Health Incentives: Reduction in Mortality

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1) Overview

1.1) Executive Summary

A major Lumarian life insurer, SuperLife, has engaged Apex Consultants to develop a health incentive program that can be bundled with SuperLife's longer-term life insurance offerings. In addition to promoting the overall health and wellbeing of its policyholders, SuperLife is also seeking to improve the profitability of its products through a reduction in expected mortality and improved product marketability. In light of these considerations, Apex Consultants proposes a Gamified Health Challenge app ("App") which can be paired with SuperLife's 20-year term life insurance product. Through the App, policyholders are incentivised to increase and track their physical activity levels through the accumulation of 'Health Points' upon engaging with different health-promoting behaviours. In evaluating the merits of this proposal, this report leverages the Actuarial Control Cycle as a framework through which to iteratively design, test and monitor the effectiveness of the proposed App. As such, this report discusses the program design, modelling assumptions and outputs, and key metrics for future monitoring.

1.2) Program Objectives

While this report focuses on pairing the App with the 20-year term insurance product, it is designed to be scalable for potential expansion to include pairing with the Single Premium Whole Life product once it has proven effective in the following facets: satisfactory reduction in mortality, sufficient return on investment, and meeting additional objectives as defined in Section 1.3 below.

1.3) Program Metrics

The effectiveness of the Program should be assessed through the different metrics that are broken down by demographic segments (i.e. age cohort, sex, Lumaria region, and face amount). In understanding how the following metrics vary across different segments, SuperLife can derive insights into the program's impact and accordingly adjust strategies to optimise effectiveness and reach. Apex Consultants proposes the following metrics:

a) Short-Medium Term

- **App adoption rate:** a high adoption rate indicates strong interest in the program.
- **Average Health Point accumulation per user:** given that policyholders accumulate points when they complete health-promoting activities through the app, this metric is an indicator of user engagement and provides insights into the extent of active utilisation.
- **Increase in sales of 20-year term insurance product:** increased product differentiation with other life insurers should drive sustainable sales growth in a competitive market.

b) Long Term

- **Long-term reduction in mortality rate:** the success of the program is ultimately underpinned by the extent to which the mortality rate reduces. SuperLife should compare mortality trends between policyholders who regularly engage with the App, policyholders who engage with the App intermittently, and non-participants.
- **Decrease in lapse rate:** if the App is successful in fostering a sense of community amongst policyholders who also perceive the program's positive impact on their wellbeing, there should be a decrease in lapse rates.

2) Program Design

2.1) Gamified Health Points System

Apex Consultants recommends the adoption of a Gamified Health Challenge app ("App") to incentivise healthier lifestyles. Through the App, policyholders can earn virtual 'Health Points' by engaging in health-promoting activities in the following categories: Physical Health, Mindfulness & Emotional Wellbeing, Lifestyle & Community, and Prevention. A comprehensive list of specific health initiatives within each category is shown in Appendix A.2. These Health Points allow policyholders to compete against each other and can also be used to unlock various rewards, with a higher point accumulation leading to better rewards (see Appendix A.6 and A.7 for more details on Health Points system and rewards respectively).

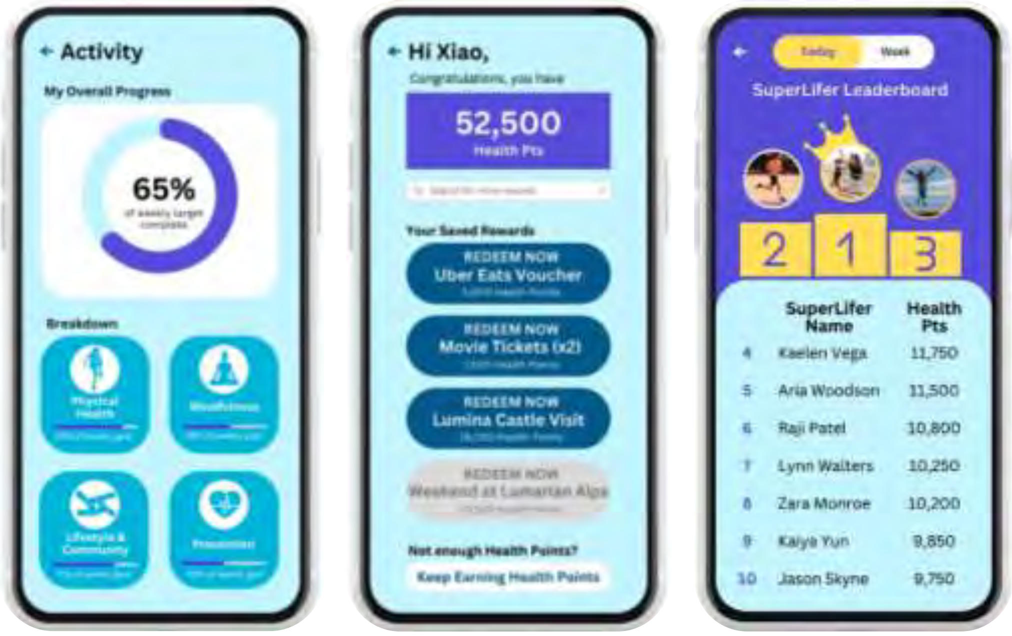

Figure 1: Prototype of Gamified Health Challenge App
(Left): Progress, (Centre): Redeem Rewards, (Right): SuperLifer Leaderboard

Figure 1 depicts a prototype of the App which allows policyholders to monitor their health-promoting behaviours and track their accumulation of Health Points. Through the App, SuperLife can also continually update their data about each policyholder's underwriting risk through real-time data collection.

In order to incentivise specific behaviours by different age cohorts, Health Points allocations should be adjusted depending on the age cohort. For instance, Safety Campaigns, which are designed to educate policyholders on safety measures at home and in daily activities, are likely to be more effective for retired policyholders (aged >65 years old) who often spend more time at home. As such, this age cohort will be awarded more points for engaging in Safety Campaigns compared to a younger policyholder. In this way, SuperLife can maximise the cost effectiveness of each health incentive by ensuring that it is aligned to the unique needs of each age cohort.

2.2) Justification
Each category of health-promoting behaviours (as listed in Section 2.1) is designed to address one of the leading causes of mortality within SuperLife's policyholder population. Within each category, the specific health-promoting activities have either been included due to their cost-effectiveness in reducing mortality and / or its alignment with specific policyholder features. The causes of death were approximately uniform across different face amounts. As such, Apex consultants did not tailor intervention strategies to specific face amounts, instead focusing on mortality trends across the whole portfolio.

2.2.1) Selecting Categories
While there are different causes of death in the in-force dataset, neoplasms and respiratory illnesses accounted for an overwhelming 33.5% and 30.0% of deaths respectively (see

Appendix B for further details). Alarmingly, 59.5% of policyholders who died from neoplasms were classified as a 'low' or 'very low' risk at the time of underwriting, suggesting that SuperLife does not currently have an accurate mechanism to test a policyholder's likelihood of contracting cancer. The World Health Organisation (WHO) suggests that prevention is the most cost-effective long-term strategy for the control of cancer and estimates that 30-50% of all cancer cases are preventable through early screening (WHO, n.d.). In light of these findings, Apex Consultants has selected 'Prevention' as one of the categories to encourage policyholders to participate in cancer prevention initiatives and preventing screenings.

In addition to preventing respiratory illnesses through activities in the 'Prevention' category (e.g. smoking cessation programs), Apex Consultants has also selected 'Physical Health' in response to high incidences of respiratory diseases in SuperLife's policyholders. Medical Studies conducted by the European Respiratory Society have concluded that regular physical activity, reduction in obesity, and better nutrition is effective for the long-term management of respiratory diseases (Ambrosino & Bertella, 2018).

Additionally, the categories 'Community & Lifestyle' and 'Mindfulness & Emotional Wellbeing' were also selected to encourage policyholders to adopt a holistic approach to healthy living. By uplifting the overall wellbeing of policyholders, these categories contribute to the holistic management of physical conditions. Indeed, emerging research demonstrates that some acute respiratory illnesses can be stress-induced (Asthma New Zealand, 2024).

2.2.2) Selecting Specific Health-Promoting Activities

Within each specific category, health-promoting activities from the list of interventions supplied by SuperLife's product development team were included due to their cost-effectiveness in reducing mortality per Crown. The cost and expected reduction in mortality were assumed to vary linearly between the lower and upper bounds. See Appendix A.3 for further details. Additionally, in recognising that T20 policyholders tend have an average age of 50.9 (slightly younger than the average of 54 across SuperLife's portfolio), there are activities that are targeted at policyholders in the 40-50 age cohort. For instance, external causes of mortality (i.e. accidents or transport-related injuries) are the third leading cause of death for T20 policyholders. Accordingly, Safety Campaigns and Travel Safety Tips have been included.

2.3) Expected Program Uptake

The App adopts a holistic approach to wellbeing and gamifies the experience by allowing policyholders to accumulate Health Points upon successfully completing various health-promoting activities. In acknowledging the diversity of the policyholders, who vary by gender, age and region, the App provides them with the flexibility to choose from a range of activities that align with their needs. In addition to incentivising sustainable long-term engagement by offering a wide variety of activities, the gamified aspect of the App also fosters a sense of community by promoting healthy competition among policyholders through features such as daily and weekly leaderboards (see Figure 2 above). Participation is also further incentivised through the rewards system, wherein policyholders can redeem their Health Points in exchange for different rewards. This incentive-based approach is supported by external literature which suggests that incentives are effective in motivating physical activity (Farooqui, 2014).

2.4) Impact of Health Initiatives

The impact of the interventions was simulated using a compound Poisson distribution to stochastically capture the expected uptake and reduction in mortality. The methodology is further explained in Section 3. Our results demonstrate that policyholders in all age cohorts will have at least one category in which a majority is expected to participate (see tables below).

Reduction in Mortality (by Category and Percentile)			
Category	**5th Percentile**	**Mean**	**95th Percentile**
Health	3.26%	4.40%	6.26%
Lifestyle	2.21%	2.89%	4.00%
Mental	2.56%	3.57%	5.31%
Physical	2.05%	2.69%	3.72%

Expected Participation (by Category and Age Cohort)				
Category	**18 – 34**	**35 – 49**	**50 – 64**	**18 – 34**
Health	23%	46%	68%	91%
Lifestyle	16%	49%	65%	65%
Mental	37%	50%	25%	25%
Physical	59%	47%	24%	12%

2.5) Implementation Timeline

Given the complexity of the App, Apex Consultants proposes a phased pilot implementation approach (outlined in Figure 2). During the initial phase (up to 6 months), SuperLife should offer the App to a pilot group of policyholders, with only subset of all possible health initiatives. After testing and refining the App with the pilot group, SuperLife should gradually increase the number of policyholders who can download the app, before expanding the number of health initiatives available to policyholders.

Figure 2: Implementation Timeline

In the initial 'Pilot group implementation', SuperLife should offer the App to policyholders who are categorised as 'moderate risk' since this cohort disproportionately accounts for 40.9% of death claims, despite only accounting for 23.8% of in-force policies. Further investigation also reveals that this cohort has a slight skew towards younger age groups where digital adoption capabilities are typically stronger.

2.6) Monitoring Outcomes

SuperLife should monitor outcomes, through the following metrics:

- In the **short-term (<2 years)**, SuperLife should assess metrics such as App adoption and utilisation rates. During the first few years of implementation, SuperLife should focus on ensuring the logistical and operational efficiency of the App by monitoring outcomes to validate assumptions and respond to any implementation challenges.
- In the **medium term (5-10 years)**, SuperLife should focus on measuring improvements in key health indicators, including a reduction in chronic disease prevalence (particularly respiratory illnesses and cancers). This timeframe is informed by longitudinal studies which have concluded that individuals should maintain a healthier lifestyle over a minimum of 6 years to experience a significant reduction in chronic diseases such as cardiovascular disease (Ding, 2021).
- Over the **long-term (>15 years)**, SuperLife should determine the reduction in mortality rates and the consistency of policyholder engagement with the App. This long-term horizon acknowledges that the adoption of healthier lifestyles, and the subsequent reduction in mortality rates, is a gradual process.

3) Pricing and Costs

3.1) Methodology

Mortality savings was calculated by projecting revised mortality rates for each individual policyholder using stochastic methods, and considering investment returns, net premium reserves and various expenses. Further details are provided in Appendix C.

3.1.1) Mortality Projection

To model historical mortality rates, the in-force policyholder dataset was fitted with the semi-parametric Cox Proportional Hazards model, which assumes a baseline mortality curve adjusted that is proportionally based on covariate values. The hazard rate is as follows:

$$h(t) = h_0(t) \times \exp\left(\sum_{i=1}^{n} x_i \beta_i\right)$$

Covariate selection was done by fitting models on a range of covariates and conducting statistical tests. Some covariates excluded due to insufficient data. The ‘sex’ and ‘smoking status’ of policyholders were the chosen covariates, with $\beta = 1.25$ and $\beta = 8.72$ respectively. Both the individual covariates are considered statistically significant; the fitted Cox model passes the likelihood ratio, Wald and log-rank tests (see Appendix C.1.1 for further details).

3.1.2) Modelling Reduction in Mortality

The impact of each intervention category was modelled using a compound Poisson model. The severity component of the compound Poisson model captures the expected reduction in mortality, while the frequency component captures the expected level of uptake (i.e. expected number of people who will participate).

$$Y = \sum_{i=1}^{N} X_i \text{ where } N \sim Poi(\lambda) \text{ and } X_i \sim Gamma(\alpha, \beta)$$

A gamma distribution was used to stochastically model the reduction in mortality for each category of intervention. The gamma distribution was selected due to its usefulness in modelling proportions, as well as its right-tailed nature to capture the fact that interventions are likely to highly effective up to a certain extent, before tapering off. The gamma distribution for each category was truncated at the assumed upper and lower bounds of mortality reduction.

3.1.3) Modelling Uptake in Health-Promoting Activities

The expected uptake of the activities was modelled using a Poisson distribution, where λ represents the expected uptake per year adjusted by the expected frequency of participation. Using results reported in the British Healthiest Workplace 2019 Survey, a study seeking to understand the participation in different health initiatives, formed the basis of uptake assumptions. Since uptake figures were reported at an aggregate level in the report, an adjustment per age cohort was applied to stratify the uptake by age cohorts. For instance, policyholders aged 25-34 are assumed to be more likely to participate in Physical Wellbeing initiatives, whereas policyholders >65 are assumed to be more likely to participate in Preventive initiatives. The level of uptake was further adjusted by the expected frequency per year such that the expected time between each activity, $E(T) = \frac{1}{\lambda}$ (assuming $T \sim Exp(\lambda)$, would be reasonable. This level of uptake was taken to be the value of λ in the Poisson model.

An example of a simulated mortality reduction is given in Figure 3 which depicts the simulated number of policyholders at a different levels of mortality reduction.

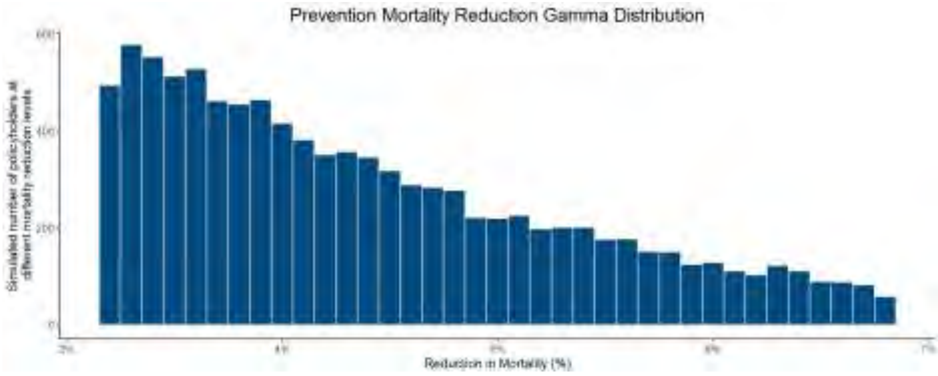

Figure 3: Reduction in Mortality

3.1.4) Individual Policyholder Projection

Apex Consultants has used a stochastic approach to simulate the characteristics of each individual policyholder at the end of each period. The characteristics of each policyholder are defined using an 8-dimensional matrix consisting of the following information:

- Issue year (fixed over time for each policyholder)
- Age (assumed to be capped at 120 years old for all policyholders)
- Projection time (number of periods remaining on the term of the policy; assumed to be ≤ 20 for T20 policies)
- Sex (male or female – fixed over time for each policyholder)
- Smoking status (smoker or non-smoker – transition between 'smoker' and 'non-smoker' at each timepoint by applying a discrete Markov transition matrix)
- Policy type (T20 or SPWL – fixed over time for each policyholder)
- Face amount (Č50,000 up to Č2,000,000 – fixed over time for each policyholder)

After initialising the loop with the current characteristics of each policyholder in the in-force dataset, the loop was projected out by simulating the characteristics of each policyholder at the end of each period. Crucially, the model projects the number of deaths at each discrete time point by varying mortality assumptions depending on age, gender, and smoking status. Additionally, to account for the impact of health-promoting activities offered via the App, the mortality rates are rated downwards by simulating a compound Poisson distribution assumption for the effectiveness and uptake of each activity (see Appendix A.4 and Section 3.1.3). In this way, the model acknowledges the differences in the responsiveness of each policyholder to the health-promoting activities and accounts for these differences in stochastic manner.

In addition, new policyholders who join at future timepoints are appended onto the matrix. Their initial characteristics are simulated based on historical data, before being projected into the future in a similar manner to policyholders who are already in-force.

At the end of each discrete timepoint, the model counts the number of deaths over the period. Since the model assumes that withdrawals can *only* occur at the end of the year, the simulation model randomly withdraws T20 policies at a fixed rate of 0.01 *after* lives are removed due to the death decrement (see Appendix C.2 for further details on withdrawal assumptions). The model then counts the number of withdrawn policies over the period. At the end of each period, policyholders are removed from the matrix if they withdraw, reach maturity, or die.

3.1.5) Expenses Projection

In projecting expenses, the model considers: claims expenses, initial expenses, commission expenses, and renewal expenses. See Appendix X for further details on expenses.

Expense Category	Assumptions	Commentary
Initial Expenses	• Č150 in acquisition costs per policy	Initial expenses are attracted due to customer acquisition costs.
Commission	• Commission expenses are a fixed proportion of premium income. • Online channels do not require commissions	Commissions differ by distribution channel with Agents being offered the largest commissions. Agents provide more personalised service and thus command a larger percentage of profit for sales.
Renewal Commission	• Renewal expenses are a fixed proportion of premium income.	SPWL policies do not attract a renewal commission as they cannot be withdrawn by policyholders.

Expected Death Claims	• Methodology to project the number of deaths at each time point is described in **Section 3.1.2**.	Claims expenses are projected by multiplying the number of deaths per face amount by the face amount.

3.1.6) Premium Calculation

The premium was calculated by calculating the gross premium reserve (excl. Commissions) and applying an additional commission + profit margin loading onto the final estimate (see Section 3.1.3). This simplistic approach for premium calculation, over applying set profit measures, signature was applied to provide a coarse base projection of the companies' total inflows. The rates were calculated based on 4% and 4.75% discount rate for the T20 and SPWL policies respectively, (see Section 3.1.4) . This ensures premium incomes are sufficient to cover future liabilities and expenses, creating a specified level of profit whilst being underpinned by SuperLife's portfolio mix when calculating the intervention.

3.1.7) Mortality Savings

Mortality savings was calculated by determining the expected value of savings arising from a reduction in death claims after implementing the App. These savings were projected to present value by assuming investment at 5.6% (the mean of simulated 1-year risk-free rates – see Section 4.1). To find savings, the cost of implementing the program was inflated to present value terms at a rate of 6% in Year 1, 4% in Year 2, then 3.5% over the remainder of the term as inflation is assumed to return to normal levels (3.5% being the mean of simulated inflation rates). The cost is subsequently subtracted from the total mortality savings.

3.2) Results

3.2.1) Reduction in Number of Deaths

Figure 4 compares the baseline number of deaths (using baseline mortality assumptions) with the revised number of deaths (assuming that the App had been implemented over the last 20 years). There is a widening gap between historical and adjusted number of deaths over time, as the initiative becomes increasingly effective given that the impacts of mortality reduction are cumulative. On average, there is a reduction in 156 deaths per year, amounting to a decrease of approximately 3000 deaths over the 20-year period.

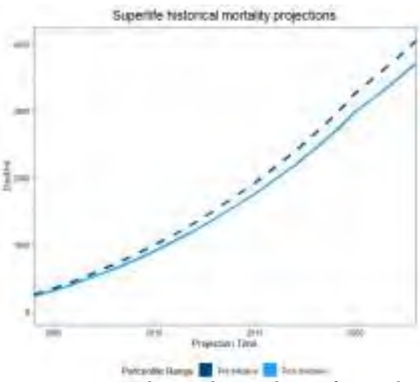

Figure 4: Adjusted Number of Deaths

3.2.2) Historical and Projected Mortality Savings

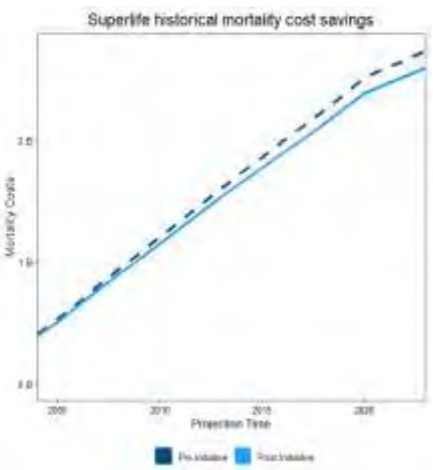

Figure 5: Historical Mortality Savings

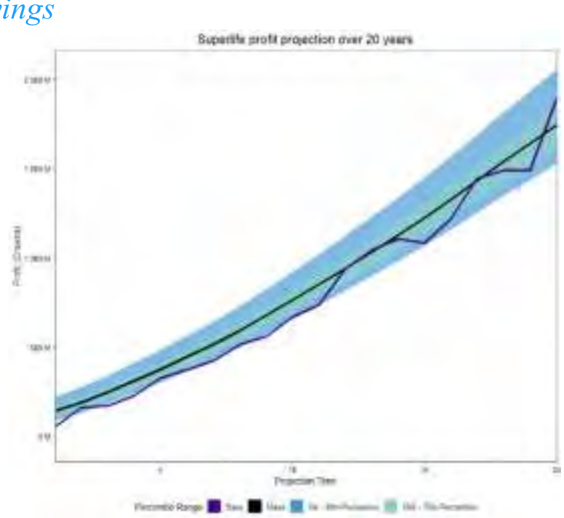

Figure 6: Projected Mortality Savings

Figure 5 pertains to the historical cost savings under the steady-state smoothed mortality assumption. There is a clear reduction in the claims costs, with an average saving of $78m per annum, totalling $1.56b over the last 20 years. The initiative is also projected to be effective over the next 20 years, as represented in Figure 6 which depicts the mean projected profit (using adjusted mortality assumptions) being consistently higher than the baseline projected profit. Figure 6 illustrates that lower percentiles of projected profitability exhibit comparatively reduced volatility. Specifically, the gap in profit between the 5th and 25th percentiles is narrower than that between the 75th and 95th percentiles.

3.3) Potential Pricing Changes

It is difficult to assess how pricing changes will affect the competitiveness of SuperLife's product in Lumaria given the lack of data regarding competitors. SuperLife should maintain the current pricing structure and consider offering discounts in the longer term if mortality rates reduce sufficiently. This analysis assumed a steady state of intervention utilisation, however, we expect this to vary over duration of implementation, as SuperLife develops a network economy. Specifically, as noted in section 2.1.3, we note that the initiative will deliver high initial costs, to develop the app infrastructure and market accordingly. We recommend SuperLife to continue with a more conservative pricing view in the medium to short term, using equity and reserves for research and development. However, we recommend SuperLife to monitor mortality trends, uptake levels and broader industry trends to assume a competitive position. Further, internally we recommend SuperLife to continue monitoring to appropriate offer discounts where relevant.

4) Assumptions

4.1) Economic Assumptions

The investment and interest rates were forecasted using historical rates from 1982 onwards. The sharp decline in interest rates, and subsequent stability in inflation after 1982, suggests that Lumaria adopted inflation targeting from 1982 onwards (see Appendix C.1.2). Both rates were forecasted using a random walk approach over 10,000 simulations. The random walk assumes normally distributed increments based on historical data mean and standard deviation, and is bounded by the observed historical values. For each future period, the 10th percentile, average, and 90th percentile values were used.

4.2) Mortality Assumptions

The Lumaria life tables were assumed to be an accurate source for projecting future mortality. The in-force policy dataset was not taken as a source for future mortality projections, as this would involve the influence of year-related trends present in the captured period. Since the life tables did not differentiate between males and females, or between non-smokers and smokers, a life table incorporating these distinctions was manually created. This life table assumes that the sex ratio at birth is 1:1. It also assumes a smoking rate of 18%, and that only people over 18 are smokers.

To create this table, an assumption was made that hazard rates amongst the different groups were proportional, using female non-smokers as the baseline.

Group	Female Non-Smoker	Male Non-Smoker	Female Smoker	Male Smoker
Ratio	1.00	1.40	2.29	3.40

4.3) Intervention Assumptions

The intervention uptake rates were assumed to reflect similar programs in real life based on the British Healthiest Workplace 2019 Survey. However, cultural and environmental differences are unknown and could affect the uptake rates drastically. Thus, a more conservative estimation was used where, the incentive of points was not considered to increment the uptake rate despite, evidence that incentives significantly increase uptake rates.

5) Risk and Risk Mitigation Considerations

5.1) Risk Assessment

The most significant risks are displayed in the risk matrix in Figure 7. A description of each risk is as follows:

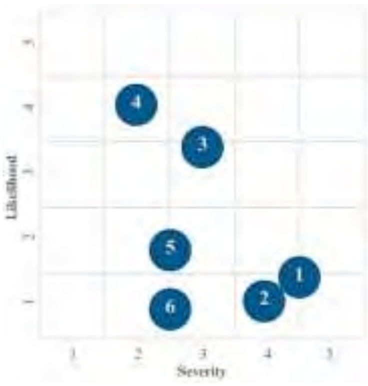

Figure 7: Risk Matrix

1. **Data security breach:** given that the app is collecting highly sensitive information, a data breach could result in financial losses through fines and lawsuits, as well as reputational damage.
2. **System failure:** technical glitches or a confusing user interface could frustrate policyholders and even deter them from engaging.
3. **Model risk:** incorrect assumptions, parameters, or data inputs may overestimate the reduction in mortality, resulting in unsustainable reward structures.
4. **Adverse changes in economic assumptions:** consistently high inflation rates may inflate the cost of the program beyond initial expectations, while persistently low investment rates may dampen the return on mortality savings.
5. **Trend risk:** unforeseen changes in future health trends, such as new diseases, may affect SuperLife's ability to effectively create health initiatives that target or prevent these diseases.
6. **Regulatory change:** unforeseen shifts in regulatory requirements, such as prohibiting the collection of personal health-related data, could disrupt the operations of the App.

5.2) Mitigation Strategies

#	Risk	Type	Mitigation
1	Data security breach	Both	Investing in data security measures such as encryption protocols, access controls and regular audits should reduce vulnerabilities in the data security. SuperLife should gradually upgrade as the data security system as the number of users increases over time.
2	System failure	Qualitative	SuperLife should seek feedback from users and make iterative improvements to the interface based on user needs and preferences. As the number of users increases, SuperLife should increase its investment into system maintenance to minimise system failures.
3	Model risk	Quantitative	SuperLife should monitor results and recalibrate model parameters in response to updated data.
4	Adverse changes in economic assumptions	Quantitative	This report includes sensitivity analysis (see 5.3) to assess the impact of changes in economic assumptions. SuperLife should also ensure that its investment portfolio is sufficiently diversified.
5	Trend risk	Qualitative	The App has been intentionally designed with scalability and agility so that SuperLife can easily add or remove specify health initiatives as needed. SuperLife should monitor health trends and emerging diseases to inform its decisions regarding whether and when to modify specific health initiatives.
6	Regulatory change	Qualitative	If regulatory changes transpired, SuperLife should collect anonymised data on an aggregated level.

5.3) Sensitivity Analysis

Assumption	Range	Commentary
3.5% inflation	≤8.6%	Inflation increases program costs over time. Inflation costs have not exceed 8.6% since 1982
Č248 / year for a 35-year old (baseline mortality)	≥ Č181	Premium costs should be sufficiently high to account for program expenses and death claim costs
Initial expense of Č150	≤ Č1720	Initial expenses detract from profitability of policies

Using assumptions detailed in Section 3 and 4, we believe that the program will be a profitable at a 70% in the immediate term to 80% confidence level in the long term. This has been determined based on the degree of uncertainty bands surrounding the simulated profit projection, in contrast to the extent of mortality savings.

6) Data and Limitations

Data Requirement	Data Sources	Data Limitations
Mortality rate	Lumaria life table (Lumaria govt)	Life table provides mortality by age only and does not provide mortality rates by sex or smoking status.
	Policyholder mortality rates (in-force policyholder dataset)	Mortality rates implied at the ends of the age spectrum are weak estimates due to low sample size or low occurrences of mortality.
Economic assumptions	Central bank of Lumaria	It is unclear whether inflation targeting practices were adopted.
Smoker – non-smoker transition rates	National Library of Medicine (USA), WHO	Cultural differences between the participants surveyed and the fictional people of Lumaria may alter the rates.
Participation Rates of Intervention	British Healthiest Workplace 2019 Survey	The survey was conducted on a voluntarily basis; selection bias may be introduced. However, a large sample size is used to reduce the bias.

6.2) Covid-19 Considerations

There was a 50% increase in mortality during the Covid periods in 2020-2023 (see Appendix D.1). In projecting the mortality rates, these anomalous rates were removed from the historical data to allow us to model the historical baseline. However, SuperLife should vigilantly monitor the impacts of Covid-19 on mortality for their policyholders and the broader Lumaria population and adjust life tables and mortality assumptions accordingly. Future adjustments should not impact the methodology described above, only the parameters and / or assumptions.

7) Final Recommendations

The proposed gamified program adopts a holistic approach to health and wellbeing and offers SuperLife's policyholders the ability to choose what health-promoting activities to engage with. In addition to being informed by medical research, the quantitative modelling also reaffirms the projected success of the program from a mortality reduction and savings perspective. As the program is designed to be gradually scaled via a phased pilot implementation approach, SuperLife should monitor the outcomes and expand the program if it proves to be successful against the metrics outlined in Section 1.3.

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Appendix A: App Design & Health-Promoting Activities

A.1) Definitions for Activity Categories

- **Physical Health:** addresses the general physical health, including fitness levels, nutritional habits to support physical functioning and vitality.
- **Mindfulness and Emotional Wellbeing:** addresses mental health to promote mindfulness to promote a holistic approach to wellbeing.
- **Lifestyle and Community:** focuses on social activities to promote social interactions and community engagement.
- **Prevention:** focused on prevention of chronic illnesses through proactive measures such as health check-ups, active risk reduction, vaccinations and promoting safe habits

A.2) Specific Health-Promoting Activities

Activity	Category	Description
Physical Health	Community Fitness Challenges	Organise fitness challenges such as park runs or step challenges within different local communities. Policyholders earn Health Points for participation in these challenges.
	Hydration Campaigns	Promote the importance of hydration through workshops, educational materials, and App notifications. Policyholders earn Health Points by attending the workshops
	Financial Incentives for Healthy Behaviour	Offer Health points for healthy habits, including (but not limited to): achieving a daily step target, heart rate increasing for a certain number of minutes, or calories burned. Policyholders earn Health Points by satisfactorily monitoring and reporting their movement (e.g. through a wearable device such as an Apple Watch or Fitbit).
	Healthy Eating Campaigns	Provide resources on nutritional guidance, healthy recipes, meal planning advice, alongside educational campaigns, to encourage healthier eating. Policyholders earn Health Points by attending workshops or tracking nutrition via a wearable device (e.g. Fitbit).
	Online Health Resources	Offer access to digital platforms with health-related information including, articles, videos, and other educational tools. Policyholders earn Health Points by reading articles or watching informational videos (capped at 2 videos or articles per day).
Mindfulness and Emotional Wellbeing	Mindfulness Programs	Introduce mindfulness practices by providing access to resources for guided meditation or deep breathing exercises. Policyholders earn Health Points by

	Holistic Stress Reduction	Provide resources for stress reduction, including video resources for yoga and self-care. Policyholders earn Health Points by viewing videos.
	Parenting Support Services	Provide resources and support for parents including educational materials such as articles or videos on parenting skills and child development and creating support groups for parents. Policyholders earn Health Points by attending support groups or engaging with educational materials.
	Wellbeing Apps	Offer apps such as BetterHelp and Headspace which provides useful resources and self-diagnosis. Policyholders can earn Health Points by undergoing a self-diagnosis assessment or engaging with provided resources.
	Environmental Wellness	Promote awareness of environmental factors affecting health and wellbeing through educational workshops or expos. Policyholders can earn Health Points by attending events.
Lifestyle and Community	Social Connection Initiatives	Organise social activities including (but not limited to) park or beach outings, museum or art gallery visits, community sporting events and community cooking challenges, to foster a sense of community. Policyholders earn Health Points by volunteering at or attending events.
	Community Gardens	Establish communal green spaces where policyholders can help to grow fruits, vegetables, and herbs. This not only promotes a sense of community, but also provides policyholders with access to organic food. Policyholders earn Health Points by visiting a community garden.
	Art and Creative Classes	Promote artistic and creative pursuits through art classes, photography classes, and pottery classes. Policyholders earn Health Points by regularly attending classes (e.g. minimum 2 classes per month).
Prevention	Incentives for Preventive Screenings	Encourage people to undergo preventive screenings by highlighting the importance of screenings. Policyholders can earn points for completing screenings.
	Cancer Prevention Initiatives	Promote behaviours to reduce the risks of developing cancer. Policyholders can earn points for completing cancer screenings,

		completing trivia quizzes relating to cancer, or completing daily or weekly health challenges such as physical activities.
	Incentives for Vaccinations	Encourage people to get vaccinated through educational content, progress challenges, and quizzes. Policyholders can earn Health Points by watching educational videos, completing quizzes, or by completing presenting proof of vaccination at a local GP or pharmacist.
	Smoking Cessation Programs	Encourage the cessation of smoking through educational videos about the harmful effects of smoking, hosting online community support groups, and providing therapy sessions. Policyholders can earn Health Points by watching videos, attending counselling and support sessions, or by completing progress milestones such as number of days last smoked.
	Safety Campaigns	Promote behaviours that prevent risk of injury in various general contexts through educational videos and quizzes. Policyholders can earn Health Points by completing trivia quizzes.
	Sun Safety Awareness	Raise awareness about the need to protect against the harmful effects of ultraviolet rays and tips to do so through educational campaigns. Policyholders can earn Health Points by watching educational videos and completing quizzes.
	Travel Safety Tips	Encourage people to do sufficient research and preparation prior to travelling through online checklists and quizzes. Policyholders can earn points through by buying travel insurance, watching safety videos, completing safety quizzes, or completing safety checklists.

A.3) Evaluating the Cost-Effectiveness of Health-Promoting Activities

The cost-effectiveness of each intervention was calculated by simply taking the median of the mortality reduction range divided by the median of the cost range.

$$\text{Cost-effectiveness} = \frac{\text{Lower Bound(Mortality)+Upper Bound(Mortality)}}{\text{Lower Bound(Cost)+Upper Bound(Cost)}}$$

A.4) Evaluating Expected Reduction in Mortality

A truncated gamma distribution was selected to stochastically model expected reduction in mortality. Number of policyholders per different mortality reduction levels were generated through a set of 10,000 simulations.

The Gamma distribution was chosen to ensure conservativity in mortality reductions, utilising the right-tailed nature of the distribution to ensure that the mortality reduction of the majority of the sample was less than the average mortality reduction. The rationale behind this conservative approach is that it is unlikely for all interventions within each category group to always maintain an effective mortality reduction at a high level (e.g. 8%). Rather, it is more reasonable to make an assumption that the overall net reduction is less than the effective level, with some interventions potentially not being as effective in reducing mortality as others.

The Gamma distribution model was simulated using a scale parameter of 1 and a shape parameter ranging from 1 to 3. The shape parameter was adjusted based on different categories of interventions. By determining whether the average mortality reduction was equal to or greater than the standard deviation of the reduction, the appropriate shape parameter was selected. Scale parameter was the same as a standardised Gamma distribution.

Simulations were also bound by the average upper and lower bound of the mortality reduction per category. The bounds were selected based on the research collated by SuperLife's product development team.

A.5) Inclusion of Specific Health-Promoting Activities

The causes of death are coded as the following under the International Classification of Diseases:

Code	Disease	Percentage of SuperLife Deaths Arising from Cause
C - D	Cancer	32.8%
I	Circulatory system (cardiovascular)	29.4%
V	Accidents	8.61%
J	Respiratory system	6.57%
K	Digestive	4.46%
E	Endocrine, nutritional and Metabolic Disorders	4.39%
A - B	infectious/parasitic diseases (communicable or transmissible)	3.77%

The selected categories of health-promoting activities have been mapped to the following targets:

- **Physical Health:** I, J, K, E
- **Mindfulness and Emotional Wellbeing:** General
- **Lifestyle and Community:** General
- **Prevention:** C-D, V, A - B

A.6) Health Points

As part of the App, policyholders will be rewarded Health Points as part of the gamification process with Health Points being convertible to rewards. 7% of the mortality profit earned by SuperLife will be utilised to fund the rewards.

Additionally, to encourage policyholders to engage in preventive health check-ups, which not only help to reduce mortality but also provide SuperLife with updated information about underwriting risk, policyholders will be rewarded with Health Points for undergoing a check-up, regardless of the outcome. If policyholders ahieve a positive outcome on these check-ups, they will be rewarded with bonus points. In this way, gamification incentivises policyholder participation and pushes them to attain healthier goals.

A.7) Rewards

- Brief justification for rationale behind the types of rewards that we will offer (e.g. promotes connection with environment, allows them to relax / de-stress etc.)
- Examples of specific rewards that we could offer

Policyholders can redeem points to earn monetary and non-monetary rewards as part of the app's gamification. In selecting the rewards, SuperLife should focus on ensuring that the reward is also conducive to positive health outcomes and are appealing enough to encourage policyholders to continue to engage with the App.

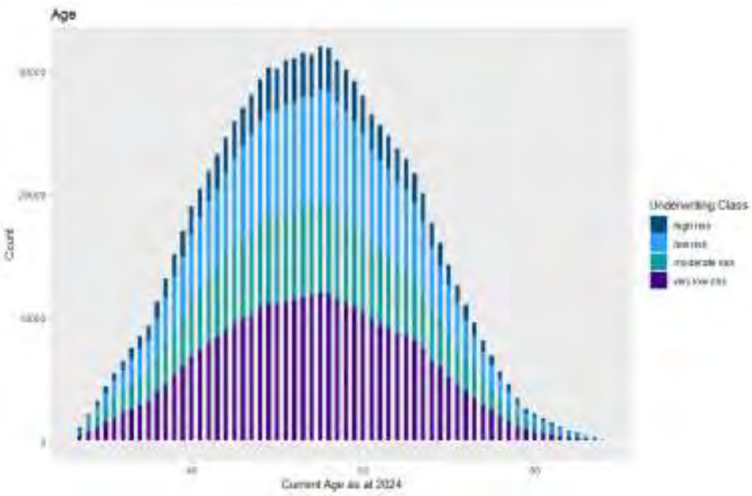
Examples of rewards includes:

Reward Example	Justification
Recognition through: • Online badges • Featuring on the App's leaderboard (see Figure 1 above)	Motivates policyholders by
Weekend or day trips to Lumaria's cultural treasures and / or natural landscapes	
Discount vouchers for groceries	
Fitness-related rewards, including: • Fitness equipment • Fitness tracking devices • Subsidised gym sessions • One-on-one sessions with a personal trainer	Policyholders are continually motivated and encouraged to maintain a consistent health routine.
Nutrition-related rewards, including: • Exclusive health content • Customised meal recipes	
Relaxation and mental-health related rewards, including: • Spa and massage treatments • Facials	Rewards policyholders for their hard work via relaxation and destressing, which are essential for a healthy lifestyle

Appendix B: In-force Policyholder Features

B.1) Age Distribution

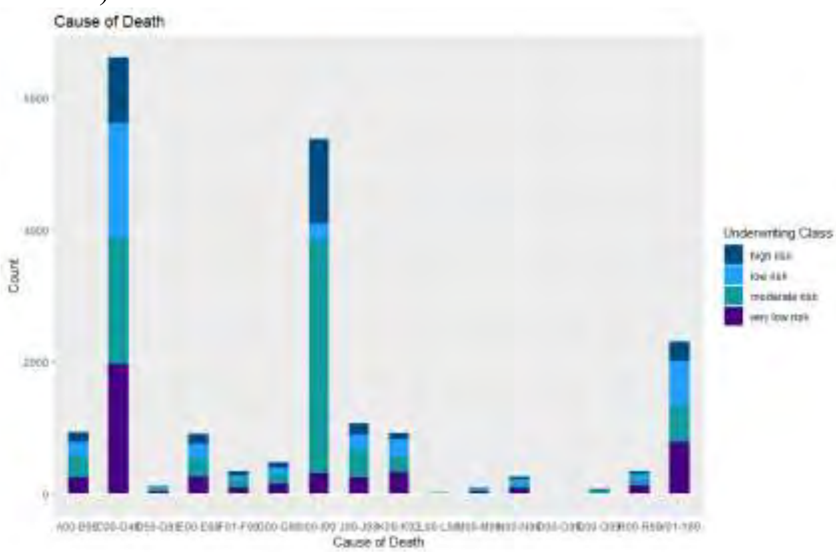
The following graph illustrates the distribution of policies, by underwriting class and by age. Each underwriting class follows a similar distribution across policyholder ages, with 'very low risk' policies accounting for the majority of policies and 'high risk' policies accounting for the least policies.



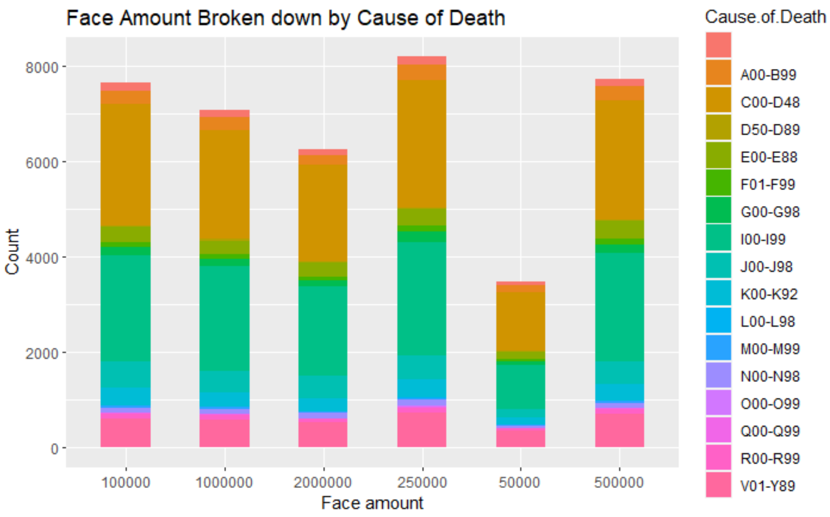
B.2) Causes of Death

The following graphs illustrate the causes of death.

The main causes of death are C00-D48 (Cancer) which has a significant proportion of deaths underwritten as low risk. I00-I99 (Cardivoscular) diseases also account for a large proportion of deaths. The secondary causes of death are V (Accidents), J (Respiratory system), K (digestive), E (Endocrine, nutritional and Metabolic Disorders) and A-B (communicable or transmissible diseases).



The causes of death are approximately uniform across different face amounts. As such, the analysis does not consider how to target illnesses within specific face amounts, instead focusing on mortality trends across the whole portfolio.



B.3) Modelling Program Uptake

The modelling of uptakes utilised the British Healthiest Workplace (BHW) 2019 Survey's results to generate the frequency assumptions for the Compound Poisson processes.

BHW was a workplace survey who's objective was to understand participation in different incentives based on varying demographic characteristics and program awareness. One of their key findings was the participation rates across certain intervention categories which were similar to the proposed Health App intervention categories. Thus, we utilised the rates to generate uptake rates per intervention categories.

BHW Categories	**Sleep and Fatigue Programs**	**Mental Health and Wellbeing**	**Medical Services**	**Fitness**	**Smoking Cessation**
Participation Rates	35.7%	39.0%	50.0%	46.5%	6.4%

Health App Categories	**Health Maintenance and Prevention***	**Lifestyle and Community**	**Mental and Emotional Wellbeing**	**Physical Health and Wellness**	**Smoking Cessation**
Participation Rates	42%	39.0%	39%	46.5%	6.4%

**Uptake rates for Sleep and Fatigue, Mental Health and Wellbeing, and Medical Services were averaged to get Health Maintenance and Prevention uptake rate of 42%.*

The next step were to generate relative uptake assumptions regarding each incentive category. The BHW did not provide demographic statistics specific to intervention categories, thus we generated a table assumption of relative uptakes based on age categories.

Category	**Ages 18-34**	**Ages 35-49**	**Ages 50-64**	**Ages 65+**
Health Maintenance and Prevention	0.5	1	1.5	2
Lifestyle and Community	0.5	1.5	2	2

Mental and Emotional Wellbeing	1.5	2	1	1
Physical Health and Wellness	2.5	2	1	0.5
Smoking Cessation	2	1.5	1	0.5

Uptake assumptions were assigned based on certain age groups being more likely to participate in certain interventions. For example, there was an assumption 65+ year olds would be 2.5 times more likely to see a doctor rather than younger age categories, thus 65+ was assigned a 2 while younger age categories had lower ratings.

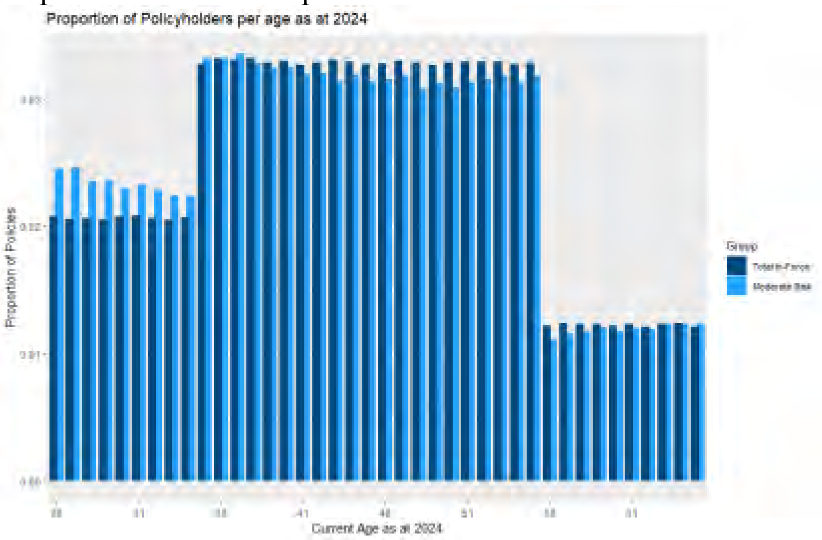
Next, utilising the general demographics of the employees in the BHW survey, we:

Base Participation Rate x Relative Uptake Assumption per age category/(proportion of employees in survey per age group*relative uptake assumption across all age categories). This generated our Frequency Assumption Table, with each cell indicating the lambda parameter of the Poisson process per age group per intervention category.

Category	Ages 18-34	Ages 35-49	Ages 50-64	Ages 65+
Health Maintenance and Prevention	23%	46%	68%	91%
Lifestyle and Community	16%	49%	65%	65%
Mental and Emotional Wellbeing	37%	50%	25%	25%
Physical Health and Wellness	59%	47%	24%	12%
Smoking Cessation	8%	6%	4%	2%

B.4) Moderate Risk Underwriting Class as Pilot Group

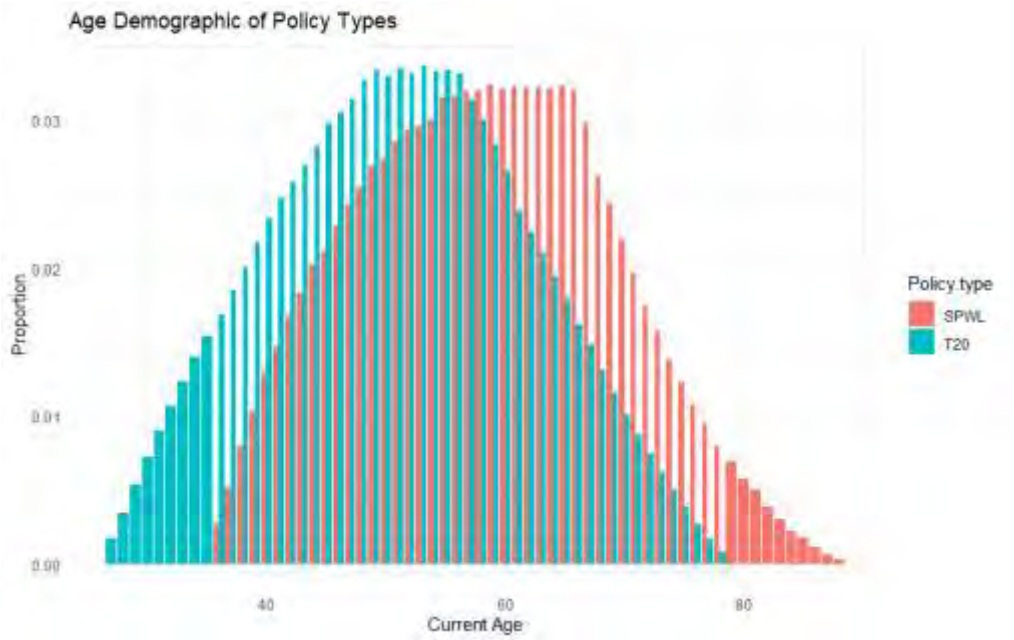
Further analysis of the 'moderate risk' policyholders reveals that it is a reasonable representation of SuperLife's portfolio, albeit skewed to younger years slightly. This is represented in the graph below, which clearly displays a greater proportion of T20 policies in younger ages compared to all in-force policies.

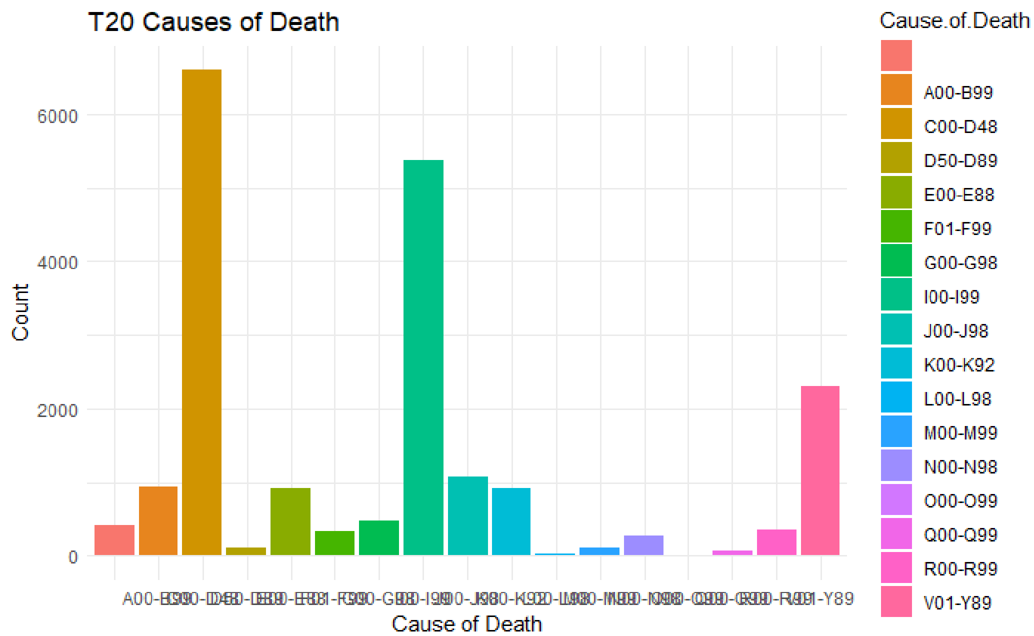


Medical research also reaffirms the selection of this group as it indicates that individuals aged <65 are more inclined to increase their physical activity when invited to participate in health incentives programs (Guthold, 2018), further justifying the initial focus on this segment.

B.5) Policy Types

The following graphs further demonstrates that T20 policyholders are on average younger than SPWL policyholders. This has clear implications on the cause of death, as depicted in the second graph. When compared to the causes of death of the entire cohort, T20 policies have a greater proportion of deaths arising from accidents.





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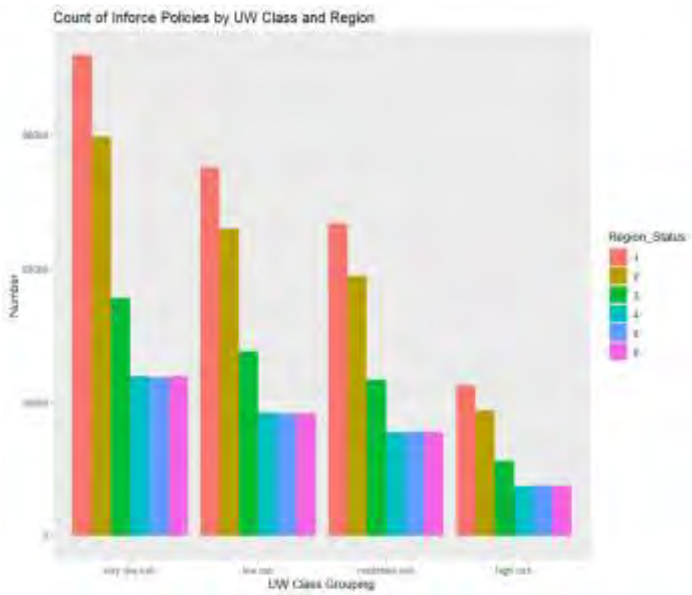
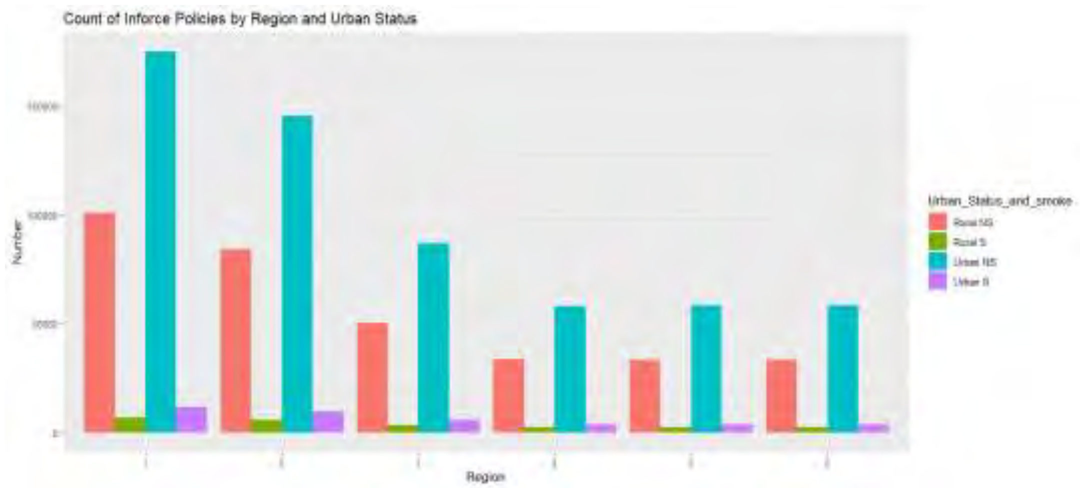
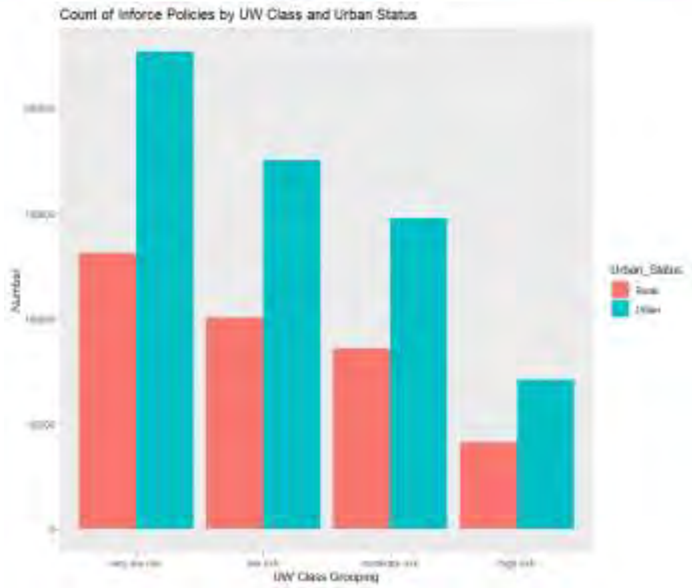
B.6) Region and Urban States

From graphs below, it can be determined that region and urban status have practically no value with identically distributed values for other variables. As such, regions were treated as non-descript. The population was modelled at an aggregate level, rather than at an individual regional level. This also helps to provide stability to the results by allowing us to use more data points.

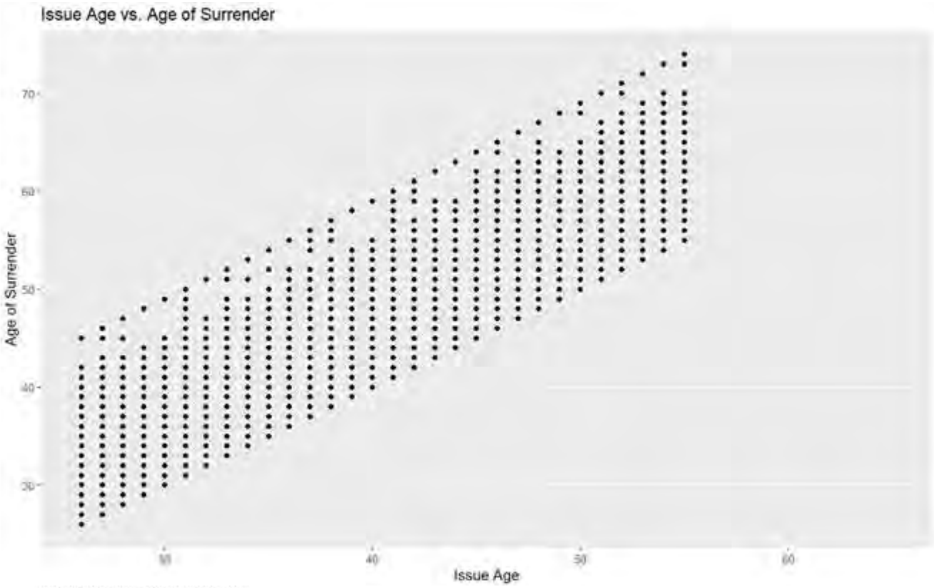


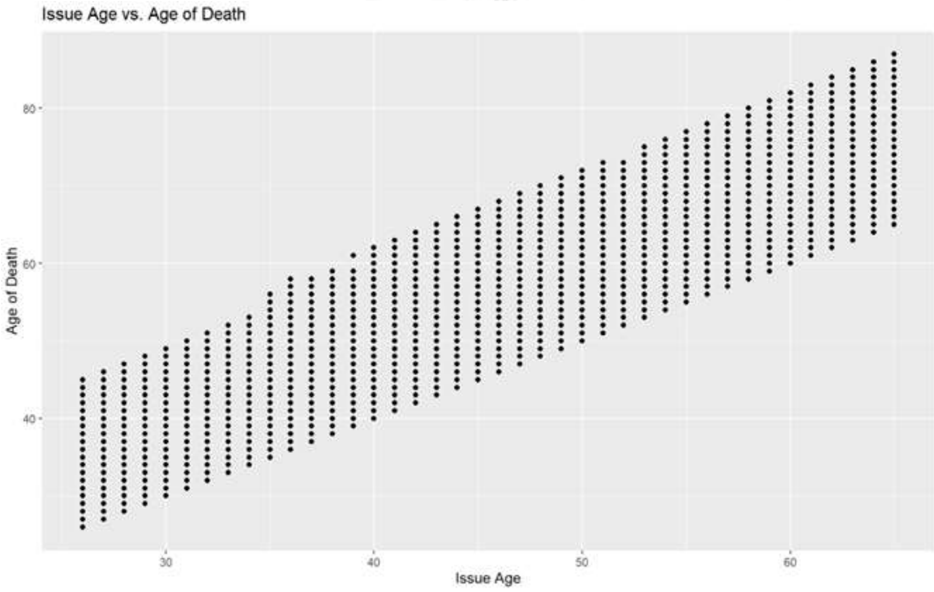




B.7) Region and Urban States

Issue age appears to have no impact on death or surrender rates thus, cohort effect can be assumed to be minimal.





Appendix C: Modelling

C.1) Assumptions

C.1.1) Mortality

A Cox Proportional Hazards model was fit to smoothly estimate the empirical mortality rates for individuals of ages 26-88 based on historical data, using the in-force policyholder dataset. This process was done because the actual rates implied by the data were highly variable, especially at the extremes of the age range where the sample size or number of deaths were low. As a result, the initial mortality assumptions proved to be unstable. This process was also relevant as there was insufficient historical data after age 88. However, the Cox Proportional Hazards model enabled us to extrapolate mortality rates based on the model's projection's.

A Cox Proportional Hazards model was selected as it afforded explainability due to its exponential distribution. We applied a weighting on the population rate with Cox regression assumptions and internal in-force data set. This was to reduce the overall population down slightly to account for SuperLife better risk selection and internal operations

Many covariates were considered for the Cox Proportional Hazards model. However, some were excluded due to confounding effects with other variables. For example, while there is a distinctive difference in mortality between different underwriting classes (particular between low and high risk classes), this difference was almost entirely due to the fact that smokers are automatically categorised as 'high' or 'moderate risks'. ~~As such,~~ As such, underwriting risk captures the difference in mortality due to smoker status rather than provide new information; it was excluded from the model. Additionally, cohort effects were also excluded as the data provided was insufficient to provide a true reflection of changes in mortality rates throughout time across the age range required.

The fitted Cox Proportional Hazards model uses Sex and Smoking Status as covariates. The results are as follows:

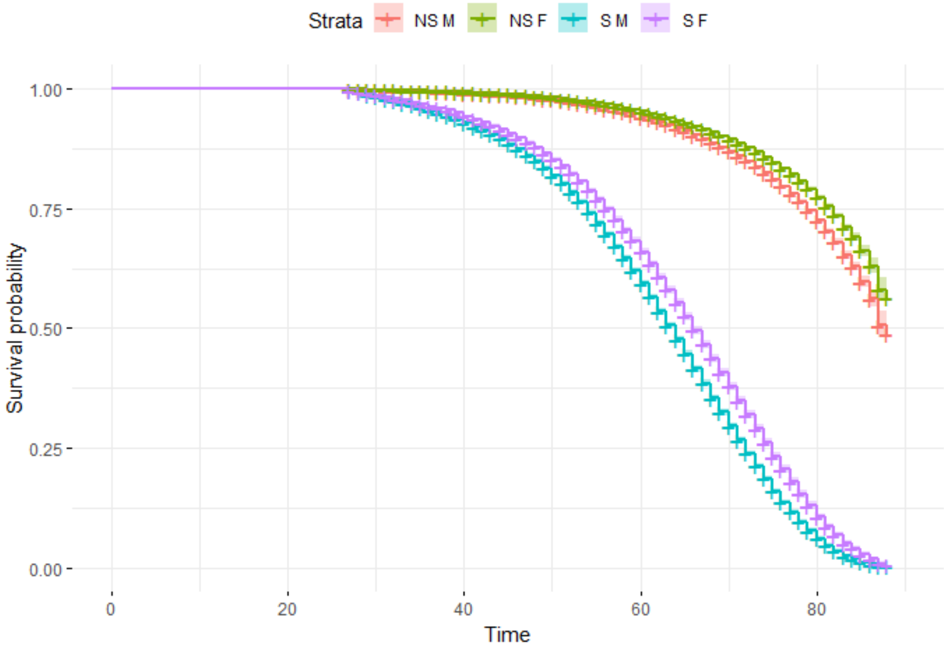
```
  n= 978582, number of events= 40376

                    coef exp(coef) se(coef)      z Pr(>|z|)
SexM             0.22531   1.25271  0.01113  20.24   <2e-16 ***
Smoker.StatusS   2.16586   8.72210  0.01076 201.34   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

               exp(coef) exp(-coef) lower .95 upper .95
SexM               1.253     0.7983     1.226     1.280
Smoker.StatusS     8.722     0.1147     8.540     8.908

Concordance= 0.664  (se = 0.002 )
Likelihood ratio test= 32971  on 2 df,   p=<2e-16
Wald test            = 45086  on 2 df,   p=<2e-16
Score (logrank) test = 66179  on 2 df,   p=<2e-16
```

This is the resulting survival curve, stratified by sex and smoking status:

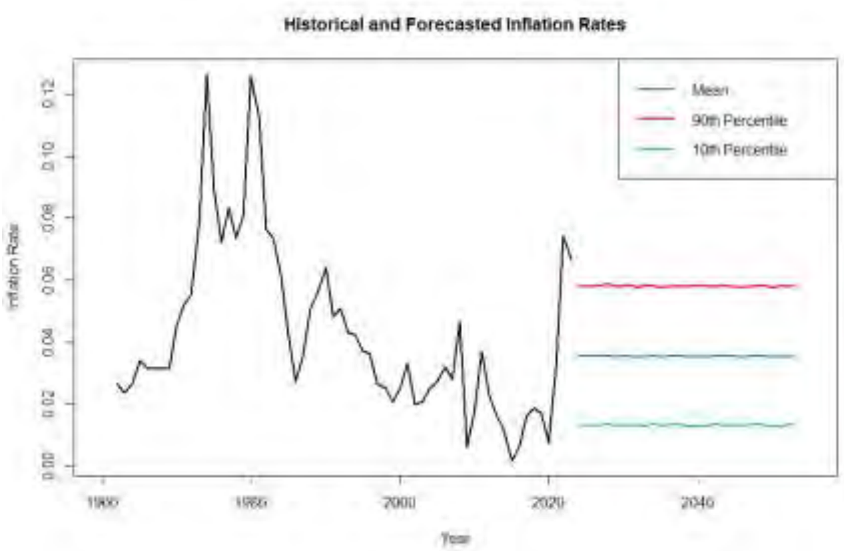


The discrepancy in survival curves between smokers and non-smokers is significant, with the model implying a hazard rate almost nine times higher for smokers.

As the in-force dataset only included individuals of ages

C.1.2) Projected Rates

The graphs clearly demonstrate a decline in interest rates after 1982 (as depicted in the graph below), with subsequent periods achieving much greater stability in interest rates. This suggests that inflation targeting was adopted after this point. This is a reasonable hypothesis given that many countries adopted inflation target practices around the 1980s to 1990s. As such, in forecasting the future rates, the rates were historical data was truncated from 1982 (i.e. historic values preceding 1982 were not included in the historical dataset).



As mentioned in Section 4.1, the historical inflation rates were simulated using a random walk process assumed to follow a normal distribution.

$$X \sim Normal(\mu, \sigma^2).$$

$$\text{where } \mu = \frac{i_{1982} + i_{1983} + \cdots + i_{2023}}{n} \text{ (where } n = 2023 - 1982 + 1)$$

$$\sigma^2 = \mathrm{SD}(i_{1982}, i_{1983}, \ldots, i_{2023})$$

The mean, 90th and 10th percentiles for each period are calculated by taking the values at those respective points across all 10,000 simulations.

An identical method was also used to forecast investment rates.

C.1.3) Expenses / Commissions

Expense	Assumption	Justification
Fixed Initial Expense	Č150 (SPWL, T20)	Based on historical (SOA ,2013) life assurance contracts for both permanent life and term life contracts. The 150 assumption is a view that comparable contracts between nations, despite conversion, will pertain to similar initial fixed costs.
Renewal (Yearly Expense)	Č35 (SPWL), Č45 (T20)	Based on historical (SOA,2013) life assurance and assurance non-acquisition costs. The lower servicing fee (to the 25th percentile), has been chosen based on no surrender/processing fees throughout the term. In contrast to the T20, SPWL has a lower servicing fee due to the longevity in force, and no annual collection of premiums.
Initial Commission Expense	Agent 80% (T20), 5%(SPWL) Telemarketer 45% (T20), 2.5% (SPWL) Online 0% (T20), 0% (SPWL)	Assume that agents have the most expertise, can help clients determine the most correct policy, hence, will have the highest commission expense. Alternatively, telemarketers will award, commission for referrals but online is expected to be non-commission (internal online programs). This is based on the SOA expense experience study assumptions, with the lower 25th percentile commissions Telemarketers and mean to upper 25th to agents.
Renewal Commission Expense	Agent –4% (T20) Telemarketer – 2% (T20) Online – 0% (T20)	Assume that T20 policies will have an additional commission expense upon renewal, with bandings based upon the SOA experience study, on proportion of non-acquisition expenses.

Profit Margin	8%	Selected based upon nominally life insurer operating profit margin in the vicinity of 2% to 10%. Hence, 8% was chosen as a conservative view and a profitable scenario for SuperLife.

C.2) Methodology

Base model assumptions have been created to provide a view on the expected proportionate increase pre and post intervention. The key drivers of the model incorporated;

- Policyholder mix (Policy type, distribution type, gender, smoking status)
- Policyholder cohorts
- New policies written
- Independent decrements (Mortality, Lapse)
- Claim and Commission Expenses
- Investment and risk discount levels

To produce a scope of uncertainty of pre and post initiative we have developed a stochastic model with variable intervention assumptions to understand the impact of the health app.

C.2.1) Design of the Stochastic Projection Model

The stochastic component applies base inputs and varies the intervention assumptions. The model has been designed as an 8-dimensional array, to split policyholder mix as detailed below:

Dimension	Justification/Application
Issue Year	• Each cohort can have difference in assumptions (initial vs. Renewal, mortality, withdrawals) and allowance has been made for future modelling/monitoring. • Different lengths in contracts (i.e. all 2001 T20 policies lapse in 2020).
Age	• Different assumptions for mortality and uptake of intervention. • Apply aging through projection periods
Projection Time	• Time in the projection window impacts assumptions based on aging, transitions and decrement assumptions.
Gender	• Different mortality assumptions across gender (significance between males and females)
Smoking Status	• Smoking status impacts mortality decrement and risk selection in the policy.
Policy Type	• Different policy types have unique characteristics (T20 and SPWL have different premium and benefit structures, hence must be priced accordingly).
Face Amount	• Impacts the total premium paid/ tracking the total mortality savings across individual policyholders.
Distribution Channel	• Different commission and expense structures, with higher commission paid to agent-based sales in contrast to online.

In the model there is specifically two key components, policyholder and payment projections.

C.2.2) Policyholder projections

Policyholder projections are recursively calculated in each projection year, following a simple algorithm:

- Take the starting number in the previous projection year, and age the participants.
- Add in new policyholders starting in that projection year.
- Remove policyholders for mortality then remove for withdraw (assuming at end of year).
- Remove additional policyholders' policies which have lapsed.

Appendix D: Further Analysis of Results

D.1) Covid-19

There was a spike in mortality during the Covid-19 period. Mortality rates from these periods have been truncated given that there is insufficient data to estimate how Covid-19 will impact future mortality rates.