INSA

AUTONOMOUS VEHICLE NAVIGATION
USAGE BASED PRODUCT LIABILITY INSURANCE

A New Autonomous Driving
UBI Derivative Insurance Product

Introduction

Autonomous driving has progressed beyond Silicon Valley hype into a real, if still nascent, part of the future automotive landscape.

Reflective of its still evolving status and capability, when the electronics and automotive players talk about autonomous driving, they categorize it into five incremental levels of complexity/capability as roughly shown in Figure 1. At present no electronics service provider or vehicle manufacturer is operationally even at Autonomous Level 1 operation, where the driver remains integral to safe operation even if at times able to disengage into "stand-by" status.

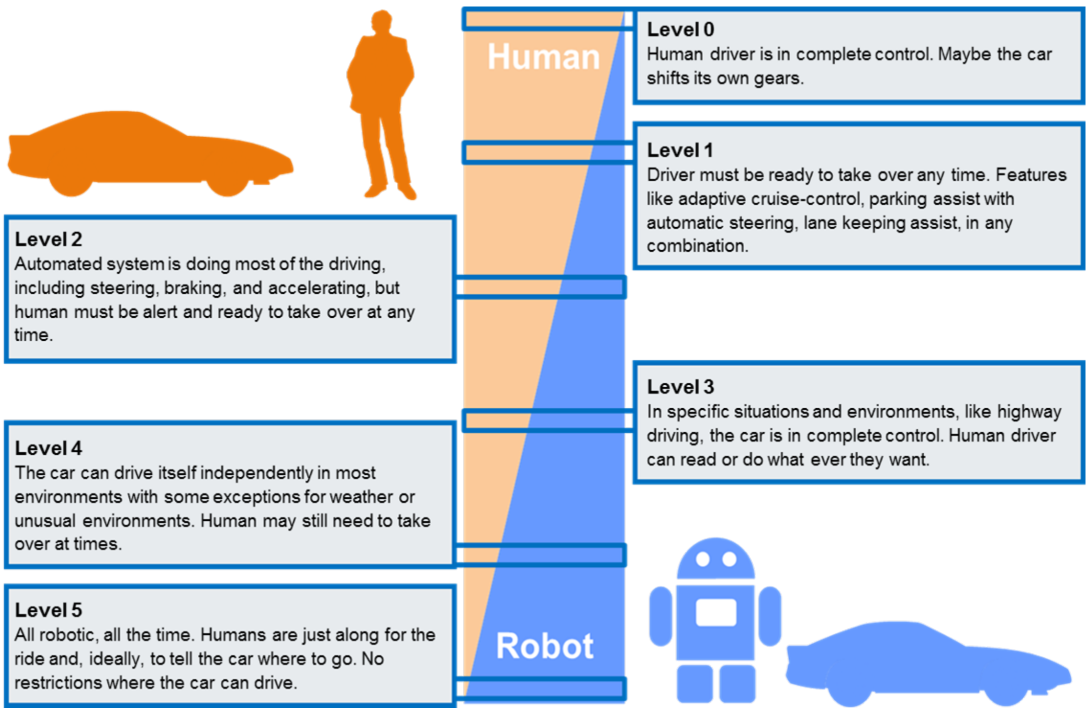


Figure 1: Levels of Autonomous Driving

However as each "Level" becomes an operational reality, the disruptive effects of autonomous vehicle operation will ripple further into allied areas beyond the vehicle systems: AI navigation logic, sensor technology, electronic map databases, vehicle networking -- into the more mundane, but increasingly critical enablers such a liability insurance coverage.

Even at this early stage in Autonomous Driving evolution, vehicle liability as "product liability" has become an agenda item in state and federal legislatures. Not surprisingly the California state legislative assembly has taken the lead (Figure 2 and Figure 3) in posing autonomously controlled vehicles as a separate, independent entity from the driver and under the legal product liability umbrella of the Autonomous Navigation Solution Provider. Accordingly, the California legislature has proceeded with legislation requiring a liability limit of up to $5 million per vehicle!
Given the pivotal role California legislature has played in crafting state and federal legislation in

vehicle emissions, air pollution and fuel economy standards, the above product liability rationale and indemnification limits need to be taken seriously.

California's vision for autonomous vehicles

If the car has no driver, then the driver can't be held responsible for accidents, so liability is likely to fall to the manufacturer of the self-driving car. So the new rules require companies deploying self-driving cars to demonstrate they have the ability—either through insurance or their own financial resources—to pay out judgments of up to $5 million in case of a crash involving their vehicles.

Driverless cars need to comply with state and local driving laws, and the new regulations require automakers to certify that they will be able to promptly update car software as those laws change. If the car is sold to a customer, the car company has to make the updates available. But the customer is responsible for making sure the updates are applied.

For vehicles that are sold to customers, manufacturers must explain how they plan to train customers on the safe operation of the vehicle.

Most experts expect early self-driving software to only operate in certain environments, *e.g.*, on pre-mapped roads and only when there's no snow on the road. Fully self-driving cars—defined as "level 3" or higher in industry jargon—will need to either hand control back to the human driver or pull over to the side of the road and stop in unapproved environments or situations. California's laws require manufacturers to describe how their cars will handle these kinds of situations.

Figure 2: Press release, California Legislative Formula for Autonomous Vehicle Liability https://arstechnica.com/tech-policy/2017/10/heres-how-california-plans-to-regulate-driverless-cars/?amp=1

The following discussion details how we use the INSA Quality Metric UBI platform to develop an actuarial framework that will enable insurers to offer Usage Based Product Liability Insurance (UBPLI) for autonomous vehicles. This will uniquely position insurers to offer a cost effective autonomous driving liability coverage to the Solution Providers based on rating how each individually equipped vehicle is autonomously driven on a monthly basis – analogous to UBI manual driving.

Because the Autonomous vehicles AI package will by necessity be constantly updated with code error corrections and improved algorithms, its driving effectiveness will be constantly changing which, in turn, will dynamically affect driving quality/safety. Hence the ability to make the UBPLI rate setting dynamic is a further key attribute for creating a powerful new UBPLI product.

California axes self-driving car rule that would limit product liability in crashes

Sub-par maintenance won't let automakers off the product liability hook

California has been happy to tweak the rules to get more self-driving cars on the road, but it still has its limits. The state's DMV has eliminated a planned rule (suggested by GM) that would have let companies avoid liability for an autonomous vehicle crash if the machine hadn't been maintained to manufacturer specs. In other words, they could have been let off the hook if your car's sensors were muddy, even if an accident was really due to bad code. The DMV ditched the idea after reading comments objecting to the potential rule. The comment period ends December 15th, and the completed regulations should take effect sometime in early 2018. California's change of heart doesn't amount to a sudden crackdown on self-driving cars, but it does reflect an evolving approach where it's not quite so willing to give brands everything they want. This might also help settle the ongoing questions about liability in driverless car crashes. If owners are less likely to be blamed for accidents, automakers may be more cautious with development in order to avoid paying for costly mistakes.

Source: Associated Press via www.engadget.com

Figure 3: Press release, California axes self-driving car rule that would limit product liability in crashes

The INSA UBPLI focus on liability rate setting by individual autonomous controlled vehicle with periodic rate update to reflect changes in driving quality/safety; ensures the insurer's ability to market the UBPLI product with highly competitive pricing to the Autonomous Navigation Solution Providers and maintain an actuarially sound business case. This contrasts with the alternative of offering the Autonomous Navigation Solution Providers an undifferentiated, blanket liability policy with no differentiation by vehicle autonomous usage profile.

Hence using INSA UBPLI, insurers can provide coverage through the Autonomous Navigation Solution Providers (e.g., Google, Apple, Intel etc.) to each of their autonomously controlled vehicles at a liability insurance rate reflecting the navigational challenges of its usage and the AI effectiveness that is being affected by the Service Provider's package in actual operation.

Being able to actuarially address each vehicle's autonomous safety rating at a micro-level, instead of a macro-level blanket policy, provides lower risk for insurers at lower rates to the Autonomous Driving Solution Providers than a "one-size-fits-all" blanket policy.

We now proceed to explain how this is accomplished.

INSA Usage Based Product Liability Insurance (UBPLI)

The following discussion of UBPLI assumes some acquaintance[1] with the INSA Driving Quality Metrics:

1. Speed Metric
2. Acceleration Metric
3. Deceleration Metric
4. Erratic Driving Metric

Basic to INSA autonomous UBI is that the vehicle when operating at levels: 2-5 -- of autonomous control is considered as a surrogate driver just like INSA would treat any additional insured human driver.

For each episode of Autonomous Driving we collect and log the data related to the four INSA Driving Quality Metrics listed above[2]. For brevity, in most of the following discussion we will imply, by mentioning “Driving Quality Metric” or in more specific process examples “Speed Metric" -- all four INSA Driving Quality Metrics. Also implied, but not shown, is that each of the four INSA Driving Quality Metrics listed above is separately compiled relative to the mileage accrued by locale: **Urban, Rural, Highway.** Hence, there are a total of 12 Driving Quality Metric entries that specify a vehicle in the following discussion and they are implied whenever we refer to “Driving Quality Metrics” or in specific process flow examples by Speed Metric.

The challenge we address is how we go from an INSA Quality Metrics methodology that allowed us to rank “manual” safe driving in relative terms for premium rebate, into individual, autonomously driven vehicle accident event “likelihood”. Jumping ahead a bit – we are addressing how we take a set of autonomous vehicle Driving Quality Metrics and reconstitute them into an **Expected Accident Frequency** – e.g., 75,000 kilometers – that becomes the basis for an actuarially sound, individualized fee structure that differentiates between autonomous vehicles based on how they are driven and the implicit autonomous navigation challenge they face in their individual driving environments.

[1] If the INSA Driving Quality Metrics are new to the reader or the reader requires a refresh, documentation is available in the previously sent document entitled: ***INSA – Technology for Usage Based Insurance***

[2] The UBPLI “surrogate driver” and its related INSA Driving Quality Metric capture risk of the driving performed under autonomous control and from the unanticipated events when the autonomous system defaults to the human driver

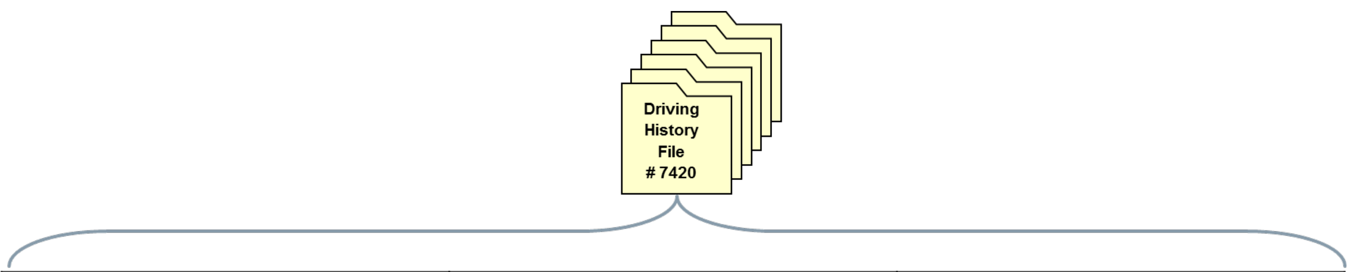
The Usage Based Product Liability Process

Step 1

Even with respect to levels 1 and 2 Autonomous Driving we are several years away from where their use becomes an established fact.

Hence, as Step 1 of UBPLI we use this operational buffer time to compile for each Quality Metric an **INSA Driving History File**.

The INSA Driving History File per Figure 4 simply contains for each UBI[3] insured vehicle (under manual control) the record of its monthly Driving Quality Metrics values. Accordingly, we thereby have for each INSA insured vehicle and for each of the respective Driving Quality Metrics a distribution curve describing the values generated and reported (for UBI purposes) over the last few years.



Urban				Rural				Highway			
Serial number	Driving Quality Metric Distributions	Average value	DAR vehicle accident history	Serial number	Driving Quality Metric Distributions	Average value	DAR vehicle accident history	Serial number	Driving Quality Metric Distributions	Average value	DAR vehicle accident history
# 7420	Speed	1.7	DAR: 72,000	**# 7420**	Speed	2,5	DAR: 72,000	**# 7420**	Speed	6.3	DAR: 72,000
	Acceleration	3.6			Acceleration	4.0			Acceleration	12.9	
	Deceleration	5.7			Deceleration	2.1			Deceleration	4.0	
	Erratic Driving	10.1			Erratic Driving	12,0			Erratic Driving	18.7	

Figure 4: General Content of Records in INSA Driving History File

Also for each vehicle in the INSA Driving History File and corresponding to its Driving Quality Metrics, several heuristics such as **Driving Accident Rate** (DAR) -- i.e., number of miles per accident event -- associated with this vehicle and its history of Driving Quality Metrics.

In the next UBPLI steps we use this INSA Driving History datum (Figure 4):

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[3] **IMPORTANT NOTE:** The UBI measurements being referred to herein can be the result of any Usage Based insurance methodology or even ad hoc collection of respective driver UBI data as covered in related patent filings. For specific details of INSA UBI and Driving Quality Metrics we refer the reader to http://www.imageautomationltd.com/insa/documents/INSA UBI Privacy and Driving Quality Metrics.pdf
However, implementation of UBPLI is not restricted to use of INSA UBI data.
In the remainder of this document we use the term, “INSA” as part of data and file labels rather than to restrict the domain of UBPLI implementation and/or intellectual property.

- Serial number manual UBI Driving History folder
- Respective Driving Quality Metric Distributions
- Respective average value of each respective Driving Quality Metric Distribution
- DAR vehicle accident history

to derive an Expected Accident Rate for individual autonomously driven vehicles.

Step 2

With the advent of autonomous driving, each such vehicle, when under AI control, will have its driving dynamics quantified as Driving Quality Metrics that are identical computationally with those compiled when under INSA Manual UBI. In operation however, the Autonomous Driving – Quality Metrics are of course separately complied as if they belonged to a surrogate authorized driver – who just happens to not be totally human.

Note: Hence from its outset UBPLI uses and is predicated upon the INSA manual driving UBI platform's Quality Metric algorithms and operational data.
Accordingly, UBPLI is integral to and protects current manual INSA UBI investment.

Although it is not discussed further in this note, since their UBPLI processing is identical, we also compile Driving Quality Metrics by Autonomous Driving "Level", as the driver may opt at times for more or less hands-on involvement. Hence what follows in Steps 2-4 will be repeated for each Autonomous Driving Level that has been driven during a report period to provide separate liability rates to the Service Provider by individual vehicle autonomous level usage.
All the above is inferred as we continue to discuss Autonomous Driving Quality Metrics

We proceed in Step 2 to compute the Autonomous Driving Quality Metrics – and let's say come up with a value for the autonomously driven Speed Metric for Locale: Urban of **2.5 kmh**.

Step 3

Per Step 2 we now use this value; 2.5 kmh as an index into the INSA Driving History File. The corresponding match is examined for its "Driving Accident Rate", let's say: **72,000** km/event.

It is now important to recall that in the INSA Driving History File, each vehicle's record consists of several years of monthly or quarterly Driving Quality Metric scores. (Figures 4 and 5).

Since computationally each of these "historic" Driving Quality Metrics is actually an "averaged value" of individual journey Driving Quality Metrics events over a reporting period, according to **Central Limit Theorem** the resulting distribution of "averaged random variables" is a Normal Distribution.
This result follows even though the related initial raw data values -- the original event distributions -- was <u>not</u> a Normal distribution – as is the likely case with Driving Quality Metrics.

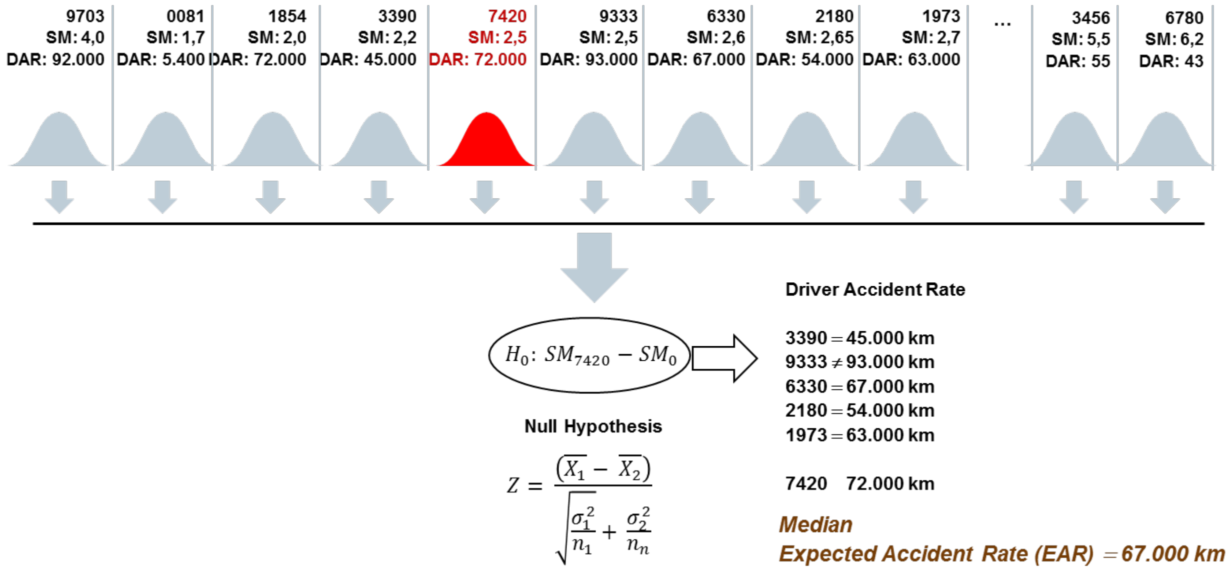

Figure 5: Using the INSA Driving History File to associate a cluster of like records based on indexing of Record 7420 using the autonomous Speed Metric value of 2.5kph

Step 4

Since the **INSA Driving History File** contains normally distributed data representing the respective histories of Driving Quality Metrics, we can now return to our example of having indexed into the **INSA Driving History File** with the Autonomous Driving Speed Metric value (i.e., 2.5 kmh).

Per Figure 5, we access the **INSA Driving History File** *ordered by Speed Metric* and collect for further statistical testing those vehicle history Records (e.g. 3390, 9333, 6330, 2180, 1973) each denoted by an average Speed Metric values (manual driving) close to the 2.5kmh autonomous Speed Metric value that matched the (average manual) Speed Metric associated with Driving History Record 7420.

Each Driving History Record respectively contains, as depicted in Figure 5, the average Speed Metric value and the related distribution of Speed Metric values recorded by reporting period. This record of Speed Metric values creates a Normal distribution per the Central Limit Theorem and hence is amenable to Null Hypothesis testing.

We can now proceed record by record in the **INSA Driving History File** to assess via Null Hypothesis testing how broad a set of adjacent records can be associated with the Speed Quality Metric value computed from the autonomously driven vehicle for which we are trying to establish an **Expected Accident Rate**. We proceed by examining record by record the Quality Metric (in our example

Speed Metric) distributions in the INSA manual driving records adjacent to our starting point (Record 7420) of Speed Metric: 2.5 kmh.

We proceed systematically via Null Hypotheses Testing as depicted in Figure 5 using the below formulation which accommodates the respective Speed Metric (Normal) distributions having different variances $\boldsymbol{\sigma_1^2}$ and $\boldsymbol{\sigma_2^2}$:

$$Z = \frac{\left(\overline{X_1} - \overline{X_2}\right)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_n}}}$$

$\overline{X}_1$ is the average Speed Quality Metric of the Driving History Record #7420 that we accessed because it matched the autonomously driven vehicle's Speed Metric: 2.5 kmh.
$\overline{X}_2$ is the corresponding average Speed Quality Metric value from an adjacent Driving History Record that we are successively examining via Null Hypothesis from the **INSA Driving History File.**
$\boldsymbol{\sigma_1^2}$ and $\boldsymbol{\sigma_2^2}$ are the corresponding variances computed from the driving history record's Quality Metric distributions compiled and stored in the INSA Driving History File from numerous prior manual driving UBI reporting periods. $\mathbf{n_1}$ and $\mathbf{n_2}$ are the respective number of data points involved.

Step 5

Returning again to Figure 5 we see five of the six historic driving records examined pass the Null Hypothesis test and we proceed to lift from them their respective Driving Accident Rate values. Having now expanded our initial Autonomous Speed Metric match on Driving History Folder #7420 to a cluster of Null Hypothesis like-related folders gives us a broader, more stable sample from which to compute the Expected Accident Rate.

The Expected Accident Rate will be associated with the autonomously driven vehicle that yielded the Speed Metric (2.5 kmh in our example) for which we will associate from historic driving data an accident likelihood to then be used for individual vehicle actuarial UBPLI purposes.

We call this accident likelihood the **Expected Accident Rate.** We compute Expected Accident Rate as the "median" of the respective Driving Accident Rates lifted from the INSA Driving History records that passed Null Hypothesis testing centered on the Speed Metric distribution in Driving History Record #7420.

We use the median value as the Expected Accident Rate and not the "average" to avoid the chance of being led astray by an anomalous Driving Accidents Rate such as a reckless driver who just "lucks-out" and never has an accident or a very good driver who just makes a bad move.
Taking the Median Driving Accident Rate from the records that passed Null Hypothesis testing hence tends to give a more reliable, stable expected value that discounts chance accidents or high-

risk drivers who somehow maintain good driving records.

Step 6

From Step 5 we see the process flow whereby we have:

1. an autonomous driving generated Quality Metric
2. envisioned the autonomous controlled vehicle's AI package as a surrogate driver,
3. mapped the autonomous driving generated Quality Metric (in the example: Speed Metric of 2.5 kmh) to a like valued record in the INSA Driving History File
4. proceeded to associate with the like valued record a cluster of other statistically matching records in INSA Driving History file
5. taken from each matched record its Driving Accident Rate value
6. computed the Expect Accident Rate as the median of the Driving Accident Rates values taken from the clustered records.

This gives us per the example in Figure 5 an Expected Accident Rate of 67,000 km/accident that represents a vehicle driven with a Driving Quality Speed Metric of 2.5 kmh.

However as mentioned earlier we will have at least twelve Driving Quality Metrics generated over an autonomous driving reporting period:

- Urban
  - Speed Metric
  - Acceleration Metric
  - Deceleration Metric
  - Erratic Driving Metric

- Rural
  - Speed Metric
  - Acceleration Metric
  - Deceleration Metric
  - Erratic Driving Metric

- Highway
  - Speed Metric
  - Acceleration Metric
  - Deceleration Metric
  - Erratic Driving Metric

Each of the above twelve Driving Quality Metrics will have also been indexed into the INSA Driving History File and thence mapped to an Expected Accident Rate as detailed above.

Our final UBPLI step to assimilate these individual Expected Accident Rates into a single "Operational" Expected Accident Rate. The **Operational Expected Accident Rate** represents the actuarial risk over all locales as captured in this array of Quality Metric values (listed above) for a given vehicle while driven under Autonomous control. The Operational Expected Accident Rate can then be used by the insurer's actuarial processing to statistically project a specific liability tariff rate by individual vehicle to be billed to the Autonomous Vehicle Navigation Service Provider reflecting where and how the subject autonomous vehicle performed.

The assimilation of the above array of 12 Driving Quality Metrics and their associated Expected Accident Rate values into a single actuarially relevant Operational Expected Accident Rate starts by recognizing that the four Driving Quality Metrics compiled respectively by locale: Urban, Rural, Highway – are largely independent markers of accident propensity.
That is for example – a good Speed Metric value for a given vehicle can frequently be associated for the same vehicle with a high-risk Deceleration Metric value[4]. Hence, in this example, the occurrence of an [5]accident is more likely to be associated with events connected with this vehicle's Deceleration and the Deceleration Metric becomes the marker most likely to be associated with an accident.

Since accident liability is incurred when any of the driving activities, measured as Driving Quality Metrics, triggers a chain of events that results in an accident, we proceed for each locale to focus on the autonomous driving generated Quality Metric that indicates the highest accident risk.

Hence by locale: Urban, Rural, Highway -- we select the respective Quality Metric value indicating the highest risk and its associated Expected Accident Rate.
We do the same for each locale so we now have three Expected Accident Rates – one per each locale. (Figure 6)

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[4] As we have discussed, AI vehicle control will likely from the outset be very good at achieving "very safe" Speed and Acceleration Metric values as they are aspects of vehicle dynamics that can be specified a priori as clear limits. AI then proceeds "mindlessly" to stay within these pre-specified limits.
In contrast, for the Deceleration and Erratic Driving Metrics, where the key event triggers are external, uncontrolled events such as caused by interaction with other vehicles, AI control, especially in early years will be problematic in many instances and reflected lower safety scores.
It is these autonomously generated "lower safety" Driving Quality Metric scores that are the focus for formulating the Operational Expected Accident Rate.

[5] This is relatively easily done by reverting to the details given in ***INSA – Technology for Usage Based Insurance*** section *Monetizing Quality Metrics into Rebates* – where the accident risk of a given Driving Quality Metric value is apportioned by its relative position under the distribution curve of like Driving Quality Metrics.

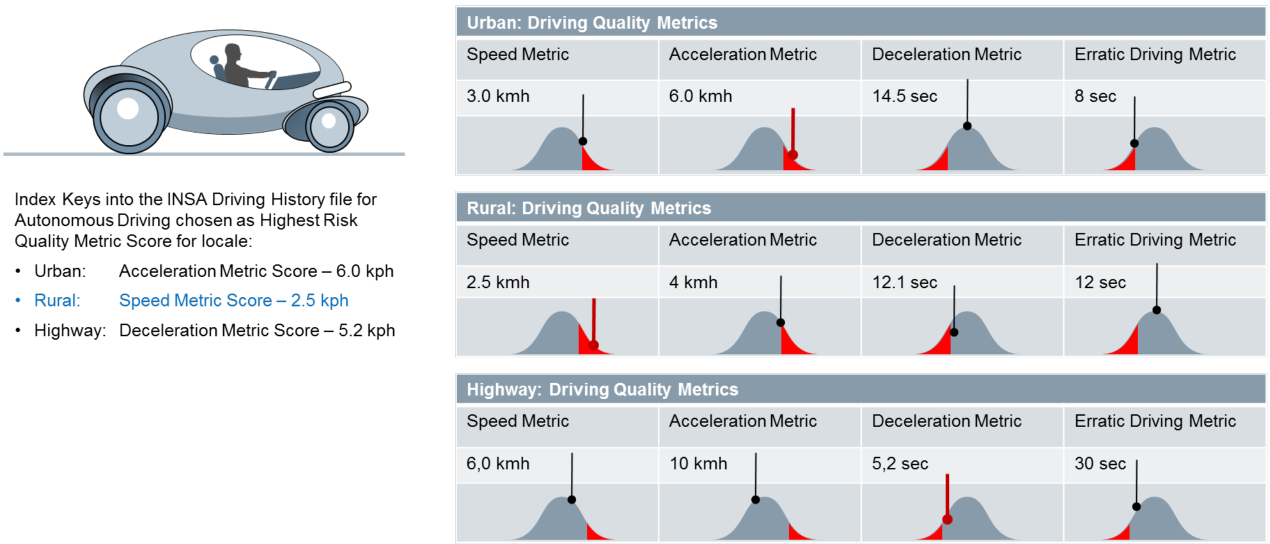

Figure 6 Autonomous Vehicle Quality Metric Scores; Points into INSA Driving History File

The Operational Expected Accident Rate (OEAR) now follows as a weighted average by taking the percentage of autonomous driving miles accrued by locale – denoted: $\%_{Urban}$, $\%_{Rural}$, $\%_{Highway}$ and combining them to create a weighted average with corresponding Expected Accident Rates by locale -- denoted: EAR_{Urban}, EAR_{Rural}, $EAR_{Highway}$.

The Operational Expected Accident Rate to be reported for actuarial conversion into an UBPLI premium follows as:

$$\mathbf{OEAR = \%_{Urban} \times EAR_{Urban} + \%_{Rural} \times EAR_{Rural} + \%_{Highway} \times EAR_{Highway}}$$

Figure 7 shows an overview of the UBPLI process.

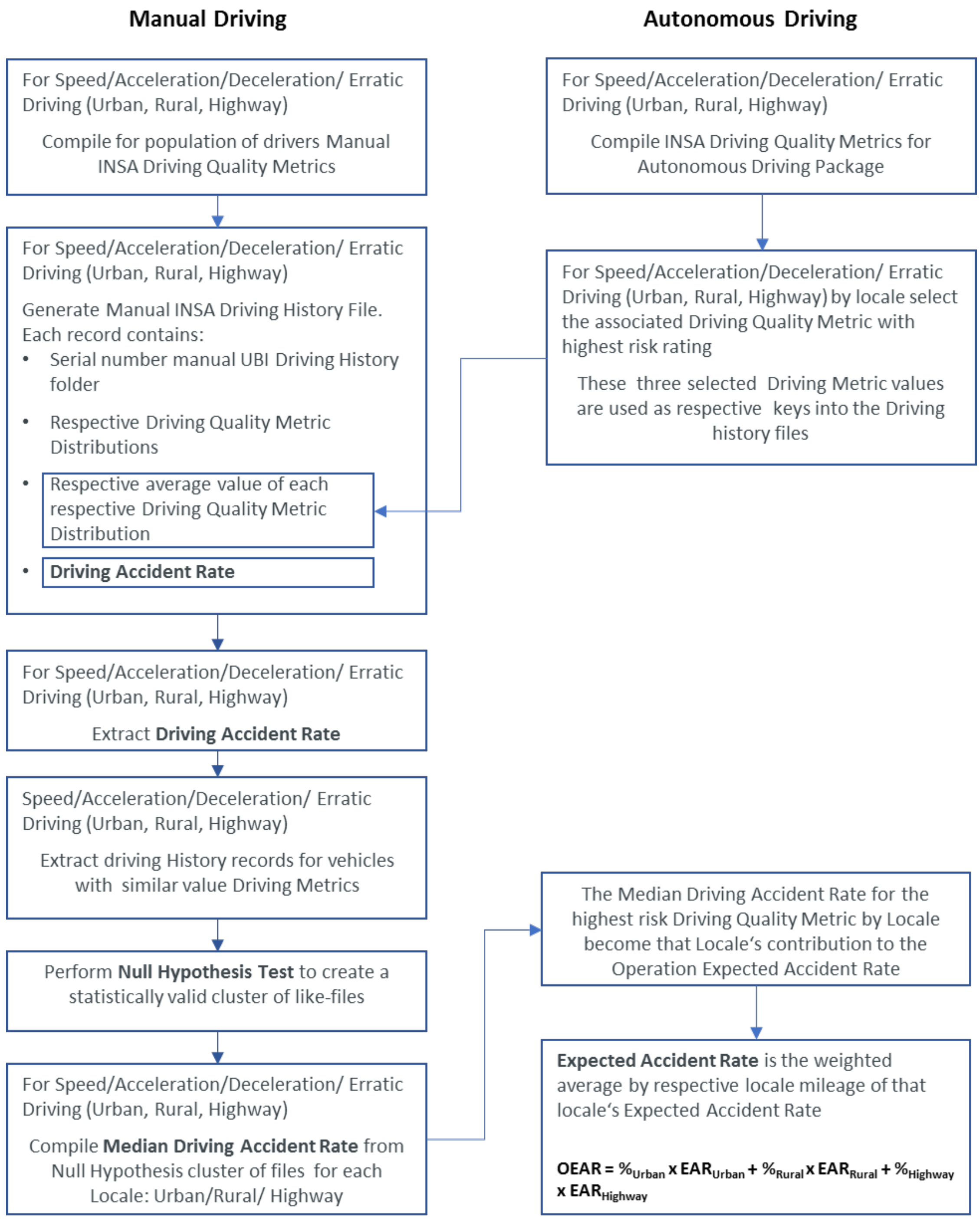

Figure 7: UBPLI process overview