SOCIETY OF ACTUARIES

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Health Incentive and Wellness Program

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UNSW

SuperLife
SAVING LIVES

Table of Contents

1 Executive Summary & Objectives

SuperLife is one of the many life insurance carriers in the country of Lumaria, who are actively trying to reduce expected mortality for their policyholders. In their creative pursuits, they have tasked Control Cycle with the responsibility of creating health incentives to reduce mortality and improve profitability. This report details a wellness plan that will incentivise Lumarian citizens to adopt healthier lifestyles to reduce mortality and increase life insurance sales based on the popularity of the proposed incentives. Once the products are made publicly available, monitoring at regular intervals (see 2.4) is required to assess the effectiveness of the program, mitigate any rise in risks, and make updates for any changes needed. The specific objectives are as follows.

1. ***Reduce expected mortality***: The wellness plan consists of 2 incentive programs, both of which have been respectively designed to reduce mortality from the most common causes of death based on SuperLife's existing and past policyholders since 2001.
2. ***Incentivise healthier behaviours***: The wellness plan provides different, fully-subsidised incentives including: regular screenings, medical tests, wellness apps, fitness trackers, and personalised health plans. The alleviation of these costs is aimed to incentivise participation by individuals of different ages, genders, and socioeconomic levels.
3. ***Increase insurance sales***: Targeted marketing strategies will be deployed to boost the company's volume of new sales. Products gain competitive advantage through the subsidised health care initiatives, catered towards individuals of all ages, sex, and backgrounds.
4. ***Increase SuperLife's economic value***: A reduction in expected mortality is expected to decrease the company's burden to payout death benefits to its policyholders. This is aimed to reduce reserves, likely causing a surplus increase, consequently increasing the monetary value of distributed earnings that can be paid out to SuperLife's shareholders.
5. ***Improve marketability and competitiveness***: By being one of the first companies to consider incorporating health incentives with long-term insurance products, the company can increase its competitiveness and market share by outperforming its competitors within Lumaria's life insurance industry.

1.1 Key Performance Metrics

Across the long and short-term, the following 6 key performance metrics will be used to assess the success, viability, and sustainability of the proposed health and wellness program. Specifically, participation rates (both new business and existing customers), and customer details regarding claim severity, frequency and lapses, may be reported quarterly. Broader measurements including testing the general financial viability and scalability of the product that require longer term horizons may be reported every 2 years. Analysis regarding the program's timelines for monitoring, designing, and implementation is provided in 2.4.

1. ***New business participation rate***: Proportion of newly acquired policyholders that are actively purchasing long-term insurance products bundled with the wellness program.
2. ***Retention participation rate***: Proportion of all existing policyholders who have switched to, or, are continuing to use long-term products bundled with the wellness program.
3. ***Satisfaction surveys***: Gather feedback from policyholders to gauge their satisfaction level with the program's coverage, content, convenience, and marketing.
4. ***Claim severity and frequency***: Number and percentage of policyholders who have died and claimed their death benefits, and analysing changes in lapse rates for the new bundled insurance product offering.
5. ***Financial viability***: Analysing financial performance and sustainability at milestones.
6. ***Scalability and Replicability***: Evaluate the program's viability to expand into its short-term products as well potentially including more health programs to be bundled with SuperLife's existing insurance product offerings.

2 Program Design

In order to incentivise Lumarian citizens to adopt healthier lifestyles and reduce mortality for individuals, the most important things to consider were the causes of death, and how an incentive could be introduced to the country which would not only assist in improving policyholder's wellness but will also increase life insurance sales for SuperLife. The most prevalent causes of death were identified as neoplasms (C00-D48) and cardiovascular diseases (I00-I99) (ICD-10, 2019). Consequently, the two health incentives drawn up are aimed to significantly prevent and reduce the occurrence of these ailments. The two final products target all age groups and individuals from both rural and urban households. They are meant to motivate individuals to adopt healthier lifestyles and include more screenings in their lives to increase awareness of their current health and how it can be improved.

2.1 Cardio Improvement App Package

In Lumaria, cardiovascular disease (CVDs) were identified to be the country's second most prominent cause of death (see Figure 1.3.7). This disease type caused approximately 31.4% of deaths for males and 25.43% for females. This first wellness product is marketed as a package which combines 2 well-being apps called CardiWell and FitSync, both of which encompass multifaceted incentives. These two apps have been created with respective goals of reducing heart failure and heart disease through screenings and weight management programs, while also targeting an individual's fitness via tracking and weight loss regimes.

Across all ages, the fixed costs associated with this incentive arises from the development and implementation cost of the apps. For the specific inclusions within the app, for example heart screenings, it is anticipated that the marketing costs reduce with age, while fitness trackers will be far more popular among younger generations and hence costs will increase for age (see Appendix 2.1.2). Further, when calculating assumed mortality reductions at various ages, heart screenings were assumed to have a considerably greater weighting, and this was implemented in the calculations. For the assumed mortality reductions, as seen in Appendix 2.1.1, the calculations demonstrate an independence of the 2 incentives involved within each app and how they are combined with different weightings to reduce mortality.

This incentive targets the individuals in Lumaria aged 20 to 35. Individuals in the younger demographic demonstrate a considerably higher propensity when adapting towards the technological environment. Further, despite the recommendation for individuals to commence regular heart screenings at the age of 20, younger cohorts fail to see the importance of traditional heart screenings and consequently are deterred away from participating, often causing individuals to miss out on their benefits (Grey, 2020). This perception is often caused by a lack of information, citing time constraints, and also concerns about affordability (Chien et al, 2020). Ultimately, this holistic approach aims to both leverage the behavioural shift among younger generations towards technology, and also addresses the common barriers faced when participating in health screening programs.

2.1.1 App 1 - CardiWell: Heart Health & Wellness Companion

The first app CardiWell combines 2 interventions, namely heart health screenings and a weight management program. The app offers 3 complimentary heart health screenings alongside a weight management program over the course of an individual's policy tenure. Upon setup of the app, a variety of user information will be collected to aid the app's inbuilt algorithm to collect key indicators for assessing heart health risks. Such factors include age, height, weight, cholesterol levels, blood pressure levels, and weight loss goals. Through input user data, the platform generates personalised weight loss regimens tailored to an individual's unique needs and preferences. This data-driven approach enables the app to aptly schedule optimal times for an individual's screenings based on the user's policy type.

2.1.2 App 2 - FitSync: Where Fitness Meets Personalised Health

FitSync aims to target cardio improvements by combining 2 interventions, namely a fitness tracking incentive and a personalised health plan, both of which aim to make health lifestyle changes which are regularly included within existing cardiac rehabilitation plans (NIH, 2022). This app integrates a fitness tracker which is provided to each policyholder on installation and is centrally used to collect health data and also offers features to synchronise information collected from CardiWell. The app leverages this comprehensive data set to construct and constantly revise personalised health plans that are tailored to each individual. The plans will contain detailed workout routines, curated diet regimes, and sleep cycle monitoring. Overall, the fitness tracker itself aims to generally incentivise healthier behaviours by providing users with real-time data to easily facilitate lifestyle adjustments.

2.2 Cancer Prevention Package: CancerShield

The most significant cause of death in Lumaria is due to neoplasms (refer to Figure 1.3.7), denoted by disease code C00-D48. It accounts for approximately 38.28% of deaths in females and 31.4% in males. Due to the high prevalence of these life threatening illnesses, the aim is to use health screenings to lower the intensity of malignant neoplasms.

The final product is "CancerShield" which consists of several health screening initiatives. This incentive is primarily targeted towards those aged 45 and above since they are more likely to undergo health screenings for a prolonged life, however young individuals are encouraged to participate in the wellness program as well. Ultimately the aim of the tests is to detect any abnormalities in the human body and if cancerous tissues are detected, they can be prevented from spreading. The package includes four components; basic health screenings, genetic tests, cancer prevention techniques and smoking cessation programs. For the assumed mortality reductions and program costs refer to Appendix 2.2, which demonstrates how all four incentives are combined to reduce mortality.

The preventative screening tests include regular checkups with doctors and consist of blood, glucose, cholesterol, haemoglobin, eye, skin, and body mass index tests. These tests will account for the fixed costs of the package as they are crucial checks needed by medical practitioners before they can refer individuals to specialists.

Genetic instability can often lead to cancerous cells developing inside the human body, thus leading to life threatening neoplasms (Vessey et al, 1999). Therefore, regular genetic screenings will help identify malignant tissues which can then undergo genomic testing to identify treatments which will inhibit the growth of such tumours. The tests will include screenings for cytogenetic, biochemical, and molecular complications.

Cancer prevention initiatives will include resources such as brochures, home kits and regular health check ups for breast, cervical, prostate, and bowel cancers. Screenings for the aforementioned cancers should essentially be conducted once every two years, therefore five cancer tests will be performed in a decade which is demonstrated in Appendix 2.2.2.

Lastly, smoking cessation programs are a crucial component of the package as, although only 12.6% of the Lumarian population accounts for smokers, it has led to a significant number of deaths for males aged 65 and older. In order to rectify this situation, this incentive will include self help guides, regular clinical check ups for nicotine and tobacco consumption and group or online support programs. However, since not many policyholders are smokers (refer to Figure 1.3.8), we will offer a surcharge of 15% to those who smoke as they will inherently require more assistance and check ups regarding their health. As for those who do not smoke, a Non-Smoking declaration will need to be filled out prior to the commencement of the program.

2.3 Marketing Strategy

Our wellness program has been designed under an acquisition marketing strategy and was supported by creating market personas (Appendix 4) to better understand SuperLife's customer base and target the right audience. The products are bundled within the longer-term life insurance offerings, namely a 20-year level term (T20) or a single premium whole life policy (SPWL) to incentivise healthy behaviours and ultimately reduce expected mortality among policyholders.

As shown in Table 1.3.14, 46% of sales have been attracted by agents, followed by 28% in the online channel and 25% through telemarketing. The varying effectiveness of these methods suggests the relative allocation of resources to these distribution channels, which we will be leveraging to successfully market the new wellness program to specific age groups.

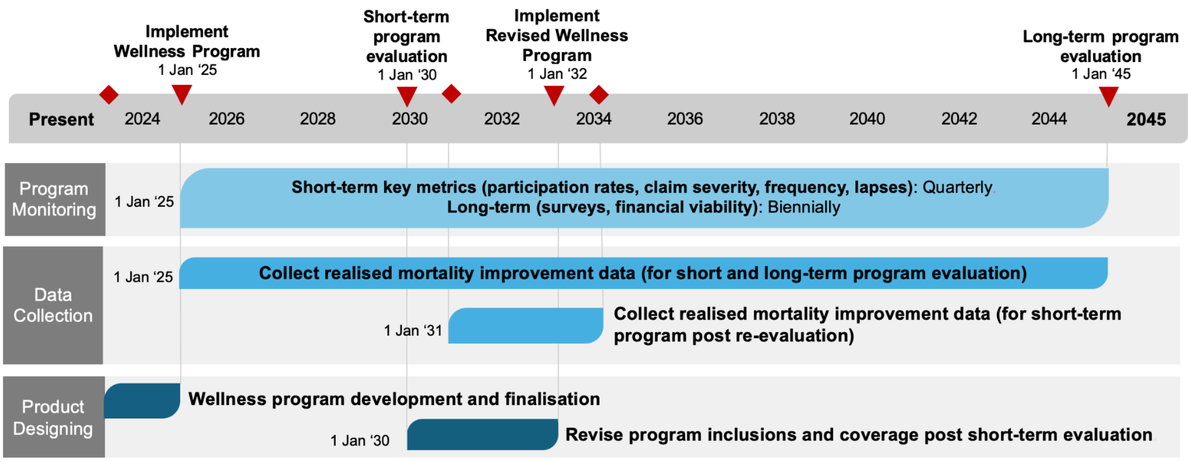
The Cardio Improvement App is focused more towards policyholders aged 20-35 (Appendix 4.1) who prefer channels such as technological applications, whereas older generations are not as quick to adapt to such incentives. Furthermore, these individuals care more about the coverage and support provided through the incentive as it will motivate them to live healthier lifestyles.

The Cancer Prevention Pack however, is targeted towards individuals aged 45 and older (Appendix 4.2) and predominantly for those who are regular smokers. These policyholders are more likely to invest in programs that will allow them to undergo regular health screenings at affordable prices, in order to identify, prevent and treat any life threatening diseases, while ensuring they retire happily in the future.

Based on the success and profitability of the wellness campaign over a 5 year timeframe, we intend to provide free health screenings on the national holiday of Super Luminova to encourage physical and health wellness, attract more customers and reward existing policyholders for their loyalty.

2.4 Timeframes for Program Evaluation

While monitoring based on the key metrics are conducted on a regular quarterly and biennial basis, longer time horizons for program evaluation where used enable time for sufficient data collection. Short-term evaluations are to be conducted every 5 years to allow for minor adjustments within the incentives included. While, long-term evaluations to potentially entirely revamp the program or include new incentives are reserved to be conducted every 20 years. This timeframe was chosen to enable SuperLife to have an entire cohort's performance metrics, as all T20 policyholders will have lapsed and a complete dataset regarding their mortality reductions and realised costs will have been collected. The following overview provides an outline of the project implementation and timeline.

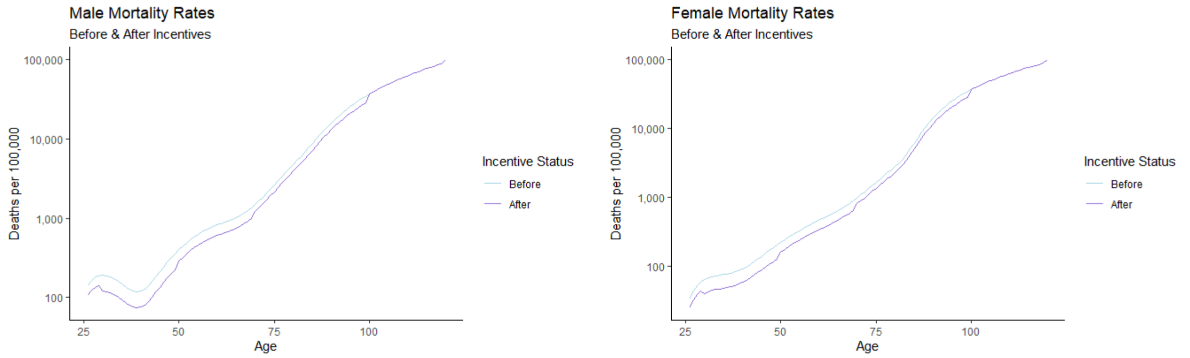


3 Pricing/Costs

3.1 Methodology

A discounted cash flow approach was used to value the program. Firstly, the Expected Present Value (EPV) of financing the 2023 Policy Start Year cohort was estimated for both the Single Premium Whole Life (SPWL) and 20-Year Term Insurance (T20) policies with no interventions in place. Then, the EPV of the same cohort was derived under the same method after factoring in the mortality improvements and costs of the interventions. The difference between the two was used to evaluate the financial benefit of the program to SuperLife. Finally, the sensitivity of this differential to varying input assumptions was assessed.

To project mortality, life tables were constructed from the SuperLife In-Force dataset. The investigation period chosen was 2015-2019 to avoid including outliers while maintaining recency, as aggregate mortality spiked sharply in the 2020-2022 period for higher ages (Figure 1.3.22). Crude death dependent decrement rates per age were estimated by dividing the sum of all deaths by the sum of all lives in force at that age across the investigation period. These were cropped of outliers at later ages, and graduated via penalised cubic splines (Figure 1.3.20 & 1.3.21). In the absence of policyholders aged 80-120 by 2023, values for this age range were interpolated from the 2010 General Population table and smoothed to fit with the manually estimated death rates. Mortality improvements were then applied to these rates.



Policies were split into SPWL and T20 components for analysis. T20 was projected until the ultimate lapse of all term insurances, and fair level premium rates per age were derived given mortality projections as well as assumptions for expenses, profit, and reserves. SPWL was projected until ultimate mortality for all policyholders and required no premium to be computed given that it had already been paid at the start of 2023. Due to computational constraints, rather than projecting all 60,000+ policyholders individually, policies were grouped by policy type, age and sex. Additionally, the lapse rate was taken as the average of observed lapse rates across the observation period for all terms (Figure 1.3.19).

3.2 Mortality Improvements and Projected Costs

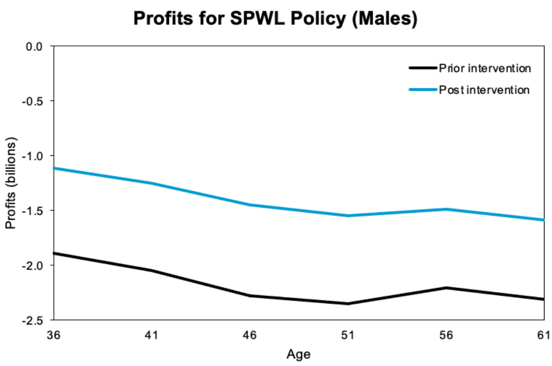
3.2.1 Methodology

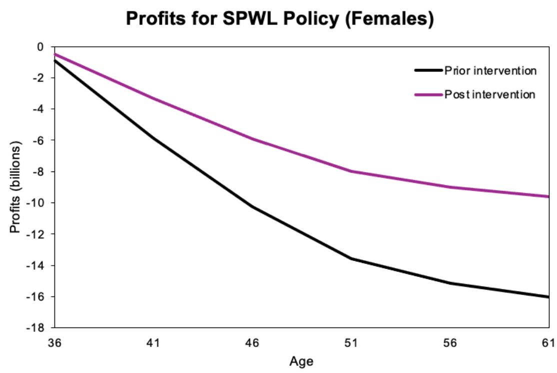
Firstly, the zeroization method was used to project reserves for males and females under the 2 different product types (T20 and SPWL). Under zeroization, reserves were calculated using ${}_{k}V\ (1 + i) = |min((CF)_{k+1} - {}_{\{k+1\}}V(ap)_{x+k}, 0)|$, where V represents reserves at the end of kth year, and (ap) represents the probability of being alive for a given year. All relevant formulae used in cash flow projection can be found under Appendix 6.2.

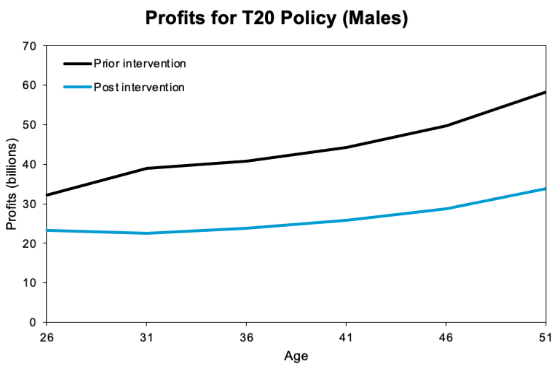
In regards to expenses, it was assumed that prior to the introduction of the intervention programs, only a management expense of Č300 would incur. After the introduction of the intervention programs, for the first year, a varying cost with age associated with implementation and marketing costs for the program will incur. Calculations were conducted for each model age point, whereby total expenses for an age were calculated by multiplying an individual's present value of expenses by the number of inforce policyholders.

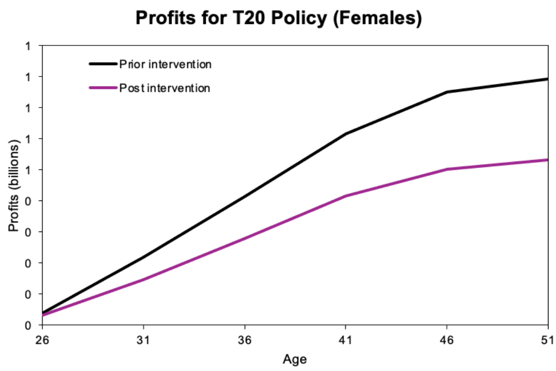
In regards to the calculation of premiums for SPWL products, since the value of the single premium had not been made available to SuperLife's valuation team, the premium was assumed to equal 0. Here, the net growth in profits and percentage growth in profits after the introduction of the program were analysed by projecting cash flows. On the other hand, for T20 products, premiums were calculated via the zeroization method as outlined in 3.3. For both products, the total profits were calculated by subtracting the present value of expenses from total premiums. To conduct a comparison of premiums before and after the intervention programs, this same premium was used as a baseline to compare the percentage growth in profit and profit margin to assess the effectiveness of our intervention programs.

The table below illustrates the change in profits after intervention programs were introduced. The proportion of policyholders participating, mortality reduction and cost can be found under Appendix 2.1 and 2.2 for each incentive program:









3.2.2 Evaluation on the Effectiveness of Wellness Program

From 3.2.1 and Appendix 5.1, it is evident that after the Wellness Program was introduced, for both male and female policyholders in SPWL, the profits have increased. Since all policyholders in force have paid their single premium, cash flows have been projected by setting premium to be 0. Nevertheless, the increase in profits have justified the effectiveness in the Wellness Program, as while the incentives have reduced policyholders' mortality it also benefits the company by demonstrating increased profits.

Contrastingly for the T20 product, as seen in section 3.2.1 and Appendix 5.2, after the introduction of the wellness program both male and female 20-year-term products significantly reduced profit. This consequence is due to the small sample size of policyholders who had entered in 2023, and the relatively high cost of the program. The detailed explanation can be found in section 6. Nevertheless, this program has reduced mortality rates for policyholders across all ages. Moreover, the company still has made a significant amount of profit, despite the negative growth rate.

3.3 Projected Premiums for Individual Policyholder

3.3.1 Methodology

For SPWL insurance product, all inforce policyholders are assumed to have paid their single premium at their entry year. Therefore, no further calculations were required.

For the 20-Year-Term Insurance product, the zeroization method was used to calculate the individual non-discount premium. The zeroization method ensures that all our products are self-supporting, and only have a single financing phase at the outset, where profits are potentially negative. This method also offers an overview of reserves required at the beginning of each year, and ensures only the cash flow in the first year could be negative. The individual non-discount premiums at point estimates are provided in the table below.

T20							
Age	**30**	**40**	**50**	**60**	**70**	**80**	**90**
Premium (Č) (Male)	7,628	8,967	10,760	14,063	26,274	55,613	117,387
Premium (Č) (Female)	7,092	8,027	9,230	10,697	18,427	40,503	105,524

4 Assumptions

4.1 Modelling Assumptions

- Assumed a cohort-based modelling approach whereby modelling premiums was conducted based on all policyholders who began their policy in 2023. Here, death benefits for both SPWL and T20 insurance products for each age were calculated by averaging the face amounts of SuperLife's in-force policyholders who only had a 1-year tenure. This was assumed to ensure the death benefit was as close to the true amount upon entering into the contract. However, for policyholders with a 1-year tenure, the in-force data did not include face values for individuals aged greater than 66 for SPWL and greater than 56 for T20. To combat this it was assumed that the death benefits for both males and females of SPWL and T20 products could be projected by using an average growth of their face amounts for the past 10 years until age 95. These rates for the 2 policy types and genders were found to approximately equal 1 (for the exact death benefit values and average growth rates refer to Appendix 3). Thus, it was assumed that the value for the death benefits remained at a constant level for the ages whereby in-force participants with ages greater than 66 and 56 for SPWL and T20 insurance products respectively.
- Assume a calendar rate interval, with age being defined as age as at last birthday.
- The wellness programs are assumed to have been well developed in coordination with a variety of health care professionals. Thus it is assumed that the majority of an individual's mortality improvements will be realised within the first year of policyholders participating in the wellness program. This implication combined with the age definition whereby an individual's age label is defined by their age last year artificially creates an instantaneous reduction in mortality in the modelling process.

4.2 Mortality Reduction and Cost Assumptions

- Marketing costs were allocated to equal 10% of the total costs for each incentive. The key marketing costs included advertising placements, telemarketing, and app/website maintenance.
- Assumed that not all policyholders would participate in both incentive programs, and there was assumed independence for the participation rates within either program for individuals at various model age points (see Appendix 2.1 and Appendix 2.2 for participation rates). These rates were based around the marketing strategies presented in 2.3, whereby the greatest rates were allocated to the ages that were being targeted in each incentive, and which by extension incurred greater marketing costs.

4.2.1 Cardio Improvement App

- It is determined that the cardio app with both heart screenings and weight management programs will outweigh any existing fitness tracker apps. Hence a weighted average was used to calculate the total mortality reduction (Appendix 2.1.1).
- Within each app 2 are incentives used, it is assumed that their effects are cumulative and hence both are independent to each other at each model age point (Appendix 2.1.1).
- For the fitness apps, the reduction in mortality was determined by the impact of physical activity on different age groups as we assume all individuals are doing the correct amount of exercise as advised by the apps. Consequently, younger ages were found to have greater reductions in mortality (Appendix 2.1.1).

4.2.2 Cancer Prevention Pack

- Greatest reduction in mortality in CancerShield is through the implementation of the smoking cessation programs (Appendix 2.2.1) as smoking causes more cancerous deaths compared to genetic defects. (Winnall, et al, 2021)
- Genetic tests for older policyholders will be more costly as opposed to younger individuals (Appendix 2.2.2) due to damaged and degraded DNA samples which make it harder to draw conclusions. Some individuals have complicated medical histories or develop diseases later on in life therefore it is more complicated to obtain accurate samples from these people early on in their lives.
- It is assumed that genetic tests are conducted once in an individual's life (except for adverse circumstances) therefore the cost is only onefold, whereas cancer screenings should be conducted once every 2 years therefore over the span of 10 years, 5 screenings should be conducted. The frequency of these tests forms the basis of the program costs as shown in Appendix 2.2.2.

5 Risk Assessment

Insurer risks are likely to arise in the developmental and monitoring stages of the wellness program, which has been suggested for SuperLife. The analysis conducted assumes that revenue and costs are immune to changes from external forces, hence the risk map and assessment aims to both identify and quantify risks according to their likelihood and impact.

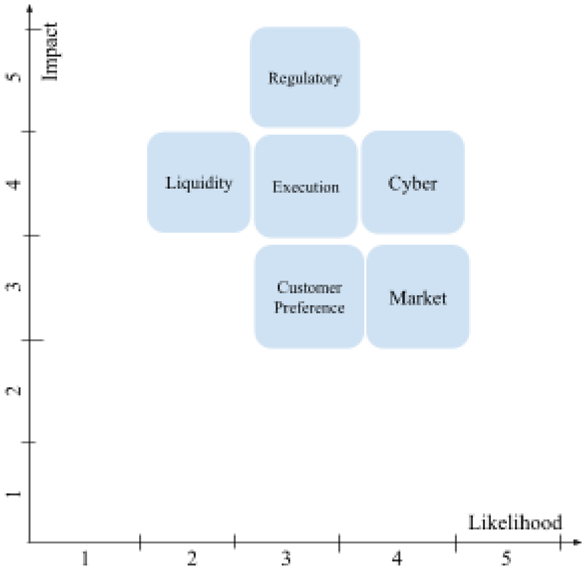
I. **Market risk**: Unexpected changes in macroeconomic conditions include (a) higher interest rates, resulting in more discounting of future cash flows (b) unfavourable movements in asset classes of interest, leading to lower investment returns.

II. **Liquidity risk**: Unexpected increase in inflation rate can reduce the real value of reserves, creating liquidity risk issues when tail-end claims are made.

III. **Execution risk**: Marketing strategies not being able to attract sufficient sales, as behavioural drivers and heuristics lead to under-insurance.

IV. **Technology/Cyber risk**: Unexpected downfall in the app system such as hacking or system outages, causing data leakages and evidently customer frustration.

V. **Changing customer preference risk**: Customers' preferences for product pricing can change based on their financial circumstances and environment. If program benefits are ineffective, risk profiles can remain the same or worsen, leading to more severe and frequent claims.



VI. **Regulatory risk**: Unexpected changes in regulation on capital requirements, data collection, and product approvals can severely impact the execution of the strategy and its profitability.

Mitigation strategies to treat the consequences of the aforementioned outcomes include:

I. Updating the pricing model regularly to strategise cost cutting measures or premium increase considerations to maintain profitability.
II. Sufficient capital to be set aside.
III. Gain customer feedback and monitor engagement results to identify effective and ineffective parts of the strategy. Employ methods such as agent training programs, expanding agent networks, and improving websites.
IV. Build and regularly maintain strong cybersecurity networks through updates to prevent hacking and data leakages
V. Engage with customers frequently through feedback collection or reminders to reduce lapse and surrender rates. Track and monitor customers' performance and adherence to the incentive programs. Improve the programs where necessary to help customers adopt healthier, mortality-reducing lifestyles.
VI. Conduct rigorous sensitivity analysis to ensure that sufficient margins have been allocated. Regularly monitor for any indications of a legislative change so that the model can be updated to capture these changes. Any losses can be made up by cutting expenses or increasing future premiums.

5.1 Sensitivity Analysis

The modelled program profitability was tested for sensitivity to the input variables of interest rate, fixed expenses, and mortality reduction incentives. This was done for both males and females aged 40 under both SPWL and T20 policies, as the majority of policyholders are clustered around this age. For T20 policies, the tested values were the percentage growth in total profits and the profit margin (given a premium based on a 10% target). For SPWL policies, given that they generate no premium income and thus record a negative profit, profitability was measured as the absolute value of the loss divided by one million; a higher number implies a lower profitability.

It was found that across both policies and sexes, the profitability is primarily sensitive to the assumed long term mean interest rate and the incentive mortality reduction impact, whilst being relatively minorly affected by the fixed costs assumptions (Appendix 5.1.2 & 5.1.3). Males within the T20 Policies were particularly sensitive to interest, with change in profit post-implementation ranging from -11.62% to -65.91% compared to females who ranged between -42.47% and -78.85% based on interest varying between 1-15%. This effect is much less pronounced in the SPWL policies. Sensitivity to mortality improvements was consistent across sexes and policy types based on a 5-29% range decrease in mortality across all ages.

6 Data and Data Limitations

Data Limitation	Solution or Assumption
Outliers exist for the mortality rates of male and female policyholders past the age of 80 by 2023.	Outliers have been removed and the death rates were estimated from the 2010 General Population table data.
The data for forecasting future mortality rates is insufficient, drawn from only 63,374 active policyholders issued in 2023.	The assumption is that life tables derived from active individuals mirror the broader population, capturing various lifestyle, health, and mortality-influencing factors.

No data is available on individuals aged between 26-35 being issued the SPWL insurance in 2023.	It is assumed that no individuals enter the SPWL contract until age 35.
No data has been provided on administrative costs and expenses associated with the firm.	A constant management expense of Č300 has been assumed for each year. After the implementation of the program, it is assumed that there is an initial upfront outflow at the beginning of year 1.
No data has been provided on capital requirements.	Capital requirement is assumed to be 1% of the death benefit multiplied by the probability of being in force for the year.
Future interest rates beyond 2023 are unknown.	Vasicek model was used to find a long-term equilibrium 1-year risk-free annual spot rate, assuming constant volatility and both mean-reverting and inflation embedded interest rates.

7 Ethical Considerations

Ethics was not able to be consistently upheld across all facets of pricing and design. Justified by the virtue ethics framework, the program has been designed to recognise the needs of different generations. For example, age-discrimination was minimised by producing a program that markets technology to younger generations, and screenings to older individuals. Smoking status was found to be statistically significant, causing a 15% premium surcharge to be applied to smokers. This decision helps to reduce financial burden, incentivise healthier lifestyles, and improve well-being. The program, however, is limited in capturing socio-economic differences, as rural and urban based geographies were not found to be statistically significant with respect to survival time. The consequent T20 annual premium, priced to be approximately 25% of an average Lumaria's annual income, reduces accessibility by lower income individuals. This can lead to life-underinsurance, which has more pronounced effects on lower income individuals who are susceptible to financial hardships.

Although gender discrimination within life tables is prohibited in many developed countries including Australia, it is unclear if this is the case in Lumaria. Gender has been used in the pricing process to achieve a more granular view on mortality rates. However, based on the fairness and justice approach, it may stimulate gender discrimination and unequal treatment of males and females in life insurance policies. Further, potential concerns arising from data privacy and cybersecurity can arise within the implementation of the Cardio app incentive. Therefore clear internal governance procedures and regular maintenance processes are needed to ensure that all sensitive information is not unethically abused.

8 Conclusion & Final Recommendation

Implementing the Cardio Improvement App and the Cancer Prevention Pack is recommended for SuperLife's ability to incentivise healthier behaviours and reduce expected mortality. The two apps, CardiWell and FitSync offer heart screenings and personalised health plans. While CancerShield includes various cancer related screening initiatives that monitor and enhance the competitiveness of insurance products, fostering marketability and leading to projected growth. Profit from SPWL is expected to grow, and losses from T20 have improved after the program's implementation. For future improvements on pricing strategy, it is recommended that factors such as underwriting class and urban/rural status should be considered in premium pricing to further alleviate ethical concerns. Finally, a larger profit margin is recommended to be applied to T20 policies to ensure consistently high growth rates for the implemented health and wellness program.

Appendix

1 Exploratory Analysis

1.1 In-force Dataset

Upon cleaning the raw data in R, 978,582 unique policy numbers were found with no duplicates. The issuance years across both T20 and SPWL policies ranged from 2001 to 2023, showing a steep decline from 2001 to 2002, before a gradual increase in policy uptake over time (Figure 1.3.1). Under the T20 insurance, 2413 policyholders have died within the first year (Figure 1.3.2). Under the SPWL insurance 2880 policyholders have died within 1 year. This could be due to adverse selection (Figure 1.3.3). The average and median age of death is ~59, with the greatest frequency of deaths observed between the ages of 60 to 65 (Figure 1.3.4). 28,201 male policyholders have died compared to 12,175 females. C00-D48 is the largest driver of deaths among females (37.47%), and the second largest driver of death amongst males (30.75%) refer to Figure 1.3.6 and 1.3.5 respectively.

From Table 1.3.13, it can be observed that 55.07% of the customer base are from regions 1 and 2. There are less rural individuals purchasing life insurance, with nearly two-thirds of policyholders coming from a rural background. Under SPWL, 63.87% of individuals are from urban areas and 36.13% are from rural areas (Figure 1.3.11). This proportion remains approximately the same with T20 policyholders. The retail distribution channel involving agents remains the largest channel, contributing consistently to 46% of policies sold across the 6 regions. This is followed by online sales and telemarketing, respectively taking up approximately 28% and 24% of sales within each region (Table 1.3.14). As seen in Figure 9.1.12, agents contributed to 72% of SPWL sales, followed by online at 18.53% and telemarketers at 9.51%. The three distribution methods are more consistent in their attraction of T20 policies, with online contributing to 34.61%, telemarketing contributing to 34.59% and agents contributing to 30.80% of sales (Figure 1.3.12).

Amongst the 4 risk classes, 88.55% of individuals insured are very low to moderate risk, with 11.45% of policyholders belonging to the high risk class. Within the four risk classes, the proportion of sum insured are the same (Table 1.3.15). This could be from ChatGPT's random generation of results. Out of 978582 policyholders in the dataset, 93.69% are non smokers and 6.31% are smokers. Smokers account for 15.75% of those with high risk and 18.92% of those with moderate risk and none across those under low and very low risk categories. There are 371,301 and 607,281 policyholders under SPWL and T20 insurance respectively. T20 has a greater proportion of smokers (8.65%) compared to the 2.48% of smokers under SPWL (Figure 1.3.9). Amongst those with SPWL insurance, 41.67% are female and 58.32% are male. Similarly amongst those with T20 insurance, 45.56% are female and 54.43% are male (Figure 1.3.10).

1.2.1 Mortality Dataset

The inforce dataset provides information on policyholders from 2001 to 2023. The time period 2015-2019 has been selected to avoid outliers, and reflect modern health dynamics. Upon plotting the male and female mortality rate over this period, Figures 1.3.17 and 1.3.18 have been plotted to show an exponential increase in mortality with age. The data becomes sparse after age 80, with observable outliers.

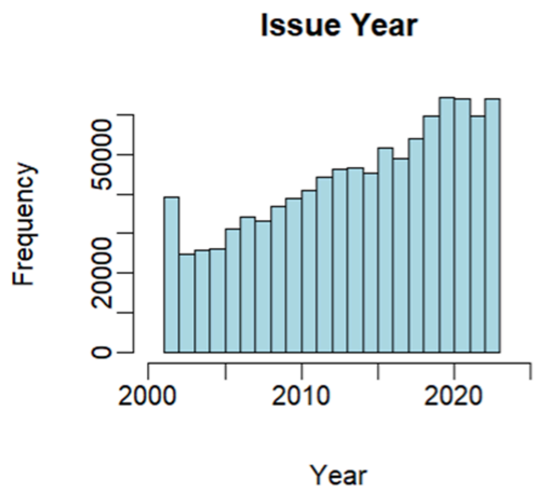
As shown in Table 1.3.16, no policy under SPWL has lapsed. All 110,889 policies lapsed by 2023 were under T20. In Figure 1.3.19, it is observable that although lapse rates are small, they increase linearly with time to policy termination. The lapse rate fluctuates nominally around a mean of 1% across the whole policy term (Figure 1.3.19).

1.2.2 Mortality Dataset

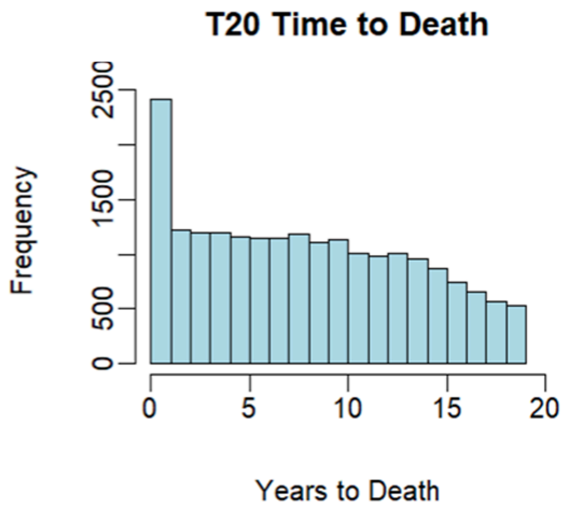
Cox regression has been used to assess the effect of risk factors on survival time. It consistently produces a low p-value when smoking status has been used as a covariate. Issuance ages 36, 37, 38, 39, 40, 45 have p-values less than 5%. When cox-regression has been applied on the underwriting class covariate, low p-values have also been obtained for low risk and very low risk underwriting classes. A log rank test on the underwriting class with p-value of 2e-08 confirms that there is statistically significant difference in survival time due to the underwriting class. Urban and rural have a large p-value of 0.6 in the cox regression and logrank test, suggesting statistical insignificance. Region, however, has a low p-value of 0.02 in the logrank test. Despite indicating significance, only smoking status will be considered as it has the smallest p-values, supported by logical associations of smoking with poor health. The other covariates will be ignored due to uncertainties of whether the p-values are influenced by potential interaction effects, sample size and other influencing factors.

1.3 Graphs and Tables

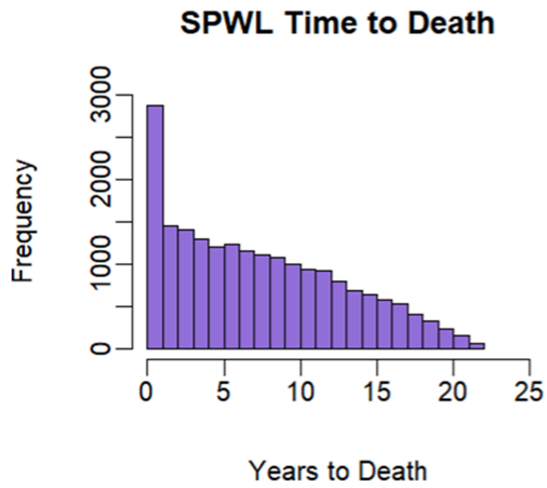
1.3.1 Issue Year



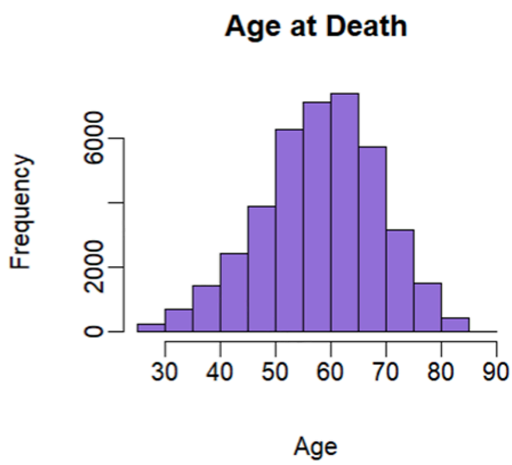
1.3.2 Time to Death (T20)



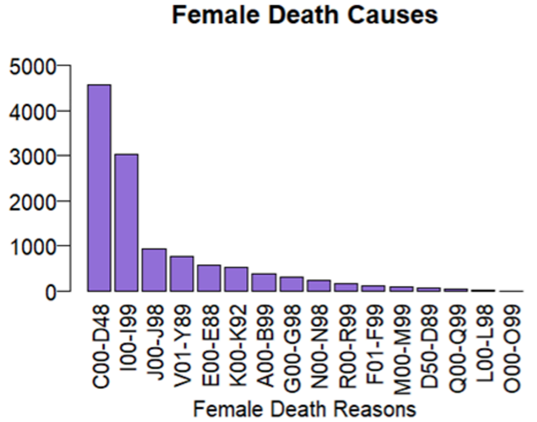
1.3.3 Time to Death (SPWL)



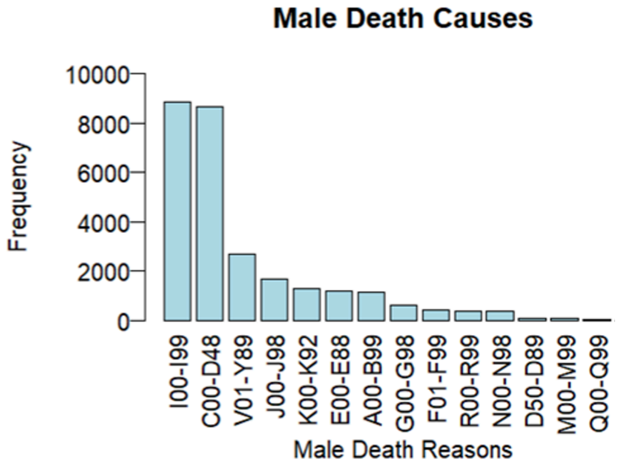
1.3.4 Age at Death



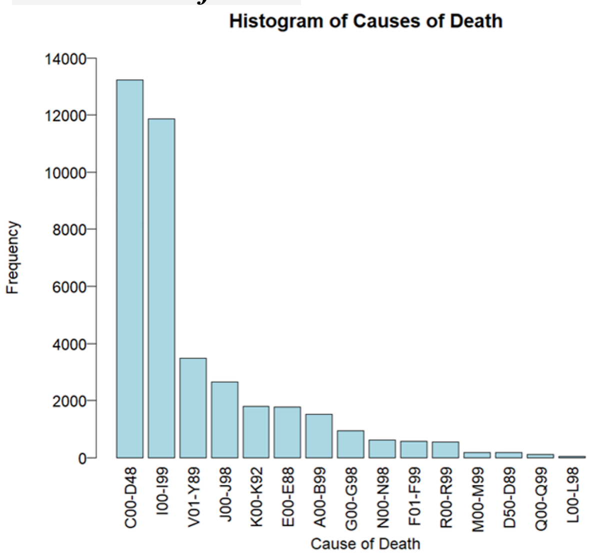
1.3.5 Causes of Death (Females)



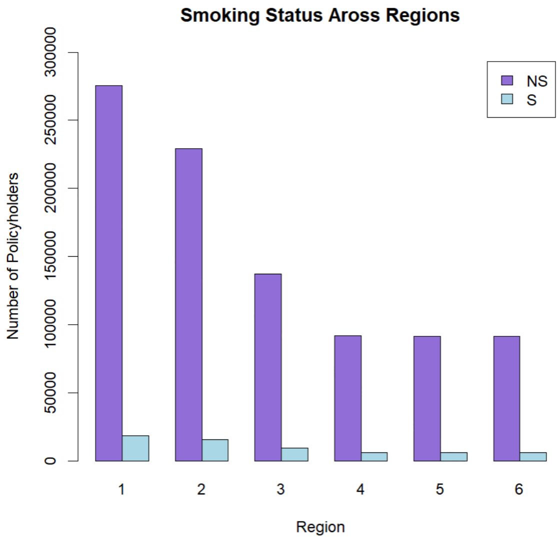
1.3.6 Causes of Death (Males)



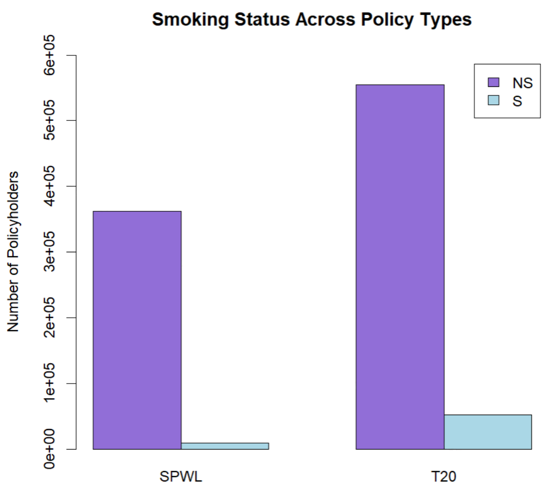
1.3.7 Causes of Death



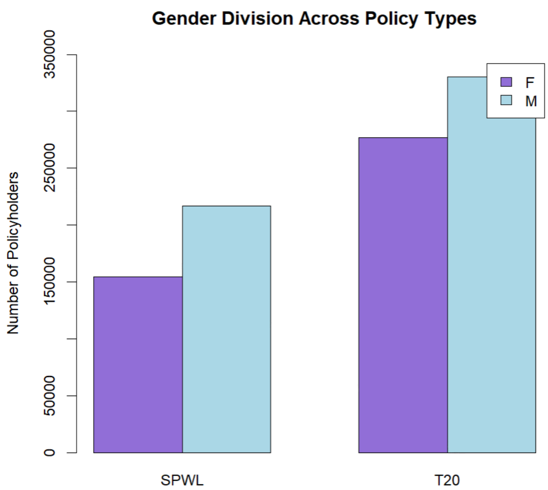
1.3.8 Smoker Status Across Regions



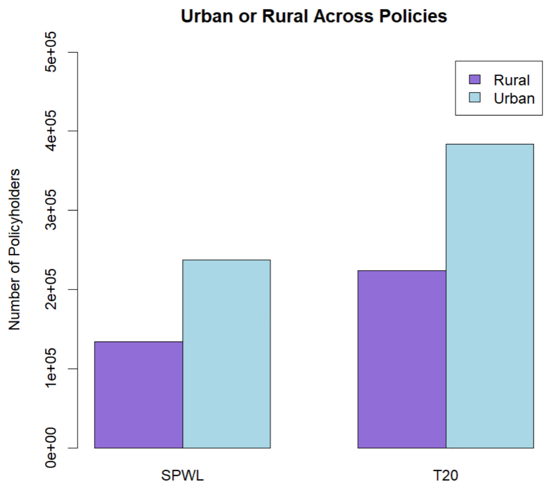
1.3.9 Smoking Status across SPWL & T20



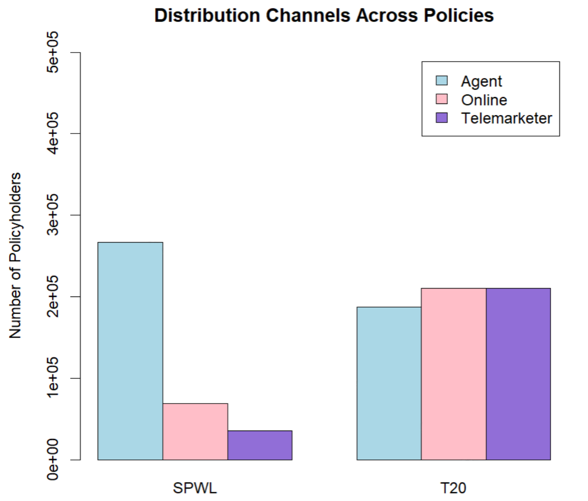
1.3.10 Gender Division in SPWL & T20



1.3.11 Urban or Rural in SPWL & T20



1.3.12 Distribution Channels across Policies



1.3.13 Location Distribution

Lumarian's Location (%)			
Region	**Rural**	**Urban**	**Total**
1	11.00	19.06	30.06
2	9.17	15.58	25.01
3	5.50	9.48	14.98
4	3.67	6.32	9.99
5	3.62	6.35	9.97
6	3.64	6.35	9.99
Total	36.60	63.40	100.00

1.3.14 Distribution Channels

Policies from Distribution Channel (%)				
Region	**Agent**	**Online**	**Telemarketer**	**Total**
1	46.45	28.57	24.98	100
2	46.52	28.39	25.09	100
3	46.42	28.63	24.96	100
4	46.37	28.38	25.26	100
5	46.24	28.64	25.12	100
6	46.27	28.46	25.27	100

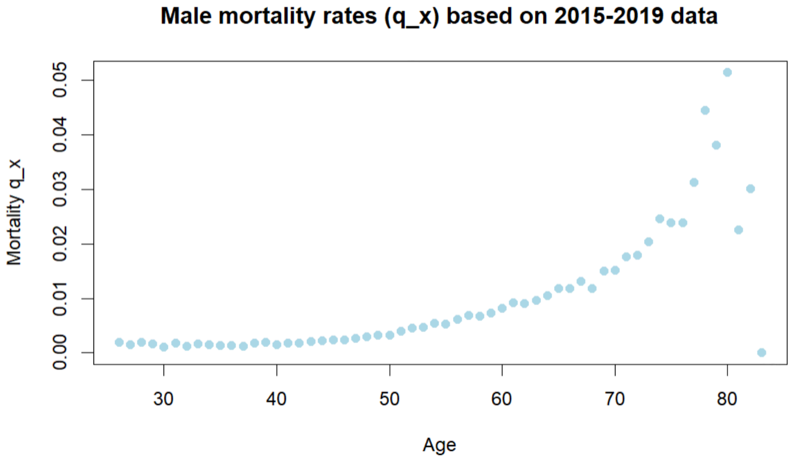
1.3.15 Underwriting Risk and Face Amount Covered

Underwriting Risk and Face Amount Covered (%)							
Risk	**50k**	**100k**	**250k**	**500k**	**1 m**	**2 m**	**Total**
High	9.89	16.34	20.97	20.89	17.19	14.69	100
Moderate risk	9.95	16.57	20.89	20.68	17.44	14.38	100
Low risk	8.71	15.95	20.36	20.56	18.23	16.20	100
Very low risk	8.76	15.97	20.48	20.60	18.03	16.17	100

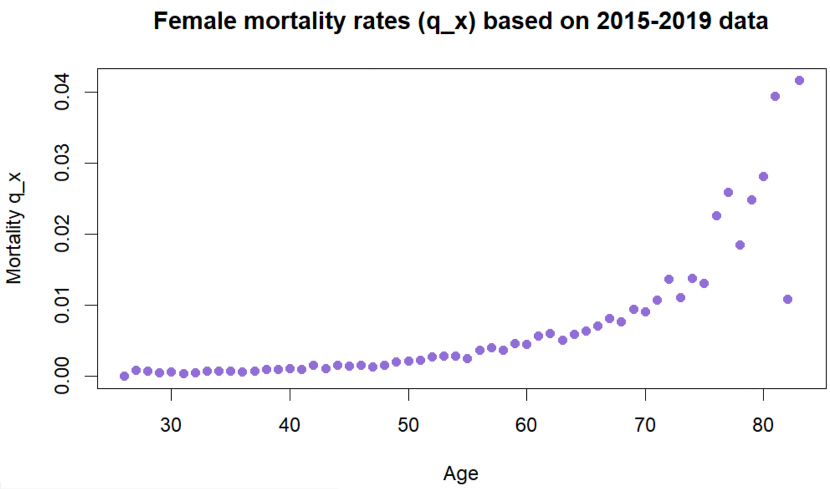
1.3.16 Active, lapsed, death status as of 2023

Active, lapsed, death status as of 2023			
Classes	**SPWL**	**T20**	**Total**
Active	351127	476190	827317
Lapsed	0	110889	110889
Dead	20174	20202	40376
Total	371301	607281	978582

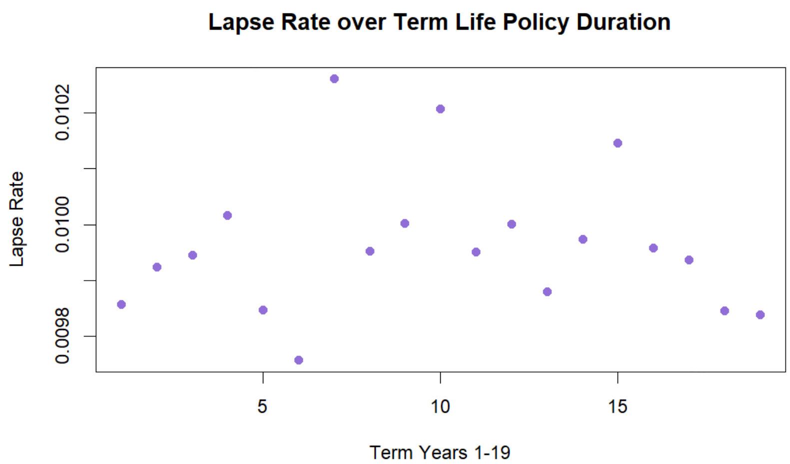
1.3.17 Male mortality rates (q_x)



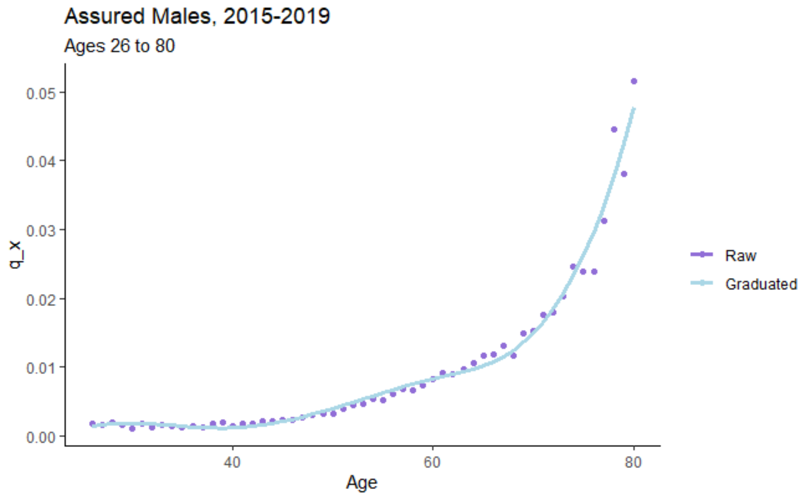
1.3.18 Female mortality rates (q_x)



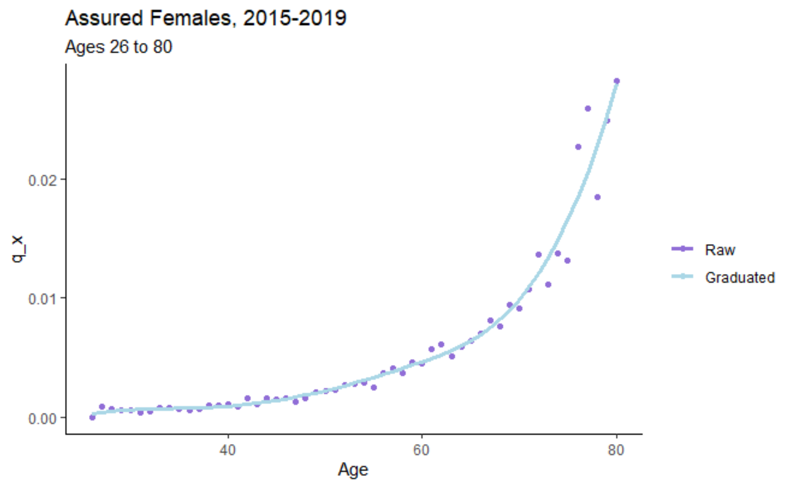
1.3.19 Lapse Rate over Term Life Policy



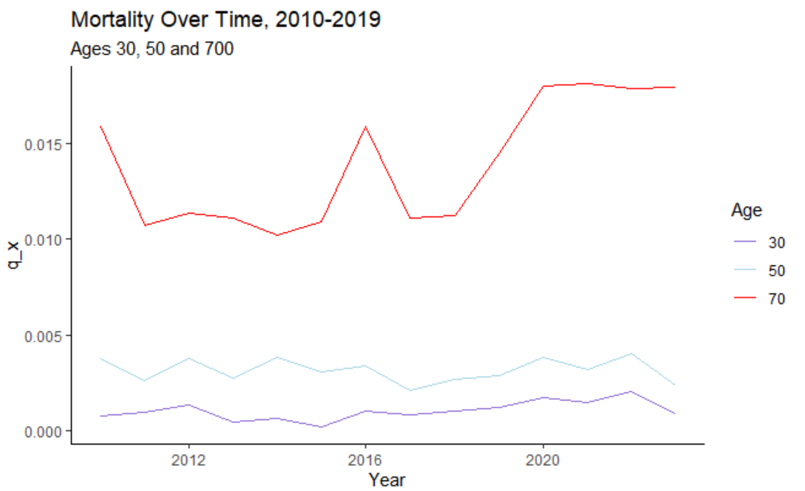
1.3.20 Graduated Male Mortality Rates (q_x)



1.3.21 Graduated Female Mortality Rates (q_x)



1.3.22 Raw Mortality Over Time



2 Mortality Reductions and Proposed Costs

2.1 Cardio Improvement App Package

Age group	Participation	Mortality reduction *	Program cost (per person) **	Fixed cost ***	Total cost
16-25	75%	12.35%	Č1635	Č50	Č1685
26-45	60%	13.24%	Č1000	Č50	Č1050
46-65	60%	13.51%	Č1120	Č50	Č1170
66-95	45%	8.60%	Č1710	Č50	Č1760

*2.1.1 Calculation of mortality reductions **

Ages	Mortality Reduction						Total Mortality Reduction
	App 1			App 2			
	Heart health screening	Weight management program	Total	Fitness tracking incentive	Personalised health plans	Total	$0.75I_1 + 0.25I_2$
Proposed Mortality Reduction	*5-10%*	*5-10%*		*3-6%*	*3-6%*		
16-25	6%	7%	1-(1-6%)(1-7%) =12.58%	6%	6%	1-(1-6%)(1-6%) =11.64%	12.35%
26-45	8%	7%	1-(1-8%)(1-7%) =14.44%	4%	6%	1-(1-4%)(1-6%) =9.76%	13.24%
46-65	10%	6%	1-(1-10%)(1-6%) =15.4%	4%	4%	1-(1-4%)(1-4%) =7.84%	13.51%
66-95	5%	5%	1-(1-5%)(1-5%) =9.75%	3%	3%	1-(1-3%)(1-3%) =5.91%	8.6%

> *Where I_1, I_2 refer to the 2 apps within the package*

*2.1.2 Calculation of program costs ***

Ages	Costs (per person)						Total Cost (per person)
	App 1			App 2			
	Heart health screening	Weight management program	Total	Fitness tracking incentive	Personalised health plans	Total	$app_1 + app_2$
Proposed Program Cost	*Č90 - Č345 per screening*	*Č175 - Č870 per program*		*Č35 - Č175 per tracker*	*Č90 - Č345 per plan*		
16-25	3*345 = Č1035	Č400	Č1435	Č200	Č50	Č250	Č1635
26-45	3*150 = Č450	Č300	Č750	Č200	Č50	Č250	Č1000
46-65	3*90 = Č270	Č600	Č870	Č100	Č90	Č190	Č1120
66-95	3*200 = Č600	Č870	Č1470	Č150	Č90	Č240	Č1710

*2.1.3 Calculation of fixed costs ****

Costs (per person)		Total Cost (per person) $app_1 + app_2$
Well-being Apps *Č10-35 per app*		
App 1	App 2	
Č35	Č15	Č50

2.2 Cancer Prevention Package

Age group	*Participation*	*Mortality reduction **	*Program cost (per person) ***	*Fixed Cost ****	*Total Cost*
16-25	20%	14.70%	Č1250	Č70	Č1320
26-45	50%	27.10%	Č2350	Č70	Č2420
46-65	60%	15.50%	Č3975	Č70	Č4045
66-95	70%	10.10%	Č1600	Č70	Č1670

*2.2.1 Calculation of mortality reductions **

Ages	**Mortality Reduction**				**Total Mortality Reduction**
	Initiatives for Preventative Screenings	**Genetic Testing**	**Cancer Prevention Initiatives**	**Smoking Cessation Programs**	
Incentive weights	0.2	0.1	0.2	0.5	$0.2I_1 + 0.1I_2 + 0.2I_3 + 0.5I_4$
Proposed Mortality Reduction	*5-10%*	*2-4%*	*5-10%*	*Up to 50%*	
16-25	10%	2%	10%	21%	14.70%
26-45	8%	2%	9%	47%	27.10%
46-65	6%	4%	7%	25%	15.50%
66-95	5%	4%	6%	15%	10.10%

> *Where I_1, I_2, I_3 and I_4 refer to the four incentives within the package*

*2.2.2 Calculation of program costs ***

Ages	**Costs (per person)**				**Total Cost (per person)**
	Initiatives for Preventative Screenings	**Genetic Testing**	**Cancer Prevention Initiatives**	**Smoking Cessation Programs**	$I_1+I_2+I_3+I_4$
Proposed Program Cost	*Č20 - Č80 per incentive*	*Č90 - Č345 per incentive*	*Č20 - Č85 per initiative*	*Č875 - Č3845 per policyholder*	
16-25	Č70	Č100	Č30*5 = Č150	Č1000	Č1635
26-45	Č70	Č150	Č40*5 = Č200	Č2000	Č1000
46-65	Č70	Č250	Č65*5 = Č325	Č3400	Č1120
66-95	Č70	Č345	Č85*5 = Č425	Č900	Č1710

> *Where I_1, I_2, I_3 and I_4 refer to the four incentives within the package*

*2.2.3 Allocation of fixed costs ****

Costs (per person)
Initiatives for Preventative Screenings
Č70

3 Death Benefits

	Males				Females			
Age	**T20**	**Growth Rate**	**SPWL**	**Growth Rate**	**T20**	**Growth Rate**	**SPWL**	**Growth Rate**
26	555097.09				459850.11			
27	555097.09				459850.11			
28	557369.61				518231.44			
29	548674.70				522211.54			
30	409883.72				513905.33			
31	609698.28				534652.51			
32	657110.61				561089.49			
33	565513.13				536176.47			
34	567177.91				579771.78			
35	590659.34				594897.96			
36	668927.79		768551.24		555497.93		726057.91	
37	477205.88		764705.88		562633.83		742290.75	
38	640599.17		717948.72		620616.57		724373.58	
39	652074.24		764705.88		587360.59		786447.64	
40	659737.42		762589.93		593373.49		773218.14	
41	639956.33		748623.85		647064.06		749473.68	
42	639277.65		822380.11		543871.60		651658.77	
43	629254.30		786618.44		625732.22		730360.93	
44	637611.61		791095.89		619626.17		775303.64	
45	713333.33		784482.76		636585.37		809815.95	
46	691880.34		832451.50		620352.25		728888.89	
47	642217.90	92.82%	760000.00		615125.24	99.16%	722792.61	
48	694916.82	108.21%	719022.69		631627.06	102.68%	782178.22	
49	675879.92	97.26%	774074.07		646990.29	102.43%	758465.01	
50	680831.64	100.73%	731319.55		658474.58	101.78%	801801.80	
51	654854.37	96.18%	724381.63		652059.93	99.03%	755741.13	
52	615415.02	93.98%	769616.03		631749.05	96.89%	800947.87	
53	700508.13	113.83%	753130.59		671535.58	106.30%	782700.42	
54	712169.81	101.66%	741710.30		650617.28	96.89%	800000.00	
55	641007.91	90.01%	742647.06		630430.53	96.90%	721088.44	
56	600104.60	93.62%	728846.15		594594.59	94.32%	740088.11	
57	***Average***	98.83%	799276.67	109.66%	***Average***	99.64%	761099.37	102.84%
58			822898.03	102.96%			725910.06	95.38%
59			780656.30	94.87%			827037.77	113.93%
60			829268.29	106.23%			788418.71	95.33%
61			780036.97	94.06%			766528.93	97.22%
62			715547.70	91.73%			785288.27	102.45%
63			783783.78	109.54%			784869.98	99.95%
64			793851.72	101.28%			786307.05	100.18%
65			754545.45	95.05%			812500.00	103.33%
66			750957.85	99.52%			698850.57	86.01%
			Average	100.49%			***Average***	99.66%

4 Marketing Personas

4.1 Cardio App Persona

MARGARET SMITH

"I am looking for a program that will motivate me to take care of my heart health"

AGE: 25
SEX: Female
WORK: Retail Sector
FAMILY : Single
LOCATION : Urban

Bio

Margaret is an aspiring store supervisor at Closet Couture and lives in an apartment in the city district of Lumaria. She has a family history of heart diseases and would like to be involved in programs that target a healthier lifestyle. Currently she is not a policyholder for SuperLife but has been informed by her uncle who is a shareholder for the company that they are planning on introducing new wellness programs through their products.

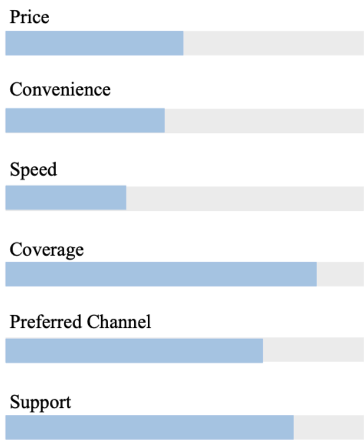
Goals

- Have heart screenings to stay updated on her heart health
- To have a tracker motivating her to live a healthier lifestyle

Frustrations

- Unsure of what financial plan to purchase
- Does not have time to go to multiple medical professionals and dietitians

Motivations



4.2 Cancer Prevention Pack Persona

GERALD JOHNSON

"I am looking for a program that will help identify and prevent cancerous risks"

AGE: 55
SEX: Male
WORK: Mining Sector
FAMILY : Married with 3 kids
LOCATION : Rural

Bio

Gerald is a regional manager for the Lumarian mining industry. He lives with his family within the rural district and has become increasingly concerned about the high risks of cancers becoming prevalent in the country, especially due to his smoking status. Currently he is not a policyholder for SuperLife but has approached the insurance company on advice on what plan he should purchase given his age, work life and the fact that he has to support his family of four.

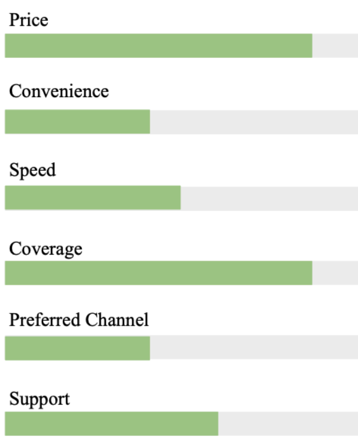
Goals

- To have regular health checks with medical professionals
- Live a healthy and financially secure lifestyle
- To retire comfortably

Frustrations

- How financially feasible are health plans
- How many health tests can be included in the purchased plan

Motivations



5 Modelling Results

5.1.1 Single Premium Whole Life

SPWL				
	Male		Female	
Age	Profits Before (Č)	Profits After (Č)	Profits Before (Č)	Profits After (Č)
(36-40)	-1,891,535,772	-1,110,722,038	-902,344,006	-508,330,131
(41-45)	-2,046,805,286	-1,248,330,882	-5,862,089,484	-3,317,270,621
(46-50)	-2,276,158,151	-1,450,259,088	-10,262,310,578	-5,924,452,810
(51-55)	-2,350,737,259	-1,548,180,337	-13,590,100,260	-8,008,492,231
(56-60)	-2,203,551,623	-1,485,980,969	-15,154,602,232	-9,011,121,377
(61-66)	-2,309,326,716	-1,583,823,578	-16,047,589,350	-9,598,184,563

SPWL						
	Male			Female		
Age	Net Growth in Expenses (Č)	Net Growth in Profits (Č)	Percentage Growth in Profits	Net Growth in Expenses (Č)	Net Growth in Profits (Č)	Percentage Growth in Profits
(36-40)	-219,687	780,813,735	41.3%	-45,368	394,013,876	43.67%
(41-45)	-207,083	798,474,404	39.0%	-226,932	2,544,818,863	43.41%
(46-50)	342,418	825,899,064	36.3%	3,503,182	4,337,857,768	42.27%
(51-55)	338,069	802,556,922	34.1%	4,299,052	5,581,608,029	41.07%
(56-60)	315,749	717,570,654	32.6%	4,575,637	6,143,480,855	40.54%
(61-66)	322,889	725,503,13	31.4%	4,675,725	6,449,404,787	40.19%

5.2 20-Year Term

T20				
	Male		Female	
Age	Profits Before (Č)	Profits After (Č)	Profits Before (Č)	Profits After (Č)
(27-30)	32,172,188	23,181,135	39,470,486	33,086,054
(31-35)	38,978,347	22,518,980	217,615,680	146,385,434
(36-40)	40,869,889	23,833,370	412,976,003	278,396,341
(41-45)	44,187,708	25,813,374	614,922,404	415,699,611
(46-50)	49,684,617	28,695,250	751,995,365	502,260,319
(51-56)	58,345,517	33,892,331	793,716,740	532,268,488

T20						
	Male			Female		
Age	Net Growth in Expenses (Č)	Net Growth in Profits (Č)	Percentage Growth in Profits	Net Growth in Expenses (Č)	Net Growth in Profits (Č)	Percentage Growth in Profits
(26-30)	690,940	-8,991,053	-27.95%	743,353	-6,384,432	-16.18%
(31-35)	302,015	-16,459,367	-42.23%	1,181,535	-71,230,246	-32.73%
(36-40)	298,779	-17,036,519	-41.68%	2,102,903	-134,579,662	-32.59%
(41-45)	305,581	-18,374,334	-41.58%	2,956,483	-199,222,793	-32.40%
(46-50)	799,069	-20,989,367	-42.25%	11,218,265	-249,735,046	-33.21%
(51-56)	877,436	-24,453,186	-41.91%	11,244,341	-261,448,252	-32.94%

5.1.2 Male Profitability Sensitivity

Males, Age 40, SPWL, Interest & Expenses

	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	13%	14%	15%
100	5961.55	4108.08	2883.26	2062.76	1505.22	1120.68	851.31	659.60	520.92	418.93	342.70	284.79	240.09	205.07	177.22
200	5988.74	4128.42	2898.75	2074.78	1514.71	1128.29	857.52	664.73	525.22	422.59	345.84	287.51	242.48	207.18	179.11
300	6015.93	4148.76	2914.25	2086.80	1524.19	1135.90	863.72	669.86	529.52	426.24	348.98	290.24	244.87	209.29	180.99
400	6043.11	4169.10	2929.74	2098.82	1533.68	1143.51	869.92	675.00	533.83	429.90	352.12	292.96	247.26	211.40	182.87
500	6070.30	4189.43	2945.24	2110.84	1543.16	1151.12	876.13	680.13	538.13	433.55	355.26	295.69	249.65	213.52	184.75
600	6097.49	4209.77	2960.73	2122.85	1552.65	1158.73	882.33	685.26	542.44	437.21	358.40	298.42	252.04	215.63	186.63
700	6124.67	4230.11	2976.22	2134.87	1562.13	1166.34	888.54	690.39	546.74	440.86	361.54	301.14	254.42	217.74	188.52
800	6151.86	4250.45	2991.72	2146.89	1571.62	1173.95	894.74	695.52	551.04	444.52	364.68	303.87	256.81	219.85	190.40
900	6179.05	4270.79	3007.21	2158.91	1581.10	1181.56	900.94	700.66	555.35	448.17	367.82	306.59	259.20	221.97	192.28
1000	6206.24	4291.12	3022.71	2170.93	1590.59	1189.18	907.15	705.79	559.65	451.83	370.96	309.32	261.59	224.08	194.16

Males, Age 40, SPWL, Mortality Improvements

	5%	7%	9%	11%	13%	15%	17%	19%	21%	23%	25%	27%	29%
5%	1153.06	1145.86	1138.54	1131.09	1123.52	1115.82	1108.00	1100.04	1091.95	1083.72	1075.36	1066.85	1058.20
7%	1145.86	1138.69	1131.41	1124.00	1116.48	1108.83	1101.05	1093.15	1085.12	1076.95	1068.65	1060.21	1051.64
9%	1138.54	1131.41	1124.16	1116.80	1109.33	1101.73	1094.01	1086.16	1078.19	1070.09	1061.86	1053.49	1044.99
11%	1131.09	1124.00	1116.80	1109.49	1102.06	1094.52	1086.86	1079.07	1071.16	1063.13	1054.97	1046.68	1038.26
13%	1123.52	1116.48	1109.33	1102.06	1094.69	1087.20	1079.60	1071.88	1064.04	1056.08	1048.00	1039.79	1031.45
15%	1115.82	1108.83	1101.73	1094.52	1087.20	1079.78	1072.24	1064.59	1056.82	1048.93	1040.93	1032.80	1024.55
17%	1108.00	1101.05	1094.01	1086.86	1079.60	1072.24	1064.77	1057.19	1049.49	1041.69	1033.76	1025.72	1017.57
19%	1100.04	1093.15	1086.16	1079.07	1071.88	1064.59	1057.19	1049.68	1042.06	1034.34	1026.50	1018.56	1010.49
21%	1091.95	1085.12	1078.19	1071.16	1064.04	1056.82	1049.49	1042.06	1034.53	1026.89	1019.15	1011.29	1003.33
23%	1083.72	1076.95	1070.09	1063.13	1056.08	1048.93	1041.69	1034.34	1026.89	1019.35	1011.69	1003.94	996.07
25%	1075.36	1068.65	1061.86	1054.97	1048.00	1040.93	1033.76	1026.50	1019.15	1011.69	1004.14	996.49	988.73
27%	1066.85	1060.21	1053.49	1046.68	1039.79	1032.80	1025.72	1018.56	1011.29	1003.94	996.49	988.94	981.29
29%	1058.20	1051.64	1044.99	1038.26	1031.45	1024.55	1017.57	1010.49	1003.33	996.07	988.73	981.29	973.76

Males, Age 40, T20, Interest & Expenses

	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	13%	14%	15%
100	-9.09%	-17.01%	-23.93%	-29.99%	-35.32%	-40.02%	-44.18%	-47.88%	-51.17%	-54.12%	-56.77%	-59.15%	-61.31%	-63.26%	-65.03%
200	-10.36%	-18.16%	-24.98%	-30.95%	-36.19%	-40.82%	-44.92%	-48.57%	-51.82%	-54.72%	-57.33%	-59.68%	-61.80%	-63.72%	-65.47%
300	-11.62%	-19.31%	-26.02%	-31.90%	-37.07%	-41.63%	-45.67%	-49.26%	-52.46%	-55.32%	-57.89%	-60.20%	-62.29%	-64.19%	-65.91%
400	-12.89%	-20.46%	-27.07%	-32.86%	-37.94%	-42.44%	-46.41%	-49.95%	-53.10%	-55.92%	-58.45%	-60.73%	-62.79%	-64.65%	-66.35%
500	-14.16%	-21.61%	-28.11%	-33.81%	-38.82%	-43.24%	-47.16%	-50.64%	-53.74%	-56.52%	-59.01%	-61.25%	-63.28%	-65.12%	-66.79%
600	-15.43%	-22.76%	-29.16%	-34.77%	-39.70%	-44.05%	-47.90%	-51.33%	-54.38%	-57.12%	-59.57%	-61.78%	-63.77%	-65.58%	-67.23%
700	-16.70%	-23.91%	-30.21%	-35.72%	-40.57%	-44.85%	-48.65%	-52.02%	-55.02%	-57.71%	-60.13%	-62.30%	-64.27%	-66.05%	-67.67%
800	-17.97%	-25.06%	-31.25%	-36.68%	-41.45%	-45.66%	-49.39%	-52.71%	-55.67%	-58.31%	-60.69%	-62.83%	-64.76%	-66.51%	-68.11%
900	-19.23%	-26.21%	-32.30%	-37.63%	-42.33%	-46.47%	-50.14%	-53.40%	-56.31%	-58.91%	-61.25%	-63.35%	-65.26%	-66.98%	-68.55%
1000	-20.50%	-27.36%	-33.34%	-38.59%	-43.20%	-47.27%	-50.88%	-54.09%	-56.95%	-59.51%	-61.81%	-63.88%	-65.75%	-67.45%	-68.99%

Males, Age 40, T20, Mortality Improvements

	5%	7%	9%	11%	13%	15%	17%	19%	21%	23%	25%	27%	29%
0.05	5.06%	6.18%	7.20%	8.17%	9.14%	10.09%	10.91%	11.65%	12.35%	12.94%	13.47%	13.97%	14.43%
0.07	6.18%	7.18%	8.13%	9.08%	10.02%	10.83%	11.56%	12.24%	12.84%	13.38%	13.87%	14.34%	14.70%
0.09	7.20%	8.13%	9.06%	9.98%	10.77%	11.50%	12.17%	12.77%	13.31%	13.78%	14.26%	14.62%	14.98%
0.11	8.17%	9.08%	9.98%	10.76%	11.47%	12.13%	12.72%	13.25%	13.72%	14.18%	14.56%	14.91%	15.25%
0.13	9.14%	10.02%	10.77%	11.47%	12.11%	12.70%	13.22%	13.68%	14.13%	14.52%	14.85%	15.19%	15.53%
0.15	10.09%	10.83%	11.50%	12.13%	12.70%	13.21%	13.66%	14.10%	14.49%	14.81%	15.14%	15.47%	15.80%
0.17	10.91%	11.56%	12.17%	12.72%	13.22%	13.66%	14.09%	14.47%	14.79%	15.11%	15.43%	15.75%	16.07%
0.19	11.65%	12.24%	12.77%	13.25%	13.68%	14.10%	14.47%	14.78%	15.10%	15.41%	15.72%	16.04%	16.35%
0.21	12.35%	12.84%	13.31%	13.72%	14.13%	14.49%	14.79%	15.10%	15.40%	15.71%	16.01%	16.32%	16.62%
0.23	12.94%	13.38%	13.78%	14.18%	14.52%	14.81%	15.11%	15.41%	15.71%	16.00%	16.30%	16.60%	16.90%
0.25	13.47%	13.87%	14.26%	14.56%	14.85%	15.14%	15.43%	15.72%	16.01%	16.30%	16.59%	16.88%	17.15%
0.27	13.97%	14.34%	14.62%	14.91%	15.19%	15.47%	15.75%	16.04%	16.32%	16.60%	16.88%	17.15%	17.40%
0.29	14.43%	14.70%	14.98%	15.25%	15.53%	15.80%	16.07%	16.35%	16.62%	16.90%	17.15%	17.40%	17.64%

5.1.3 Female Profitability Sensitivity

Females, Age 40, SPWL, Interest & Expenses

	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	13%	14%	15%
100	14059.26	9848.10	7032.34	5122.67	3808.12	2889.12	2236.33	1764.99	1419.00	1160.78	964.89	813.90	695.71	601.82	526.19
200	14150.97	9916.63	7084.51	5163.12	3840.04	2914.75	2257.23	1782.31	1433.54	1173.16	975.55	823.18	703.86	609.04	532.65
300	14242.68	9985.16	7136.68	5203.56	3871.96	2940.37	2278.14	1799.62	1448.09	1185.53	986.21	832.45	712.01	616.27	539.10
400	14334.39	10053.70	7188.85	5244.01	3903.88	2966.00	2299.05	1816.94	1462.63	1197.91	996.87	841.73	720.16	623.49	545.56
500	14426.10	10122.23	7241.02	5284.45	3935.79	2991.62	2319.95	1834.25	1477.18	1210.29	1007.52	851.00	728.31	630.72	552.02
600	14517.81	10190.76	7293.19	5324.90	3967.71	3017.24	2340.86	1851.57	1491.73	1222.67	1018.18	860.28	736.46	637.95	558.47
700	14609.52	10259.29	7345.36	5365.35	3999.63	3042.87	2361.76	1868.89	1506.27	1235.05	1028.84	869.55	744.61	645.17	564.93
800	14701.23	10327.82	7397.53	5405.79	4031.55	3068.49	2382.67	1886.20	1520.82	1247.42	1039.50	878.83	752.77	652.40	571.39
900	14792.94	10396.36	7449.70	5446.24	4063.47	3094.12	2403.57	1903.52	1535.36	1259.80	1050.16	888.11	760.92	659.63	577.84
1000	14884.64	10464.89	7501.87	5486.69	4095.39	3119.74	2424.48	1920.83	1549.91	1272.18	1060.81	897.38	769.07	666.85	584.30

Females, Age 40, SPWL, Mortality Improvements

	5%	7%	9%	11%	13%	15%	17%	19%	21%	23%	25%	27%	29%
5%	3025.55	3007.94	2990.17	2972.23	2954.11	2935.83	2917.37	2898.74	2879.93	2860.95	2841.78	2822.44	2802.90
7%	3007.94	2990.55	2972.99	2955.26	2937.38	2919.32	2901.10	2882.72	2864.16	2845.43	2826.52	2807.44	2788.19
9%	2990.17	2972.99	2955.65	2938.15	2920.49	2902.68	2884.70	2866.56	2848.26	2829.79	2811.15	2792.34	2773.37
11%	2972.23	2955.26	2938.15	2920.88	2903.47	2885.89	2868.16	2850.28	2832.23	2814.03	2795.66	2777.13	2758.44
13%	2954.11	2937.38	2920.49	2903.47	2886.29	2868.96	2851.49	2833.86	2816.08	2798.15	2780.06	2761.81	2743.41
15%	2935.83	2919.32	2902.68	2885.89	2868.96	2851.89	2834.68	2817.31	2799.80	2782.15	2764.34	2746.38	2728.27
17%	2917.37	2901.10	2884.70	2868.16	2851.49	2834.68	2817.72	2800.63	2783.40	2766.02	2748.50	2730.83	2713.02
19%	2898.74	2882.72	2866.56	2850.28	2833.86	2817.31	2800.63	2783.81	2766.86	2749.77	2732.54	2715.18	2697.67
21%	2879.93	2864.16	2848.26	2832.23	2816.08	2799.80	2783.40	2766.86	2750.19	2733.40	2716.47	2699.40	2682.20
23%	2860.95	2845.43	2829.79	2814.03	2798.15	2782.15	2766.02	2749.77	2733.40	2716.90	2700.27	2683.52	2666.63
25%	2841.78	2826.52	2811.15	2795.66	2780.06	2764.34	2748.50	2732.54	2716.47	2700.27	2683.95	2667.51	2650.95
27%	2822.44	2807.44	2792.34	2777.13	2761.81	2746.38	2730.83	2715.18	2699.40	2683.52	2667.51	2651.39	2635.15
29%	2802.90	2788.19	2773.37	2758.44	2743.41	2728.27	2713.02	2697.67	2682.20	2666.63	2650.95	2635.15	2619.25

Females, Age 40, T20, Interest & Expenses

	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	13%	14%	15%
100	-40.76%	-46.13%	-50.82%	-54.91%	-58.49%	-61.65%	-64.44%	-66.91%	-69.10%	-71.06%	-72.82%	-74.39%	-75.81%	-77.09%	-78.26%
200	-41.61%	-46.91%	-51.52%	-55.55%	-59.08%	-62.19%	-64.94%	-67.37%	-69.54%	-71.47%	-73.20%	-74.75%	-76.15%	-77.41%	-78.55%
300	-42.47%	-47.69%	-52.23%	-56.20%	-59.68%	-62.74%	-65.44%	-67.84%	-69.97%	-71.87%	-73.57%	-75.10%	-76.48%	-77.72%	-78.85%
400	-43.33%	-48.47%	-52.94%	-56.84%	-60.27%	-63.28%	-65.95%	-68.31%	-70.41%	-72.28%	-73.95%	-75.46%	-76.81%	-78.04%	-79.15%
500	-44.19%	-49.24%	-53.65%	-57.49%	-60.86%	-63.83%	-66.45%	-68.77%	-70.84%	-72.68%	-74.33%	-75.81%	-77.15%	-78.35%	-79.45%
600	-45.05%	-50.02%	-54.35%	-58.14%	-61.46%	-64.38%	-66.95%	-69.24%	-71.27%	-73.09%	-74.71%	-76.17%	-77.48%	-78.67%	-79.74%
700	-45.90%	-50.80%	-55.06%	-58.78%	-62.05%	-64.92%	-67.46%	-69.71%	-71.71%	-73.49%	-75.09%	-76.52%	-77.82%	-78.98%	-80.04%
800	-46.76%	-51.58%	-55.77%	-59.43%	-62.64%	-65.47%	-67.96%	-70.17%	-72.14%	-73.90%	-75.47%	-76.88%	-78.15%	-79.30%	-80.34%
900	-47.62%	-52.35%	-56.47%	-60.08%	-63.23%	-66.01%	-68.47%	-70.64%	-72.58%	-74.30%	-75.85%	-77.23%	-78.48%	-79.61%	-80.64%
1000	-48.48%	-53.13%	-57.18%	-60.72%	-63.83%	-66.56%	-68.97%	-71.11%	-73.01%	-74.71%	-76.23%	-77.59%	-78.82%	-79.93%	-80.93%

Females, Age 40, T20, Mortality Improvements

	5%	7%	9%	11%	13%	15%	17%	19%	21%	23%	25%	27%	29%
5%	7.87%	8.20%	8.50%	8.80%	9.08%	9.36%	9.63%	9.91%	10.18%	10.46%	10.73%	11.01%	11.28%
7%	8.20%	8.50%	8.79%	9.07%	9.34%	9.60%	9.87%	10.14%	10.41%	10.68%	10.95%	11.22%	11.49%
9%	8.50%	8.79%	9.06%	9.32%	9.59%	9.85%	10.11%	10.38%	10.64%	10.91%	11.17%	11.43%	11.70%
11%	8.80%	9.07%	9.32%	9.58%	9.84%	10.10%	10.35%	10.61%	10.87%	11.13%	11.39%	11.64%	11.90%
13%	9.08%	9.34%	9.59%	9.84%	10.09%	10.34%	10.60%	10.85%	11.10%	11.35%	11.60%	11.86%	12.11%
15%	9.36%	9.60%	9.85%	10.10%	10.34%	10.59%	10.84%	11.08%	11.33%	11.57%	11.82%	12.07%	12.31%
17%	9.63%	9.87%	10.11%	10.35%	10.60%	10.84%	11.08%	11.32%	11.56%	11.80%	12.04%	12.28%	12.52%
19%	9.91%	10.14%	10.38%	10.61%	10.85%	11.08%	11.32%	11.55%	11.79%	12.02%	12.26%	12.49%	12.73%
21%	10.18%	10.41%	10.64%	10.87%	11.10%	11.33%	11.56%	11.79%	12.02%	12.24%	12.47%	12.70%	12.93%
23%	10.46%	10.68%	10.91%	11.13%	11.35%	11.57%	11.80%	12.02%	12.24%	12.47%	12.69%	12.92%	13.14%
25%	10.73%	10.95%	11.17%	11.39%	11.60%	11.82%	12.04%	12.26%	12.47%	12.69%	12.91%	13.13%	13.34%
27%	11.01%	11.22%	11.43%	11.64%	11.86%	12.07%	12.28%	12.49%	12.70%	12.92%	13.13%	13.34%	13.55%
29%	11.28%	11.49%	11.70%	11.90%	12.11%	12.31%	12.52%	12.73%	12.93%	13.14%	13.34%	13.55%	13.76%

6 Formulas

6.1 Interest Rate Calculations

Long run equilibrium interest rate (b) was calculated using the ordinary least squares method with the Vasicek Model.

$$\mathrm{E}[r_t] = r_0 e^{-at} + b(1 - e^{-at})$$

and variance

$$\mathrm{Var}[r_t] = \frac{\sigma^2}{2a}(1 - e^{-2at}).$$

Consequently, we have

$$\lim_{t \to \infty} \mathrm{E}[r_t] = b$$

and

$$\lim_{t \to \infty} \mathrm{Var}[r_t] = \frac{\sigma^2}{2a}.$$

6.2 Cash Flow Projection

- Cash flow at the end of the kth year after zeroization is given by: $max((CF)_k - k\_V\ (ap)_{x+k-1}, 0)$.
- Interests grown on the insurance fund is given by: $I = (premium - expenses) \times i$
- Death benefits at the end of each year is calculated by: $DB = DB\ per\ person \times (aq)_x^d$.
- Capital each year is calculated by: $Cap = capital\ requirement \times DB\ per\ person \times (ap)_x$.

Bibliography

Chien, S.-Y., Chuang, M.-C., & Chen, I.-P. (2020). Why People Do Not Attend Health Screenings: Factors That Influence Willingness to Participate in Health Screenings for Chronic Diseases. International Journal of Environmental Research and Public Health, 17(10), 3495. https://www.mdpi.com/1660-4601/17/10/3495 (Accessed: 2 March 2024).

Grey, H. (2020) *When Should You Have a Heart Health Checkup?*, Healthline. Available at: https://www.healthline.com/health/heart-health/scheduling-heart-health-checkup (Accessed: 2 March 2024).

International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD-10) (2019). Available: https://icd.who.int/browse10/2019/en (Accessed 27 February 2024).

National Heart, Lung, and Blood Institute (NIH) (2022). Available: https://www.nhlbi.nih.gov/health/heart-failure/treatment (Accessed 2 March 2024).

Vessey, C. J., Norbury, C. J., & Hickson, I. D. (1999). Genetic disorders associated with cancer predisposition and genomic instability. *Progress in nucleic acid research and molecular biology*, *63*, 189–221. https://doi.org/10.1016/s0079-6603(08)60723-0 (Accessed: 10 March 2024).

Winnall, WR & Winstanley, MH. 3.24. (2021) Genetic influences on tobacco-caused disease. In Greenhalgh EM, Scollo, MM and Winstanley, MH [editors]. *Tobacco in Australia: Facts and issues.* Melbourne: Cancer Council Victoria. Available: https://www.tobaccoinaustralia.org.au/chapter-3-health-effects/3-24-genetic-influences-on-tobacco-caused-disease (Accessed: 1 March 2024).

R-Code

```
working_direc <- "C:/Users/zhouu/Downloads/Final Year UNSW/ACTL4001/SOA Project"
setwd(working_direc)
require("openxlsx")
require("dplyr")

data <- read.xlsx("Inforce Dataset.xlsx")
raw_data <- data[-c(1:2),]
colnames(raw_data) <- raw_data[1,]
inforce_data <- data.frame(raw_data[-1,])
columns_to_convert <- c("Year.of.Death", "Year.of.Lapse", "Issue.year")
inforce_data[columns_to_convert] <- lapply(inforce_data[columns_to_convert], as.numeric)

inforce_data2 <- inforce_data %>%
  mutate(active = is.na(Year.of.Death) & is.na(Year.of.Lapse),
         time_to_death = ifelse(!is.na(Year.of.Death), as.numeric(Year.of.Death - Issue.year), 
        NA),
         time_to_lapse = ifelse(!is.na(Year.of.Lapse), as.numeric(Year.of.Lapse - Issue.year), 
        NA),
       age_at_death = Year.of.Death - Issue.year + as.numeric(Issue.age))

anyDuplicated(inforce_data2$Policy.number) #None
length(unique(inforce_data2$Policy.number)) #978582

SPWL <- subset(inforce_data2, inforce_data2$Policy.type == "SPWL")
T20 <- subset(inforce_data2, inforce_data2$Policy.type == "T20")
C00_D48_deaths <- subset(inforce_data2, Cause.of.Death == "C00-D48")
term_time_to_death <- subset(inforce_data2, Policy.type == "T20")$time_to_death
WL_time_to_death <- subset(inforce_data2, Policy.type == "SPWL")$time_to_death

par(mfrow = c(2, 2))
par(mar = c(6, 5, 4, 2), mgp = c(3, 0.5, 0))

# Appendix 8.1.3.1
hist(inforce_data2$Issue.year, xlim = c(2000, 2025), col = "light blue", xlab = "Year", main = 
        "Issue Year")

# Appendix 8.1.3.2
hist(term_time_to_death, xlim = c(0, 20), col = "light blue", main = "T20 Time to Death", 
        xlab = "Years to Death")

# Appendix 8.1.3.3
hist(WL_time_to_death, xlim = c(0,25), ylim = c(0, 3000), col = "medium purple", main = 
        "SPWL Time to Death", xlab = "Years to Death")

# Appendix 8.1.3.4
hist(inforce_data2$age_at_death, main = "Age at Death", xlab= "Age", ylab = "Frequency", 
        col = "medium purple")
```

```
# Appendix 8.1.3.5
females_data <- subset(inforce_data2, Sex == "F")
num_female_deaths <- sum(!is.na(females_data$Death.indicator)) # 12175 females have died
f_cause_death <- sort(table(females_data$Cause.of.Death), decreasing = TRUE)
barplot(f_cause_death, las = 2, xlab = "Female Death Reasons", ylab = "Frequency", ylim =
        c(0,5000),
    main = "Female Death Causes", col = "medium purple")

# Appendix 8.1.3.6
males_data <- subset(inforce_data2, Sex == "M")
num_male_deaths <- sum(!is.na(males_data$Death.indicator)) # 28201 males have died
m_cause_death <- sort(table(males_data$Cause.of.Death), decreasing = TRUE)
barplot(m_cause_death, las = 2, xlab = "Male Death Reasons", ylab = "Frequency", ylim =
        c(0,10000),
    main = "Male Death Causes", col = "light blue")

# Appendix 8.1.3.7
barplot(sort(table(inforce_data$Cause.of.Death), decreasing = TRUE), xlab = "Cause of
        Death", ylab = "Frequency", main = "Histogram of Causes of Death", ylim = c(0,
        14000), las = 2, col = "light blue")

# Appendix 8.1.3.8
barplot(table(inforce_data$Smoker.Status, inforce_data$Region), beside = TRUE, col =
        c("medium purple", "light blue"), xlab = "Region", ylab ="Number of Policyholders",
        main = "Smoking Status Aross Regions", legend = TRUE, ylim = c(0,300000))

# Appendix 8.1.3.9
smoking_policy_type <- table(inforce_data2$Smoker.Status, inforce_data2$Policy.type)
smoking_policy_type_prop <- prop.table(smoking_policy_type, margin = 2)
barplot(smoking_policy_type, beside = TRUE, legend = TRUE, col = c("medium purple",
        "light blue"), ylim = c(0,600000), ylab = "Number of Policyholders", main =
        "Smoking Status Across Policy Types")

# Appendix 8.1.3.10
sex_policy_type <- table(inforce_data2$Sex, inforce_data2$Policy.type)
prop.table(sex_policy_type, margin = 2)
barplot(sex_policy_type, beside = TRUE, legend = TRUE, col = c("medium purple", "light
        blue"), ylim = c(0,350000), ylab = "Number of Policyholders", main = "Gender
        Division Across Policy Types")

# Appendix 8.1.3.11
urban_rural_policy <- table(inforce_data2$Urban.vs.Rural, inforce_data2$Policy.type)
urban_rural_policy_prop <- prop.table(urban_rural_policy, margin = 2)
barplot(urban_rural_policy, beside = TRUE, legend = TRUE, col = c("medium purple", "light
        blue"), ylim = c(0,500000), ylab = "Number of Policyholders", main = "Urban or
        Rural Across Policies")

# Appendix 8.1.3.12
distribution_policy <- table(inforce_data2$Distribution.Channel, inforce_data2$Policy.type)
distribution_policy_policy_prop <- prop.table(distribution_policy, margin = 2)
```

```
barplot(distribution_policy, beside = TRUE, legend = TRUE, col = c("light blue", "pink",
        "medium purple"), ylim = c(0,500000), ylab = "Number of Policyholders", main =
        "Distribution Channels Across Policies")

# Appendix 8.1.3.13
prop.table(table(inforce_data2$Region, inforce_data2$Urban.vs.Rural))*100

# Appendix 8.1.3.14
prop.table(table(inforce_data2$Region, inforce_data2$Distribution.Channel), margin =
        1)*100

# Appendix 8.1.3.15
prop.table(table(inforce_data2$Underwriting.Class, inforce_data2$Face.amount), margin =
        2)*100

# Appendix 8.1.3.16
SPWL_summary <- SPWL %>%
  summarize(
    n_SPWL = n(),
    n_Death = sum(!is.na(Year.of.Death)),
    n_Lapse = sum(!is.na(Year.of.Lapse)),
    n_Active = n_SPWL - n_Death - n_Lapse
  )

T20_summary <- T20 %>%
  summarize(
    n_T20 = n(),
    n_Death = sum(!is.na(Year.of.Death)),
    n_Lapse = sum(!is.na(Year.of.Lapse)),
    n_Active = n_T20 - n_Death - n_Lapse
  )


###############################################
############### Statistical Tests #################
###############################################
death.subset <- subset(inforce_data2, !is.na(Year.of.Death))
death.cox <- coxph(Surv(time_to_death) ~ Issue.age + as.factor(Sex) +
as.factor(Smoker.Status)+as.factor(Underwriting.Class)
             +as.factor(Urban.vs.Rural)+Region, data = death.subset)
summary(death.cox)
# policy type, issue age, sex, region
death.cox2 <- coxph(Surv(time_to_death) ~ Issue.age + as.factor(Sex) +
as.factor(Smoker.Status), data = death.subset)
summary(death.cox2)

# death.age
deathtime.cox<-coxph(Surv(time_to_death) ~ age_at_death, data = death.subset)
summary(deathtime.cox)
```

```
# underwriting.class
underwriting.cox<-coxph(Surv(time_to_death)   ~   as.factor(Underwriting.Class),   data   =
death.subset)
summary(underwriting.cox)

#conduct log-rank test to test the significance of rural vs urban
death.surv<-Surv(death.subset$time_to_death)
urban.logrank<-survdiff(death.surv ~ as.factor(death.subset$Urban.vs.Rural))
urban.logrank

face.cox <- coxph(Surv(time_to_death) ~ Face.amount, data = death.subset)
summary(face.cox)

#log-rank test on the significance of different region
region.logrank<-survdiff(death.surv ~ death.subset$Region)
region.logrank

#log-rank test on different underwriting class
underwrite.logrank<-survdiff(death.surv ~ as.factor(death.subset$Underwriting.Class))
underwrite.logrank

#log-rank test on different face amount
face.logrank<-survdiff(death.surv ~ death.subset$Face.amount)
face.logrank
face.cox <- coxph(Surv(time_to_death) ~ Face.amount, data = death.subset)
summary(face.cox)


#Data Table Calculations
##
    ----------------------------------------------------------------------------------------------------
    --------------
library(data.table)
library(dplyr)
library(splines)
library(ggplot2)
library(scales)


##
    ----------------------------------------------------------------------------------------------------
    --------------
mortality_data                                                                                      <-
    data.table(read.csv("https://cdn-files.soa.org/research/srcsc/2024-srcsc-superlife-infor
    ce-dataset.csv", skip = 3))


##
    ----------------------------------------------------------------------------------------------------
    --------------
```

```
mortality_per_year <- c()
for (year in 2002:2023){
  deaths <- mortality_data[Year.of.Death == year,.N,]
  lives <- mortality_data[Issue.year <= year][
    (Year.of.Death >= year & is.na(Year.of.Lapse)) |
                        (Year.of.Lapse >= year & is.na(Year.of.Death) |
                          (is.na(Year.of.Death) & is.na(Year.of.Lapse))), .N]
  mortality_per_year <- c(mortality_per_year, deaths/lives)
}
plot(2002:2023,mortality_per_year)


##
        ------------------------------------------------------------------------------------------------------------------
        --------------
AM_lt <- data.table("Age" = 26:83, "Lives" = 0, "Deaths" = 0)
AF_lt <- data.table("Age" = 26:83, "Lives" = 0, "Deaths" = 0)
setkey(AM_lt, Age)
setkey(AF_lt, Age)

for (year in 2015:2019){
  year_table <- mortality_data[Issue.year <= year & Sex == "M"][
    (Year.of.Death >= year & is.na(Year.of.Lapse)) |
                        (Year.of.Lapse >= year & is.na(Year.of.Death) |
                          (is.na(Year.of.Death) & is.na(Year.of.Lapse))),][, Age := (Issue.age + year
        - Issue.year)][,                                   .(Lives = .N, Deaths = sum(Year.of.Death
        == year & !is.na(Year.of.Death))),                                          Age]
setkey(year_table, Age)
merged_table <- year_table[AM_lt, on = "Age"] %>% replace(is.na(.), 0)
merged_table[, `:=`(Lives = Lives + i.Lives, Deaths = Deaths + i.Deaths)]
AM_lt <- merged_table[, .(Age, Lives, Deaths)]

year_table <- mortality_data[Issue.year <= year & Sex == "F"][
    (Year.of.Death >= year & is.na(Year.of.Lapse)) |
                        (Year.of.Lapse >= year & is.na(Year.of.Death) |
                          (is.na(Year.of.Death) & is.na(Year.of.Lapse))),][, Age := (Issue.age + year
        - Issue.year)][,                                   .(Lives = .N, Deaths = sum(Year.of.Death
        == year & !is.na(Year.of.Death))),                                          Age]
setkey(year_table, Age)
merged_table <- year_table[AF_lt, on = "Age"] %>% replace(is.na(.), 0)
merged_table[, `:=`(Lives = Lives + i.Lives, Deaths = Deaths + i.Deaths)]
AF_lt <- merged_table[, .(Age, Lives, Deaths)]
}


##
        ------------------------------------------------------------------------------------------------------------------
        --------------
AM_lt <- AM_lt[,q_x := Deaths/Lives]
AF_lt <- AF_lt[,q_x := Deaths/Lives]
```

```
plot(AM_lt$Age, AM_lt$q_x)
plot(AF_lt$Age, AF_lt$q_x)
AM_lt <- AM_lt[Age <= 80]
AF_lt <- AF_lt[Age <= 80]


##
        ----------------------------------------------------------------------------------------------------
        --------------
model <- lm(q_x ~ bs(Age, knots = c(40, 60), degree = 3, Boundary.knots = range(Age)),
        data = AM_lt)
AM_lt$graduated_q_x <- predict(model, AM_lt)

model <- lm(q_x ~ bs(Age, knots = c(40, 60), degree = 3, Boundary.knots = range(Age)),
        data = AF_lt)
AF_lt$graduated_q_x <- predict(model, AF_lt)

plot(AM_lt$Age, AM_lt$graduated_q_x)
plot(AF_lt$Age, AF_lt$graduated_q_x)


##
        ----------------------------------------------------------------------------------------------------
        --------------
lapse_table <- data.table("Term" = 1:19, "Lives" = 0, "Lapses" = 0)
for (year in 2001:2023){
year_table <- mortality_data[Issue.year <= year & Policy.type == "T20"][
   (Year.of.Death >= year & is.na(Year.of.Lapse)) |
                      (Year.of.Lapse >= year & is.na(Year.of.Death) |
                                   (is.na(Year.of.Death) & is.na(Year.of.Lapse))),][, Term := (year -
        Issue.year + 1)][,.(Lives = .N,                    Lapses = sum(Year.of.Lapse ==
        year & !is.na(Year.of.Lapse) & is.na(Year.of.Death))), Term]
setkey(year_table, Term)
merged_table <- year_table[lapse_table, on = "Term"] %>% replace(is.na(.), 0)
merged_table[, `:=`(Lives = Lives + i.Lives, Lapses = Lapses + i.Lapses)]
lapse_table <- merged_table[, .(Term, Lives, Lapses)]
}
lapse_table <- lapse_table[,lapse_rate := Lapses/Lives]
plot(lapse_table$Term, lapse_table$lapse_rate, xlab = "Term Years 1-19", ylab = "Lapse
        Rate", main = "Lapse Rate over Term Life Policy Duration", pch = 19, col = "light
        blue")


##
        ----------------------------------------------------------------------------------------------------
        --------------
policies_in_force_SPWL <- mortality_data[is.na(Year.of.Death) & is.na(Year.of.Lapse) &
        Policy.type == "SPWL" & Issue.year == 2023][,
                    Age := (Issue.age + 2023 - Issue.year)
                    ][,
```

```
                        .(Number = .N, Sum_Insured = sum(Face.amount)),
                        .(Policy.type, Age, Sex, Smoker.Status)]

policies_in_force_T20 <- mortality_data[is.na(Year.of.Death) & is.na(Year.of.Lapse) &
     Policy.type == "T20" & Issue.year == 2023][,
                           Age := (Issue.age + 2023 - Issue.year) ][,Term := (2023 - Issue.year +
     1)
                        ][,
                        .(Number = .N, Sum_Insured = sum(Face.amount)),
                        .(Policy.type, Age, Term, Sex, Smoker.Status)]


##
     ---------------------------------------------------------------------------------------------------
     --------------
mortality_over_time_30 <- c()
mortality_over_time_50 <- c()
mortality_over_time_70 <- c()
for (year in 2010:2023){
   year_table <- mortality_data[Issue.year <= year][, Age := (Issue.age + year -
     Issue.year)][Age == 30][
  (Year.of.Death >= year & is.na(Year.of.Lapse)) |
                (Year.of.Lapse >= year & is.na(Year.of.Death) |
                                 (is.na(Year.of.Death) & is.na(Year.of.Lapse))),][,
     .(Lives = .N, Deaths = sum(Year.of.Death == year & !is.na(Year.of.Death))),
     Age]
 mortality_over_time_30 <- c(mortality_over_time_30, year_table$Deaths/year_table$Lives)

     year_table <- mortality_data[Issue.year <= year][, Age := (Issue.age + year -
     Issue.year)][Age == 50][
  (Year.of.Death >= year & is.na(Year.of.Lapse)) |
                (Year.of.Lapse >= year & is.na(Year.of.Death) |
                                 (is.na(Year.of.Death) & is.na(Year.of.Lapse))),][,
     .(Lives = .N, Deaths = sum(Year.of.Death == year & !is.na(Year.of.Death))),
     Age]
 mortality_over_time_50 <- c(mortality_over_time_50, year_table$Deaths/year_table$Lives)

     year_table <- mortality_data[Issue.year <= year][, Age := (Issue.age + year -
     Issue.year)][Age == 70][
  (Year.of.Death >= year & is.na(Year.of.Lapse)) |
                (Year.of.Lapse >= year & is.na(Year.of.Death) |
                                 (is.na(Year.of.Death) & is.na(Year.of.Lapse))),][,
     .(Lives = .N, Deaths = sum(Year.of.Death == year & !is.na(Year.of.Death))),
     Age]
 mortality_over_time_70 <- c(mortality_over_time_70, year_table$Deaths/year_table$Lives)
}
```

```
## 
        ---------------------------------------------------------------------------------------------------
        --------------
mortality_comparison <- data.table("Year" = 2010:2023, "Age 30" =
        mortality_over_time_30, "Age 50" = mortality_over_time_50, "Age 70" =
        mortality_over_time_70)

ggplot(mortality_comparison, aes(x = Year)) +
  geom_line(aes(y = `Age 30`, colour = "30")) +
  geom_line(aes(y = `Age 50`, colour = "50")) +
  geom_line(aes(y = `Age 70`, colour = "70")) +
    scale_colour_manual(values = c("30" = "#9370db",
                                   "50" = "#add8e6",
                                   "70" = "red")) +
    labs(title = "Mortality Over Time, 2010-2019",
       subtitle = "Ages 30, 50 and 70",
       x = "Year",
       y = "q_x",
       colour = "Age") +
  theme_classic()


## 
        ---------------------------------------------------------------------------------------------------
        --------------
ggplot(AF_lt, aes(x = Age)) +
  geom_point(aes(y = q_x, colour = "Raw"), size = 1.5) +
  geom_line(aes(y = graduated_q_x, colour = "Graduated"), size = 1.125) +
  scale_colour_manual(values = c("Raw" = "#9370db",
                                 "Graduated" = "#add8e6")) +
  labs(title = "Assured Females, 2015-2019",
       subtitle = "Ages 26 to 80",
       x = "Age",
       y = "q_x",
       colour = "") +
  theme_classic()

ggplot(AM_lt, aes(x = Age)) +
  geom_point(aes(y = q_x, colour = "Raw"), size = 1.5) +
  geom_line(aes(y = graduated_q_x, colour = "Graduated"), size = 1.125) +
  scale_colour_manual(values = c("Raw" = "#9370db",
                                 "Graduated" = "#add8e6")) +
  labs(title = "Assured Males, 2015-2019",
       subtitle = "Ages 26 to 80",
       x = "Age",
       y = "q_x",
       colour = "") +
  theme_classic()
```

```
## 
        ----------------------------------------------------------------------------------------------------
        --------------
combined_genders <- read.csv("combined genders.csv")


## 
        ----------------------------------------------------------------------------------------------------
        --------------
ggplot(combined_genders, aes(x = Age)) +
  geom_line(aes(y = 100000*Males.Before, colour = "Before")) +
  geom_line(aes(y = 100000*Males.After, colour = "After")) +
    scale_colour_manual(values = c("Before" = "#add8e6",
                                   "After" = "#9370db")) +
    labs(title = "Male Mortality Rates",
       subtitle = "Before & After Incentives",
       x = "Age",
       y = "Deaths per 100,000",
       colour = "Incentive Status") +
  scale_y_log10(labels = scales::comma) +
  theme_classic()

ggplot(combined_genders, aes(x = Age)) +
  geom_line(aes(y = 100000*Females.Before, colour = "Before")) +
  geom_line(aes(y = 100000*Females.After, colour = "After")) +
    scale_colour_manual(values = c("Before" = "#add8e6",
                                   "After" = "#9370db")) +
    labs(title = "Female Mortality Rates",
       subtitle = "Before & After Incentives",
       x = "Age",
       y = "Deaths per 100,000",
       colour = "Incentive Status") +
  scale_y_log10(labels = scales::comma) +
  theme_classic()


## 
        ----------------------------------------------------------------------------------------------------
        --------------
write.csv(AM_lt, "Male_Life_Table.csv")
write.csv(AF_lt, "Female_Life_Table.csv")
write.csv(lapse_table, "Lapse_Table.csv")
write.csv(policies_in_force_SPWL, "Policies_in_Force_SPWL.csv")
write.csv(policies_in_force_T20, "Policies_in_Force_T20.csv")
```