[SAMSARA SIGNALS]

COMPOUNDING RISK REPORT

How different safety signals combine to influence incident likelihood

SAMSARA™

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What patterns reveal that single events can't

For years, fleet safety has been built around the individual event. A speeding incident gets logged. A harsh brake gets flagged. A phone glance gets reviewed. The structure has worked — but the question safety leaders ask most often hasn't changed: Which patterns of driving behavior actually matter, and how do we surface them early enough to potentially change an outcome?

That question is hard to answer one event at a time. A driver with three harsh brakes per month might be perfectly safe. Another with the same number might face greater risk because of what else is happening alongside that behavior. Modern telematics generates more signals than any one manager can act on, and almost none of them in isolation tells you where to focus.

The finding at the center of this research is simple to state and significant in its implications: Risk lives in the combination of driving behaviors, not in any one of them — and those combinations are identifiable long before a crash occurs. Drivers involved in crashes usually aren't having a sudden bad day. They are driving in identifiable patterns over time, and those patterns can be visible weeks in advance.

While the world — and our data — will always evolve, the concentration is striking: The 10% of drivers ranked highest based on these patterns account for as much as 47% of crashes, while the top 30% account for as much as 76%.

That changes what is possible for safety leaders. By concentrating their most intensive coaching on just 10% of drivers, they can reach the group associated with nearly half of crashes. From there, a strong safety culture and self-coaching can reinforce safer decisions across the broader workforce — giving managers a way to focus their limited time where it can have the greatest impact without losing sight of everyone else.

This is a meaningful step forward: Safety leaders can identify the behavioral patterns most associated with crashes, prioritize human intervention where it matters most and give drivers more opportunities to improve on their own — often with weeks to spare. None of this is theoretical. It is drawn from the everyday work of the safety managers, drivers and operations leaders who use this technology to make their fleets, and our roads, safer.

ARPAN PODDUTURI
HEAD OF SAFETY PRODUCT AT SAMSARA

About this analysis

The findings in this report are drawn from Samsara's proprietary Risk Model (patent-pending), trained and evaluated on aggregated data from a sample period of July 1 – December 15, 2025.

Samsara's Risk Model uses approximately 50 features spanning four categories: driving behavioral patterns (speeding tendencies, mobile usage, harsh events), exposure (how much time a driver spends on the road, including miles driven and driving concentration), context (the environment in which that driving occurs — road type, urban or rural setting, nighttime conditions, weather), and developmental factors (driver tenure, coaching history). Context is called out separately because it interacts with both driving behavior and exposure to create meaningfully different risk profiles.

The report assesses the relative risk of each behavior by comparing its rate of very-high-risk classifications with the rate across the full dataset. "Very high risk" is a relative classification — it indicates a comparatively elevated likelihood of a crash; it is not a prediction that a crash will occur. Even within the highest-risk tier, crashes remain rare; the value of the classification lies in identifying where risk is most concentrated, not in predicting individual outcomes. If 10% of drivers across the full dataset are classified as very high risk, compared with 50% of records exhibiting a particular behavior, the relative rate associated with that behavior is 5x.

Findings reflect statistical association. Where the report refers to behaviors as credible contributors to risk, this reflects analytical judgment grounded in the data rather than formal causal inference. Detailed methodology appears at the end of this report.*

What we found

Four key numbers tell the story.

5.4x

Drivers exhibiting combined mobile use, distraction, and harsh braking are 5.4x more likely than the average driver to be classified in the highest risk tier.

~50%

The top 10% of risk-ranked drivers account for 47% of crashes.
Risk concentrates.

76%

The top 30% of risk-ranked drivers account for 76% of crashes.
Prioritization is the highest-leverage move a fleet can make.

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When comparing a driver who is subsequently involved in a crash with one who is not, the model prioritizes the crash-involved driver three out of four times. This holds across both the next-day and seven-day evaluation windows.

Crash risk exists in the combination of driving behaviors, not in any one of them — and the combinations tend to be visible weeks before a crash.

THE PROBLEM

Why single behaviors don’t tell the full story

Fleet safety has long been built around a simple idea: identify risky driving behaviors, coach them down, repeat. It works — up to a point.

The data confirms that single behaviors carry real risk. These numbers are real, and they matter. They are the foundation that decades of safety programs have been built on. But none of them on its own is a strong basis for prioritization.

How single behaviors associate with crash likelihood

Behavior	Crash likelihood as compared to drivers without behavior
Harsh braking	1.8x more likely to crash
Mobile usage	1.7x
Distracted driving	1.7x
Speeding events	1.5x
Rolling stops	1.5x
Drowsy driving	1.4x
Harsh turns	1.3x
Night driving	1.3x
Following-distance events	1.2x

A 1.3x to 1.8x increase in crash likelihood, spread across hundreds of drivers, doesn't tell a fleet manager which drivers to focus on. It tells them that every driver who brakes hard, uses their phone, or speeds is somewhat more likely to be involved in a crash — which describes most of their fleet, most of the time. The signal is real but too diffuse to act on.

A fleet manager looking at any one of these signals across hundreds of drivers still faces the same problem: too many events, not enough clarity about which patterns are actually elevating risk. Single-behavior signals force managers to triage events. They don't tell managers which drivers to focus on.

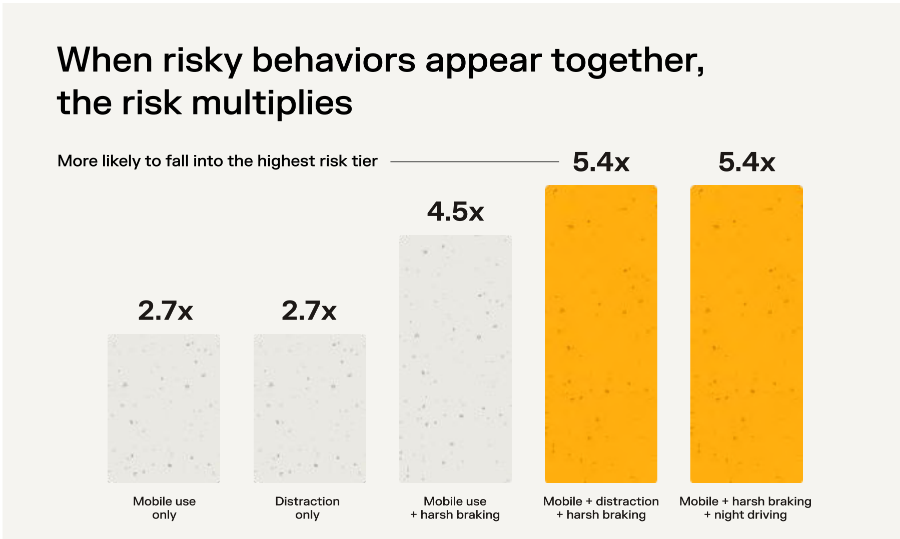
The more consequential question isn't whether a behavior is risky in isolation. It's what happens when behaviors appear together.

THE COMPOUNDING EFFECT

Risk doesn't add — it compounds

When risky driving behaviors appear together, the risk doesn't add. It compounds.

To see this, we grouped drivers into profiles based on combinations of behavioral and contextual factors, then measured how likely each group was to fall into the highest risk tier compared to the overall driver population. The result — what we call lift — tells us where risk concentrates.



Driver profile	Likelihood of falling into the highest risk tier, compared to the overall driver population
Mobile use + distraction + harsh braking	5.4x more likely to fall into highest-risk tier
Mobile use + harsh braking + night driving	5.4x
Mobile use + harsh braking	4.5x
Mobile use only	2.7x
Distraction only	2.7x
Light speeding only	1.3x
Night driving only	1.3x
Freezing-trip exposure only	1.0x

A driver who uses their phone while driving is 2.7x more likely than the overall driver population to fall into the highest risk tier. Add harsh braking and that figure rises to 4.5x. Add night driving on top of that, and it reaches 5.4x.

Each behavior added doesn't increase risk by the same amount — it multiplies what's already there. The combination of mobile use, distraction, and harsh braking produces a risk concentration 2x greater than any of those behaviors measured alone.

This is the pattern that single-behavior monitoring cannot see. Not because the individual signals are wrong, but because they were never designed to capture what happens when they stack. We call it compounding risk: the idea that crash risk lives more in the combination than in the component.

Why this matters

The shift from looking at single behaviors to looking at combinations changes what's possible for a fleet safety program. Single-behavior signals force managers to triage events. Pattern-based identification lets them triage drivers — focusing attention where multiple risk factors are stacking, not chasing every individual alert.

It also changes what coaching can be about. Coaching a driver on a single harsh braking event is a narrow conversation. Coaching a driver whose harsh braking shows up consistently alongside mobile use and distraction is a different one — anchored in a real pattern of how that driver operates, not an isolated incident.

Aggressive driving, distraction, and speeding are credible drivers of crash risk

A causal analysis sharpens the picture further. The model reads not events but tendencies — a consistent pattern of driving behavior across trips and over time, often in conditions that amplify its impact. A driver isn't flagged for braking hard once. They're flagged for a pattern of how they drive.

Across model specifications and statistical methods, three behavior families stand out: aggressive driving, distracted driving, and speeding-related patterns. These are not just associated with crash risk. They are credible drivers of it. In practical terms, this means that reducing these behaviors should reduce crash risk, all else equal — rather than merely moving alongside crash risk as a correlate.

These behavioral constructs also proved more informative and stable than many of their individual component signals. Rather than relying on isolated events — a single mobile-use alert, one harsh braking instance — the composite measures consistently captured broader patterns of driver behavior that were more strongly related to crash outcomes across analyses.

Speeding warrants a specific note. In the lift table above, light speeding alone shows modest concentration at 1.3x, which might suggest it's a secondary factor. The causal picture is different. Speeding's significance comes not from how dramatically it concentrates risk in any one driver profile, but from how prevalent it is across the fleet. When a behavior is common enough, even a moderate per-driver effect adds up to a substantial share of total crashes at scale. Speeding is that kind of risk.

These three behavior families are also the most coachable. They are the most reliable, most causally grounded targets for any pattern-based safety program.

A note on context

Conditions like night driving, freezing temperatures, and urban exposure also influence crash risk — but on their own, they sit close to the fleet-wide rate. A night-only driver profile or a freezing-only profile is largely indistinguishable from the overall driver population. It's only when those conditions appear alongside behavioral patterns that they meaningfully amplify risk.

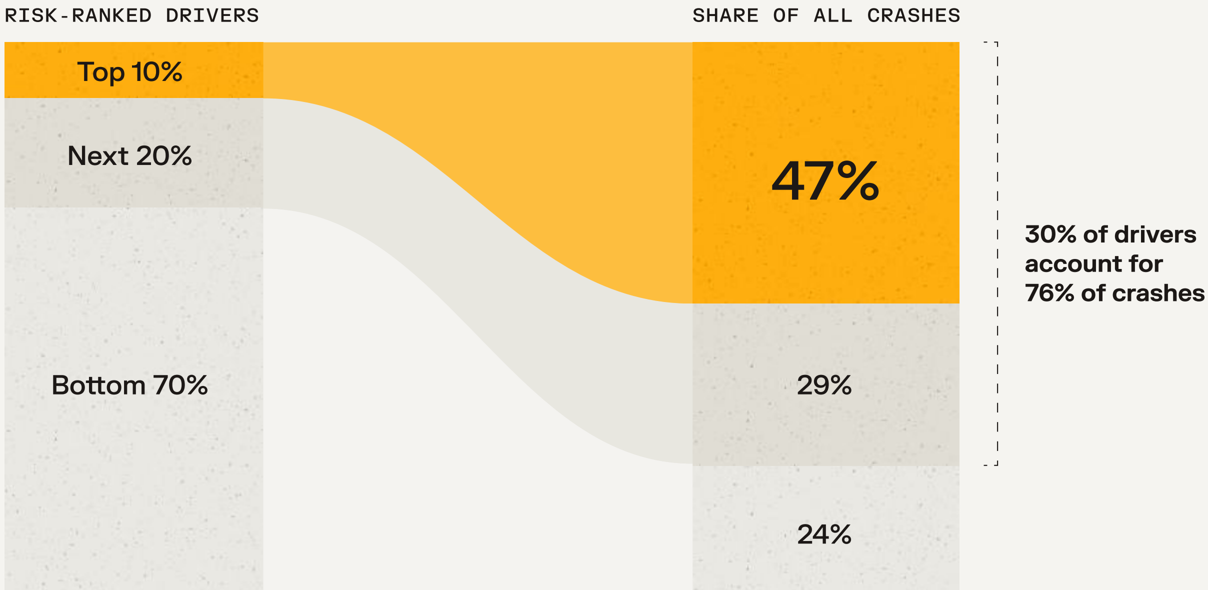
That's an important distinction. Context is interpretive: it helps explain why a behavior carries more risk in a particular setting. But context is not a coaching target. You can't coach away weather or geography. You can coach driving behavior. Pattern-based safety programs should focus there.

The signal isn't in any single behavior. It's in the way they combine.

Where crash risk concentrates

Crashes are not evenly distributed across drivers. They concentrate in a small group.

Share of crashes by risk-ranked group



Risk-ranked group	Crash likelihood	Share of all crashes
Top 10%	3.1x	47%
Top 30%	2.1x	76%

Crash likelihood is expressed as a multiple of the overall driver population rate.

This concentration is what makes prioritization the highest-leverage move a fleet can make. Even modest gains in coaching the top decile can translate into meaningful reductions in crashes at scale.

And the compounding finding is what makes that prioritization reliable. The reason the top 10% accounts for so many crashes is precisely that those drivers tend to exhibit combinations of behavioral patterns — not single events. Pattern-based identification is what lets a manager look at a list of risk-ranked drivers and trust that the names at the top are the names that warrant attention first.

10%

of drivers account for nearly half of all crashes

30%

account for more than three-fourths of crashes

What these patterns look like in practice

The compounding pattern is easier to grasp through sample profiles than through statistics. Below are **three composite profiles** — illustrative, not specific to any individual — that show what compounding risk looks like in the real world, and what it doesn't.

Profile 01 — Risky environmental factors

Pattern observed	High night-driving exposure and frequent freezing-temperature trips. No notable behavioral risk factors. Moderate driving volume.
Pattern stability	Context-only profile. No combination of risky behaviors observed across the 60-day window.
Coaching priority	Low to typical — sits near the fleet-wide average.
Takeaway	Context alone doesn't compound into elevated risk. The conditions matter, but they're not the highest priority for coaching.

Profile 02 — Singular risky behavior

Pattern observed	Frequent mobile usage during driving. Otherwise unremarkable behavior. Daytime, urban driving.
Pattern stability	One behavior observed consistently across the 60-day window. No other behavioral patterns of concern.
Coaching priority	Medium — modestly elevated, but not in the highest tier.
Takeaway	One behavior alone, even when persistent, is a weak signal. Notable, but not where the strongest risk lives.

Profile 03 — Multiple risky behaviors in combination

Pattern observed	Frequent mobile use. Multiple distracted-driving events. Repeated harsh braking events. Observed in combination across the same 60-day window.
Pattern stability	Pattern visible across the full 60-day window. Already identified as high priority for coaching weeks before any incident.
Coaching priority	Very high priority for coaching. Identifiable in advance.
Takeaway	This is what compounding risk looks like. And this is when it becomes visible.

THE WAY FORWARD

Seen in advance: the window for action

Identifying which drivers are most at risk is valuable. Identifying them early — before an incident occurs — is what makes that identification actionable.

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When comparing a driver who is subsequently involved in a crash with one who is not, the model prioritizes the crash-involved driver three out of four times.

The model's core advantage is consistency. The driving behavioral patterns it identifies don't appear overnight. A driver classified as high risk today was very likely classified the same way last week, and the week before. These are tendencies that show up across trips, across weeks, and across conditions. High-risk drivers don't become high-risk suddenly.

That stability is what enables early identification. Because the same patterns persist over time, the model sees the same signal well before any incident occurs.

How reliably does it find the right drivers? When comparing a driver who is subsequently involved in a crash with one who is not, the model prioritizes the crash-involved driver three out of four times. This holds across both the next-day and seven-day evaluation windows. The model is not catching a moment — it is reading a pattern that has been there all along.

For fleet managers, this changes the nature of the safety conversation. The question shifts from "what just happened?" to "which drivers should we focus on this week?" — and the model provides a consistent, reliable answer to that question before anything has gone wrong.

Prediction vs. prioritization

Samsara's Risk Model is not designed to predict whether a specific driver will crash on a specific day. Crashes are rare and depend on many factors outside any model's view.

The model is designed to rank drivers by their relative risk based on the behavioral patterns they exhibit — and to do so consistently enough, far enough in advance, that fleets can act on the information.

Prioritization, not prediction, is where pattern-based risk identification creates value.

“Coaching Priority shows us exactly where to focus—down to the specific locations, behaviors, and drivers driving risk. That clarity empowers us to take targeted action and elevate safety across our entire fleet.”

TOM KARNOWSKI
VICE PRESIDENT, ENVIRONMENTAL, HEALTH, AND SAFETY AT USIC

CHECKLIST: FROM INSIGHT TO ACTION

Pattern-based risk identification changes how a fleet safety program can be organized.
Five practical implications follow from the findings in this report.

1. Coach behavioral patterns, not isolated events

Single, minor events are noise. Combinations of driving behaviors over time are signals. Coaching conversations anchored in real, repeated patterns — not one-off incidents — are more credible to drivers and more effective at producing change.

2. Prioritize the most credible levers

Aggressive driving, distracted driving, and speeding-related patterns are the strongest, most stable, and most causally credible drivers of crash risk in our analysis. Speeding's significance comes not from how dramatically it concentrates risk in any one driver profile, but from how prevalent it is across the fleet — making it one of the highest-leverage targets at scale. All three are coachable. These behavior families should anchor any pattern-based safety program.

3. Use context to interpret, not to coach

Night driving, weather, and route mix help explain why certain driving behaviors carry more risk in certain settings. They aren't a coaching target on their own. Use context to scope and interpret risk, not as a substitute for behavioral change.

4. Use risk ranking as a behavioral-pattern triage

A small share of drivers accounts for the bulk of crash risk. Pattern-based identification is what makes triage reliable. When a driver appears at the top of a risk-ranked list, it's because of consistent driving behavioral patterns visible over weeks — not one bad day. That's the signal coaching programs should respond to.

5. Read impact at the right scale

Crashes are rare events. In any given period, even an effective safety program may not produce a visible change in crash counts. The impact becomes statistically clear when measured across sufficient exposure — enough drivers, enough miles, enough time for the math to work. That's when pattern-based coaching produces results that are visible not just operationally, but in the numbers.

CONCLUSION

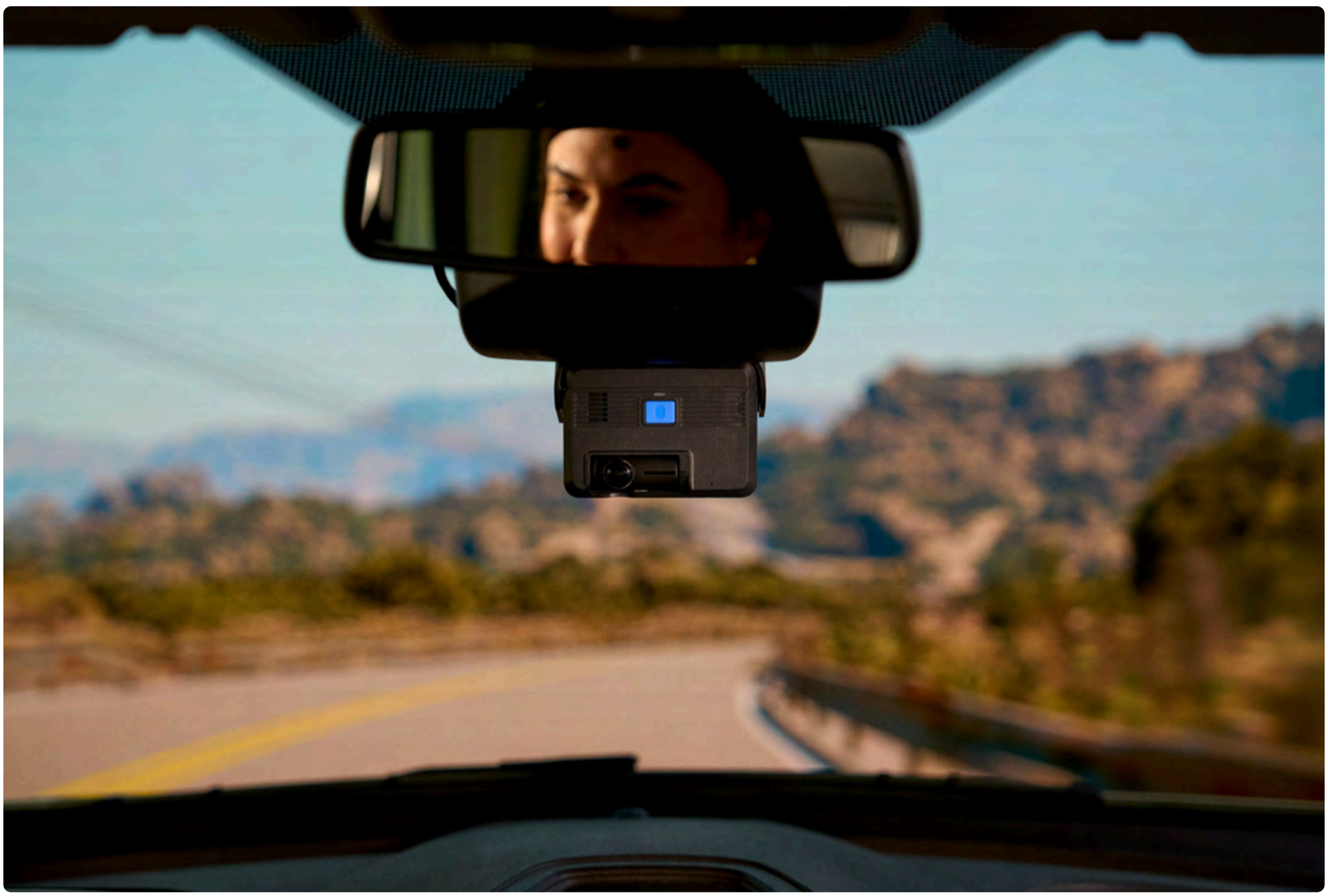
The future of fleet safety

For decades, fleet safety improved by getting better at responding to incidents. The next chapter is about getting better at recognizing the patterns that precede them.

Compounding risk is the foundation of that shift. As data depth grows, so does our ability to see how driving behaviors interact, how context amplifies risk, and how prioritization can be made more precise. Future iterations of the model will incorporate more granular behavioral signals, sharper context modeling, and improved interpretability.

The principle, however, won't change. Risk exists in the combination, and the combination is what makes it identifiable in advance.

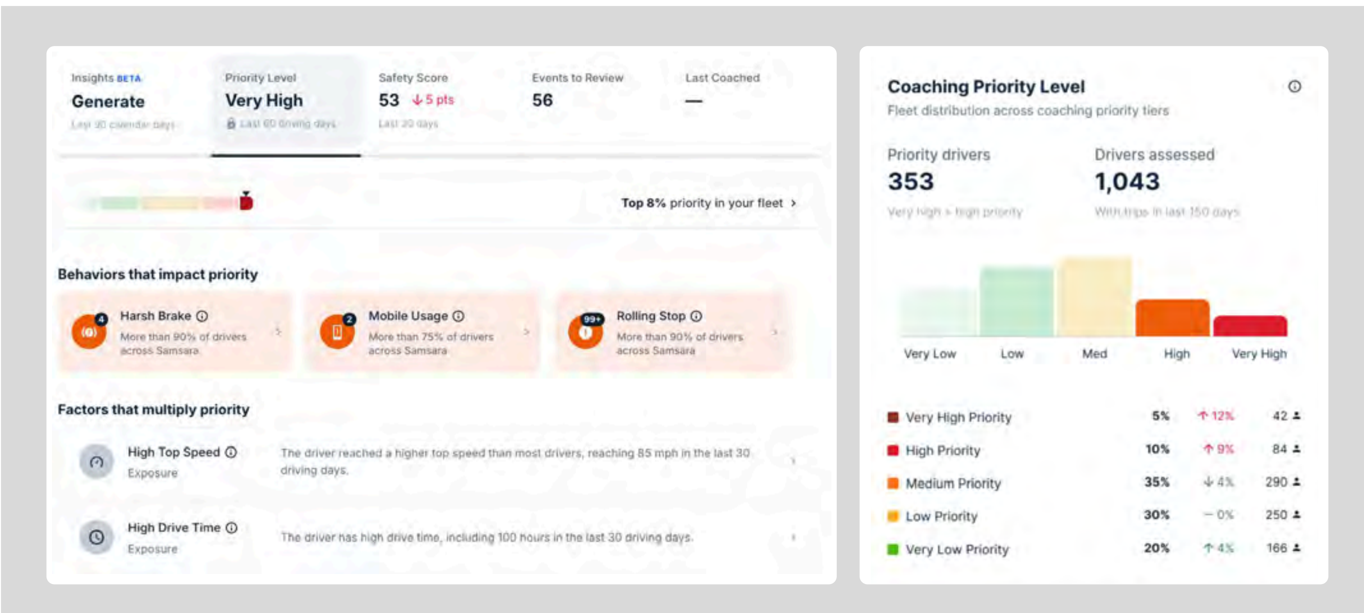
We share these findings because the more the industry understands about how risk compounds, the safer our roads become. The industry has spent decades measuring individual behaviors. The evidence suggests the next step is measuring how they combine. That's where the risk is. And it's where the opportunity is too.



Take action at scale with Samsara’s world-class AI-powered coaching

Underpinned by the Risk Model, Coaching Priority is Samsara's proprietary framework for surfacing and prioritizing coaching opportunities across your fleet — the only solution of its kind available today.

The AI-powered feature evaluates ~50 factors, including driving history, weather, and driving behavioral patterns, to give managers a single view that highlights where coaching will have the greatest impact, while drivers who are already building strong habits receive automated self-coaching to keep them on track.



~50 risk factors

Coaching Priority evaluates approximately 50 risk factors and benchmarks your fleet against crash data from the Samsara Network. With more than 30 trillion data points and 100 billion miles driven annually, it gives Samsara's AI unmatched accuracy in spotting preventable patterns.

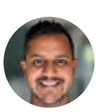
Focus your efforts

Coaching Priority consolidates these signals into a single view that shows where coaching attention matters most and how it's trending over time. Managers can see which drivers, teams, or tags drive risk exposure, then drill into individual profiles to find the root cause.

Maximize your impact

Focus coaching resources where they will make the most impact. Empower drivers with the knowledge of exactly which driving behaviors they can address to be safer.

“By concentrating their most intensive coaching on just 10% of drivers, [managers] can reach the group associated with nearly half of crashes. From there, a strong safety culture and self-coaching can reinforce safer decisions across the broader workforce — giving managers a way to focus their limited time where it can have the greatest impact.”



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HEAD OF SAFETY PRODUCT AT SAMSARA

How this analysis was done

Sample and scope

The findings in this report are drawn from Samsara's Risk Model (patent pending). Training and evaluation used aggregated data from a sample period of July 1 – December 15, 2025. The dataset spans drivers and fleets across multiple industries and regions.

Model overview

The model uses approximately 50 features across four categories:

- **Behavioral patterns:** speeding tendencies (including severity), mobile usage, distracted driving, harsh braking and turning, following distance, lane departure, rolling stops, drowsy driving.
- **Context:** the conditions in which driving occurs: time of day, weather, road type, urban vs. rural environments, and similar factors. Context can interact with risky behaviors such that the same behavior might have different risk implications depending on whether it occurs in a relatively low-risk or high-risk driving environment.
- **Developmental factors:** driver tenure on the platform, repeat coaching indicators where available.
- **Exposure:** Most behavioral and exposure features are measured over rolling windows (commonly 60 driving days), so the model reflects tendencies and history rather than single isolated events.

Risk tiers and ranking

The model looks at safety behaviors, including crashes, and divides drivers into buckets ranging from very low to very high risk. The model is optimized for ranking and tier separation rather than literal probability statements such as "probability of crash next Tuesday."

Validation

The model achieves an Area Under the Curve (AUC) of 0.75 on the evaluation sample, meaning that when comparing any driver who later crashed to a random driver who didn't, the model correctly ranks the crash-involved driver as higher risk approximately three times out of four. Crash concentration metrics (10% accounting for ~50% of crashes; 30% accounting for 76%) are computed on the same evaluation sample.

Lead-time analysis

For drivers who experienced a crash on a day they were classified high or very high risk, we measured the share who were also classified high or very high risk on driving days preceding the crash (5, 10, 20, and 30 driving days prior). Drivers who did not drive on a given prior date were counted as not high risk for that day, making the lead-time figures conservative.

Causal analysis

Portions of this report describe certain behaviors — aggressive driving, distracted driving, and speeding-related patterns — as credible drivers of crash risk. These claims are based on causal analysis using methods including double machine learning (DML) with calibration and causal forests for policy ranking. Across specifications, these three behavior families show consistent directional effects and stable rankings, with calibrated results indicating meaningful real-world impact at fleet scale.

Other findings in this report — including the lift figures for combined behavioral profiles — describe statistical association rather than causation. They identify where risk concentrates in the data, not the causal effect of any single combination.

Limitations

Crashes are rare events. At small fleet scale, intervention impact may not be observable in crash counts within a given period; at large fleet scale, the impact becomes visible. Not every feature is a causal lever — some variables are useful for identifying risk but are not appropriate intervention targets. Cold-start mitigations are applied for drivers and fleets with limited history to prevent sparse data from dominating risk estimation.

ABOUT SAMSARA

Samsara (NYSE: IOT) is the pioneer of the Connected Operations® Platform, which is an open platform that connects the people, devices, and systems of some of the world's most complex operations, allowing them to develop actionable insights and improve their operations. With tens of thousands of customers across North America and Europe, Samsara is a proud technology partner to the people who keep our global economy running, including the world's leading organizations across industries in transportation, construction, wholesale and retail trade, field services, logistics, manufacturing, utilities and energy, government, healthcare and education, food and beverage, and others. The company's mission is to increase the safety, efficiency, and sustainability of the operations that power the global economy.

About Samsara Signals

Samsara Signals is an ongoing data storytelling program that surfaces what we're learning from billions of miles of operational data. Each report focuses on a single finding worth understanding — distilled from research, modeling, and analysis across the Samsara platform — and translated for the leaders building the future of physical operations.

Building one of the world's largest operational datasets

30T+

data points

100B+

miles traveled

380K+

accidents prevented last year with Samsara's help

The information provided in this report is for general informational purposes only. Samsara does not guarantee you will achieve any specific results if you follow any advice in the report.

GLOSSARY

Key terms

Lift
How much more likely a group of drivers is to fall in the highest risk tier compared to the average driver. A lift of 5.4x means a group is 5.4 times more likely than average.

Risk tier
A categorical grouping (very low, low, medium, high, very high) assigned by the model based on a driver's risk relative to the broader population.

Behavioral pattern
A driver-level tendency observed over a rolling window (typically 60 driving days), reflecting habitual behavior rather than individual events.

Compounding risk
The phenomenon by which combinations of risky driving behaviors are dramatically more concentrated in crash risk than any of the same behaviors observed in isolation.

Exposure
How much, when, and under what conditions a driver is on the road. Includes driving time, distance, time-of-day, weather, and road context.

Contextual factor
A condition (such as night driving or freezing weather) that interprets and amplifies behavioral risk but is not itself a coaching target.

AUC
Area Under the ROC Curve. A measure of how well the model prioritizes drivers who crash above drivers who don't. An AUC of 0.75 means the model ranks correctly about three out of four times.

Causal driver
A factor for which causal analysis indicates a credible directional effect on crash risk, not merely an association. In this report: aggressive driving, distracted driving, and speeding-related patterns.

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