Cracking the Mobile Code

Best Practices for a Mobile Telematics Program

2019
Now that we’ve moved to mobile telematics, usage-based insurance is poised for widespread adoption.
Owned by 81% of U.S. adults, smartphones are pervasive and they don’t require costly technology or inconvenient installation. 1

Customers also prefer using their smartphones to collect driving data. When one of the largest auto insurers offered customers the option of providing telematics data via a device or a smartphone app, more policyholders chose the app. With a mobile telematics program, insurers can connect with customers and provide immediate feedback on safe and unsafe driving habits.

Perhaps more importantly, while OBD-II devices can verify vehicle mileage and do a good job detecting speeding, hard-braking, aggressive turns and the time of day that a vehicle is driven, device-based data can’t tell you who is driving the car during different trips. You also won’t know if the driver is sending texts at 65 mph or checking a navigation app at a red light. Mobile devices capture meaningful driving behavior for individual drivers, including distracted driving, which causes almost one in 10 fatal crashes. 3

By using a mobile telematics program to leverage the predictive power of driving behavior Arity has found you can improve the loss ratio by more than 50% on the highest risk drivers and improve retention on less risky drivers. But the success of a telematics program depends on the degree to which the rating plan and the models on which it is based reflect actual driving behaviors, the risk that those behaviors will cause an accident, and the actual cost of claims, accounting for the impact of both frequency and severity.

This may sound obvious, but it’s not easy. Before you can accurately model driving behavior, you have to discern meaningful information from a chaotic mass of mobile sensor data. To define the aspects of driving behavior that best predict future insurance losses, you need to match a large volume of insurance claims to data collected from smartphone sensors. Shortcuts that attempt to get around these challenges — such as using OBD-II data for modeling instead of mobile data, or using modeled collisions instead of actual claims — just don’t work, and, in fact, they can make things worse. For example, an analysis shows that incorporating telematics rating based on proxies for accidents instead of actual claims will make your rating plan less accurate than using traditional rating factors alone. 4

Auto insurers have spent the last two decades investing millions of dollars to increasingly refine algorithms for segmenting and pricing risks with greater degrees of granularity and accuracy. Mobile telematics holds the promise of improving profitability by, among other things, producing even more accurate insurance rates and providing feedback that helps customers develop safer driving habits, with the ultimate goal of reducing losses. But as with risk segmentation, even small mistakes in models for driving behavior can have costly consequences, including mispricing that could lead to adverse selection, poor retention and regulatory pushback.
Despite the challenges, it is possible to crack the code on accurate pricing based on driving behavior with mobile telematics. We believe the seven tenets outlined in this whitepaper are key.
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Collect high quality mobile telematics data

There’s a reason insurers are just beginning to realize the promise of mobile telematics data: it’s hard to get it right. If the goal is to accurately match rates with risks, you need large volumes of high quality, richly detailed mobile telematics data and a large volume of claims data matched to those trips. Doing it right also requires a relentless commitment to research, testing and ongoing refinement to ensure you can:

- distinguish benign phone movements from risky driving behaviors
- analyze the context in which those behaviors occur
- recognize which behaviors result in accidents and insurance claims
- ascertain both the frequency and severity of those claims by matching mobile telematics data with actual loss data

Fundamentally, a model is only as good as the data fed into it. Collecting high quality mobile telematics data poses a significant challenge, particularly at the level of detail required to isolate risky driving behaviors and the context in which they occur. Managing the collection of massive amounts of data is one issue; the bigger issue is that unlike data from fixed telematics devices, sensor data captured through a smartphone is messy and difficult to decipher.

Continuous collection of GPS and other sensor data (from accelerometers, gyroscopes, magnetometers, mapping and navigation systems, etc.) provides information about driving behaviors and contextual information about the conditions under which they take place. But to benefit from this information, you have to find ways to mitigate constraints in the smartphone itself.

Avoiding the Drain
You need a balance that allows you to capture all the data required to detect driving behaviors and contextual information, without putting an unnecessary drain on the smartphone battery or eating up the driver’s cell phone data plan. Customers will reject an app that consistently drains their phone battery or requires a more expensive data plan. They also will reject an app that doesn’t adequately explain how it’s using and protecting their data.
Imperfect GPS Data
While mobile phones generally have more accurate GPS than OBD-II devices, variable GPS accuracy remains a data-quality concern. GPS-enabled smartphones are typically accurate to within a 16-foot radius under open sky, but accuracy gets worse near buildings and trees, where signals could be blocked. A robust mobile model will account for imperfect GPS data that can make it difficult to capture crucial information about when trips start and end. Mistakes identifying trips starts and stops will interfere with the ability to detect whether the person is driving or using other modes of transportation, such as traveling by bus or train.

Operation System Differences
The models also must account for discrepancies between Android and Apple operating systems, which have fundamental differences in sensors, clock timing and activity recognition. Modelers need to look at discrepancies in key performance indicators to identify differences as well as perform an analysis of the residuals to ensure there is no unfair discrimination in driving behaviors captured due only to the type of phone a driver uses.

Operating system version changes can also have an important impact on data quality. In one example, a change from iOS 10 to iOS 11 produced an anomaly in recording speed that incorrectly showed drivers moving at race car speeds. This kind of glitch, if not addressed proactively, will not only rattle the confidence of customers but also produce inaccuracies in the models. You have to be vigilant about new releases and quickly identify and respond to anomalies.
Models should be built upon credible, sensor-specific data

To be credible, a risk-based algorithm must be based on a large volume of high-quality, sensor-specific data reflecting millions of trips and billions of miles driven. This allows you to best identify the predictors of driving behavior, calibrate new variables and respond as factors change.

Telematics variables and associated relativities must reflect the data being sourced, or your policies will be mispriced. If you are using a telematics program that relies on an OBD-II device, the model should be based on data gathered through a fixed device and claims based on those trips. Likewise, for a mobile telematics program, the data in the model should be based on telematics gathered through a smartphone app and claims associated with those trips.

Given the longer experience with fixed telematics devices and the challenges in modeling with mobile data, it may be tempting to base a mobile telematics program on data from OBD-II devices. Doing so, however, can produce significant mispricing that even good normalization can’t correct for. Using device data also precludes the use of highly predictive distracted driving data.

Mismatch in Loss Cost

Arity conducted an experiment creating a loss model for a mobile telematics program that relied on OBD-II device data and compared the results of the predictions based on the mobile data to actual losses. The model using device data overestimated loss costs on high-risk customers and underestimated loss costs for low-risk customers. Furthermore, the rank order of customers within some driving behavior variables were different.

One reason for the mismatch is that the type and quality of data provided by OBD-II devices and mobile sensors vary greatly. While the fixed devices provide data about the vehicle and all its drivers, sensors in smartphones capture the behavior of an individual driver. Different types of sensors also collect data in different ways, resulting in variations in reported behaviors. For example, while both OBD-II and app-based sources can identify common variables, like speed and rate of change in speed, there will be differences in reported behaviors by virtue of the way each source collects these features.

Building a model on device data and using it for mobile programs leads to inaccurate predictions and doesn’t account for phone handling.
TENENT THREE

An insurance risk model based on modeled collisions instead of insurance losses will destroy the effectiveness of your rating plan

For driving behaviors to accurately predict losses, it’s not enough to determine if an accident could have happened. Rather, you need to know if an accident did occur, if a claim was filed and the cost of that claim. This requires you to attach rich loss data to your telematics data.

Loss-based models are significantly better at achieving rate plan accuracy than models that rely on proxies for claims based on simulated accidents. In fact, proxy-based scores can actually make rating plans less accurate than if driving behaviors weren’t counted at all.

Proxies Are Less Predictive
Arity research shows that proxies for accidents, such as extreme rates of deceleration, may be adequate for segmenting the highest- vs. lowest-risk drivers, but they are not accurate enough to establish rating factors within broad segments. Incorporating the results from the proxy-based score into a rating plan made it nearly five times less predictive of loss than a rating plan without a score (Figure 1).

There are several reasons for this, but one stands above the rest: simulated accidents are a poor proxy for loss. It is difficult to identify true collisions, especially those at lower speeds, and the signal from these proxies cannot discern whether the accident resulted in an insured claim or how expensive that claim was. While behaviors demonstrated through a simulated accident could lead to a loss, they can also show as behaviors that were used to prevent one. If simulated losses are created through hard braking, then the correlation between “accidents” and hard braking will appear to be 100%. This statistical fallacy will override many valid interactions.

Furthermore, a collision frequency that is four times higher than average does not translate to a four times higher propensity for loss. The loss data suggests that the propensity for loss may be higher than average, but it is much less than the proxy-based model indicates. Consequently, proxy-based scores can result in premiums that overcharge these policies, and a policyholder with a very low predicted collision frequency would be undercharged.

Don’t Ignore Severity
The most important factor that you miss when models use a proxy for collisions instead of actual claims data is the cost of the loss. A telematics loss model that cannot accurately account for severity will result in a much larger spread in indicated relativities than is truly warranted.
No Fix for Proxy-based Scores
Could a more sophisticated proxy-based score ever be good enough? Probably not. Since the simulated proxy of extreme braking destroys the effectiveness of the rating plan, it’s hard to imagine how any proxy-based score could make up enough ground to be better than a model derived from actual losses. To “fix” proxy-based scores would require a credible volume of loss data associated with telematics trip data. Without that, it is a guessing game that could further damage the effectiveness of the rating plan.

The differences are powerful. Incorporating the loss-based score into a rating plan results in up to a 10x improvement in rating-plan accuracy compared to the rating plan with an indicated proxy-based score (Figure 2) and up to a 3.5x improvement compared to traditional factors alone.

This improvement occurs because the claims data enables the loss-based model to produce segment rating factors that truly reflect the insured risk within each segment, not just the directional risk between groups.
A rating plan that seeks to leverage driving behavior should include distracted driving because it’s highly predictive of loss and not highly correlated with other dangerous driving behaviors.

Looking at the most serious crashes, federal highway safety data suggests driver distraction contributed to about 3,000 fatal crashes in 2017, with about 14% of them associated with cell phones. The numbers are likely much higher because of underreporting.

Insurers pay a significant proportion of distracted driving costs. The percentage of insurance losses attributed to distracted driving tripled from 2011 to 2018 as smartphone penetration increased from 35% to 81%. The cost is now estimated at about $9 billion a year.

But how much are the distracted drivers in your book of business costing you? Arity research correlating mobile sensor data with associated insurance claims shows that on average, the most distracted drivers have a loss cost more than 1.5 times that of the least distracted drivers.

Isolating Distracted Driving Losses
Despite the predictive nature of distracted driving, many telematics programs ignore it. One reason is that it’s really hard to connect the dots between phone movements, risky driving and insurance losses. Can you tell which phone movements indicate distracted driving? Do you understand which distracted driving behaviors produce losses and whether those behaviors are captured in other ways? Can you ascertain which distracted driving behaviors are really risky, and which aren’t? The effort to overcome these obstacles is a worthwhile endeavor, because the dangers and the costs of distracted driving are too great to ignore.

The imperative to incorporate distracted driving in insurance rates becomes even clearer when you realize that distracted driving is not highly correlated with other behaviors detected by telematics sensors. Arity research found that in a given month only 18% of variation in distracted driving could be explained by miles driven, braking and speeding behavior — common behaviors detected by an OBD-II device.

Figure 3
The most distracted drivers have loss cost 1.5x higher

Source: Arity
So the question is how do we measure a driver’s actual interactions with their devices and correlate those movements with loss?

While a phone’s sensors can track usage and movement events, it’s easy to draw incorrect conclusions. Distracted driving algorithms that rely solely on sensor information — such as accelerometers, gravitometers, gyroscopes, etc. — will be subject to false positives and false negatives.

An ongoing naturalistic distracted driving experiment can validate assumptions about why and when phone movements are happening. In the experiment, inward facing dashboard cameras record actual driving behaviors while a smartphone application performs a comprehensive collection of telematics information. From the dashboard cameras, perfect labels for sessions of distracted driving—both when it occurred and what mode it was—can be derived.

The naturalistic data also helps to identify patterns of phone movements that constitute distraction while driving. Is a passenger using the driver’s phone? Could the lack of movement when a phone is in a hands-free cradle actually mask distracted driving behavior?

To assess the relative risks of distracted driving behaviors, you need to take into account two fundamental considerations: context and mode. Context defines the conditions at the time of the behavior, such as how fast the car is moving, weather conditions and the amount of traffic. Mode defines the behavior taking place: Is the driver texting? Talking on the phone? Playing a game? Taken together, context and mode offer deeper insight into the extent of the distractions and the impact on driving risk and ultimately predicted losses.

For the best overall prediction, a distracted driving variable must be rooted in physical intuition and honed on data: using sensors, operating system interactions, and contextual information. And the behaviors must be matched with a large volume of claims data to develop a rating variable that will lead to more accurate pricing.
Our inability to act on what we know about the dangers of using a cell phone while driving is not all that surprising

The technology in smartphones is engineered to be addictive, delivering bursts of dopamine-fueled pleasure with every text message and push notification.

In a recent Arity survey, almost one-fourth of drivers said they were in an accident caused by distracted driving. Although 89% of respondents believe drivers should rarely, if ever, be allowed to text or use the web on their phone, nearly all of them admitted to using their phone while driving and 98% reported seeing other drivers who were dangerously distracted. The problem is most acute among the least experienced drivers: More than 60% of young drivers admit to using phones to text and watch videos.

When it comes to distracted driving, there’s a serious cognitive disconnect. We know it’s dangerous, but we do it anyway. A study published one year before the release of the first iPhone showed that just a 2-second glance away from the road doubles the likelihood of a crash. It takes 5 seconds to read a text, during which time you can travel the length of a football field at 55 mph. And reading texts isn’t even the most dangerous way in which drivers use their phones when they are behind the wheel.
A telematics loss model should account for traditional rating factors

Insurers continue to use traditional rating factors like number of vehicles, garaging location, years of driving experience, and accident and violation history as proxies for how many miles a car is driven, where it is driven, when it is driven, and how safely it is driven. A model built on an analysis of driving behaviors must identify correlations with other variables in the plan to avoid double counting signal. For example, driving behaviors like phone handling are highly correlated with age, a traditional characteristic. You want to ensure you are not double-counting that signal.

**Isolating the Telematics Signal**

To accurately incorporate driving behavior into an existing rating plan, the behaviors and relativities should isolate the signal explained by telematics and account for the correlation with the traditional factors. To avoid instability, the model must include a large volume of reliable traditional data and mobile telematics data along with claims data associated with those trips. The absence of robust underlying traditional data will require after-the-fact adjustments to both telematics and underlying traditional factor selections.

A model built on an analysis of driving behaviors must identify correlations with other variables in the plan to avoid double counting signal.
A continuous connection can increase the reliability of the driving behaviors used in pricing and extend an insurer’s relationship with your customer.

Many telematics programs provide a snapshot of driving behavior over a limited amount of time. But as driving behaviors become more of a leading predictor in the rating plan, it will be more important that models reflect shifts in behavior.

That’s because driving behavior can change over time, most notably with aging and as mobility patterns shift for new jobs, hobbies or family obligations. Driving behavior might also change over time due to changes in sleep patterns, emotional distress or new distractions.

People change their behavior when they know they are being monitored, but it’s unclear if they revert to riskier driving behavior when telematics monitoring ends. A continuous connection should increase reliability by capturing changes in driving behavior over time. It can also eliminate any bias created if drivers “game the system” by driving differently during a limited period of connection.

**Building a Stronger Relationship**

A continuous connection also provides an opportunity to increase the frequency of positive interactions and build a stronger relationship with your customer. For instance, you have the opportunity to provide customers with valuable feedback on their driving, detect when a customer needs roadside assistance or automatically call emergency services when it is determined that they may be in a collision. Another avenue that is continually being refined is to change customer driving behaviors based on timely feedback on driving events, such as distracted driving.
A telematics model should evolve as mobile data and claims provide deeper insights into driving behavior over time.

The pricing of insurance policies based on driving behavior derived from mobile telematics is in its infancy. Data scientists and actuaries continue to test, analyze and refine mobile telematics loss models to incorporate changes in smartphones, including operating system features and battery sufficiency, and the increasing amount of mobile-based loss data. They also continue to incorporate potential changes in driving behaviors that, ideally, would result from telematics-driven feedback on safe and unsafe driving habits.

To develop an effective driving behavior model, data scientists must use an iterative approach to refine variable definitions and define new variables. An iterative approach starts with a behavior concept based on a hypothesis tested with high-frequency data generated from a small population. As the behavior model is put into use, data scientists revise variables based on customer behaviors and continually evaluate the correlation of behaviors to loss costs. This approach can only work with actual insurance loss information.
Conclusion

Insurers today are eager to leverage the predictive power of mobile telematics to produce more accurate insurance rates based on distracted driving and other driving behaviors. But even small mistakes in models for driving behavior can have costly consequences, producing a rating plan that is even less accurate than one dependent only on traditional rate factors. The most critical step toward mitigating the challenges of mobile telematics — the key to cracking the code — is ensuring the right knowledge and experience is applied to reap a true return on the investment.
Footnotes


4 Arity research, March 2018.


8 Arity analysis.

9 Arity proprietary research.

Arity is a mobility data and analytics company that provides data-driven solutions to companies invested in transportation to enable them to make mobility services smarter, safer, and more economical. Insurance companies, automobile OEMs, shared mobility companies, and governments turn to Arity to better understand driving behavior, manage risk, operate more safely, and ultimately increase their bottom line. The Arity platform is built on nearly 143 billion miles of historical driving data, more than 16 million active telematics connections and 10 years experience analyzing driving data from cars and mobile devices. As a licensed rating service organization, Arity makes it easy for insurance companies to subscribe to their pre-approved telematics models, available in more than 40 states. With global offices and a Chicago headquarters, Arity was founded by The Allstate Corporation and launched in 2016. Visit www.arity.com for more information.