Autonomous Vehicle Liability: The Nexus of Disruptive Change and Insurer New Business Opportunity

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Preface

In previous INSA/Autonomous documentation[1], our focus has been the innovation of insurance product solutions required for AI-control vehicles wherein the vehicle operator has morphed from a driver into an observer and on-demand driver and with further AI sophistication into being just another passenger.

This document addresses the key business and marketplace issues that are prerequisites for insurers to bridge from their current practices to addressing the paradigm shifts in liability indemnification, brokerage, and new the new perspective that need to be conveyed to customers associated with AI vehicle control.

Competitively, insurers need to be well-positioned to take advantage of the transformation wrought by each associated paradigm shift. In the insurance space, each shift both radically and succinctly transforms the marketplace as it ripples through existing structural, actuarial, brokerage, and consulting products and services. This business disruption started with the debut Self Driving Level 1 and gains momentum as the scope of AI control expands through SAE Levels 2 – 5. (Figure 1)

Figure 1: Society of Automobile Engineers Specification: 5 Levels of AI Vehicle Control, Source: SAE International 2021

Despite the prevalence of "doom & gloom" predictions, the Autonomous Vehicle paradigm shift can be leveraged upon as a "positively disruptive" business/revenue creation catalyst for the First Movers insurance providers. The doom and gloom predictions remain though, but as the business mission burden of "late-movers".

The pivotal shifts that reshape liability indemnification from an insurer standpoint are:

[1] Usage Based Product Liability Insurance (UBPLI) and Assisted Autonomous Driving Usage Based Insurance (AADUBI)

1. The rise of Autonomous Vehicle Solution Providers (AVSP) [2] who become the dominant vehicle (product) liability customers. They consolidate formally individual vehicle driving liability policies under their self-driving liability auspices, thereby creating a new class of “institutional” clients – each with a critical mass of individual usage-based autonomous vehicle policy requirements shaping a new, dynamic insurance market.

2. The need for a fundamentally secure control and dissemination backbone for proprietary AVSP vehicle performance data consolidation and reduction.

3. Disruptive changes to the underpinnings of current actuarial analytics, brokerage processes, insurance practices, and customer relationships. These changes leave an operational void that INSA/Autonomous fills starting with such new concepts/products as Micro Continuous Brokerage[3] (MCB).

4. Revamping the insurance/brokerage operational model and analytics to address a new industry benchmark of continuously optimizing premium price structure -- thereby directly monetizing AVSP R&D and codebase maintenance -- as improved AI vehicle safety is directly mapped to decreased liability premiums.

Further detailed in this document is an end-to-end re-engineering of the automotive liability insurance business space that corresponds to these paradigm shifts. Proceeding with this new insurance landscape, the focus shifts to the reshaped and restructured autonomous vehicle insurance products, new brokerage operational requirements, reorientation of risk management, and the critical changes and new techniques required for actuarial data acquisition/reduction. In the context of putting the above into perspective; potential marketplace repositioning and the impacts on revenue (positive/negative) are discussed.

[2] AVSP refers to the AI driving technology providers such as Tesla, Mobileye/Intel, Cruise/GM, Waymo/Google, Mercedes …etc.

[3] Micro Continuous Brokerage, as will be fully detailed in this document, is protected IP and constitutes the operational cornerstone reshaping the way autonomous vehicle liability insurance interacts with AVSPs, Insurers, and consultancy services

Introduction

Autonomous vehicle paradigm shifts and consequences

The first automobile liability insurance policy was issued in 1897 by Travelers Insurance of Hartford, Connecticut to a Mr. Gilbert J. Loomis. If Mr. Loomis' descendants in 2021 were to give that original, dawn -of-the-last-century auto liability policy to any agent or broker – the content and liability terms and conditions would be immediately recognizable and executable by any underwriter. In contrast, Loomis's hand-made, one a kind vehicle would not be safely drivable by the vast majority (probably over 99%+) of current drivers.

The reason for this divergence is that Liability Insurance has not had to confront the radical market changes and disruptive paradigm shifts that the mechanical aspects of the auto industry had to face and overcome. On the other hand, although actuarial methods and computational tools have changed, there has been no fundamental change in the definition of "automobile liability" or "responsible party".

This serene business space is about to be transformed though with the advent of autonomous vehicles. In this new Liability Insurance and Risk Management space, liability can no longer necessarily be attributable to a human driver, but rather it is inextricably linked to AI-based vehicle control. With the vehicle operator having been transformed initially into an observer/on-demand driver (SAE Autonomous Levels 1 -3: Driver Assist) and then into a passenger (SAE Autonomous Levels 4-5: Full Self-Driving) – the basic premise of human interaction and fallibility that underpins liability insurance products and risk management is no longer relevant.

Against this background of abridging or abrogating the auto operator role, hands-free driving, regardless of duration, will be the epicenter of disruptive paradigm shifts in auto liability insurance risk management.

Auto insurance is a clearly segmented business space. Accordingly, the self-driving paradigm shift will evidence itself differently with respect to Insurance Products, Adjudication, Brokerage, Consulting, Underwriting, etc. INSA/Autonomous provides solutions and new insurance products that address significant aspects of several of the above.

However, the most pronounced paradigm shifts and those that will most directly affect insurer revenue relate to the disruption of current liability insurer – customer relationship, inapplicability of legacy products, and methods underlying brokerage and underwriting – in net***: End-to-End Actuarial Risk Management***.

Effect of Self-Driving Paradigm Shifts: AVSP Consolidation of Auto Insurer Customer Base

To date, the automotive insurance marketplace reflects the genesis of auto insurance policies being largely individually sourced. Hence, for example in the US roughly 250 million vehicles are insured that, except for rental, business, and transport fleets[4], are individually owned with individual owner/operator-initiated liability policies. The individual personal liability policy market is dominated by private, first-line insurers like Allstate, Liberty Mutual, Progressive, AXA, Admiral, Aviva, etc.

The advent of autonomous driving will at first augment (Levels 1-3) and then, relatively rapidly, replace individually sourced liability policies (Levels 4-5) thereby creating the respective critical masses that are the prerequisite for Swiss Re and other institutional client fleet insurers to entry into the self-driving vehicle liability marketplace.

As detailed in prior documentation, Usage-Based Product Liability Insurance (UBPLI) and Assisted Autonomous Driving Usage-Based Insurance (AADUBI) which includes AI to Operator Transfer of Control Quality Metric – create a new insurance reality. Integral to this new insurance product space is a massive new business opportunity reflecting that autonomous vehicle liability insurance becomes an extension of "product liability" insurance. This is the consequence of the driver's transition from an operator into the role of Observer (AI Levels 1 - 3) and with the debut of AI Levels (4 - 5) control into a passenger.

Hence, every vehicle sold with the moniker: "Self-Driving", while still being privately owned, will require the Autonomous Driving Solution Provider[5] (**AVSP**), to assume and retain product liability where their AI control is installed. This creates critical mass clustering by AVSP of literally many tens of millions of policies.

These bundles of individual vehicle policies, under the auspices of respective AVSPs, represent a new force and core challenge to the stability of the traditional first-line auto insurance sector. This market disruption represents the tip of a transformational insurance business opportunity for First Movers who can uniquely service the AVSP's insurance requirements.

Figure 2 and Figure 3 show the shift from an Insurer-centric personal liability marketplace addressing 250 million individual customers to an AVSP–centric product liability model where a small number of competing AVSPs dominate and can force transformation upon legacy insurers. This paradigm shift, as it will be shown in detail later in this document, forces legacy liability insurers to reengineer their processes and products around "disruptive solutions" that continuously optimize premiums to reflect the maturing of technology while providing AVSP a new cost-saving metric. to rationalize their mammoth R&D and codebase maintenance costs.

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[5] Such as Tesla, Baidu, Mobileye/INTEL, Waymo/Google, Mercedes etc.

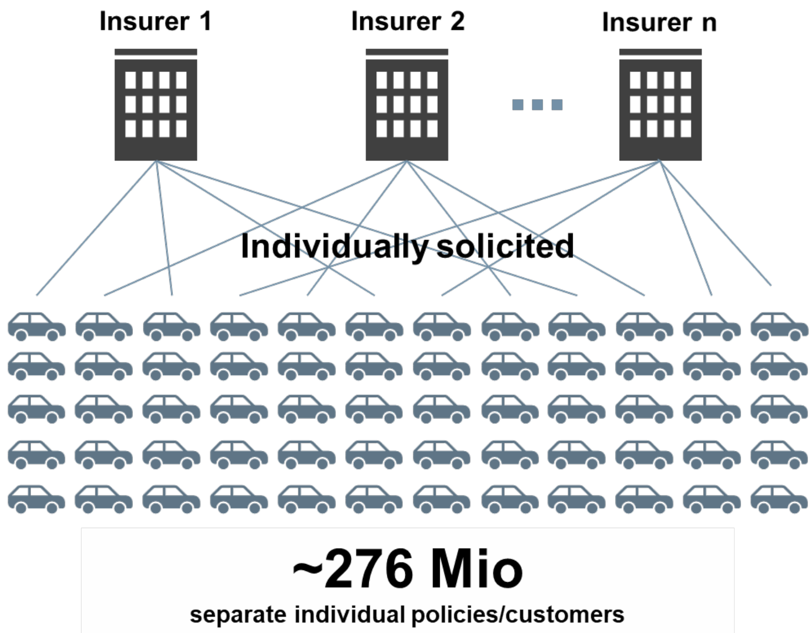

Figure 2: Current Discrete Policy Insurance Marketplace

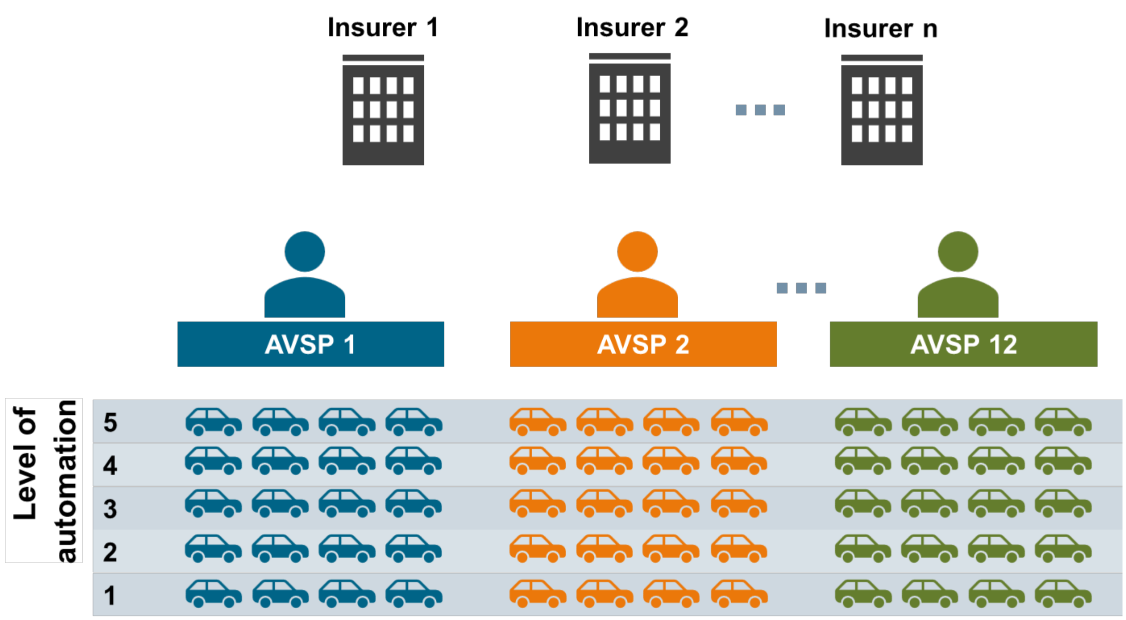

Figure 3: Auto Insurance Market Consolidated under AVSP Auspices

With the restructuring of the liability insurance marketplace from more than 250 million individually registered vehicles, each representing a sales opportunity into less than a dozen AVSPs—*the new Insurer customer base*, the necessity of capturing 1st Mover Advantage becomes a primary order of business. This is a marketing strategy matter that we will address as we go further into the competitive marketing advantages that are implicit in how INSA is operationally structured and the creation of IP barriers to competitive entry.

Autonomous Vehicle Risk Management and Brokerage
A New Actuarial Frontier

The marketplace circumstance for insurers and brokerage changes fundamentally with the introduction of AI-controlled (autonomous) vehicles.

The entry of AVSPs as the responsible parties for liability related to their respective AI-Control products[6] in each of the vehicles wherein they are installed. Hence each AVSP (presently about 25 in number likely decreasing in the next 5 years to less than 10 independent competitors) will become the "customer", each representing to the insurer/broker the liability insurance needs of millions of vehicles *while under their (AVSP) autonomous self-driving control*.[7]

The AI-Control insurance products to be brokered will need to address liability that emanates from an intellectual product created by employees of an organization (a corporate legal entity) that "failed", case in point, with no direct human involvement in a manner that incurs liability responsibility – a classic description of **product liability**.

Maintaining such "product liability" coverage with an optimal premium structure for each of its installed AI-controlled vehicles will be a critical AVSP operational focus for achieving a competitive cost advantage that goes directly to increasing the bottom-line profit. However, the efficacy of such new INSA/Autonomous like Usage-Based Product Liability Insurance (UBPLI)[8] and Autonomous Assisted Driving Usage-Based Insurance (AADUBI)[9] and other future new insurance products developed by the industry is integrally tied to have a new brokerage framework with robot traits – some positive and some negative.

Positive Robotic Traits (Examples)

- driver malfeasants – e.g., DUI, narcotics
- no driving skill regression – e.g., age, medication, fatigue
- no distractions: mobile phoning, texting
- no emotion: road rage, time pressure

Negative Robotic Traits

These are nearly impossible to state with distinct cross-the-board attributes (i.e. intrinsic limitation). However, we can capture the challenge of autonomous vehicle "liability risk management" in one utterance truism:

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[6] The details and rationale of the transition of liability from *Personal* to *Product* Liability are given in the Usage Based Product Liability Insurance (UBLI)

[7] There will remain for SAE Levels 1 – 3 equipped vehicles, a complementary liability domain dealing with driver/operator liability responsibility for interacting with the AI-control system and when under traditional operator control. This adjunct liability business space of transitional and traditional liability insurance products, coexist in the same vehicle as the AI vehicle control liability and while not discussed in this document, it suffices to say that AON and Verisk are well positioned to absorb major parts of this evolving business.

[8] UBPLI documentation

[9] AADUBI documentation

➔ ***No AI-control product today or in the committed future is capable of passing the road test for an <u>unrestricted driver's license</u>!***

Although hard to differentiate, these subpar AI-control exposures are the result of **the current and open-ended limitation of AI to encompass human situational awareness and reliably perform associative reasoning[10].** For this framework in which the pros and cons of robotic attributes reside and interact, we must fundamentally reengineer our brokerage and supporting risk management business models. Overriding all the robotic trait churn, we have a unique business requirement to continuously optimize the premium structure to reflect a clear characteristic, evident for each AVSP's AI-control product: Autonomous vehicle "safe driving characteristics" improve in a continuous, monotonic[11] trend (no regression).

To structure brokerage around this non-human, monotonic robotic driving trait we must first understand what operationally underpins improving Autonomous Vehicle safety. In that pursuit, we encounter the final and Tipping Point Paradigm Shift.

Reengineered Autonomous Vehicle Brokerage: Tipping Point Paradigm Shift

To achieve premium optimization consistent with the monotonically increasing safety trend broached above with respect to autonomous driving – with a trend however that differs by AVSP and respective vehicle -- we need to first fully understand the factors buttressing the paradigm shift and forcing the Tipping Point necessitating the fundamental re-engineering of brokerage and the totality of insurer risk management.

Forcing the Tipping Point

Autonomous vehicle AI control is estimated to require in the neighborhood of 1 Billion lines of computer instruction code[12] (LOC)! This is massive considering the Microsoft Windows operating system requires just 50 Million LOC.
The footnoted source stating 1 Billion lines of code may not be so surprising given other citations sizing the number of LOC *<u>executing just on the vehicle computer at 400-500 Million lines.</u>*[13] Hence, adding server and mapping database software makes the stated 1 Billion LOC seem quite reasonable.

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[10] Associative reasoning is the ability to handle "edge case" (dark brown and black swan) by reasoning from "life experience".

[11] Monotonic is a well-defined mathematical term meaning "always increasing or always decreasing". In our case and in the following discussion, monotonic means "always increasing/improving" – pauses are possible but never a decrease/regression.

[12] A further useful comparative code sizing: Self-driving cars will need around one billion lines of computer code – nearly 1,000 times more than the 145,000 NASA needed to land Apollo 11 on the moon. https://www.autoexpress.co.uk/car-news/106617/driverless-cars-will-require-one-billion-lines-of-code-says-jlr#:~:text=Self%2Ddriving%20cars%20will%20need,Apollo%2011%20on%20the%20moon.

[13] https://www.autonews.com/technology/automakers-rush-take-back-their-software-codes

The last piece of the paradigm shift puzzle is that even professionally produced code, upon release into operations, contains coding errors.

There are numerous different estimates given for errors per 1000 lines of code that could be used to estimate the total number of errors we should expect in an operational self-driving release – some as high as 50 errors per 1000 LOC.
A more conservative[14] code error estimation follows from:[15]

- 20% of total LOC is executable (hence we can remove from the total LOC sizing of code errors trusted components such as the Linux kernels).
- Assume a moderate rate of 10 errors per 1,000 LOC and scale that down by further assuming only a 10% chance that a given code error meaningfully changes this AI-control outcome
  ➔ Final estimate: 1 error per 1,000 LOC
- Based on the complexity and size of the AI-Control software, each coding error correction creates approximately 0.33 new errors elsewhere in the codebase

Doing the arithmetic, we get as our working assumption that in an operational setting we will face *per autonomous driving release **266,000** coding errors -- each with the potential of affecting, unpredictably and adversely, autonomous control and thereby creating a potential product liability accident event*!

The projected numbers of code errors in shipped AI-control logic, vehicle, and servers, are addressed by very large, post-ship staff who reacts to operational reports of “anomalies” and performs continuing test case error searching. A hundred code errors and more may surface per week that are ranked in severity/importance, corrected, and very carefully send “over the air” and remotely installed in respective AVSP installed vehicles.
Fixes, called code error patches (CEP), are pushed out to the AVSP fleet as quickly as operationally possible – because any unnecessary delay could lead to massive liability if a serious accident occurred that would have likely been avoided by an unnecessarily delayed CEP. Hence CEPs are sent out very frequently – at least several times a week when a new release is shipped.

[14] However, on the optimistic end since most AI Vehicle control coding will be new, complex, and real-time
[15] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4629271/

Disruption & Re-engineering in Brokerage & Consulting

Disruption and Re-engineering are very powerful concepts with respect to Business Revenue Stability and Planning. When we seek to make these concepts relevant to the case in point – Brokerage and Risk Management of autonomous vehicle liability – they manifest themselves as:

- **Disruption:** Current actuarial tools that depend on random sampling[16] and to a lesser degree on assumptions of Gaussian normal distributions will fail in their legacy liability assessment roles.

- **Re-engineering:** Almost every process step in the liability brokerage and risk management process flow is altered or fundamentally changed.

Disruption

In brokerage, regardless of the scale, the cornerstone requirement is to be able to generate on-demand for each individual vehicle an objective, statistical likelihood of liability occurrence over a given stretch of time.

Current actuarial statistical methods for "forecasting" future vehicle operator liability are based on "prior registered driver information". In technical jargon: via actuarial techniques, the prior information "captures and explains" the observed and measured variance present in the dependent variable[17] . An example is the conventional practice of forecasting driver liability (X, dependent variable) based on prior existing recorded data (Y, Z ... etc., independent variables) such as driver: *age, postal code, the record of traffic citations/accidents, mileage, education, socio-economic status, etc.* . Underlying the analytics of statistical forecasting is that all prior informational data was compiled from a homogenous, stable snapshot of reality via unbiased (i.e. random) sampling.

If any of the following conditions:

- unbiased random sampling performed on an assumed stable population,
- raw data homogeneity with variation following a Gaussian normal distribution,
- minimal skew (3rd moment around the mean) and kurtosis (4th moment around the mean),
- stability – no fundamental changes during the period of sampling and forecasting,

are not met, the statistical models thereby initialized, and their related actuarial forecasts of liability likelihood are WORTHLESS!

With Autonomous vehicles, there is no longer any prior (relevant human) data on which to predicate forecasting the likelihood of autonomous driving liability. This, however, is not yet the Disruptive

[16] The key disruption from which the rest follows

[17] The dependent variable is the term "X" on the left of the equal sign: $X = a + bY + cZ + \dots$. It is the term we wish to forecast statistically (explain its prior observed variations) via relevant prior data (Y, Z, ...etc. – Independent variables)

paradigm shift that transforms brokerage and risk management since we can replace the current brokerage dependence on inference from prior (human driver) data with autonomous vehicle dynamic performance data.[18]

Such vehicle dynamic performance data is currently collected in real-time during vehicle transit and is presently being used to improve actuarial forecasting in millions of human-controlled vehicles by a process called Usage-Based Liability Insurance. Hence, moving from forecasting liability based on driver profile data to vehicle dynamic performance data is not an invalidating exposure but rather a positive move.

Disruptive Paradigm Shift: Insurers & Brokers Unhinged

The disruptive paradigm shift that forces the transformation of Autonomous Vehicle insurance and brokerage processes/products, becomes apparent when we examine the unforeseeable consequences of "correcting computer code errors". Earlier in this section, we derived a moderate estimate of the number of software errors in the shipped AI-control software codebase, vehicle, and servers, of **266,000 errors**. Software error corrections, sometimes referred to as "code error patches" (CEP), for legal reasons, need to be dispatched as promptly as possible to each of the AVSP-installed vehicles in the field. Over-the-air update (like with smartphones and PCs) is used while errors detected and corrected in server resident codebase are directly patched during daily maintenance.

These coding errors, their detection, and correction are asynchronous and almost random, although we can assume more focus is given to modules directly involved in vehicle dynamic control.

The disruptive impact on brokerage results from the fact that for autonomous vehicles, driving characteristics will not only change/improve with periodic new software releases[19] but will likely individually improve as much, if not more, from some of the CEPs (made remotely and applied continuously via over-the-air or directly on the AVSP server.)
As we need to account liability-forecasting-wise for each error "CEP", it is important to keep in mind that every vehicle is likely to be affected differently and even the same vehicle's AI-control impact will differ with respect to its Usage-Based driving patterns encountered as mileage is accrued.

This asynchronous rhythm of frequent, but unpredictable changes in AI-control makes it statistically impossible to maintain a stable, unbiased data sampling environment as required to accurately compute the critical Gaussian normal statistics used in forecasting liability e.g., mean, variance[20], etc.– reflecting the sampled dynamic vehicle properties such as speed, acceleration, deceleration, etc.

Compilation of respective Gaussian Normal distributed statistics requires at least 30 – 50 sampling sessions of unbiased autonomous vehicle dynamic data (AVDP) sampling. However, during this required

[18] Dynamic aspects refer to measures of vehicle parameters: speed, acceleration, deceleration, rapidity of lane change, erratic driving -- as quantifiable by standard UBI Scoring algorithms
[19] https://insideevs.com/news/532664/tesla-fsdv10-released-closed-beta/
[20] Especially Variance will be adversely affected. This follows, since any AI- controlled vehicle performance change, due to Updates (Code error patches and new releases) will almost always be "positive improvement" with respect to safety.
Given this data trend-- variance over the period of time required for Gaussian statistics will be highly skewed – making statistical projections -- "unpredictably inaccurate".

random sampling window, each vehicle's AI-control codebase and ancillary server files will have been updated and altered more than a dozen times!

The lack of accurate autonomous vehicle dynamic statistics removes the cornerstone of brokerage liability forecasting[21], creating the Paradigm Shift Tipping Point, and the current driver/operator brokerage and risk management model implodes.

This figurative "implosion" becomes an end-to-end disruption of the total underlying brokerage statistical forecasting model because the ongoing injection of error correction patches, complemented with new release debuts, on any occasion may invalidate any prior collected autonomous vehicle statistical data. Doubling down on this disruption is that every patch or new release affects each autonomous vehicle's performance differently – and its prior collected statistical data.

Hence, in the evolving autonomous vehicle liability brokerage model, we need to also be able to optimize the premium structure while addressing liability "as if a vehicle's (surrogate) driver" may change at any time – invalidating all prior statistics. Current manual driving actuarial methods would not support premium optimization where the "skill behind the wheel" was influx – even more so where the "AI surrogate-driver" is a constantly evolving unknown property.

A Snapshot of the Insurer and Brokerage Business Transformation

When we consider how insurance is reengineered and how data aggregation and scoring are expanded in the process of addressing the many new facets of autonomous vehicle insurance, brokerage and risk management, it becomes clear that almost every aspect of the insurance business and actuarial risk management is affected. It will also become obvious that the re-engineered principles of operation play in favor of those insurers who proactively position themselves to uniquely leverage their products and processes to meet these paradigm shifts as a once-in-decades business opportunity.

The re-engineering of autonomous vehicle insurance, brokerage, and risk management closely links those services to AVSP data acquisition. Thereby autonomous driving liability risk management and associate actuarial activities become integral and dependent on a new genre of usage-based data acquisition and reduction/parameterization. Accordingly, the CMB solution and its unique adjuncts, seamlessly engage and enable First Movers to drive a favorable modus operandi with the AVSPs while driving advantageous teaming opportunities with legacy/new insurers[22] required to create a new domain of integrated end-to-end solution models.

The requirement that insurers consistently meet AVSP expectations of premium optimization and the potential to provide a quid pro quo for R&D and code-based maintenance overhead costs, provides First Movers with a renewed position to regain the "center of the board" in dealing with the critical mass AVSP customers.

[21] **Note:** Because vehicle dynamic data statistics as compiled on Usage Based criteria, the same error patch that makes a significant improvement for one vehicle may register no discernable change for another like vehicle.
[22] Since autonomous vehicle liability is largely a derivative of product liability i.e. INSA/UBPLI, many legacy product insurers may enter the Autonomous Vehicle liability space.

These are the fundamentals of a new business and revenue stream opportunity not seen since the post-WW2 personal auto ownership boom.

Re-engineering Liability Insurance, Brokerage, and Consulting

Continuous Micro Brokerage (CMB)

CMB and its associated new methodology for data acquisition and reduction are required when sampling AI -controlled vehicles. The ongoing R&D improvement for safety/performance as well as the associated codebase maintenance will require frequent remote, over-the-air updates and refreshes. Each such asynchronous alteration of the codebase can uniquely and unpredictably change the AI control characteristics of each self-driving vehicle on the road. This creates severe statistical problems that interfere with achieving accurate statistical sampling of autonomous vehicle dynamic data critical for actuarial risk management.

With new AI-vehicle control releases and the asynchronous, almost random timing with which software coding errors are fixed/patched, the AVDPs currently used to infer usage-based AI-control driving quality are potentially[23] in flux. This continuing, asynchronous flux in the AI control software creates a fundamental actuarial problem if we continue to base our data acquisition on standard Gaussian Normal statistical methods. During the 40 – 60 periods of autonomous driving that Gaussian models would require to be randomly sampled to converge to reliable mean, variance, and higher-moment estimates, well over a dozen AI-codebase changes will likely occur in any given vehicle. Each such update has the potential to alter the AI control characteristics and hence, in an autonomous vehicular world, the AI logic will be in flux[24] and not amenable to statistical characterization requiring long-term stability to enable random AVDP sampling. Attempting to do autonomous vehicle brokerage risk management while ignoring the ongoing codebase flux, would bias/distort the critical mean and variance and other Gaussian statistical parameter estimates[25]. In consequence Brokerage and Risk Management liability forecasting for autonomous vehicles using Gaussian statistical methods would prove too inaccurate for Brokerage pricing and critical asset risk management.

Hence, the CMB (Continuous Micro Brokerage) model makes recourse to "statistical filtering[26]" to address the analytical impacts of AI-controlled vehicle paradigm shifts.

CMB brokerage uses Filtering to rapidly converge to the respective AVDP to be used for UBPLI (Usage-Based Product Liability Insurance) and AADUBI (Assisted Autonomous Driving Usage-Based Insurance as well, for that matter, as well as any legacy techniques that the insurer may want to continue to use.

Filtering not only addresses the paradigm shifts resulting from codebase flux due to CEP activity and

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[23] The term "potentially" is used because we are assessing safe driving quality in a Usage Based framework. Therefore, not every CEP will may affect relevant aspects of the AI-Control in the region and manner of driving this vehicle is used.
[24] With every vehicle affected differently.
[25] Skew and Kurtosis respectively
[26] Risk management actuarial use of Kalman Filtering is common for "Liability Reserving" Forecasting and other statistical analytics going back to at least the mid-1980's

new function release system updates but also resolves and enables us to converge to each of the respective vehicle's AVDP values in an optimally swift manner.
By "optimally swift" we mean that by introducing Filtering we can actually "customize" our convergence to the current AVDP values based on introducing another channel of system status information, that offer pre-knowledge that directly adjusts Filter parameters so coincident new data input will converge to any AVDP changes within days, not months, of code changes. This is the core facility that enables CMB to reliably assert if AI-control alterations/improvements warrant a reassessment of each respective vehicle's liability premium rate structure.

Enabling an AVSP to assess premium savings versus the corresponding expenditures involved in AI-control R&D and codebase Quality Control is a major factor in assessing the efficacy of CMB. This dimension in CMB enablement of AVSP cost accounting and R&D and codebase Quality Control valuation represents a unique, bonus planning resource for competitive marketing.

The resulting new business opportunities reflect the core business benefits gained by First Movers having anticipated market changes and intercepted with creative re-engineering solutions AVSP's core requirements and internal cost accounting.

What is Data Collection Filtering and how is it applied to brokerage and risk management

The re-engineering of brokerage and insurer risk management starts by addressing the impact of codebase asynchronous updates that adversely affect the fundamentals of Gaussian statistical methods that to date are the backbone of current practice. To solve the problems of autonomous vehicles, Statistical Filtering is employed.

There exist several basic filtering techniques that meet the CMB requirements. The simplest approach is the well-known "Rolling Average" that can be adapted to perform Filtering. However, to provide fine-tuned control of CMB brokerage, we have chosen to adopt Kalman Filtering (KF). [27] (Figure 4)

KF is the most widely used method of Filtering in support of applications where the raw data, i.e. *AVDP input,* is embedded in a rapidly changing operating environment, e.g. *road traffic random encounters, and* subject to externally-controlled system flux:

- *asynchronous code error patches (CEP)*
- *firmware updates*
- *new system function releases*

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[27] At first blush, the literature on Statistical Filtering techniques may seem complex. In reality though, it has simpler data collection requirements and is more flexible than Gaussian based statistical methods of parameter forecasting. As a starting point, I recommend the below, brief (5 minute) videos. Together they show in simple terms and examples how one commonly used approach to statistical filtering -- Kalman Filtering –works and make its application to CMB more apparent.
https://www.youtube.com/watch?v=CaCcOwJPytQ
https://www.youtube.com/watch?v=tk3OJjKTDnQ

- *sensor driver updates/hardware upgrades—repair*
- *etc.*

Analogous to detecting and converging to a given AVDP value is the most widely used KF application: support for tracking fast-moving objects, like aircraft and missiles as they rapidly change their course and trajectories. The role of KF in re-establishing aircraft tracking after a course adjustment is fundamentally the same as re-estimating and rapidly re-converging to a vehicle's AVDPs after AI-control base code/sensor update induced flux[28].

There is also one important facet of CMB KF processing that differs from normative KF processing. This facility vests CMB with a convergence speed that can be assumed to be swifter than that of normative KF convergence – for our special case of re-establishing statistically accurate AVDP values after system flux. The CMB facility we will now discuss, Code Status Change (CSC), directly augments normative Kalman Gain to customize CMB convergence to reflect all information available to us surrounding the execution of each AVDP's related random sampling.

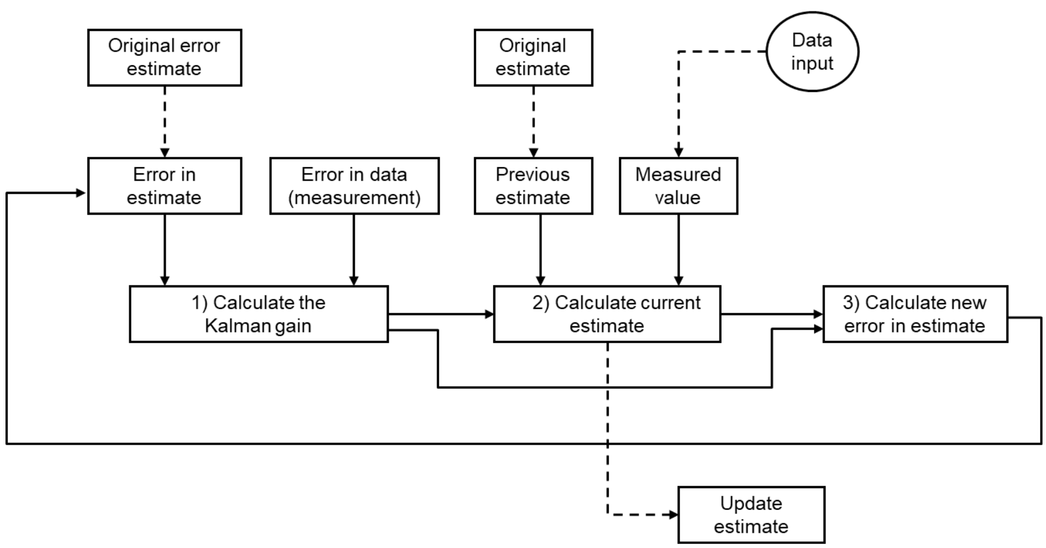

Figure 4: Normative Kalman Filtering Processing to Converge to a Parameter Estimate

Code Status Change Augmentation of Normative Kalman Gain

In normative KF, the relative "quality" of sample information that initializes the gain after each data sampling is derived from a ratio of respective variances commutated for Data Sampling(t) and its predecessor Data Sampling $(t-1)$.

The normative formulation of Kalman Gain: $\sigma_{Gain} = \frac{(\sigma_{t-1})}{(\sigma_{t-1}+\sigma_t)}$ directly governs the weight given

[28] In both applications we need to re-establish statistical forecasting integrity quickly after a "state-change" while receiving relatively few noisy/not absolutely precise data points.

respectively to Data Sample(t) versus Data Sample $(t-1)$ when the next KF recursive estimate of the target value is computed.

As outlined earlier in this document, integral to Kalman Filtering's recursive structure is a process step called: **"Kalman Gain". Kalman Gain is computationally adjusted as** each successive data point[29] is fed into the KF process. The Gain in normative KF contains our best assessment of the "quality" of the new data relative to at least the previous data point that entered the KF process and determines how much weight is given to all the previously computed estimates of the target value. This can be viewed as the computational weight given computational "memory".
The basic premise in the Kalman Gain formulation is that the lower a respective prior or current data sample variance is, the more reliable it is (i.e., the less noise it contributes to the converging estimate). Hence, according to the Kalman Gain (KG) value $(0 < KG < 1)$ it determines the weight of the newest data sampling in the next KF processing step. This Gain formulation has been shown in the literature to provide "optimal" convergence. Optimal convergence in the normative KF application sense means the fewest recursive passes through the KF before its output converges, statistically, to the subject sought value.

The literature discusses numerous specialized Kalman Gain formulations related to various statistical filtering applications. However, they all have a common computational structure whereby gain is computed from and meant to represent characteristics of the input data being filtered. In contrast, our CSC augmented KF gain (CSC/Gain) represents another information channel, separate from the numerical input being randomly sampled.
Hence, while CMB uses normative KF formulation, the Kalman Gain value is further adjusted reflective to code and system likely flux status by the addition of the CSC/Gain value.

The CSC/Gain maintains the normative Kalman Gain value (σ_{Gain}) computed from the respective AVDP(t) and AVDP $(t-1)$ data point random samples. The CSC/Gain now uniquely augments the σ_{Gain} value by infusing an additional channel of intelligence to bridge between prior filtered AVDP $(t-1)$ and the current filtering of AVDP(t) where the AVDP(t)'s data points were sampled after a flux likely occurred in the code and/or system base (i.e., code error patching, new code release, sensor update, etc.).

The underlying rationale of and the role played by the CSC-Gain is as follows:

- The CSC-Gain represents information from an independent, non-data-channel advising the Kalman calculation process (Figure 5) that the code/stem base has been updated
- We can reasonably assume that based on rigorous AVSP Quality Control and Testing, any newly introduced code patches or sensor updates will have a positive effect on AI-Control or no measurable change at all. Since we precluded regression, we can assume that the reported code flux results in a Monotonic trend of improved autonomous driving quality/safety.
- The use of KF allows convergence to AVDP values much faster than Gaussian statistical methods. By introducing CSC/Gain to augment Kalman Gain after a code/system update, the KF convergence is accelerated further -- so the *postcode*/system flux AVDP parameter values converge in days versus

[29] A "data point" is an AVDP value that has been compiled and computed from vehicle dynamic data while under AI-Control during a specified duration: e.g. 200 KM of accrued mileage.

weeks for Gaussian methods. We also know when AVDP values are stable enough for brokerage use or if a new flux has likely taken place

- The resulting CMB business model and enhanced profit potential follow from:

  ➔ The faster we can analytically converge and quantify remedial changes to AVDP values, the more expeditiously the AVSP customer set can classify the improved AI-Control versus their insurer's liability premium structure

  ➔ CMB compares the updated AVDP values against a premium re-optimization threshold for the respective autonomous vehicle that was previously negotiated between AVSP and Insurer.

  ➔ The AVSP can audit and reduce premium costs reflective of their R&D and Quality Control progress and investment.

  ➔ Considering the millions of autonomous vehicles per AVSP – the savings potential via CMB is enormous

Given the framework laid out above, the fundamentals of CSC/Gain and the Augmented Kalman Filtering follow directly as:

1. Kalman Filtering and Kalman Gain have well-known analytic properties that we need to retain.

2. When by the "information channel" we receive a signal from the AVSP of a codebase flux we proceed to adjust the [30] σ_{Gain} value computed for *AVDP(t) and AVDP(t-1) based on respective variance by now introducing a factor in the range of 25% for code changes and within the range of 30% for sensor hardware/firm update/upgrades.*

3. As CSC/Gain continues to adjust the value of Kalman Gain as outlined in 2. above, while at each time step AVDP(n) and AVDP(n+1), we perform Null Hypothesis testing to compare the respective means and variance between AVDP(n) and AVDP(n+1) data samples. When both Null Hypotheses are accepted at least two consecutive times, the CSC/Gain is turned off until new advice of code flux is received via the AVSP to CMB information channel.

   Alternatively, we can gradually scale back the CSC/Gain adjustment using the p-value of each sequence of Null Hypotheses to diminish the CSC effect on Kalman Gain as the AVDP (n) converges to the current value of AVDP.

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[30] The rationale and numeric range of the CSC/Gains adjustment of the Kalman Gain leverages on the properties of the Kalman Filter we are using being a continuous linear function – and that we keep within the analytic constrains of the Kalman Gain (i.e. the total σ_{Gain} remain Less Than or Equal to 1)
Increasing Kalman Gain weighting coincident with the ASDP advise of codebase flux due to code error patches etc. – enables AVDP(t) to more likely propagate forward in time and speed convergence to the current AVDP value.

4. The operational burden for respective AVSPs of transferring dynamic data on a respective vehicle basis to the Data Consolidator is negligible since they need to collect it in real-time for autonomous control. The data on code changes and new releases used by CMB/CSC is directly available from standard Quality Control management.

Complete details of all aspects of CMB and CSC/Gain are available in the related patent filings and will be made available upon request.

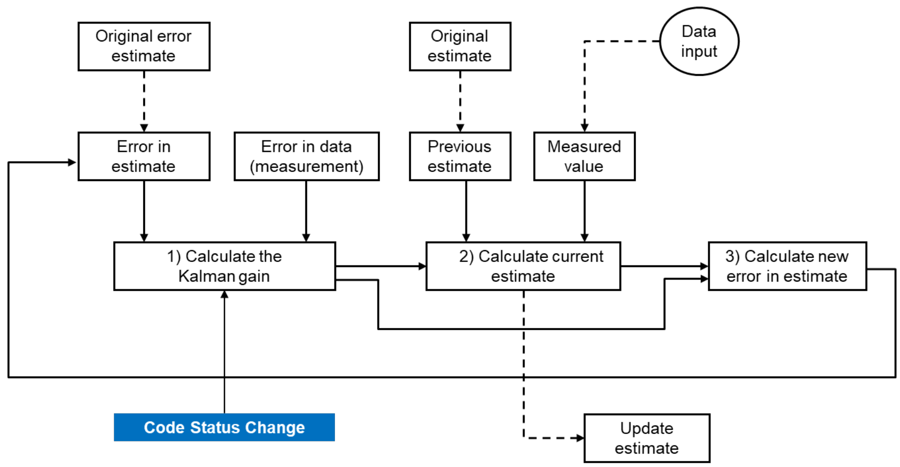

Figure 5: Kalman Filtering with Enhanced Convergence using Code Status Change/Gain Augmented Kalman Gain

The CSC augmented Kalman Filtering, is a cornerstone of the core CMB process. Both are IP protected and fit together in the process flow as shown in Figure 6.

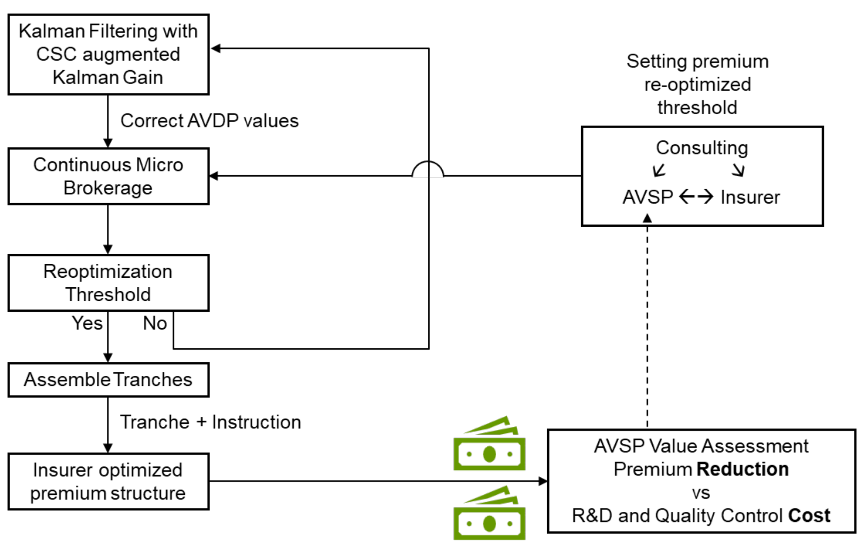

Figure 6: CMB Process Flow