



AUTONOMOUS VEHICLE INSURANCE



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1 Executive Summary

The insurance market of Carbia faces new challenges and opportunities due to the introduction of Autonomous Vehicles (AVs). With positive expectation on AV insurance market, Safelife faced problems of:

- No pioneers in the market
- No current AVs legislation
- Requirement to meet 20 - 25% business goal by 2030

We, as the consulting team for Sofia, recommend a comprehensive plan consisting of high initial price, awareness programs, price matching strategy, premium rider plan, driving reward program and blockchain technology. These plans are supported by 10-year pure premium forecast on different scenarios, sensitivity analysis for company goal, reasonable assumptions, supplementary government legislation and liability assignment with reduced risks. In conclusion, Safelife should initialize the new AV policy with the current traditional automobile policies to achieve the management goal.

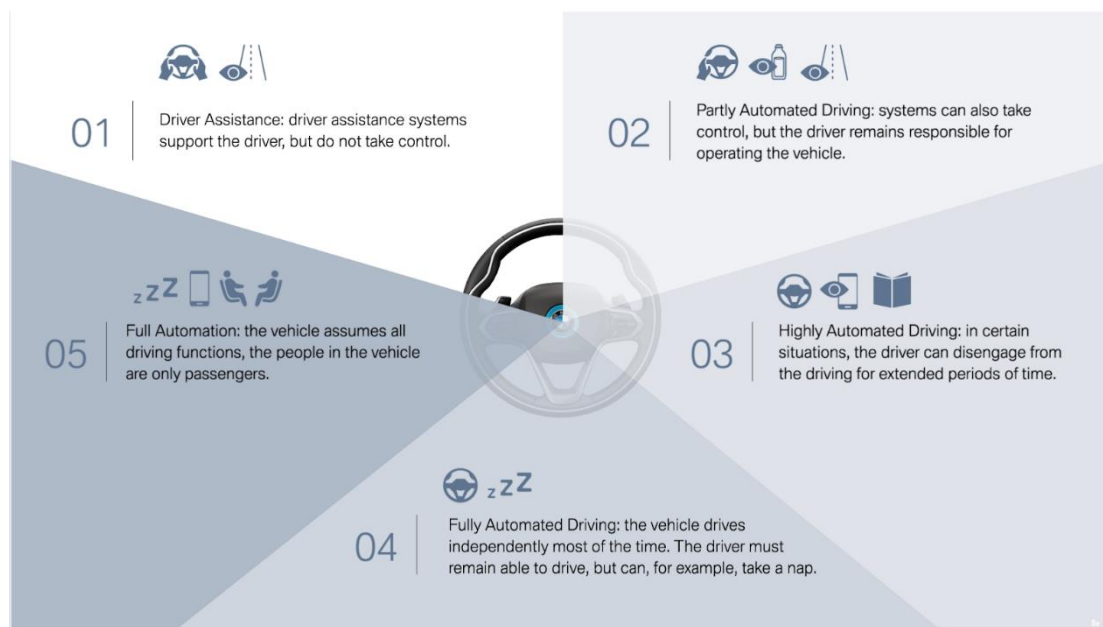
2 Market Analysis

2.1 Market Assessment

Autonomous vehicle is defined as “a vehicle capable of navigating district roadways and interpreting traffic-control devices without a driver actively operating any of the vehicle's control systems” (Autonomous Vehicle, 2019). Under the scenario, AVs are about to change the automobile industry. With historical data indicating 94% of accidents attributed to human errors, the introduction of AVs will dramatically reduce the accident frequencies. (Kumar & Sundarraj, 2018) According to the U.S Highway Commission, there are 5 stages defined for AVs, with each

stage describing the extent to which the automobile take over the tasks and responsibilities with human driver (Automated Vehicles for Safety, 2018).

In our analysis, since Carbia is a highly-developed country, we would make projections for future growth based on U.S. automobile market. Despite the uncertainty of AVs future, optimists predict AVs will eventually occupy vehicle market and thus will replace most of the human-driving-vehicles (Litman, 2019).



2.2 Influence

2.2.1 Manufacturer

As automation technology develops, all the AVs will be owned by manufacturers, leading with more financial obligation and regulatory requirements for safety.

2.2.2 Infrastructure

The introduction of AVs will transform the infrastructure of a country as AVs require advanced road conditions, requiring revamped infrastructures to meet the operation goal.

2.2.3 RideShare

Since individual ownership of vehicle is expected to shift in future, rideshare business with AVs is expected to reach optimization, increasing the exposure liability of the companies.

2.2.4 Insurance Market

Premium calculations will be redefined for AVs insurance market. Nowadays, the commercial auto usage-based insurance (UBI) focuses on the driving behavior and traveling distance. However, for AV insurance, the vehicle data, components and software will be more vital. In the long-term, driving skills are becoming less important and risk classes will be merged.

3 Assumption

3.1 Market Assumption

In today's United States vehicle market, the most advanced AVs is in partial automation stage and driver is necessary to monitor the environment. As Carbia's government is developing AV and insurance legislation in US, we will mirror Carbia's market by United States and use Transport Systems Catapult's AV market forecast as reference (Market Forecast, 2017).

Based on a study by AIG Singapore, among the 80% of the adults who do not currently drive an autonomous vehicle, 44% of them voiced out that they are willing to buy, rent, share or travel in a vehicle that has autonomous feature. We, therefore, believe autonomous vehicles market adoption will follow progressive scenario (The Future of Mobility, 2017).

Scenario	Description and reference points	CAV uptake (share of new vehicle sales)		
		2025	2030	2035
Progressive	Follows global uptake projections from Goldman Sachs, 2015 ¹² and high global uptake projections from McKinsey 2016 ¹³ - Safe and reliable technical solutions fully developed and introduced by mass market leaders before 2025 - Significant cost reductions to hardware (following similar trends to smartphones) are achievable in the next 10 years - Levels of scepticism can be reduced in a short time frame, supported by the regulatory environment and the rapid solution of remaining technological challenges.	2025	2030	2035
		L3: 11%	L3: 29%	L3: 54%
		L4/5: 0.4%	L4/5: 8%	L4/5: 30%
Central	Follows global uptake projections set out in BCG, 2015 ¹⁴ - Assumes that uptake is governed predominantly by consumer willingness to pay; possible effects of regulations (e.g. those mandating autonomy) are not accounted for - Uptake is based on comparing projections of cost reductions (which are based on extensive industry consultation and cost trends for existing ADAS technology) with consumer willingness to pay (based on survey results)	2025	2030	2035
		L3: 11%	L3: 18%	L3: 15%
		L4/5: 0.3%	L4/5: 3%	L4/5: 10%
Obstructed	Follows low global uptake projections from McKinsey 2016 ¹⁵ - Technical and cost challenges for L5 are not addressed in the next 10 years - Regulations (excluding those in the UK) do not enable sufficient use of CAVs in varied environments - Negative publicity following incidents; consumers take longer to trust the technology	2025	2030	2035
		L3: 0.2%	L3: 3%	L3: 5%
		L4/5: 0%	L4/5: 0.2%	L4/5: 3%

Source:

https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/642813/15780_TS_C_Market_Forecast_for_CAV_Report_FINAL.pdf

3.2 Legal Assumption

3.2.1 Ethic Consideration

Manufacturer

In the context that the introduction of AVs is able to reduce the accident rate, it comes with the moral reason to promote automation technology such that manufacturers shall not take heavy responsibility. Therefore, an AVs manufacturers tort liability will be implemented in our policy to alleviate the risk of both manufacturer and Safelife (Hevelke, 2015).

AV Owners

AVs would have higher accident rates in early stage due to technology limit. Owners have to acknowledge that accidents will occur under drivers' no faults conditions. Ethically speaking, drivers should take responsibility as a form of a "Strict Liability".

3.2.2 Responsibility

Responsibility belonging

Once system failure causes accidents and were traced by event data recorder, manufacturers will take main responsibility. If the accidents are caused by external factors, like extreme weather, responsibility will be assigned to driver side.

3.3 Policy Making Assumption

3.3.1 Liability Distributions

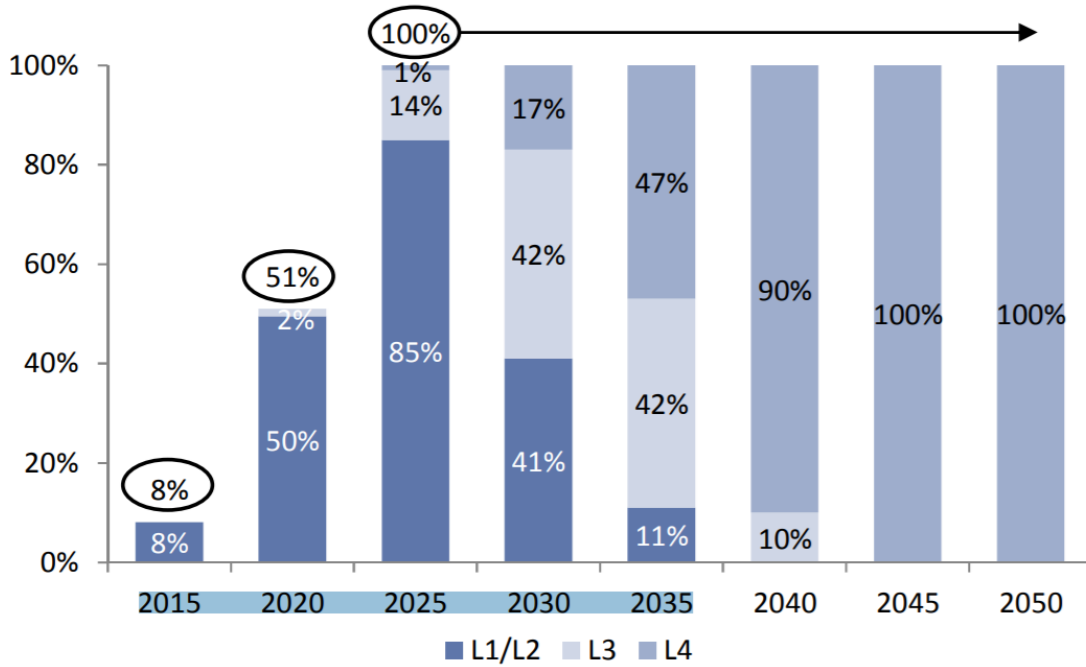
As we mentioned in 3.2, AV drivers shall take partial responsibility (pay small portion of liability) due to "Strict Liability" while manufacturer take main responsibility (manufacturers pay for big portion of the liability) for automation system failure accidents.

3.3.2 Frequency, Severity & Exposure Model

As mentioned in 2.1, accident frequencies will be reduced as the drivers take less control of the vehicles. On the other hand, even though severity of AVs will be higher as LiDAR detectors or other advanced components will be implemented on AVs, few research is available to quantify the loss. For accessibility, we assume severity will stay the same. Having the US automotive market reflecting the Carbia's market, there are approximately 12 million vehicles went out of service, with nearly 270 million vehicle registered in recent

5 years. Dividing the number of vehicle recycled by the average number of registered vehicle per year, we come out with 4.5% of recycle rate as our baseline assumptions. Besides, we assume that the percentage of AV quarterly increment follows that in sales distribution as exhibit 9, with Safelife policy exposure also grows with national AV market. More detail explanation will be available in the appendix.

Exhibit 9: Model Level 3 and 4 launching in 2018 and 2025 in N America
North America light vehicle sales penetration forecast



Source: Goldman Sachs Global Investment Research.

4 Recommendation

4.1 Government Regulation

4.1.1 Liability Assignment

Based on liability system 3.3.1, government will require both manufacturers and drivers to purchase their respective policies. Under the new regulation, cost of the accidents while

the system has the control (in Stage 3-5) would be liable to manufacture as the driver does not operate the vehicle. As stage goes from 3 to 5, the portion paid by manufacturers' policy will increase correspondingly.

4.1.2 Systematic Failure

Even though the automation can dramatically reduce human errors, the systematic failure of AVs (same failure in majority of one model) will cause huge losses. Under the new law regulation, insurance company will still cover the loss incurred during a systematic failure that is above certain percentage. In addition, payment limit of systematic failure should be stated and agreed in insurance policy.

4.1.3 Data Collection

All simulation data from manufacturer will be required. Manufacturer will notify the government and insurance company with audited written report of simulation data analysis in timely basis to quantify the risks. In addition, the data event recorder must be installed to ensure real-time data transmission.

4.2 Company Execution Plan

- To obtain first adopter benefits, anticipated launch data will be set to 1st of January 2020. More data will be obtained for analysis and forecast to preempt the futures markets. By assuming growth of company's policies mirrors that of Carbia's vehicle market, Safelife's AV policies will reach 21% in 10 years. With that, we suggest Safelife to keep the Non-AV policies with new AV policies. A new department focuses on AV insurance product will be established, responsible for data analytic, underwriting and modeling.

- Brookings Institute’s study indicates only the young adults (age range 18-34) showed rather positive attributes towards AVs compared to all age groups. (West, 2018). Thus, a comprehensive plan is offered to better expand the market.
 - Short Term (3 years): With low market acceptance in the beginning, we shall set relatively **high initial price** to ensure profit. Gaining the positive reputations in the AV industry, we shall expand our customer base. As market analysis indicating people not confident about AV’s future, we will have **awareness programs to build confidence** within the public about AVs. By that, these people will most probably return to us when they are ready for AVs. Along this awareness plan, we can provide further discount to the customers if proven they were one of the participants from those programs. Achieving the corporate social responsibility (CSR) on AVs education and building the network of future policyholders, we believe that it is a win-win situation for Safelife.
 - Mid Term (5 years): We anticipated that quick follower will pick up short after we launch the product. In order to keep the current customer pool and attract more new customers, firstly, we would introduce the **price matching strategy**. If the customers find any competitor with a lower price, we will match the lower price. Also, we will revise the premium rates periodically to always ensure a competitive rate. Secondly, we will introduce the **premium rider plan**. If the policyholder’s claim total amount is below a prefixed amount, Safelife will refund portion of the premium paid.
 - Long Term (10 years): We shall encourage use of automation while driving to better quantify the risks. We therefore will introduce **driving reward program**. Drivers

will earn cash points as the autonomous system is in use, as the cash points can be used to reduce policy premiums. Besides, **blockchain** will be used to store insurance database with **smart contract technology** to achieve automatic payment, when the event data recorder sent the information to trigger the smart contract on accidents.

5 Future Projections

5.1 Forecasted Pure Premium

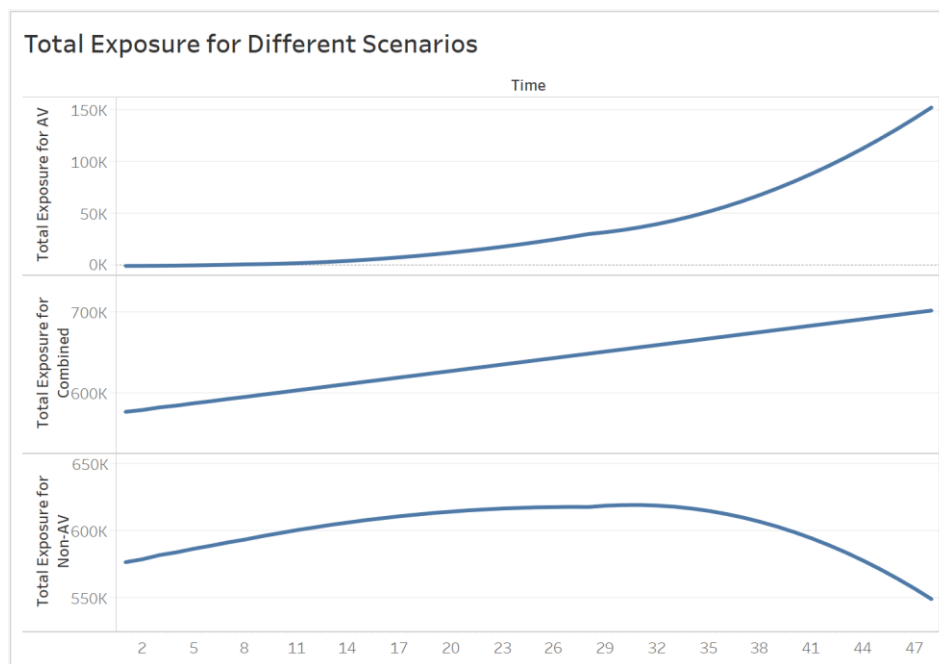


Chart 1

By fitting historical data in the time series model based on our assumption in 3.3.2, non-AV exposure shows positive upward trend up until 33rd quarter and then decreases after that. On the other hand, both the only-AV and Combined (AV and non-AV) exposures increase all the way until 10th year. (Chart 1)

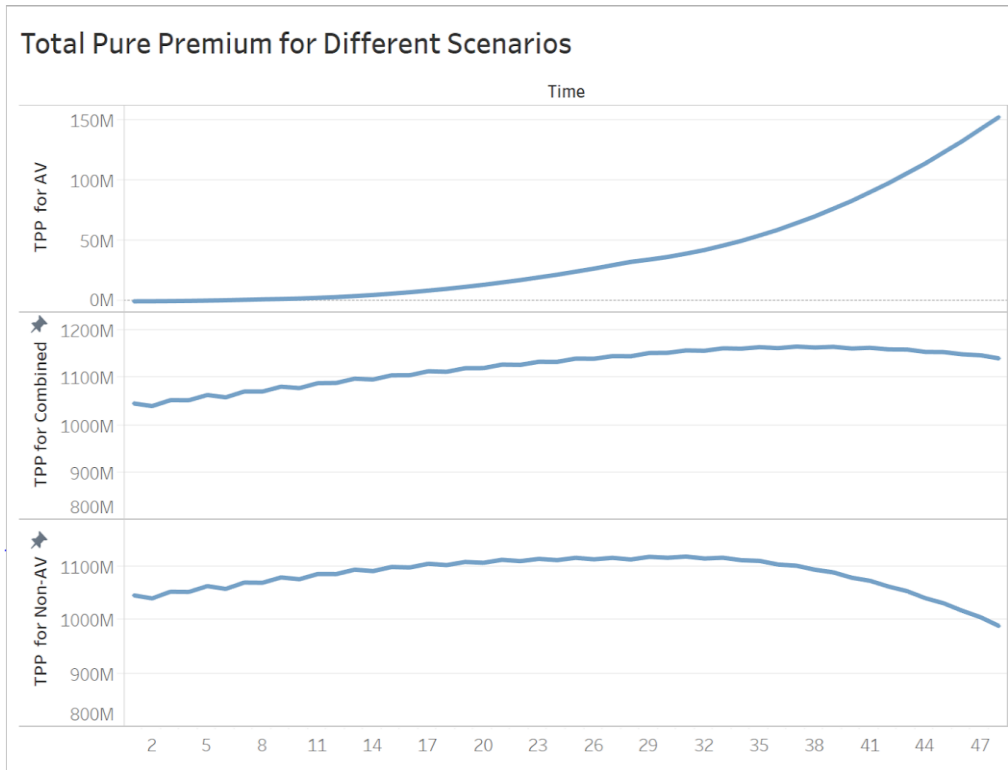


Chart 2

From the Non-AV (benchmark) and Combined scenarios, expected loss will increase and eventually decrease around 32nd quarter. It is beneficial for Safelife since the future expected loss decreases despite the increasing exposures of total vehicle. (Chart 2)

As total pure premium (TPP) for AV increases with time and TPP for both combined and Non-AV increase then decrease, initial conclusion can be drawn as the Non-AV policies would be Safelife’s preference because the expected loss decreases with increasing exposure. However, this phenomenon is misleading after we investigate further. Calculating the total pure premium per exposures (TPPPE) for different scenarios by dividing TPP with respective exposure, we observe that AV policies are the primary reason for decreasing the expected pure premium. The observed “decrease” of Non-AV total premium is attributed by the decreased exposure showed in Chart 1. With that, we recommend Safelife should continue with the traditional automobile policy and the new AV insurance policy (Chart 3).

Total Pure Premium Per Exposure on Different Scenarios

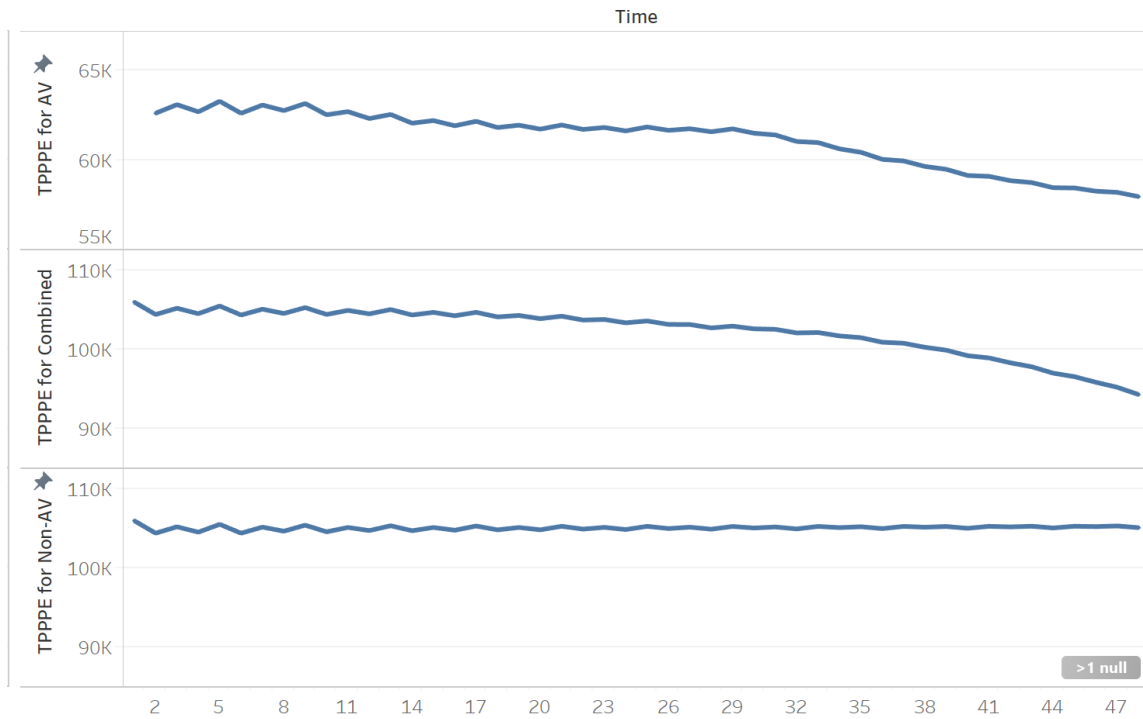


Chart 3

5.2 Sensitivity Test

Input variable	Frequency Adjustment	Severity Adjustment
L1/12	0.9	1
L3	0.6	1
L4/5	0.2	1
	New Policy Portion (between 0.2 & 0.25)	
	0.2178663	

We set our baseline as above. According to our estimation, Safelife AVs exposure portion will reach 21.78663% at the end of 10 years. Based on our analysis, with portion between 21.78663% and 25%, AV's pure premium would be higher than benchmark and non-AV's pure premium would be lower. Despite that, the total pure premium would decrease. If Level 3 AVs cannot

decrease as much accident rate as expected, then AV's pure premium and total pure premium would be higher, vice versa. If Level 4, 5 AVs fail to reduce frequency lower than or equal to 10%, AV personal pure premium would decrease with commercial pure premium increases, leading to increment in total pure premium. If AVs severity is higher, then both personal and commercial pure premium would have higher.

6 Risk Not Addressed

6.1 Risk of Recommendation

6.1.1 First Adopter

Safelife will face first adopter risk. Focusing on pricing of AVs insurance, many risks that are not able to be quantified and thus omitted in forecast.

6.1.2 Claim Handling

Based on new government regulation, two separate policies are insured for individual autonomous vehicle. Risk occurs when the novelty of the technology is bound to create confusion as responsibility of an accident might not be judged. The risk will be theoretically higher at early adoption phase as both autonomous vehicles and human-driver vehicles will be on the road at same time (Devotta, 2017).

6.2 Risk of Assumptions

6.2.1 Cybersecurity Threat

Based on the research of Bayesian Network on cybersecurity threat on AVs, the resulted maximum likelihood risk level for different qualitative classification of cybersecurity risks are 0.6% for 'None', 27.58% for 'Low', 42.15% for 'Medium', 26.17% for 'High' and 3.5% for 'Critical' (Sheehan, Murphy, Mullins and Ryan, 2018). Although there are different

percentages available for different class of cybersecurity risks, there isn't enough quantitative data and experiment available on the relationship between cybersecurity risks and the operation of AVs. Thus, we chose to omit this risk.

6.2.2 Severe Weather Condition

Based on the U.S Department of Transportation, they released a report with regards to the possible risk on the AVs on severe weather condition (Sundararajan & Zohdy, 2016). With regards to severe weather condition, heavy rain or snow will prevent the Light Detection and Ranging (LiDAR) from accurate data reporting; foggy condition will induce the AVs for wrong selection of travel speed. Therefore, more development on the data collection and data adoption are expected.

6.2.3 Software Malfunction:

Although the existence of ISO 26262 development V process (5 major areas: driver out of the loop, complex requirement, non-deterministic algorithms, inductive learning algorithms and fail-operational systems) has provided a methodical framework to test on various software challenges by the AVs, there still exist some challenges. For instance, for non-deterministic and statistical algorithms, it is difficult to reproduce the same deterministic behavior in an integrated system despite the availability of pseudo-random number stream in unit (Koopman & Wagner, 2016). This complexity has lead us to exclude the possibility of system malfunction in our current calculation.

7 Appendix

7.1 Data

7.1.1 Data Limitation

7.1.2 Data Processing (include code and thought process)

A. Data Processing

Frequency-severity modeling is the main method used for the premium forecast in our report.

Based on this method, the premium is calculated by the following formula:

$$\text{Pure Premium} = \text{Frequency} * \text{Severity} * \text{Exposure}$$

Our model is based on assumptions in section 3.1. With those assumptions, we believe that our projection reflects the real-life situation in a large extent. While we quantified as many factors as possible, we failed to include the risks mentioned in section 6. In the following sub-sections, we will explain how we calculated and predicted each component in the formula above.

A. 1 Frequency:

Based on our assumptions, we made forecast from historical data. We adopted the method of time series and used ARIMA model to predict the frequency of each of the five categories of insurance coverages. For every risk class and personal/commercial property, we fitted the best ARIMA model for the frequency (number of claims divided by car-years of exposure) and made predictions from first quarter of 2019 to fourth quarter of 2030. The output of times series models gave us the expected frequency for each subgroup, which is used for calculating the expected pure premium.

A. 2 Severity:

As we assumed that the severity (number of claims / exposure) remains the same over the time, we used the historical data to look for the distribution of severity. We considered the commercial and personal policies separately, and for each of them we came up with five different severity models based on five different insurance coverages. We fitted the data to classical severity distributions including logistic distribution, gamma distribution, normal, and log normal distribution. Then, we selected the best distribution based on the AIC, Q-Q plot and P-P plot. At last, we used moment matching estimation to estimate the parameters of the selected distribution

and got the expected value from there. The expected value from the selected distribution is used to calculate the expected pure premium.

During the calculation process, we found that the observation of risk class SSH at the third quarter of 2018 is an extreme value. With this observation, the square of skewness for the severity data is over 8. Without this observation, the square of skewness for the severity is below 2. Although it is hard for us to determine whether this point is an outlier or not, we decide to exclude this data point in order to get a better fitted distribution.

A. 3 Exposure:

For each risk class and each personal/commercial property, we made forecast on expected exposure based on historical data by using time series. We firstly selected the best ARIMA model for each subset and make predictions until fourth quarter of 2030, and then we calculate the change of exposure of each quarter. We approached this by subtracting each quarter's exposure by that of previous quarter and combining the difference with number of recycled old vehicles. Based on our research which mentioned in the section 5, the recycle rate of each year is 4.5%, and the equivalent recycle rate of each quarter is 1.14%, calculated by the following equation $((1-x)^4 = 1-0.045)$.

As the change of expected exposure of each quarter includes all types of automations. We also approximated the percentage of Level 0 - 2, Level 3 and Level 4/5 automations in the expected exposure. Based on our assumptions and researching, we estimated the car sales percentage of each type of automations level from the report of *Monetizing the rise of Autonomous Vehicles* (p.16). The chart in the report shows the forecast of percentage of sales of each type of automations level at 2020, 2025, 2030 etc. We approximated the percentage data of each quarter

by making a straight line between data points and worked out the formula. For each type of automations, the number of newly insured vehicles is the product of expected exposure and the market formula. Respectively, the total number of insured vehicles of each automation is the sum of newly insured vehicles of that automation in previous quarters.

Exposure	Level 0-2	Level 3	Level 4/5
Personal	X	Y	Z
Commercial	P	Q	R

A. 4 Number of Claims

Number of claims is the product of frequency and exposure. During actual calculation, we made distinctions for different coverage areas and personal/commercial property. We also took different levels of automation into consideration. Our research and assumption suggest that the frequency for each class would be 60% of original level (60%a) for Level 3 automation, composed of 50% from human error (50%a) and 10% from car issues (10%a). In Level 4/5, frequency would be 10% of original level (10%a), which only composed of issues caused by car.

Frequency	Level 0-2	Level 3	Level 4/5
Personal	a	50% a + 10% a	10% a
Commercial	b	50% b + 10% b	10% b

Total No. Claims	Five Different Coverage
Personal	$X*a + Y*50\%a$
Commercial	$P*b + Q*60\%b + R*10\%b + Y*10\%a + Z*10\%a$

1. For total number of claims in the “Personal” category:

It is composed of total number of claims in Level 0-2 in the personal category, as well as total number of claims in Level 3 in personal category caused by human error;

2. For total number of claims in the “Commercial” category:

It is composed of total number of claims for all levels of automation in the commercial category.

We calculated in this way because in Level 3-5, all the claims made due to mechanical errors and vehicle issues are considered as “Commercial”, based on previous discussion.

A.5 Expected Pure Premium

For the premium forecast, we want to calculate the expected premium. The expected pure premium by the following formula:

$$\text{Expected Pure Premium} = \text{expected frequency} * \text{expected severity} * \text{expected exposure}$$

During the calculation process, we calculated the expected pure premium for each of the risk class, personal/commercial property, as well as five different coverages.

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