time2yearsWaitQuote(Quote,InterviewID,Malady) implies time2yearsWaitQuote(Quote,InterviewID,Malady) | 1;
R9	greenQuote(Quote), time5yearsWaitQuote(Quote,InterviewID,Malady) implies -greenQuote(Quote);
R10	-greenQuote(Quote), time5yearsWaitQuote(Quote,InterviewID,Malady) implies time5yearsWaitQuote(Quote,InterviewID,Malady) | 1;
R11	greenQuote(Quote), time10yearsWaitQuote(Quote,InterviewID,Malady) implies -greenQuote(Quote);
R12	-greenQuote(Quote), time10yearsWaitQuote(Quote,InterviewID,Malady) implies time10yearsWaitQuote(Quote,InterviewID,Malady) | 1;
R13	greenQuote(Quote), dropQuote(Quote) implies -greenQuote(Quote);
R14	-greenQuote(Quote), dropQuote(Quote) implies dropQuote(Quote) | 2;
R15	time2yearsWaitQuote(Quote,InterviewID,Malady), dropQuote(Quote) implies -time2yearsWaitQuote(Quote,InterviewID,Malady);

Rule Name	Rule Body
R16	-time2yearsWaitQuote(Quote,InterviewID,Malady), dropQuote(Quote) implies dropQuote(Quote) | 2;
R17	time5yearsWaitQuote(Quote,InterviewID,Malady), dropQuote(Quote) implies -time5yearsWaitQuote(Quote,InterviewID,Malady);
R18	-time5yearsWaitQuote(Quote,InterviewID,Malady), dropQuote(Quote) implies dropQuote(Quote) | 2;
R19	time10yearsWaitQuote(Quote,InterviewID,Malady), dropQuote(Quote) implies time10yearsWaitQuote(Quote,InterviewID,Malady);
R20	-time10yearsWaitQuote(Quote,InterviewID,Malady), dropQuote(Quote) implies dropQuote(Quote) |2;
R21	noMaladies(Quote) implies greenQuote(Quote);
R22	time2yearsWaitQuote(Quote,InterviewID,Malady), ?=(Malady,x00_allo) implies uwEvaluation(Quote,InterviewID,Malady);
R23	uwEvaluation(Quote,InterviewID,Malady), time2yearsWaitQuote(Quote,InterviewID,Malady), ?=(Malady,x00_allo) implies -time2yearsWaitQuote(Quote,InterviewID,Malady);
R24	time5yearsWaitQuote(Quote,InterviewID,Malady), ?=(Malady,x00_allo) implies uwEvaluation(Quote,InterviewID,Malady);
R25	uwEvaluation(Quote,InterviewID,Malady), time5yearsWaitQuote(Quote,InterviewID,Malady), ?=(Malady,x00_allo) implies -time5yearsWaitQuote(Quote,InterviewID,Malady);
R26	evalRight(Quote,InterviewID,Malady) implies evaluation(Quote,InterviewID,Malady);
R27	health_Risk_Profile(Quote,InterviewID,Malady,Weight), propabilty(Quote,Propabilty), broker(Broker), -?lowPropability(Propabilty),

Rule Name	Rule Body
	?=(Weight,3), ?=(Broker,13943) implies reinsurance(Quote,InterviewID,Malady);

Table 3. Prudens Knowledge Base

Here is a brief elaboration of each rule defined in the Prudens framework:

- R1: If a quote has a health risk profile with a weight of 0 (no risk), it is classified as a greenQuote, indicating standard underwriting terms.
- R2: A quote with a health risk profile weight of 1 implies a two-year waiting period, reflecting a medium risk level.
- R3: For a health risk weight of 2 and low probability, a five-year waiting period is implied, indicating a higher risk.
- R4: If the health risk weight is 2 but without low probability, a two-year waiting period is applied, indicating a nuanced assessment based on the probability factor.
- R5: A health risk weight of 3 with no low probability suggests a ten-year waiting period, implying a very high risk.
- R6: A health risk weight of 3 with low probability leads to the dropping of the quote, indicating an unacceptable level of risk.
- R7: If a quote is initially green but later identified with a two-year wait condition, the green status is revoked.
- R8: Maintains the two-year waiting condition unless the quote is green.
- R9: Revokes the green status of a quote if it is identified with a five-year wait condition.
- R10: Maintains the five-year waiting condition unless the quote is green.
- R11: Revokes the green status if a ten-year waiting condition is identified.
- R12: Maintains the ten-year waiting condition unless the quote is green.
- R13: If a quote is green but later identified for dropping, the green status is revoked.
- R14: Ensures that a quote is dropped unless it is green.
- R15: Revokes a two-year waiting condition if the quote is identified for dropping.
- R16: Ensures the dropping of a quote unless a two-year wait is identified.

- R17: Revokes a five-year waiting condition if the quote is identified for dropping.
- R18: Ensures the dropping of a quote unless a five-year wait is identified.
- R19: Maintains a ten-year wait condition even if the quote is identified for dropping.
- R20: Ensures the dropping of a quote unless a ten-year wait is identified.
- R21: If no maladies are identified in a quote, it is classified as green.
- R22: Initiates underwriter evaluation for a quote with a two-year wait condition and specific malady criteria (x00_allo).
- R23: Revokes a two-year waiting condition post-underwriter evaluation if specific criteria are met.
- R24: Initiates underwriter evaluation for a quote with a five-year wait condition and specific malady criteria.
- R25: Revokes a five-year waiting condition post-underwriter evaluation if specific criteria are met.
- R26: Indicates that a quote is up for evaluation if it meets certain right-to-evaluation criteria.

Appendix B

Code

B.1 Project Structure

The code of the proposed system is available at the following GitHub repository, https://github.com/aperanton/cduw. In this section we present the structure of the project by describing the various folders and files:

- Models Folder
  - Connection.py
  - Libs_Import.py
  - Health_Risk_Profiles.py
  - Manual_Tasks_Included.py
  - Without_Manual_Tasks.py
  - Models_Creation.py
  - Top_Brokers.py
- Assistant Folder
  - Connection.py
  - Libs_Import.py
  - Fetch_Health_Risk_Profiles.py
  - Fetch_Quote.py
- Prudens Folder
  - Output_handle.py
  - JavaScript files
  - wrappers.py
- Models Evaluation Folder
  - Interactive notebooks

- Quote_info_app Folder
    - Django templates
    - Django models
    - Django forms
    - Django views
- Root Level Scripts
    - Hrp_decision.py
    - Connection.py (Same as in other folders, possibly a shared resource)
    - Libs_Import.py (Same as in other folders, possibly a shared resource)

Each folder serves a specific function within the codebase, from fetching data and creating models (Models Folder) to querying and applying algorithms for specific quotes (Assistant Folder) and handling the knowledge base model (Prudens Folder). The root level scripts provide overarching functionality that ties different components of the system together. The Models Evaluation Folder contains notebooks for model testing, and the Quote_info_app Folder consists of Django-specific files for the web application structure.

B.2 Models Interaction

The below flowchart illustrates the architecture of the Digital Underwriting Assistant system. Django models interact with the application, handling requests for knowledge base objects and underwriting rules. Various Python scripts like `**output_handle.py**`, `**wrappers.py**`, `**hrp_decision.py**`, and others work in tandem to process quotes, health risk profiles, and broker information. The system uses libraries and methods to fetch data and execute algorithms, providing the necessary outputs for decision-making. All these components are neatly encapsulated within the `**duw_assistant**` folder, signifying a modular and organized codebase.

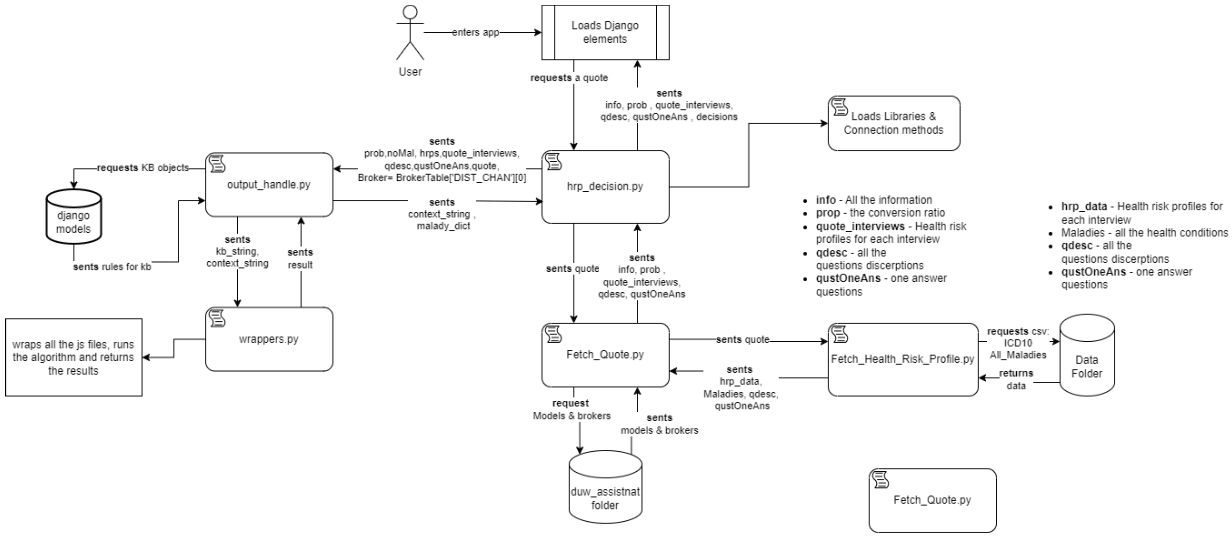


Figure 27. Case of User Validating Quote

Appendix C

Custom Tables

C.1 Data Flow Diagram

The Digital Underwriting Assistant system's essential parts and information flow are displayed in the below data flow diagram. The central component is Health Risk Profiling, which uses information from DB2 and MongoDB databases to generate risk profiles based on personal health information gathered from telehealth interviews.

One important measure that can be obtained from these profiles is the Conversion Ratio, which shows the probability that quotes will become policy. It makes use of models that forecast this chance based on variables including coverage specifics, incident and damage data, and if a quote requires manual labour.

Additional analytical components such as Fraud Detection and Lifetime worth Score employ data to estimate a policyholder's long-term worth and evaluate the likelihood of fraud, respectively. These revelations support the evaluation and decision-making procedures as a whole.

Ultimately, the system produces actionable outputs that offer underwriters recommendations for actions based on the collected data and processed insights. These recommendations may relate to new policy designs, changes to the scope of coverage, or other underwriting procedures. The system architecture makes it easier to take a thorough, data-driven approach to underwriting, which improves the organization's underwriting process' accuracy and speed.

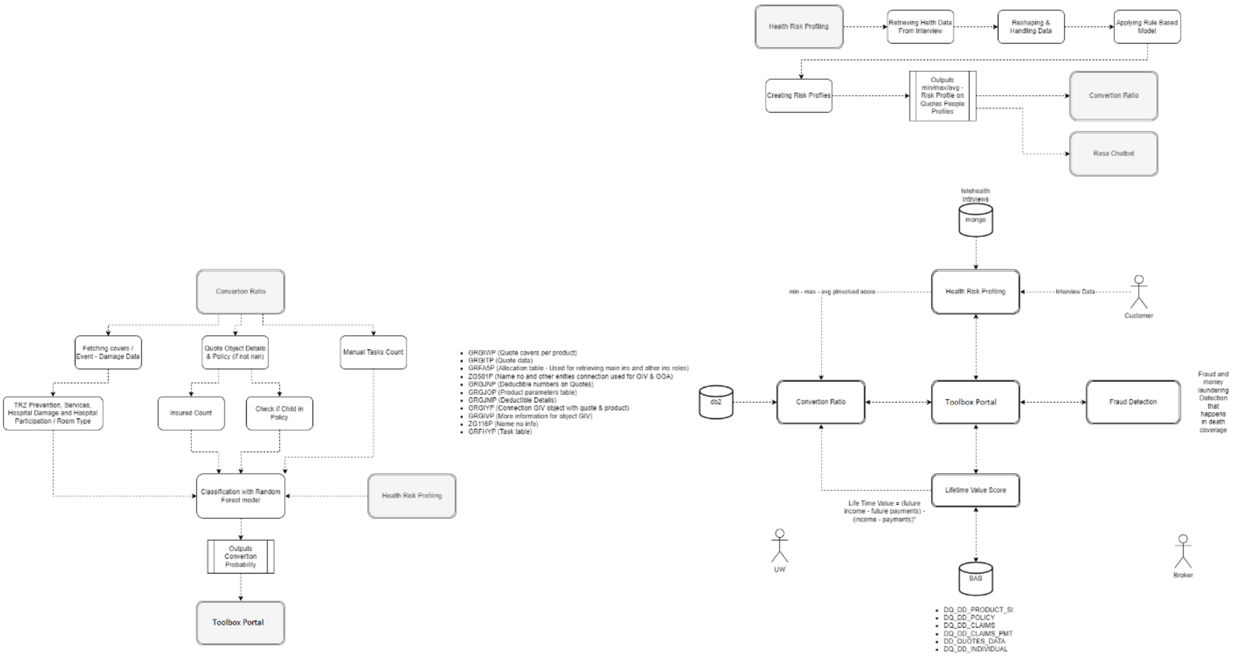


Figure 28. Data Flow Diagram

C.2 Tables from Stage 0 – Quote Creation

dfCust:

	taskNumber	entTypeT125	entTypeT125Desc	allocationTypeTFA6	allocationTypeTFA6Desc	startDateTask	allocationStatusTFA7	allocationStatusTFA7Desc
0	001084195	116	Name	500	Customer	2022-01-27	100	Open Allocation
1	001084195	116	Name	505	Main insured	2022-01-27	100	Open Allocation
2	001678954	116	Name	500	Customer	2022-09-22	100	Open Allocation
3	001678954	116	Name	505	Main insured	2022-09-22	100	Open Allocation
4	001678954	116	Name	506	Spouse insured	2022-09-22	100	Open Allocation

allocationStatusTFA7Desc	nameNumber	nameDesc1	nameDesc2	surname	birthDate	personNumber	gender	startDateEntity	addressNumber	postCode
Open Allocation	14752617	ΑΡΓΥΡΩ	ΠΑΝΑΓΙΩΤΗΣ				2	2021-01-06	11405710	153 41
Open Allocation	14752617	ΑΡΓΥΡΩ	ΠΑΝΑΓΙΩΤΗΣ				2	2021-01-06	11405710	153 41
Open Allocation	14826163	ΕΥΑΓΓΕΛΟΣ	ΝΙΚΟΛΑΟΣ				1	2021-02-08	11378092	145 76
Open Allocation	14826163	ΕΥΑΓΓΕΛΟΣ	ΝΙΚΟΛΑΟΣ				1	2021-02-08	11378092	145 76
Open Allocation	14837302	OLGA	VASILI				2	2021-02-12	10815775	145 76

customerAddress:

	allocationTypeTFA6Desc	nameNumber	nameDesc1	nameDesc2	surname	birthDate	startDateEntity	addressNumber	streetName	StreetNumber
0	Customer	14752617	ΑΡΓΥΡΩ	ΠΑΝΑΓΙΩΤΗΣ						
1	Main insured	14752617	ΑΡΓΥΡΩ	ΠΑΝΑΓΙΩΤΗΣ						
2	Customer	14826163	ΕΥΑΓΓΕΛΟΣ	ΝΙΚΟΛΑΟΣ						
3	Main insured	14826163	ΕΥΑΓΓΕΛΟΣ	ΝΙΚΟΛΑΟΣ						
4	Spouse insured	14837302	OLGA	VASILI						

StreetNumber	floor	placeName	country	postCode
26-28		ΑΓ.ΠΑΡΑΣΚΕΥΗ	GR	153 41
26-28		ΑΓ.ΠΑΡΑΣΚΕΥΗ	GR	153 41
35-45		ΔΙΟΝΥΣΟΣ	GR	145 76
35-45		ΔΙΟΝΥΣΟΣ	GR	145 76
			GR	145 76

dfCustExtra:

	taskNumber	entTypeT125	entTypeT125Desc	allocationTypeTFA6	allocationTypeTFA6Desc	startDateTask	allocationStatusTFA7	allocationStatusTFA7Desc
0	001084195	116	Name	500	Customer	2022-01-27	100	Open Allocation
1	001084195	116	Name	505	Main insured	2022-01-27	100	Open Allocation
2	001678954	116	Name	500	Customer	2022-09-22	100	Open Allocation
3	001678954	116	Name	505	Main insured	2022-09-22	100	Open Allocation
4	001678954	116	Name	506	Spouse insured	2022-09-22	100	Open Allocation

5 rows × 29 columns

›cationStatusTFA7Desc	nameNumber	nameDesc1	...	personObjectNumber	typeOfInsuranceT178	typeOfInsuranceDesc	occupationAreaT303	occupationAreaDesc
Open Allocation	14752617	ΑΡΓΥΡΩ	...	000511338	105	Main Insured person ...		NaN
Open Allocation	14752617	ΑΡΓΥΡΩ	...	000511338	105	Main Insured person ...		NaN
Open Allocation	14826163	ΕΥΑΓΓΕΛΟΣ	...	000524228	105	Main Insured person ...		NaN
Open Allocation	14826163	ΕΥΑΓΓΕΛΟΣ	...	000524228	105	Main Insured person ...		NaN
Open Allocation	14837302	OLGA	...	000526644	106	Spouse ...		NaN

occupationAreaDesc	employmentTypeT653	acceptanceTypeT170	acceptanceTypeDesc	riskClass	annualSalary
NaN	222		NaN	2	0.0
NaN	222		NaN	2	0.0
NaN	338		NaN	1	0.0
NaN	338		NaN	1	0.0
NaN	560		NaN	2	0.0

dfCreator:

	taskNumber	entTypeT125	entTypeT125Desc	allocationTypeTFA6	allocationTypeTFA6Desc	startDateTask	allocationStatusTFA7	allocationStatusTFA7Desc
0	000409294	116	Name ...	400	Quote creator ...	20201030.0	100	Open Allocation ...
1	000455171	116	Name ...	400	Quote creator ...	20201206.0	100	Open Allocation ...
2	000423037	116	Name ...	400	Quote creator ...	20201110.0	100	Open Allocation ...
3	000413446	116	Name ...	400	Quote creator ...	20201103.0	100	Open Allocation ...
4	000421778	116	Name ...	400	Quote creator ...	20201110.0	100	Open Allocation ...

ationStatusTFA7Desc	nameNumber	nameDesc1	nameDesc2	surname	birthDate	personNumber	gender	startDateEntity	addressNumber	postCode
Open Allocation ...	10052427							19980804.0	11424666	117 45
Open Allocation ...	12985737	ΕΛΕΝΗ	ΚΩΝΣΤΑΝΤΙΝΟΣ					20180601.0	10175329	152 32
Open Allocation ...	13901106	ΓΕΩΡΓΙΟΣ	ΑΝΔΡΕΑΣ					20191025.0	11412343	136 72
Open Allocation ...	12480502							20170516.0	10231159	546 24
Open Allocation ...	11167306	ΜΙΧΑΗΛ	ΙΩΑΝΝΗΣ					20130802.0	10580791	185 43

dfBroker:

	taskNumber	entTypeT125	entTypeT125Desc	allocationTypeTFA6	allocationTypeTFA6Desc	startDateTask	allocationStatusTFA7	allocationStatusTFA7Desc
0	001474713	478	Sales channel ...	200	Broker ...	2022-07-01	100	Open Allocation ...
1	001657338	478	Sales channel ...	200	Broker ...	2022-09-15	100	Open Allocation ...
2	001434894	478	Sales channel ...	200	Broker ...	2022-06-18	100	Open Allocation ...
3	001434879	478	Sales channel ...	200	Broker ...	2022-06-18	100	Open Allocation ...
4	001286872	478	Sales channel ...	200	Broker ...	2022-04-23	100	Open Allocation ...

A7Desc	salesDistChannel	nameNumber	nameDesc1	nameDesc2	surname	birthDate	personNumber	gender	startDateEntity	addressNumber	postCode
cation ...	00128	10012301							1995-02-07	10029325	151 25
cation ...	00126	10020391	ΑΝΑΣΤΑΣΙΟΣ	ΣΩΚΡΑΤΗΣ					1996-01-31	10842551	551 33
cation ...	00126	10020391	ΑΝΑΣΤΑΣΙΟΣ	ΣΩΚΡΑΤΗΣ					1996-01-31	10842551	551 33
cation ...	00126	10020391	ΑΝΑΣΤΑΣΙΟΣ	ΣΩΚΡΑΤΗΣ					1996-01-31	10842551	551 33
cation ...	00126	10020391	ΑΝΑΣΤΑΣΙΟΣ	ΣΩΚΡΑΤΗΣ					1996-01-31	10842551	551 33

brokerAddress:

	allocationTypeTFA6Desc	salesDistChannel	nameNumber	nameDesc1	nameDesc2	surname	birthDate	startDateEntity	addressNumber
0	Broker ...	00128							10029325
1	Broker ...	00126							10842551
2	Broker ...	00451							10015753
3	Broker ...	00570							10011084
4	Broker ...	00510							11424666

addressNumber	streetName	StreetNumber	floor	placeName	country	postCode_y
10029325	ΛΕΩΦ. ΚΗΦΙΣΙΑΣ	74			GR	151 25
10842551	ΕΠΑΝΩΜΗΣ	26			GR	551 33
10015753	ΦΙΛΕΛΛΗΝΩΝ	25			GR	105 57
10011084	ΠΟΛΥΤΕΧΝΕΙΟΥ	45			GR	546 25
11424666	Λ.ΣΥΓΓΡΟΥ & ΛΑΓΟΥΜΙΤΖΗ	40			GR	117 45

dfQuote:

	quote	startDate	endDate	issueDate	firstIssueDate	lobT164	lobDesc	standardTypeT161	standardTypeDesc	nextInstalmntDate	...	paymentTypeDesc
0	04033974	20201030.0	20210130.0	20201030.0	20201030.0	299	Life On ...	100	Standard tariff ...	0.0	...	Giro/Via Post Office ...
1	04034433	20201030.0	20210128.0	20201030.0	20201030.0	299	Life On ...	100	Standard tariff ...	0.0	...	Giro/Via Post Office ...
2	04035191	20201101.0	20210201.0	20201101.0	20201101.0	299	Life On ...	100	Standard tariff ...	0.0	...	Giro/Via Post Office ...
3	04035192	20201101.0	20210201.0	20201101.0	20201101.0	299	Life On ...	100	Standard tariff ...	0.0	...	Cash/Check (Manual) ...
4	04035193	20201101.0	20210202.0	20201102.0	20201102.0	299	Life On ...	100	Standard tariff ...	0.0	...	Giro/Via Post Office ...

rows × 21 columns

renewalMonth	paymentFreq	instalmentPremium	dutyPremium	cumlStampDuty	amountOutstanding	buisinessUnit	nameNumberSalesChan	nameNumberPolicyHol
10.0	1.0	1065.62	278.73	0.0	1344.35	102	11565317	14640
10.0	2.0	602.99	151.76	0.0	754.75	102	10052427	14641
11.0	1.0	757.20	185.89	0.0	943.09	102	11422120	14644
11.0	1.0	644.96	162.14	0.0	807.10	102	11133073	14644
11.0	1.0	2089.22	547.72	0.0	2636.94	102	12763385	14644

dfObjects:

	quote	agreement	lobT164	lobDesc	personNumber	objectTypeT125	objectTypeDesc
0	04142536		299			GIV	Pending Life Insured Person ...
1	04225611		299			GIV	Pending Life Insured Person ...
2	04323640		299			GIV	Pending Life Insured Person ...
3	04378825		299			GIV	Pending Life Insured Person ...
4	04382104	12129216	299			GGA	LifeInsured Person ...

objectTypeDesc	objectNumber	entityRelT125	entityRelDesc	name1	name2	surname
Pending Life Insured Person ...	000511338	10008	Ονομα ...			
Pending Life Insured Person ...	000524228	10008	Ονομα ...			
Pending Life Insured Person ...	000545385	10008	Ονομα ...			
Pending Life Insured Person ...	000556559	10008	Ονομα ...			
LifeInsured Person ...	100356527	10008	Ονομα ...			

PersonGIV:

	quote	prod	objectGIV	startDate	endDate	lobT164	lobDesc	eventTypeT110	eventTypeDesc	damageTypeT159	...	basePremium	sumInsured
0	04719667	0006	000618115	20220214.0	0.0	299	Life On ...	784	TRZ HOSPITAL (FAMILY) ...	565	...	227.76	1000000.0
1	04719667	0007	000618115	20220214.0	0.0	299	Life On ...	787	TRZ 3rd DEGREE ...	552	...	9.24	0.0
2	04719667	0004	000618115	20220214.0	0.0	299	Life On ...	780	TRZ PREVENTION ...	550	...	10.08	0.0
3	04719667	0005	000618115	20220214.0	0.0	299	Life On ...	781	TRZ SERVICES ...	551	...	14.76	0.0
4	04719667	0002	000618115	20220214.0	0.0	299	Life On ...	781	TRZ SERVICES ...	550	...	0.00	0.0

5 rows × 25 columns

sumInsured	conditionsTypeT317	productStatusT156	productStatusDesc	agreement	personNumber	name1	name2	surname
1000000.0	100	101	POLICY ...	12099653				
0.0	100	101	POLICY ...	12099653				
0.0	100	101	POLICY ...	12099653				
0.0	100	101	POLICY ...	12099653				
0.0	100	101	POLICY ...	12099653				

dfStage:

	taskNumber	taskDesc1	quote	stageNumber	stageTypeTFIP	stageNumberDesc	entryDate
0	001084195			0001	120	On Broker & Customer ...	2022-01-27
1	001084195			0002	320	Underwiting Evaluation ...	2022-04-18
2	001084195			0003	330	Final Evaluation Acceptance ...	2022-05-03
3	001084195			0004	340	On Issuing ...	2022-05-05
4	001084195			0005	330	Final Evaluation Acceptance ...	2022-05-05

dfPremium:

	quote	productNumber	instalmentPremium	flatFee	fee	tax	stampDuty	auciliaryFund
0	04676788	0001	12.71	0.0	1.27	2.10	0.0	0.0
1	04676788	0002	0.00	0.0	0.00	0.00	0.0	0.0
2	04676788	0003	9.74	0.0	0.97	1.61	0.0	0.0
3	04676788	0004	80.56	0.0	8.06	13.29	0.0	0.0
4	04676788	0005	7.83	0.0	0.78	1.29	0.0	0.0

C.3 Stage 1- Basic Pendencies

dfUW:

	taskNumber	entTypeT125	entTypeT125Desc	userNumber	allocationTypeTFA6	allocationTypeTFA6Desc	startDate	allocationStatusTFA7
0	001679068	FAE	Web User Details ...	00007206	110	UW Allocation ...	20220922.0	100
1	001675986	FAE	Web User Details ...	00007206	110	UW Allocation ...	20220921.0	100
2	001674999	FAE	Web User Details ...	00007206	110	UW Allocation ...	20220921.0	100
3	001668991	FAE	Web User Details ...	00007206	110	UW Allocation ...	20220920.0	100
4	001668987	FAE	Web User Details ...	00007206	110	UW Allocation ...	20220920.0	100

allocationStatusTFA7	allocationStatusTFA7Desc	userName	name1	surname
100	Open Allocation ...		KATEPINA	
100	Open Allocation ...		KATEPINA	
100	Open Allocation ...		KATEPINA	
100	Open Allocation ...		KATEPINA	
100	Open Allocation ...	...	KATEPINA	

dfPend:

	pendNumber	quote	startDate	endDate	pendTypeHDTFA0	pendTypeHDDesc	pendTypeDTTFA1	pendTypeDTDesc	assignedRoleTFA2	assignedRoleDe
0	109924487	04142536	20220127.0	20220419.0	103	Life Quotes ...	42150	Αντίγραφο Ταυτότητας Συμβαλλόμενου ...	119	Συμβαλλόμενος
1	109924499	04142536	20220127.0	20220127.0	103	Life Quotes ...	42110	Policy Holder e-approval pending ...	119	Συμβαλλόμενος
2	109416897	04378825	20211222.0	20220105.0	103	Life Quotes ...	42150	Αντίγραφο Ταυτότητας Συμβαλλόμενου ...	119	Συμβαλλόμενος
3	109416909	04378825	20211222.0	20211222.0	103	Life Quotes ...	42110	Policy Holder e-approval pending ...	119	Συμβαλλόμενος
5	110578305	04382104	20220526.0	20220615.0	103	Life Quotes ...	42150	Αντίγραφο Ταυτότητας Συμβαλλόμενου ...	119	Συμβαλλόμενος

assignedRoleDesc	entTypeT125	entTypeDesc	assignedEntNumber	resolutionTFCY	resolutionDesc
Συμβαλλόμενος ...	116	Name ...	14752617		NaN
Συμβαλλόμενος ...	116	Name ...	14752617		NaN
Συμβαλλόμενος ...	116	Name ...	14987448		NaN
Συμβαλλόμενος ...	116	Name ...	14987448		NaN
Συμβαλλόμενος ...	116	Name ...	14996622		NaN

sla120:

	quote	taskNumber	taskDesc1	taskDesc2	stageNumber	userType	userCode	allocationTypeTFA6	allocationTypeDesc	seqNumber	seqNumber	ta
2	04718304	000994395	Life On - ΚΩΝΣΤΑΝΤΙΝΟΣ ΜΑΥΡΟΜΜΑΤΗΣ - Life Tele UW		120	FA5	028071318	500	Customer ...	0	0	
3	04718304	000994395	Life On - ΚΩΝΣΤΑΝΤΙΝΟΣ ΜΑΥΡΟΜΜΑΤΗΣ - Life Tele UW		120	FA5	028071319	200	Broker ...	1	1	
4	04718304	000994395	Life On - ΚΩΝΣΤΑΝΤΙΝΟΣ ΜΑΥΡΟΜΜΑΤΗΣ - Life Tele UW		120	FA5	028071318	500	Customer ...	2	2	
5	04718304	000994395	Life On - ΚΩΝΣΤΑΝΤΙΝΟΣ ΜΑΥΡΟΜΜΑΤΗΣ - Life Tele UW		120	FA5	028071317	431	TeleHealth Doctor ...	3	3	
6	04718304	000994395	Life On - ΚΩΝΣΤΑΝΤΙΝΟΣ ΜΑΥΡΟΜΜΑΤΗΣ - Life Tele UW		120	FA5	028071316	110	UW Allocation ...	4	4	

seqNumber	targetType	targetNumber	targetAllocTypeTFA6	targetAllocTypeDesc	startDate	endDate	originalDueDate	buisinessTypeTFIM	buisinessType
0	FA5	028071316	110	UW Allocation ...	20211214.0	20211214.0	0.0	602	Document upload ...
1	FA5	028071316	110	UW Allocation ...	20211214.0	20211215.0	0.0	111	New Tele UW ...
2	FA5	028071316	110	UW Allocation ...	20211214.0	20211214.0	0.0	111	New Tele UW ...
3	FA5	028071316	110	UW Allocation ...	20211214.0	20211215.0	0.0	111	New Tele UW ...
4	FA5	028071319	200	Broker ...	20211215.0	20211215.0	20211216.0	111	New Tele UW ...

C.4 Stage 2 - Telehealth

dfAp:

	_id	version	creator	createdDate	modifier	modifiedDate	notes	status	communicationHandle
0	61b650a46dde5671b5b8ae15	1	07558	2021-12-12 19:42:28.154	NaN	2021-12-12 19:42:28.154	None	INITIALIZED	6975884713
1	61b6f49d6dde5671b5b8ae3e	1	07558	2021-12-13 07:22:05.676	NaN	2021-12-13 07:22:05.676	None	INITIALIZED	6975884713
2	61d2ad53c2dcaac5dfc53b6a	1	12258	2022-01-03 08:01:23.705	NaN	2022-01-03 08:01:23.706	None	INITIALIZED	6937317199
3	61d9a3d6c2dcc92ef501f5cc	1	60149	2022-01-08 14:46:46.254	NaN	2022-01-08 14:46:46.255	None	INITIALIZED	6989164167
4	61b646c06dde5671b5b8ae11	5	07558	2021-12-12 19:00:16.142	07558	2021-12-13 09:32:32.624	<<Εισερχόμενη>> ININ-WRAP-UP-TIMEOUT	COMPLETED	6975884713

communicationHandle	timeFrame	reminderStatus	customer	provider	personsInvolved	history
6975884713	{'type': 'gr.generali.gbox.api.domain.TeleHeal...	NOT_SENT	15342836	NaN	15342836	[]
6975884713	{'type': 'gr.generali.gbox.api.domain.TeleHeal...	NOT_SENT	15343008	NaN	15343008	[]
6937317199	{'type': 'gr.generali.gbox.api.domain.TeleHeal...	NOT_SENT	15374286	NaN	15374262	[]
6989164167	{'type': 'gr.generali.gbox.api.domain.TeleHeal...	NOT_SENT	15383512	NaN	15383511	[]
6975884713	{'type': 'gr.generali.gbox.api.domain.TeleHeal...	SENT	15342826	adamantia.chatzikou@generali.gr	15342826	[{'version': 1, 'creator': {'entityCode': '000...

history	syncStatus	startTime	endTime	relatedEntityId	conversationId
[]	None	NaT	NaT	{'entityCode': '04718128', 'entityType': 'GIT'}	NaN
[]	None	NaT	NaT	{'entityCode': '04718188', 'entityType': 'GIT'}	NaN
[]	None	NaT	NaT	{'entityCode': '04729467', 'entityType': 'GIT'}	NaN
[]	None	NaT	NaT	{'entityCode': '04733068', 'entityType': 'GIT'}	NaN
[{'version': 1, 'creator': {'entityCode': '000...	None	2021-12-13 09:27:08.273	2021-12-13 09:30:32.548	{'entityCode': '04718126', 'entityType': 'GIT'}	NaN

dfInt:

	_id	interviewId	interviewToken	personId	nameCode	quotationCode	date	questions	
0	61b70fbcc2dce0680b51192f	101	TWsbf6ScVUzcDPa3EF5l	fe6b22dbe5ca64e3bd1deeadf79e52ae	15342826	04718126	Dec 13, 2021 12:00:00 AM	[{'code': 'root.Q0_8', 'description': 'Intervi...	[{'i
1	61b70fbcc2dce0680b511930	101	TWsbf6ScVUzcDPa3EF5l	fe6b22dbe5ca64e3bd1deeadf79e52ae	15342826	04718126	Dec 13, 2021 12:00:00 AM	[{'code': 'root.Q0_8', 'description': 'Intervi...	[{'i
2	61b99a3bc2dc80a5a2b2d884	104	h4HZSyfWKPTwNh67epi1	aec38944e2a62c8f16db81879eb4cb4b	15343321	04718304	Dec 15, 2021 12:00:00 AM	[{'code': 'root.Q0_8', 'description': 'Intervi...	[{'i
3	61b9a2d3c2dc80a5a2b2e2bd	118	Pirf3zLsh9hfKliH7bpZ	bff4ee1d0b5da796bad0983f4d60572e	15343322	04718304	Dec 15, 2021 12:00:00 AM	[{'code': 'root.Q0_8', 'description': 'Intervi...	[{'i

...

questions:

	code	description	submittedAnswers	_id	nameCode	quotationCode
0	root.Q0_8	Interview ID	[101]	61b70fbcc2dce0680b51192f	15342826	04718126
1	root.Q0	Κωδικός Υποψηφίου	[fe6b22dbe5ca64e3bd1deeadf79e52ae]	61b70fbcc2dce0680b51192f	15342826	04718126
2	root.Q0_2	Ασφαλιστικό Πρόγραμμα	[299]	61b70fbcc2dce0680b51192f	15342826	04718126
3	root.Q0_3	Ηλικία Υποψηφίου	[46]	61b70fbcc2dce0680b51192f	15342826	04718126
4	root.Q0_1	Φύλο Υποψηφίου	[Ανδρας]	61b70fbcc2dce0680b51192f	15342826	04718126

questionsTab:

code	_id	nameCode	quotationCode	root.Q0	root.Q0_1	root.Q0_2	root.Q0_3	root.Q0_8	root.Q10	r
0	61b70fbcc2dce0680b51192f	15342826	04718126	[fe6b22dbe5ca64e3bd1deeadf79e52ae]	[Ανδρας]	[299]	[46]	[101]	[οχι]	
1	61b70fbcc2dce0680b511930	15342826	04718126	[fe6b22dbe5ca64e3bd1deeadf79e52ae]	[Ανδρας]	[299]	[46]	[101]	[οχι]	
2	61b99a3bc2dc80a5a2b2d884	15343321	04718304	[aec38944e2a62c8f16db81879eb4cb4b]	[Ανδρας]	[299]	[40]	[104]	[οχι]	
3	61b9a2d3c2dc80a5a2b2e2bd	15343322	04718304	[bff4ee1d0b5da796bad0983f4d60572e]	[Γυναίκα]	[299]	[39]	[118]	[οχι]	
4	61b9a3abc2dc80a5a2b2e3f4	15343323	04718304	[efef955a65e38ab3d6b7ab49a50b9f2a]	[Γυναίκα]	[299]	[7]	[114]	[οχι]	

5 rows × 278 columns

root.Q10	root.Q10_1	...	root.QC33	root.QC34	root.QC35	root.QC36	root.QC4	root.QC5	root.QC6	root.QC7	root.QC8_1	root.QC9
[οχι]	NaN	...	[Iqos]	[]	NaN	NaN	NaN	NaN	[]	[Φοράει φακούς]	NaN	NaN
[οχι]	NaN	...	[Iqos]	[]	NaN	NaN	NaN	NaN	[]	[Φοράει φακούς]	NaN	NaN
[οχι]	NaN	...	[]	[]	NaN	NaN	[Σκολικοειδεκτομή σε παιδική ηλικία, Χολεκυστε...	NaN	[]	NaN	NaN	NaN
[οχι]	NaN	...	[Διακοπή από τον 07/2021]	[]	NaN	NaN	[Σκολικοειδεκτομή 2018, Αδενοειδείς εκβλαστήσε...	NaN	[]	NaN	[αναφορά παραπάνω]	NaN
[οχι]	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	[]	[Υπερμετροπία, φέρει γυαλία]	NaN	NaN

questionsDesc:

	code	value
0	root.Q0	Κωδικός Υποψηφίου
1	root.Q0_1	Φύλο Υποψηφίου
2	root.Q0_2	Ασφαλιστικό Πρόγραμμα
3	root.Q0_3	Ηλικία Υποψηφίου
4	root.Q0_8	Interview ID

scoresDecision:

groupName	_id	nameCode	quotationCode	NO_MORE_QUESTIONS	NUMBER_OF_RESETS	SG_ADEN_EKBL_626_1	SG_ADEN_EKBL_628
0	61b70fbcc2dce0680b51192f	15342826	04718126	false	0		
1	61b70fbcc2dce0680b511930	15342826	04718126	false	0		
2	61b99a3bc2dc80a5a2b2d884	15343321	04718304	false	1		
3	61b9a2d3c2dc80a5a2b2e2bd	15343322	04718304	false	0		
4	61b9a3abc2dc80a5a2b2e3f4	15343323	04718304	false	0		

scoresTab:

groupName	_id	nameCode	quotationCode	ANSWER_Q0_1	ANSWER_Q10	ANSWER_Q10_1	ANSWER_Q10_1_1	ANSWER_Q10_2
0	61b70fbcc2dce0680b51192f	15342826	04718126	Άνδρας	οχι			
1	61b70fbcc2dce0680b511930	15342826	04718126	Άνδρας	οχι			
2	61b99a3bc2dc80a5a2b2d884	15343321	04718304	Άνδρας	οχι			
3	61b9a2d3c2dc80a5a2b2e2bd	15343322	04718304	Γυναίκα	οχι			
4	61b9a3abc2dc80a5a2b2e3f4	15343323	04718304	Γυναίκα	οχι			

5 rows × 510 columns

R_Q10_2	ANSWER_Q10_3	ANSWER_Q10_4	...	SG_YPOSPADIAS_628	SG_dyslipidaimia_117	SG_dyslipidaimia_119	SG_dyslipidiamia_627	SG_dyslipidaimia_630	S
			...		117				
			...		117				
			...		117				
			...		117				
			...		117				

SG_dyslipidiamia_630	SG_gastrenteriko_117	SG_gastrenteriko_631	SG_kal_neop_der_628	SG_neop_der_626_3	Subvalue_SG_BMI
	117				
	117				
	117				
	117				
	117				

scoresDescription:

	groupName	category	description
0	NO_MORE_QUESTIONS	DECISION	Automatically set to true by the rules engine ...
1	SG_PATH_KAK_GON_AR_626_1	DECISION	Παθήσεις κακώσεις αριστερού γόνατος και επιπλο...
2	SG_PATH_KAK_GON_DE_626_1	DECISION	Παθήσεις κακώσεις δεξιού γόνατος και επιπλοκές...
3	SG_PATH_KAK_GON_AMFO_626_1	DECISION	Παθήσεις κακώσεις Γονάτων άμφω και επιπλοκές γ...
4	SG_PATH_KAK_THMSS_627	DECISION	Παθήσεις Κακώσεις Θωρακικής Μοίρας Σπονδυλικής...

decisions:

	type	description	value	name	_id	nameCode	quotationCode
0	LIFE	Επασφάλιστρο λόγω ΔΜΣ	20658 -101	DG_BMI	61b70fbcc2dce0680b51192f	15342826	04718126
1	LIFE	Ασφάλιση με κανονικούς όρους	20656 - 100	DG_Αρτηριακή Υπέρταση	61b70fbcc2dce0680b51192f	15342826	04718126
2	LIFE	Ασφάλιση με κανονικούς όρους	20656 - 100	DG_Δυσλιπιδαιμία	61b70fbcc2dce0680b51192f	15342826	04718126
3	LIFE	Ασφάλιση με κανονικούς όρους	20656-100	DG_Matia_Orasi	61b70fbcc2dce0680b51192f	15342826	04718126
4	LIFE	Ασφάλιση με κανονικούς όρους	20656-100\t	DG_Aftia_Myti_Laimos	61b70fbcc2dce0680b51192f	15342826	04718126

decisionTab:

name	DG_AIMOPOIHTIKO	DG_ANAPNEYSTIKO	DG_AYTOANOSA	DG_Aftia_Myti_Laimos	DG_BMI	DG_Covid_19	DG_DERMA	DG_EPEMV_NOSHL	DG_EPIPLE(
0	[20656 -100]	[20656-100]	[20656 - 100]	[20656-100\t]	[20658 -101]	[20656 -100]	[20656-100]	[20656 -100]	[20656 - 1(
1	[20656 -100]	[20656-100]	[20656 - 100]	[20656-100\t]	[20658 -101]	[20656 -100]	[20656-100]	[20656 -100]	[20656 - 1(
2	[20656 -100]	[20656-100]	[20656 - 100]	[20656-100\t]	[20656 - 100]	[20656 -100]	[20656-100]	[20920 - 101]	[20656 - 1(
3	[20656 -100]	[20656-100]	[20656 - 100]	[20656-100\t]	[20656 - 100]	[20656 -100]	[20656-100]	[20920 - 101]	[206!
4	[20656 -100]	[20656-100]	[20656 - 100]	[20656-100\t]	[20656 - 100]	[20656 -100]	[20656-100]	[20656 -100]	[20656 - 1(

decisionsDesc:

	name	value	description
0	DG_AIMOPOIHTIKO	20656 -100	Ασφάλιση με κανονικούς όρους
1	DG_AIMOPOIHTIKO	20923 -101	Αναιμία και επιπλοκές για 3 έτη
2	DG_AIMOPOIHTIKO	20925	Απόρριψη ασφάλισης λόγω Λεμφώματος Non Hodgkin
3	DG_AIMOPOIHTIKO	20657	Εκτίμηση από UW
4	DG_AIMOPOIHTIKO	20924 -101	Αναιμία και επιπλοκές με δικαίωμα επανεκτίμησης

C.5 Stage 3 –Tasks

dfPendAuto:

	pendNumber	quote	startDate	endDate	pendTypeHDTFA0	pendTypeHDDesc	pendTypeDTTFA1	pendTypeDTDesc	assignedRoleTFA2	assignedRoleDe
20973	109742022	04730016	2022-01-04	2022-01-12	103	Life Quotes ...	60387	Ενδοκολπικός Υπέρηχος (U/S) - Υπέρηχος Έσω Γε...	115	Κυρι ασφαλισμένος
20974	109742023	04730016	2022-01-04	2022-01-12	103	Life Quotes ...	60375	Βιοχημικές Εξετάσεις ...	115	Κυρι ασφαλισμένος
20975	109742024	04730016	2022-01-04	2022-01-12	103	Life Quotes ...	60331	Test Παπανικολάου (Test Pap) ...	115	Κυρι ασφαλισμένος
20976	109742025	04730016	2022-01-04	2022-01-12	103	Life Quotes ...	60430	Μαστογραφία ...	115	Κυρι ασφαλισμένος
20977	109742026	04730016	2022-01-04	2022-01-12	103	Life Quotes ...	60381	Γενική Εξέταση Ούρων ...	115	Κυρι ασφαλισμένος

assignedRoleDesc	entTypeT125	entTypeDesc	assignedEntNumber	resolutionTFCY	resolutionDesc
Κυρίως ασφαλισμένος ...	116	Name ...	15375626		NaN
Κυρίως ασφαλισμένος ...	116	Name ...	15375626		NaN
Κυρίως ασφαλισμένος ...	116	Name ...	15375626		NaN
Κυρίως ασφαλισμένος ...	116	Name ...	15375626		NaN
Κυρίως ασφαλισμένος ...	116	Name ...	15375626		NaN

dfTaskAsgn:

	QUOTE	ENTITYTYPEA	ENTITYNUMBERA	quoteDesc	GENUSERA	ALLOCTYPEA	PARENTTASK	ENTITYTYPEB	ENTITYNUMBERB	ALLOCTYPEB	ROLE
0	04872043	FHY	001284892	Για να μπορέσουμε να ελέγξουμε το αίτημα σας γ...	032842944	420	001223177	478	12910368	200	Br
1	04872043	FHY	001284892	Για να μπορέσουμε να ελέγξουμε το αίτημα σας γ...	032842941	410	001223177	FAE	00009737	110	All
2	05002754	FHY	001459084	1) Σας υπενθυμίζουμε ότι θα πρέπει να αποσταλε...	036999570	420	001447748	116	15752124	505	ins
3	05002754	FHY	001459084	1) Σας υπενθυμίζουμε ότι θα πρέπει να αποσταλε...	036999565	410	001447748	FAE	00009604	110	All
4	05002754	FHY	001473325	1) Σας υπενθυμίζουμε ότι θα πρέπει να αποσταλε...	036999570	420	001447748	116	15752124	505	ins

ALLOCTYPEB	ROLETYPE	ROLENAME1	ROLENAME2	ROLENAME3
200	Broker ...			
110	UW Allocation ...			
505	Main insured ...			
110	UW Allocation ...			
505	Main insured ...			

sla320

	quote	taskNumber	taskDesc1	taskDesc2	stageNumber	userType	userCode	allocationTypeTFA6	allocationTypeDesc	seqNumber	seqNumber	targe
6	047				320	FA5	028110248	110	UW Allocation ...	0	0	
7	047				320	FA5	028110248	110	UW Allocation ...	1	1	
20	047				320	FA5	029032354	110	UW Allocation ...	0	0	
21	047				320	FA5	029032354	110	UW Allocation ...	1	1	
22	047				320	FA5	029032357	200	Broker ...	2	2	

seqNumber	targetType	targetNumber	targetAllocTypeTFA6	targetAllocTypeDesc	startDate	endDate	originalDueDate	buisinessTypeTFIM	buisinessType
0	FA5	028110251	200	Broker ...	2021-12-20	2021-12-22	2021-12-27	602	Document upload ...
1				NaN	2021-12-22	2021-12-22	0		NaN
0	FA5	029032357	200	Broker ...	2022-03-28	2022-03-29	2022-04-04	602	Document upload ...
1				NaN	2022-03-29	2022-03-29	0		NaN
2	FA5	029032354	110	UW Allocation ...	2022-03-29	2022-03-29	2022-03-30	602	Document upload ...

extensions:

	_id	taskCode	type	options
0	5afe73b6f9e5df08e3563914	000000904	050	[{'option': 'προχωράμε σε έκδοση με ειδικό όρο...
1	5b044a23f9e5df08e3563921	000001164	050	[{'option': 'θα τεθεί εξαίρεση για: παθήσεις ...
2	5b059018f9e5df08e3563928	000001294	050	[]
3	5b059047f9e5df08e3563929	000001295	050	[]
4	5b059aa0f9e5df08e356392a	000001321	050	[{'option': 'θα τεθεί εξαίρεση για παθήσεις θυ...

dfManualMongo:

	QUOTE	ENTITYTYPEA	ENTITYNUMBERA	quoteDesc	GENUSERA	ALLOCTYPEA	PARENTTASK	ENTITYTYPEB	ENTITYNUMBERB	ALLOCTYPEB	ROLETY
0	04965679	FHY	001582389	Τελική εκτίμηση ...	034960651	420	001397340	116	15716928	505	M insure
1	04965679	FHY	001582389	Τελική εκτίμηση ...	034960646	410	001397340	FAE	00009604	110	I Allocat
2	04742603	FHY	001209759	Τελική εκτίμηση ...	030876596	420	001075883	116	15429480	505	M insure
3	04742603	FHY	001209759	Τελική εκτίμηση ...	030876591	410	001075883	FAE	00010881	110	I Allocat
4	04742603	FHY	001215300	Τελική εκτίμηση ...	030876596	420	001075883	116	15429480	505	M insure

ALLOCTYPEB	ROLETYPE	ROLENAME1	ROLENAME2	ROLENAME3	_id	taskCode	type	options
505	Main insured ...				62f3a9154df23f4abd5657f7	001582389	050	[{'option': 'Θα πρέπει να αποσταλούν γνωματεύσ...
110	UW Allocation ...				62f3a9154df23f4abd5657f7	001582389	050	[{'option': 'Θα πρέπει να αποσταλούν γνωματεύσ...
505	Main insured ...				62414216e554ce2e537b1453	001209759	050	[{'option': 'παθήσεις μαστών και επιπλοκές με ...
110	UW Allocation ...				62414216e554ce2e537b1453	001209759	050	[{'option': 'παθήσεις μαστών και επιπλοκές με ...
505	Main insured ...				6242fcf1e554ce2e537b3286	001215300	050	[{'option': 'παθήσεις μαστών και επιπλοκές για...

C.6 Stage 4 – Policy Creation

sla330:

	quote	taskNumber	taskDesc1	taskDesc2	stageNumber	userType	userCode	allocationTypeTFA6	allocationTypeDesc	seqNumber	seqNumber	targe
8	04720816	000999006	Life On - ΣΟΦΙΑ ΓΕΩΡΓΙΟΣ ΜΥΛΩΝΑ - Life Tele UW		330	FA5	028110251	200	Broker ...	0	0	
9	04720816	000999006	Life On - ΣΟΦΙΑ ΓΕΩΡΓΙΟΣ ΜΥΛΩΝΑ - Life Tele UW		330	FA5	028110253	505	Main insured ...	1	1	
10	04720816	000999006	Life On - ΣΟΦΙΑ ΓΕΩΡΓΙΟΣ ΜΥΛΩΝΑ - Life Tele UW		330	FA5	028110251	200	Broker ...	2	2	
11	04720816	000999006	Life On - ΣΟΦΙΑ ΓΕΩΡΓΙΟΣ ΜΥΛΩΝΑ - Life Tele UW		330	FA5	028110248	110	UW Allocation ...	3	3	
23	04729552	001042701	Life On - ΑΙΚΑΤΕΡΙΝΗ ΓΡΗΓΟΡΙΟΣ ΜΟΙΡΑ - Life Te...		330	FA5	029032354	110	UW Allocation ...	3	3	

targetType	targetNumber	targetAllocTypeTFA6	targetAllocTypeDesc	startDate	endDate	originalDueDate	buisinessTypeTFIM	buisinessType
FA5	028110248	110	UW Allocation ...	2021-12-22	2021-12-22	0	602	Document upload ...
FA5	028110248	110	UW Allocation ...	2021-12-22	0	0	602	Document upload ...
FA5	028110248	110	UW Allocation ...	2021-12-22	2021-12-24	2021-12-23	602	Document upload ...
FA5	028110251	200	Broker ...	2021-12-24	2021-12-24	2021-12-27	602	Document upload ...
FA5	029032357	200	Broker ...	2022-03-31	2022-03-31	2022-04-01	602	Document upload ...

dfPolicy:

	quote	agreementNumber	issueDate	firstIssueDate	lobT164	lobDesc	renewalMonth	paymentFreq	amountOutstanding	requestNumber
0	04035734	11976865	2020-12-29	2020-12-29	299	Life On ...	12.0	2.0	554.91	00140000136717205
1	04035900	11969712	2020-12-04	2020-12-04	299	Life On ...	12.0	12.0	68.42	00140000136205367
2	04036092	11974042	2020-12-21	2020-12-21	299	Life On ...	12.0	12.0	66.36	00140000136656346
3	04036238	11965375	2020-11-19	2020-11-19	299	Life On ...	11.0	1.0	595.67	00140000136103935
4	04036473	11966089	2020-11-23	2020-11-23	299	Life On ...	11.0	2.0	925.25	00140000136120053

requestNumber	DIASpaymentCode	typeOfRequestTG79	typeOfRequestDesc	openClosed
00140000136717205	14000013671720575109	150	FastPay ...	2
00140000136205367	14000013620536775108	150	FastPay ...	2
00140000136656346	14000013665634675102	150	FastPay ...	2
00140000136103935	14000013610393575101	150	FastPay ...	2
00140000136120053	14000013612005375101	150	FastPay ...	2

PersonGGA:

	agreement	prod	objectGGA	startDate	endDate	lobT164	lobDesc	eventTypeT110	eventTypeDesc	damageTypeT159	...	instalmntPremium	sumInsured
0	12131848	0001	100356862	2022-06-23	0	299	Life On ...	781	TRZ SERVICES ...	550	...	1.06	0.0
1	12131848	0002	100356862	2022-06-23	0	299	Life On ...	781	TRZ SERVICES ...	550	...	0.00	0.0
2	12131848	0003	100356862	2022-06-23	0	299	Life On ...	781	TRZ SERVICES ...	550	...	0.81	0.0
3	12131848	0004	100356862	2022-06-23	0	299	Life On ...	780	TRZ PREVENTION ...	552	...	2.47	0.0
4	12131848	0005	100356862	2022-06-23	0	299	Life On ...	781	TRZ SERVICES ...	551	...	1.23	0.0

5 rows × 23 columns

sumInsured	desc1	desc2	desc3	quote	personNumber	name1	name2	surname
0.0	LO Υπηρεσίες Basic Τηλεσυνεδρίες με Γιατρούς ...	...	...					
0.0	LO Υπηρεσίες Basic Ψυχολόγος - Διατροφολόγος ...	...	...					
0.0	LO Υπηρεσίες Basic Γυμναστής ...	...	...					
0.0	LO Πρόληψη Premium ...	...	...					
0.0	LO Υπηρεσίες Standard ...	...	...					

dfRequest:

	quote	policy	requestDate	actNumb	actCode	actCodeDesc
0	04034433	11958902	2021-06-30	517083667	10179	Επαναφορά Συμβολαίου
1	04034433	11958902	2021-03-13	504426393	10123	Ανανέωση
2	04034433	11958902	2020-10-30	477858031	10170	Create Policy from Quote
3	04034433	11958902	2020-11-06	478640090	10057	Πρόσθετη Πράξη
4	04034433	11958902	2021-09-11	525437547	10123	Ανανέωση

sla200

	quote	taskNumber	taskDesc1	taskDesc2	stageNumber	userType	userCode	allocationTypeTFA6	allocationTypeDesc	seqNumber	seqNumber	targe
12	04720816	000999006	Life On - ΣΟΦΙΑ ΓΕΩΡΓΙΟΣ ΜΥΛΩΝΑ - Life Tele UW		200	FA5	028110251	200	Broker ...	0	0	
13	04720816	000999006	Life On - ΣΟΦΙΑ ΓΕΩΡΓΙΟΣ ΜΥΛΩΝΑ - Life Tele UW		200	FA5	028110250	500	Customer ...	1	1	
25	04729552	001042701	Life On - ΑΙΚΑΤΕΡΙΝΗ ΓΡΗΓΟΡΙΟΣ ΜΟΙΡΑ - Life Te...		200	FA5	029032357	200	Broker ...	0	0	
26	04729552	001042701	Life On - ΑΙΚΑΤΕΡΙΝΗ ΓΡΗΓΟΡΙΟΣ ΜΟΙΡΑ - Life Te...		200	FA5	029032356	500	Customer ...	1	1	
40	04729547	001042800	Life On - Γ. ΚΟΥΝΑΔΗΣ & ΣΙΑ ΟΕ - Life Tele UW		200	FA5	029033070	200	Broker ...	0	0	

targetNumber	targetAllocTypeTFA6	targetAllocTypeDesc	startDate	endDate	originalDueDate	buisinessTypeTFIM	buisinessType
028110248	110	UW Allocation ...	2021-12-24	0	0	602	Document upload ...
028110248	110	UW Allocation ...	2021-12-24	0	0	602	Document upload ...
029032354	110	UW Allocation ...	2022-03-31	0	0	602	Document upload ...
029032354	110	UW Allocation ...	2022-03-31	0	0	602	Document upload ...
029033067	110	UW Allocation ...	2022-02-04	0	0	602	Document upload ...

reactivePend:

	quote	policy	requestDate	actNumb	actCode	actCodeDesc	status
0	04724148	12096980	2022-04-05	567465774	20934	Αυτόματη ακύρωση	reactivated pending
1	04724148	12096980	2022-02-04	557741321	10170	Create Policy from Quote	reactivated pending
2	04724148	12096980	2022-05-13	573316807	10179	Επαναφορά Συμβολαίου	reactivated pending
3	04826083	12118124	2022-07-01	583043337	20934	Αυτόματη ακύρωση	reactivated pending
4	04826083	12118124	2022-06-24	582118642	10057	Πρόσθετη Πράξη	reactivated pending

WtRenewal:

	quote	policy	requestDate	actNumb	actCode	actCodeDesc
272	04038757	11966229	2020-11-23	480509263	10170	Create Policy from Quote
273	04038757	11966229	2021-01-22	491124928	20934	Αυτόματη ακύρωση
539	04082576	11968237	2021-01-29	499068900	20934	Αυτόματη ακύρωση
540	04082576	11968237	2020-11-30	481205195	10170	Create Policy from Quote
903	04040336	11969767	2020-12-04	481772446	10170	Create Policy from Quote

pend:

	quote	policy	requestDate	actNumb	actCode	actCodeDesc	status
0	04628305	12088687	2022-01-03	540718686	10170	Create Policy from Quote	pending
1	04728770	12088909	2022-01-04	542131362	10170	Create Policy from Quote	pending
2	04714629	12088949	2022-01-04	542174146	10170	Create Policy from Quote	pending
3	04681668	12088965	2022-01-04	542190246	10170	Create Policy from Quote	pending
4	04672421	12089138	2022-01-04	542277720	10170	Create Policy from Quote	pending

notDeliv:

	quote	policy	requestDate	actNumb	actCode	actCodeDesc	status
10	04038757	11966229	2020-11-23	480509263	10170	Create Policy from Quote	not delivered
11	04038757	11966229	2021-01-22	491124928	20934	Αυτόματη ακύρωση	not delivered
12	04082576	11968237	2021-01-29	499068900	20934	Αυτόματη ακύρωση	not delivered
13	04082576	11968237	2020-11-30	481205195	10170	Create Policy from Quote	not delivered
14	04091865	11971743	2021-02-09	500323974	20934	Αυτόματη ακύρωση	not delivered

delivered:

	quote	policy	requestDate	actNumb	actCode	actCodeDesc	status
0	04034433	11958902	2021-06-30	517083667	10179	Επαναφορά Συμβολαίου	delivered
1	04034433	11958902	2021-03-13	504426393	10123	Ανανέωση	delivered
2	04034433	11958902	2020-10-30	477858031	10170	Create Policy from Quote	delivered
3	04034433	11958902	2020-11-06	478640090	10057	Πρόσθετη Πράξη	delivered
4	04034433	11958902	2021-09-11	525437547	10123	Ανανέωση	delivered

paidCncld:

	quote	policy	requestDate	actNumb	actCode	actCodeDesc	status
0	04034433	11958902	2021-06-30	517083667	10179	Επαναφορά Συμβολαίου	delivered but cancelled
1	04034433	11958902	2021-03-13	504426393	10123	Ανανέωση	delivered but cancelled
2	04034433	11958902	2020-10-30	477858031	10170	Create Policy from Quote	delivered but cancelled
3	04034433	11958902	2020-11-06	478640090	10057	Πρόσθετη Πράξη	delivered but cancelled
4	04034433	11958902	2021-09-11	525437547	10123	Ανανέωση	delivered but cancelled

active:

	quote	policy	requestDate	actNumb	actCode	actCodeDesc	status
11151162	04038225	11963286	2022-09-29	598687439	10123	Ανανέωση	active paid
11151163	04038225	11963286	2022-09-29	598687439	10123	Ανανέωση	active paid
11151164	04038225	11963286	2020-11-12	479394183	10170	Create Policy from Quote	active paid
11151165	04038225	11963286	2020-11-12	479394183	10170	Create Policy from Quote	active paid
11151166	04038225	11963286	2021-10-09	529050955	10123	Ανανέωση	active paid

dfCncld:

	quote	policy	firstIssueDate	exitDate	cnclType	cnclTypeDesc	actNumb	actType	actTypeDesc
0	04037757	11960878	2020-11-06	2021-12-06	102	Πελάτης:πρωτοβουλία ...	536575693	10150	Ακύρωση Συμβολαίου ...
1	04038757	11966229	2020-11-23	2020-11-23	116	Ακύρωση λόγω μη παράδοσης ...	491124928	20934	Αυτόματη ακύρωση ...
2	04039344	11972413	2020-12-15	2022-06-15	100	Εταιρία:μη πληρωμή ασφ/τρων ...	592648501	20934	Αυτόματη ακύρωση ...
3	04040336	11969767	2020-12-04	2021-02-04	102	Πελάτης:πρωτοβουλία ...	499949263	10150	Ακύρωση Συμβολαίου ...
4	04040959	11964349	2020-11-16	2021-11-16	100	Εταιρία:μη πληρωμή ασφ/τρων ...	544378989	20934	Αυτόματη ακύρωση ...

dfStatusCode:

 # table containing quotes that have a status of:

 # 'reactivated pending', 'pending', 'not delivered','delivered but cancelled', 'active paid'

	quote	policy	status
0	04724148	12096980	reactivated pending
1	04826083	12118124	reactivated pending
2	04960525	12133893	reactivated pending
3	04628305	12088687	pending
4	04728770	12088909	pending

dfStatusCode1:

	quote	policy	status
0	04724148	12096980	reactivated pending
1	04826083	12118124	reactivated pending
2	04960525	12133893	reactivated pending
3	04628305	12088687	pending
4	04728770	12088909	pending

temp:

	quote	prod	objectGIV	startDate	endDate	lobT164	lobDesc	eventTypeT110	eventTypeDesc	damageTypeT159	...	benefitTypeT155	benefitTypeDesc	ir
0	04033974	0001	000485311	2020-10-30	0	299	Life On ...	781	TRZ SERVICES ...	550	...	255	GENERALI Doctor ...	
1	04033974	0002	000485311	2020-10-30	0	299	Life On ...	781	TRZ SERVICES ...	550	...	256	Psychologist-Nutritionist ...	
2	04033974	0003	000485311	2020-10-30	0	299	Life On ...	781	TRZ SERVICES ...	550	...	257	Digital Trainer ...	
3	04033974	0004	000485311	2020-10-30	0	299	Life On ...	782	TRZ OUT OF HOSPITAL ...	550	...		NaN	
4	04033974	0005	000485311	2020-10-30	0	299	Life On ...	780	TRZ PREVENTION ...	551	...		NaN	

5 rows × 21 columns

benefitTypeDesc	instalmntPremium	premiumFactor	basePremium	sumInsured	conditionsTypeT317	productStatusT156	productStatusDesc	sum
GENERALI Doctor ...	12.71	0.0	12.71	0.0	100	101	POLICY ...	25.42
Psychologist-Nutritionist ...	0.00	0.0	0.00	0.0	100	101	POLICY ...	0.00
Digital Trainer ...	9.74	0.0	9.74	0.0	100	101	POLICY ...	19.48
NaN	80.56	0.0	80.56	0.0	100	101	POLICY ...	161.12
NaN	24.81	0.0	24.81	0.0	100	101	POLICY ...	49.62

dfPremium:

	quote	freq	productNumber	instalmentPremium	flatFee	fee	tax	stampDuty	auciliaryFund	sum
0	04033974	1.0	0001	12.71	0.0	1.27	2.10	0.0	0.0	14.81
1	04033974	1.0	0002	0.00	0.0	0.00	0.00	0.0	0.0	0.00
2	04033974	1.0	0003	9.74	0.0	0.97	1.61	0.0	0.0	11.35
3	04033974	1.0	0004	80.56	0.0	8.06	13.29	0.0	0.0	93.85
4	04033974	1.0	0005	24.81	0.0	2.48	4.09	0.0	0.0	28.90

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