OCX Cognition™

Breakthrough Approaches to Managing Customer Risk

Predictive Tools that Transform Insights and Drive Improvement

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Understanding Customer Risk

No matter their size or sophistication, enterprises struggle to understand how their operational performance affects the attitudes and behaviors of their customers. They fail to see customer risk or opportunity before it is too late to address at reasonable cost, if at all. Their customer facing teams lack a single view of the customer that is calibrated around the operational performance that matters. They are stuck working reactively and inefficiently.

When thinking about customer risk in the customer experience universe, the principal concern is with an environment where, because of lifetime value economics, the future value of a customer is greater than the present financials would indicate. That gap means that if simply looking at short-term indications, could mean missing out on the full value of the customer. The principle behind customer risk management, then, reflects that imbalance between short term and long term. The need: Control the long-term economics and have useful tools to be able to do so.

Fortunately, it's now possible to manage customer risk using a set of breakthrough tools. In this publication, we explore three key takeaways about tools for managing customer risk:

- Effective tools for managing customer risk are critical in large part because humans do a poor job of estimating it. Machine learning can supplement and complement human judgement for timely and accurate assessments of risk, and perfection is not necessary.
- Three breakthrough tools for customer risk management deliver previously impossible assessments that allow companies to act in time to change predicted outcomes. Together they deliver accurate predictions, attributable to operational factors.
- The ongoing interactions between predictive account scoring, the data-driven customer journey framework, and customer-optimal performance indicators improve each element. In the process, they provide insights into company strengths and weaknesses even before they are fully implemented.

Characteristics of Effective Predictive Tools

Wise companies naturally want to reduce customer risk, but even the most committed have been hampered by a lack of effective tools. But it's possible to describe the somewhat familiar attributes of risk management tools that would be truly beneficial.

- Firstly, customer risk management tools need to be **accurate**. We want a realistic assessment of risk, better at the very least than what simply guessing would indicate.
- We look for a tool to be **analytic**, in the sense that it tells us why that risk exists. If we don't know that, then there's not much we can do to address the risk.
- An effective tool should be **prescriptive**, in that it indicates what to do in the event of this risk occurring.
- Importantly, a tool should be **actionable**. Here, that commonly used word means that insights from the tool meet an operational standard of control, so that companies understand which operational change will have an effect on the risk in question.
- Lastly, and perhaps most critically, a useful tool for managing customer risk should be **timely**.

The timeliness of a risk management tool has an outsized role in its efficacy, for the simple reason that delayed information actually has a disproportionate impact on risk. Think about this like an early diagnosis of some serious medical condition. The timing factor actually turns out to be more decisive than the accuracy in some instances. That's because even with all other attributes in place, if the information is too late, it doesn't matter. Conversely, if you have good timely information, it might be the case that you can afford less accuracy or less clarity on what to do, because you have more time to do it.

A key point here: We need effective tools for managing customer risk because human judgement is not especially effective at assessing it.

Three Synergistic Customer Risk Management Tools

Keeping in mind both the characteristics of effective risk management tools and humans' lack of skill in predicting risk, let's talk about three breakthrough tools that work synergistically to solve problems of managing customer risk. Although they have standalone value to an enterprise, working together they feed off one another to become much more powerful.

The three breakthrough tools:

Predictive account scoring. This the ability to use analytics to predictively score risk – or health, if you prefer – at the account level.

Data-driven customer journey framework. This tool outperforms traditional customer journey design approaches and is instrumental in building predictive models.

Customer-optimal key performance indicators. Thinking of KPIs from a customer perspective ensures we're measuring the areas that enable our organization to focus on improving what matters to customers.

Predictive Account Scoring

To begin an exploration of the first of the breakthrough customer risk management tools, first consider the purpose of scoring the risk of accounts (alternatively, the term "account health" could apply). Essentially, scoring serves to assign each customer account to a category of risk. In the widely used and understood Net Promoter® approach, these categories would be Promoter, Passive, and Detractor. We'll take these categories as our examples here.

A random guess about whether a customer is a Promoter, Passive, or Detractor has about a one in three chance of being correct. By adding some information that narrowed down the odds, it's relatively easy to move to a fifty-fifty chance of being correct. Such a change is not a huge improvement – and those odds are not objectively excellent – but even so the improved odds are extremely valuable, because if played out over many decisions, the different is very material.

This example illustrates that it's not necessary to seek perfection when we engage in prediction. It's enough to find better ways to improve our predictive outcomes. It's not helpful, in the end, to make great the enemy of good, especially given the impossibility of 100% accuracy in prediction.

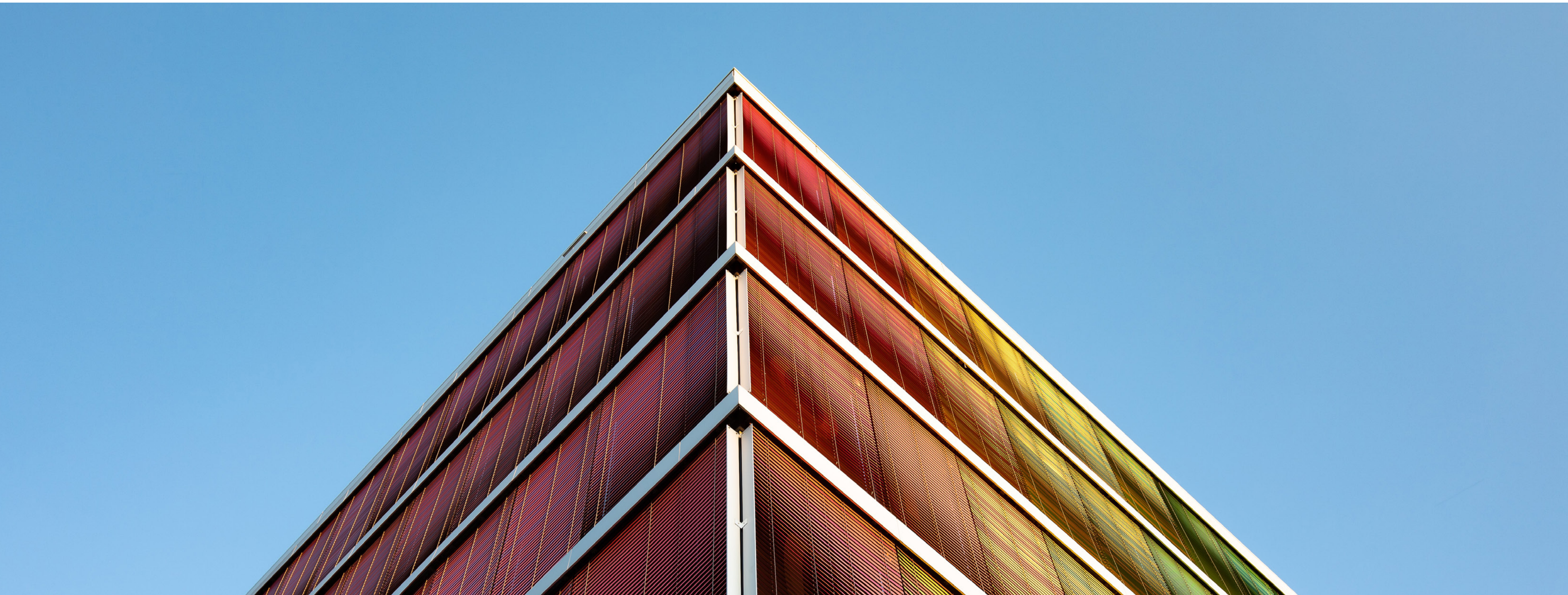
The Fundamentals of Prediction

A few fundamental concepts underlie the belief that we can make predictions about customers and the risk we assign to accounts.

Firstly, we know that customers are predictable; they behave rationally. It's easy to believe customers are capricious or unreasonable, but especially in business-to-business settings, customers actually behave in fairly predictable fashion. Even imperfect rationality is sufficient to base our prediction around. Customers who buy under certain assumptions, who are treated certain ways, and who experience their interactions with a company in certain ways have a much higher probability of a satisfactory outcome. It's not 100%, but it's better historical assessments – or guesses – would suggest.

Secondly, customers react to cumulative experiences; what happened in the past weighs very heavily on how they evaluate the present. So, prediction is not just a matter of looking at what just happened, it's a matter of looking at what's happened over time. Every experience the customer has modifies the probability that they're a Promoter. A technical support call or a product defect or a new product experience modifies that probability.

Finally, we also know from research that humans and machines make better decisions together. In other words, smart businesses don't seek to understand whether a given predictive algorithm is better than people. Instead, the question is how to apply human intelligence (which is excellent for certain tasks) to machine intelligence (which better at different tasks) to create a better outcome overall. The ideal system is one that generates predictions using algorithms and technology, then couples that with human judgment.



Building Blocks of Predictive Tools

Three building blocks are critical for building effective predictive tools for customer risk:

- Collecting high-quality, high-frequency data
- Training technology to think like customers
- Alerting humans about relevant insights in a timely way

Today, organizations are able to capture more and more data about interactions with customers; we can think of this as the "data exhaust" of customer experiences. This first building block is arguably the most important, because at the end of the day you can't go back in time and imagine data that you've never had. So, organizations that are effective in capturing high quality data will have a substantial advantage over those that don't. Every interaction with a customer is an opportunity to collect information, and companies should prioritize understanding how best to do so.

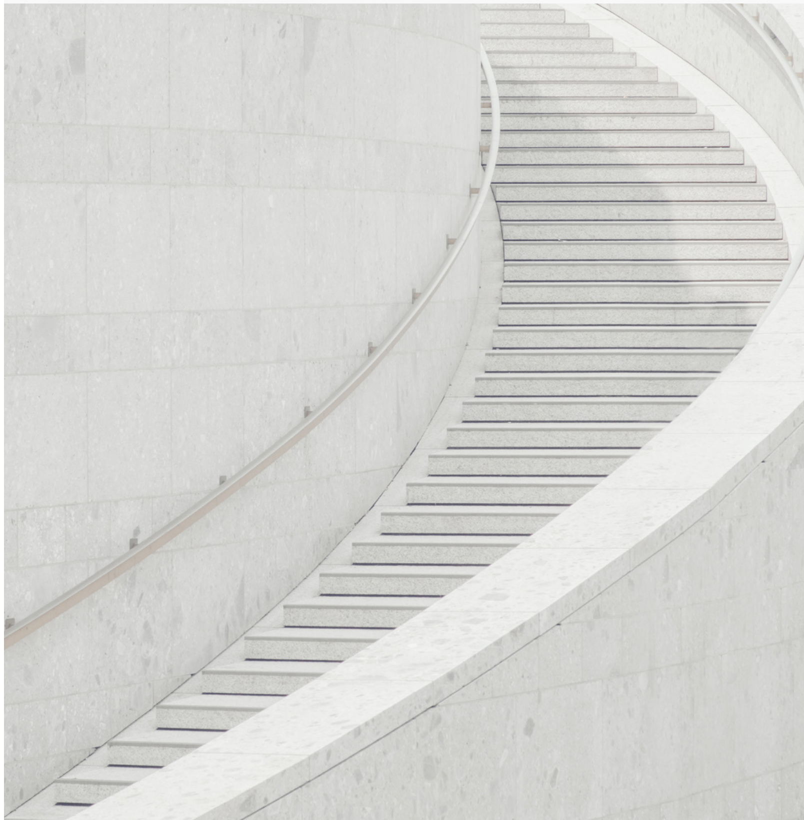
The second building block is the ability to actually take advantage of that data, via the technology of machine learning. This seems complex, but it's increasingly a valuable applied science. For the purpose of developing tools for predicting customer risk, machine learning is the idea that you can train a computer to think like your customer thinks. Customers certainly won't answer 100 survey questions every day, but machines can be trained to do just that on their behalf. The outcome: Machine learning engines can analyze customer experience data to predict risk at the account level.

The third building block is the fundamental idea of the importance of people. Since machines plus humans make the best decisions, the goal with predictive information of any kind is to be able to get it into the hands of people as an influence on their decision making. We want human beings to take the information, process it, modify their own perspectives, and take action accordingly. It's therefore critical to deliver information in easy-to-understand formats and settings, ideally with prescriptions for action. If information is complicated or difficult, it doesn't drive action. If it's not easy to access, it might as well not exist.

A New Twist on Customer Surveys

Customer "data exhaust" provides the raw experiences needed to drive a machine learning engine, but that data alone can't train the engine to think like a customer. Fortunately, customer relationship survey data provides an effective way to get a collective view of what customers think, but only if collected in a specific manner tailored to machine learning.

Tailoring surveys to their new purpose – as training inputs for machines learning – requires a shift for most companies. Most survey designs are poorly suited to this task, failing to deliver the kinds of data sets that work to teach machines to think like customers and therefore produce accurate risk predictions.



The Payoff of Prediction

Predicting customer risk is only desirable because of its outcomes and impact on the business, so it's worth recapping the elements of the payoff of effective risk prediction tools.

Know where you stand with every customer, every day. The daily customer intelligence analytics produced by an effective customer risk prediction tool compare extremely favorably to typical survey programs, whose data is six to 12 months out of date. Survey-based insights also have the disadvantage of low response rates; they fail to give insights on every customer.

Get updates on customer risk as they happen. The most important factor in the effectiveness of predictive tools is timeliness, because it allows customer-facing teams to act while their interventions can make a difference.

See the signal, not the noise. Humans bombarded with excessive information soon learn to ignore it. Predictive tools that filter out noise – information that doesn't impact the customer significantly – allow teams to focus on only things that really matter.

Improve human judgement. Effective predictive tools generate insights humans can't, and in that way complement the particular strengths and skills of human decision makers.

Data-Driven Customer Journey Framework

A data-driven customer journey framework is the second breakthrough tool for managing customer risk. Understanding how customers proceed through journeys, how they interact with companies along the way, and how they produce data as they do so become very useful a tool for effectively organizing customer data. A data-driven customer journey framework is critical for effective predictions, but it's also useful in its own right as a tool for understanding how customers behave. Fundamentally, improved insight on how customers make choices benefits all customer experience improvement work.

Differentiation is a key element of an effective customer journey framework. Customers don't value every aspect of a value chain equally; some have relatively low value, some are relatively critical. Consequently, customer reactions to improvements in each aspect of the journey vary widely.

Improvement in some areas of the journey can be greeted with a bit of a shrug, or improvement may be valued up to a certain point, then not beyond that level. These are often called hygiene factors. For other elements of the customer journey, any form of performance is greeted with a warm reception from customers because those are positive surprises to them. To get to that kind of model, we need to understand how to build the right kind of data-driven journey framework.

From Traditional View to Accurate Matrix

The problem with the traditional approach to customer journeys is that we think of them as we process information as humans, which is very linearly. We tend to think of a journey as point A to point B to point C.

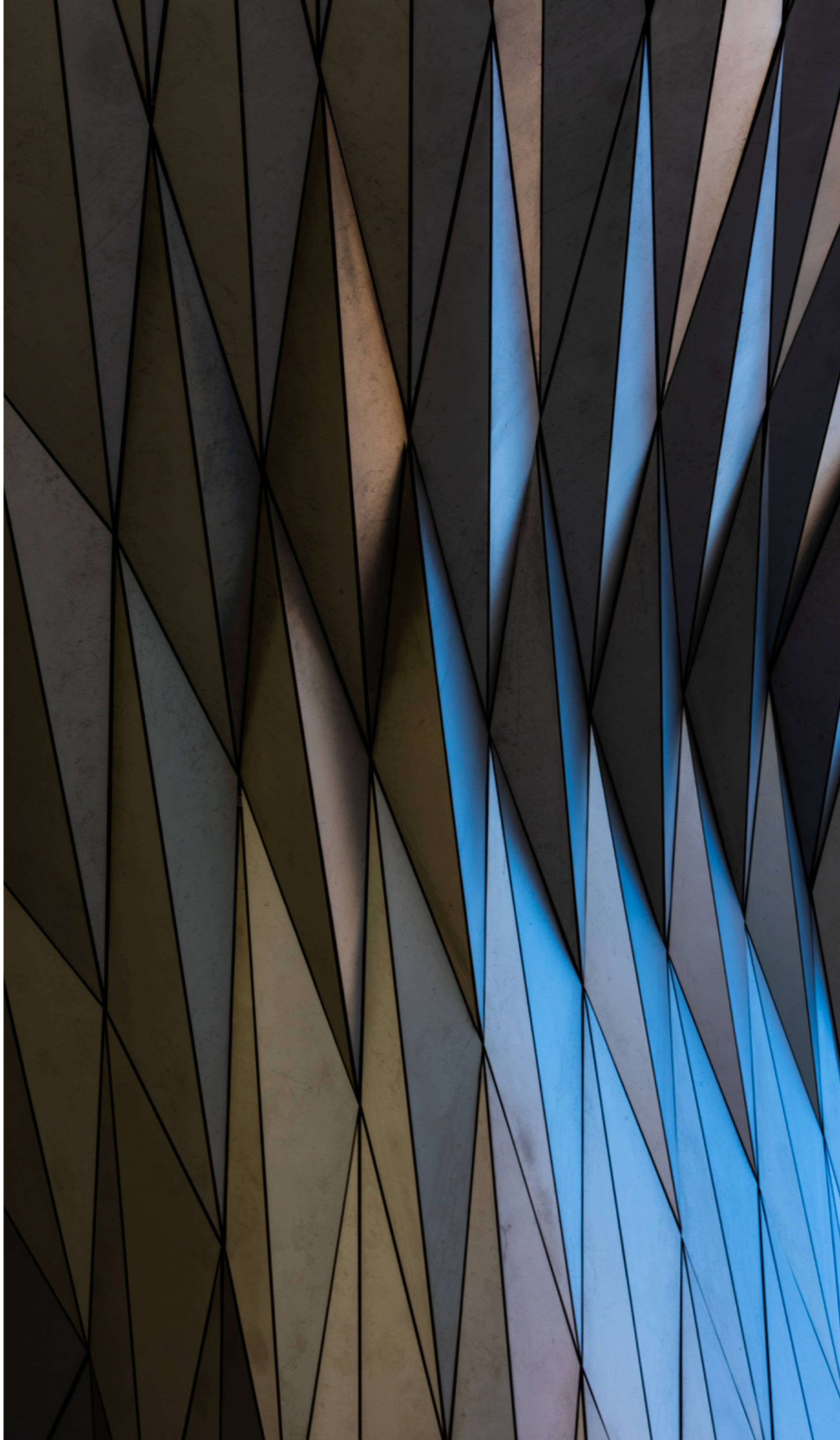
But the reality is that most journeys these days are hybrids of digital and non-digital experiences, which look much more complicated. In fact, customers interact with companies in looping, iterative patterns. While such journeys can be hard to represent visually, they lend themselves well to data models that map out in a matrix the many ways different elements of journeys interact with each other.

The end result is a coefficient map of how different combinations of customer experience interact to model out journeys.

Despite the seeming complexity of data-driven customer journey framework, some key elements streamline our outcomes:

- A relatively small number of events almost always fully explain outcomes. While predictive accuracy may not reach 100% when analysis is limited to 6-10 elements of the journey, it generally comes close enough.

- Customer relationship surveys, when correctly designed, are powerful tools for surfacing the relevant elements of the customer journey, using tools like relative impact analysis.



Poor Surveys, No Predictions

Though a correctly designed customer relationship survey provides a definitive input to predicting customer risks, most customer surveys in place today fail that this task. All too commonly, survey design produces data that has no signal.

Traditional survey design measures elements of the customer journey thought to matter to customers. In other words, surveys test the hypotheses of their designers about what's important in the customer journey. Many customer surveys include a good deal of compromise, driven by internal considerations and the desires of stakeholders. Often, survey results deliver little to no signal, but interpretation and storytelling during results presentations often hide the failure and ensure that it continues in future surveys.

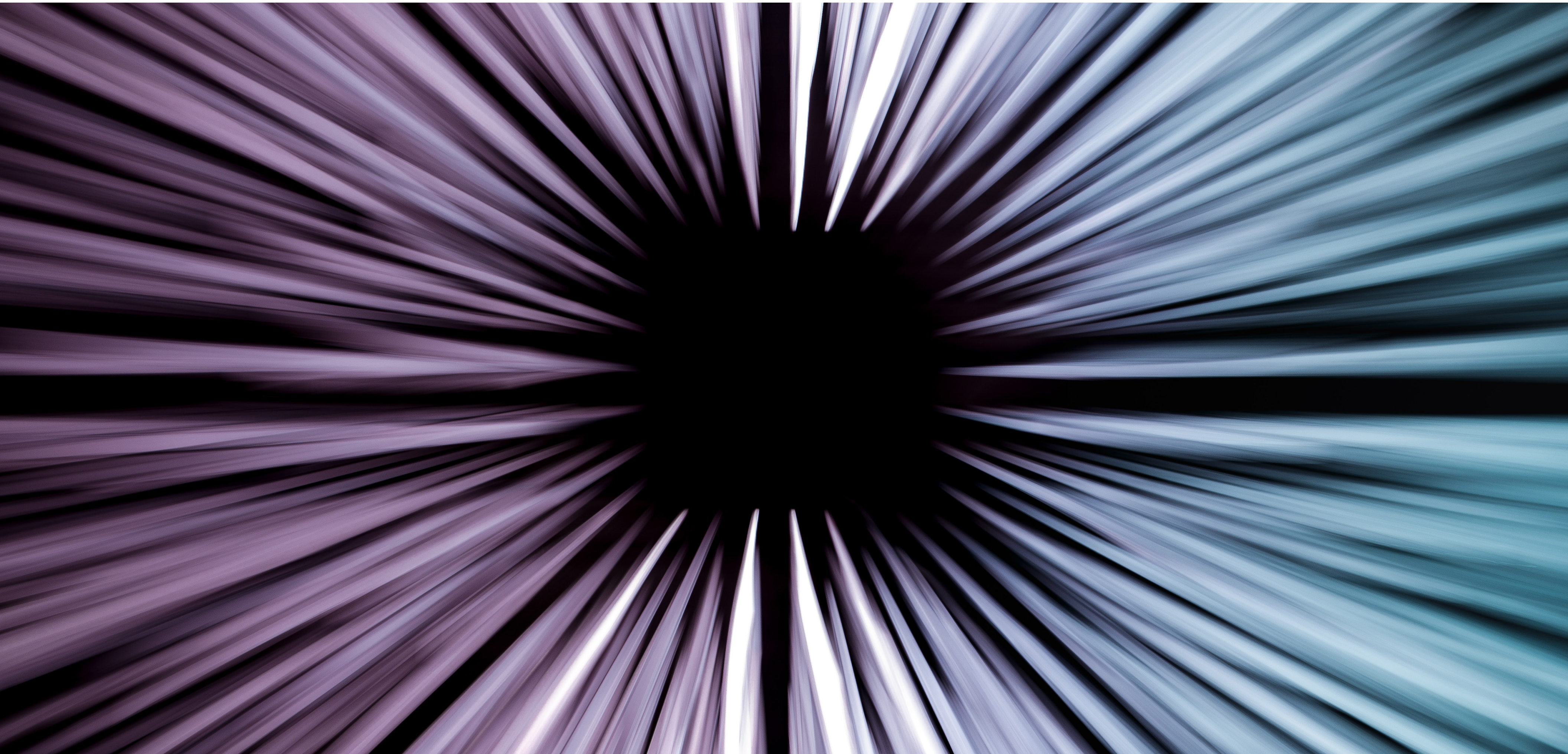
But machines lack storytelling skill, and therefore starkly expose the deficiency in customer survey data. Machine learning engines that don't see a signal in the data will say so; the solution is a data set better suited to the task.

Often, poor questions generate the poor data. For example, a customer asked "How would you rate our support?" might think of the support they receive from their periodic interactions with the account team, though the question was intended to ask about the technical support organization. Confused customers give answers to the questions they believe there are being asked. Sloppy language or framing creates ambiguity that often results in customers giving the right answers to the wrong question, or vice versa.

Separating Signal from Noise

Effective decision-making collaboration between humans and machines benefits from machines' skill at discarding noise and elevating signal. Humans tend to believe that the narrative we already have in mind is important, and we interpret data to support our biases. Machines, in contrast, don't care about existing narratives; if a favorite survey question doesn't uncover a meaningful signal, a machine analysis makes the failure clear. As a result, the connection between good survey design and machine learning is bi-directional; the machine learning designs inform better journey designs and vice versa.

A shortcut for designing customer surveys that deliver better signal for machine analysis relies on a simple journey/question hierarchy. The approach allows precise question definitions and structures related to the customer journey, reflecting the correct layer of journey disaggregation for the survey process. For example, questions about support are asked differently than those about sales.



Outcomes of the Data-Driven Framework

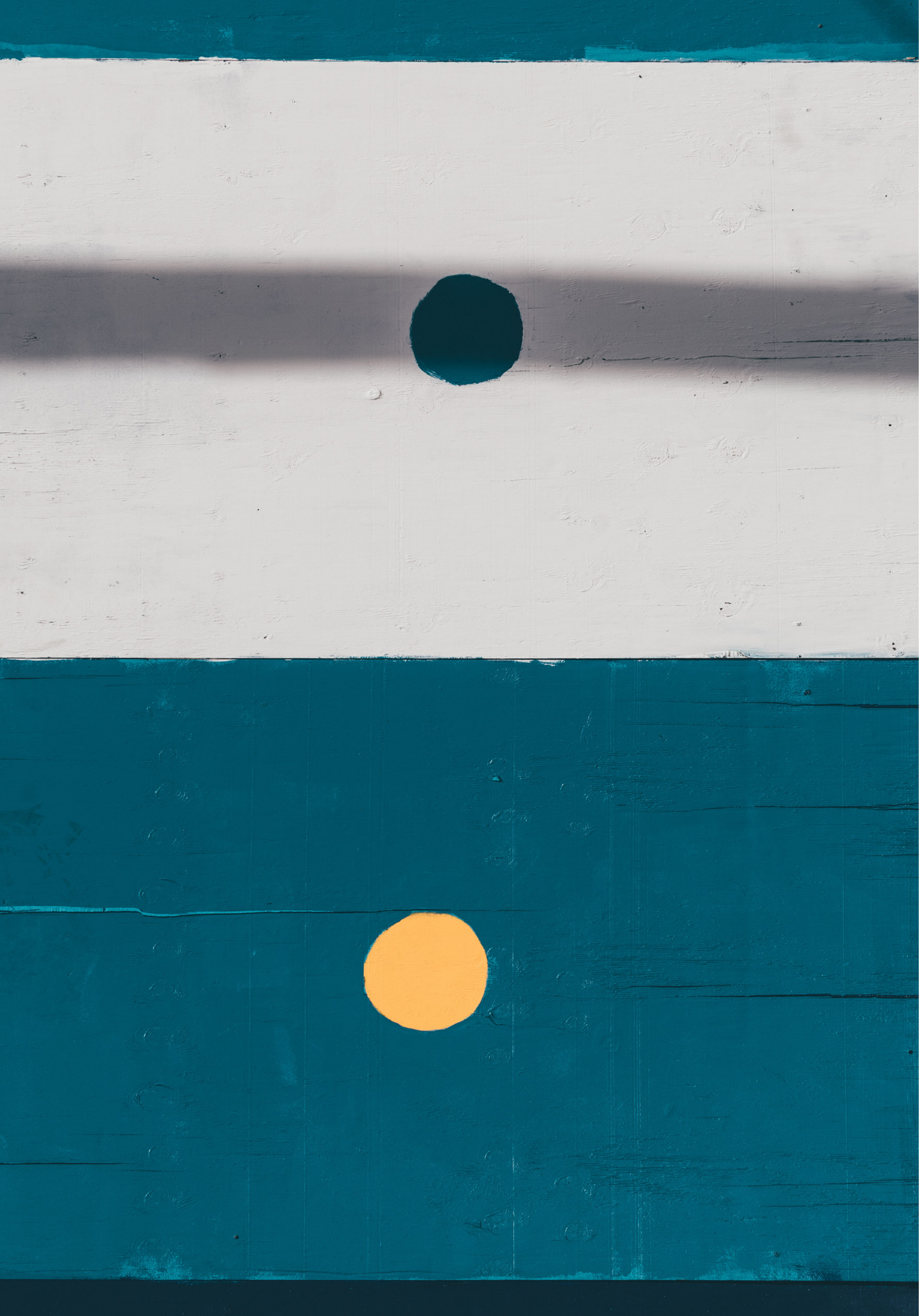
The objective of the data-driven customer journey framework is to create a mathematical recipe for creating Promoters. The recipe explains that if a company takes a certain set of actions, there's a high likelihood of creating Promoters. We can't count on that result with compete certainty, but it's probabilistically the most likely outcome.

Simpler versions of the formula are easier to execute; most organizations can probably manage no more than three to five specific key performance indicators. A limited focus can be effective, with the critical caveat that target performance must be correctly calibrated to customer expectations. To be effective, the recipe requires both the right metric, and the right level of performance.

Additionally, the metrics for a recipe have to be in combination, so they're complimentary. Customers don't care about individual metrics. Instead, they care about the overall experience created by all these metrics in combination. A success recipe based on a combination of factors requires more calculation, but yields greater accuracy and better outcomes.

To use the data-driven customer journey framework effectively, these rules of thumb are key:

- **Derive the customer journey from the data itself.** Too many customer journeys are based on a hypothetical understanding of the customer, without using data to determine its choices. Avoid using a subjective view of how customers proceed through journeys.
- **Simplify models as much as possible.** Significantly simplified customer journey frameworks outperform complex mappings. Focus on *relatively* critical elements.
- **Calibrate performance targets to customer expectations.** It's important to calibrate the journey to the level of performance customers require, and test how critical stages respond to changes in performance.
- **Improve human judgement.** Effective predictive tools generate insights humans can't, and in that way complement the particular strengths and skills of human decision makers.



Customer-Optimal Key Performance Indicators

Key performance indicators (KPIs) are not a new idea; the balanced scorecard concept has been around for 15 years or so. The emphasis when the concept originated was, correctly, on balance. But the balance element – which could also be thought of as weighting – is typically lost in implementation, and as a result, KPIs are often ineffective.

It's important to clearly state that by "customer-optimized KPIs," we mean operational metrics in the business that are linked to the high impact elements of the customer journey and weighting in favor of customer perspectives. The metrics and their target levels need to be customer driven, not internally driven.

In contrast to this ideal, most KPIs today are badly designed when it comes to representing a customer perspective. They are often internally oriented, meaning they are designed in alignment with the internal organization. As a result ,different teams have KPIs that reflect only their internal span of control, which the customer doesn't care about.

Internal vs. Customer-Oriented KPIs

When teams self-determine how they measure a given KPI, the metric may not be what the customer cares about. And worst of all, internal teams tend to set goals that are both selfishly oriented, and also in isolation from other functions, meaning that they don't look at their role within the overall customer journey.

Consider a logistics organization deciding to measure a shipment from the factory gate to the customer and setting the goal – the performance target -- at five days, because it's achievable. But customers don't care about that shipment-to-delivery metric. They would rather know what the order-to-delivery schedule is, and in any case, they don't think five days is the right goal. As a result, the organization is essentially relying on an unweighted, unbalanced metrics view. And that leads to the very common, very unfortunate outcome that even organizations that hit their numbers are not creating Promoters.

The alternative is that performance metrics need to be pressure tested against the customer journey data model, and pressure tested against a machine learning model. Then the metrics become customer determined, and they are significantly weighted based on customer viewpoint.

Ironically, this pressure testing may mean some organizations don't seem to have very ambitious goals, but it's fine to set unambitious targets if customers don't care about the metric.

Internal Metric	**Customer Metric**
Driven by organizational structure	Driven by the customer journey
Self-determined measures and goals	Customer-determined measures and goals
Unweighted/unbalanced	Weighted by customer viewpoint

Integrating the Three Breakthrough Tools for Machine Learning

We've approached the problem of predicting customer risk from multiple dimensions: How we build predictive models, how we organize data driven journeys, and how we figure out ways to create customer driven KPIs. These three breakthrough tools are key to pulling together an effective solution to the challenge.

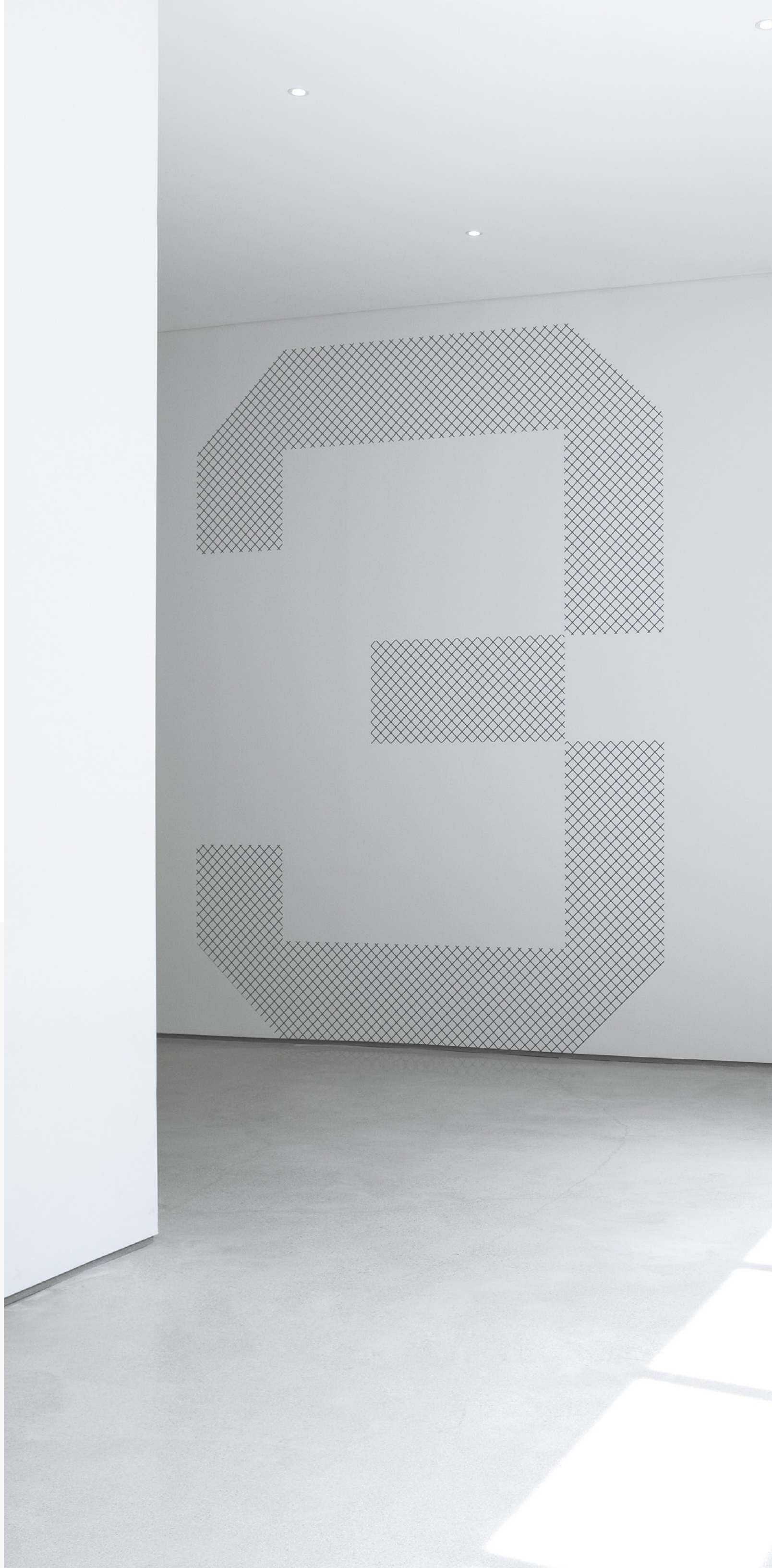
While each tool offers independent value, they gain effectivity when they work together. That way, they create the best possible outcome, the right kind of journey framework, resulting in the right kind of things being measured by the relationship survey, which provides a data set that enables us to teach the machine how to think.

The machine in turn tells us that we're measuring the right things, and it links them to those operational KPIs, so that we can become prescriptive. In other words, process capitalizes on machine learning techniques, predictive science, data driven journey design, better types of relationship surveys, all working together.

Risk Prediction Tools

Here's a reminder of the three breakthrough tools that work synergistically to solve problems of managing customer risk:

- **Predictive account scoring.** This the ability to use analytics to predictively score risk at the account level. We could also call this account health.
- **Data-driven customer journey framework.** This tool outperforms traditional customer journey design approaches and is instrumental in building predictive models.
- **Customer-optimal key performance indicators.** Setting KPIs from a customer perspective let companies drive improvements that matter to customers.



Applying Machine Learning Effectively

Applying machine learning to create effective predictions of risk – in time to change the predicted outcomes – relies on a specific value chain, summarized here. Customer journeys are what create Promoters or Detractors.

Customer journeys are best understood in a data-driven framework. Journeys can be broken down into sub-stages, and those can be linked to operational data sets. One these value chains have been accounted for, the job of the machine learning mode then becomes to uncover the coefficients and mathematical links from the operational elements to the profiles for Detractor or Promoter customers.

The machine learning model operates in a subtractive mode, since most elements are not instrumental in shaping customer experience opinions. Those elements will be discarded for not being closely correlated or for not generating sufficient signal. What remains is a subset of operational indicators across the stages of the journey that interactively affect the customer perception of their experience. It's a complex but effective model that ultimate delivers predictive CX analytics.

Machine learning creates this mathematical model with great accuracy, revealing the formulas for understanding how customer think, and making ongoing updates to those models and data as experiences update and evolve. That's what allows accurate predictions, attributable to operational factors.

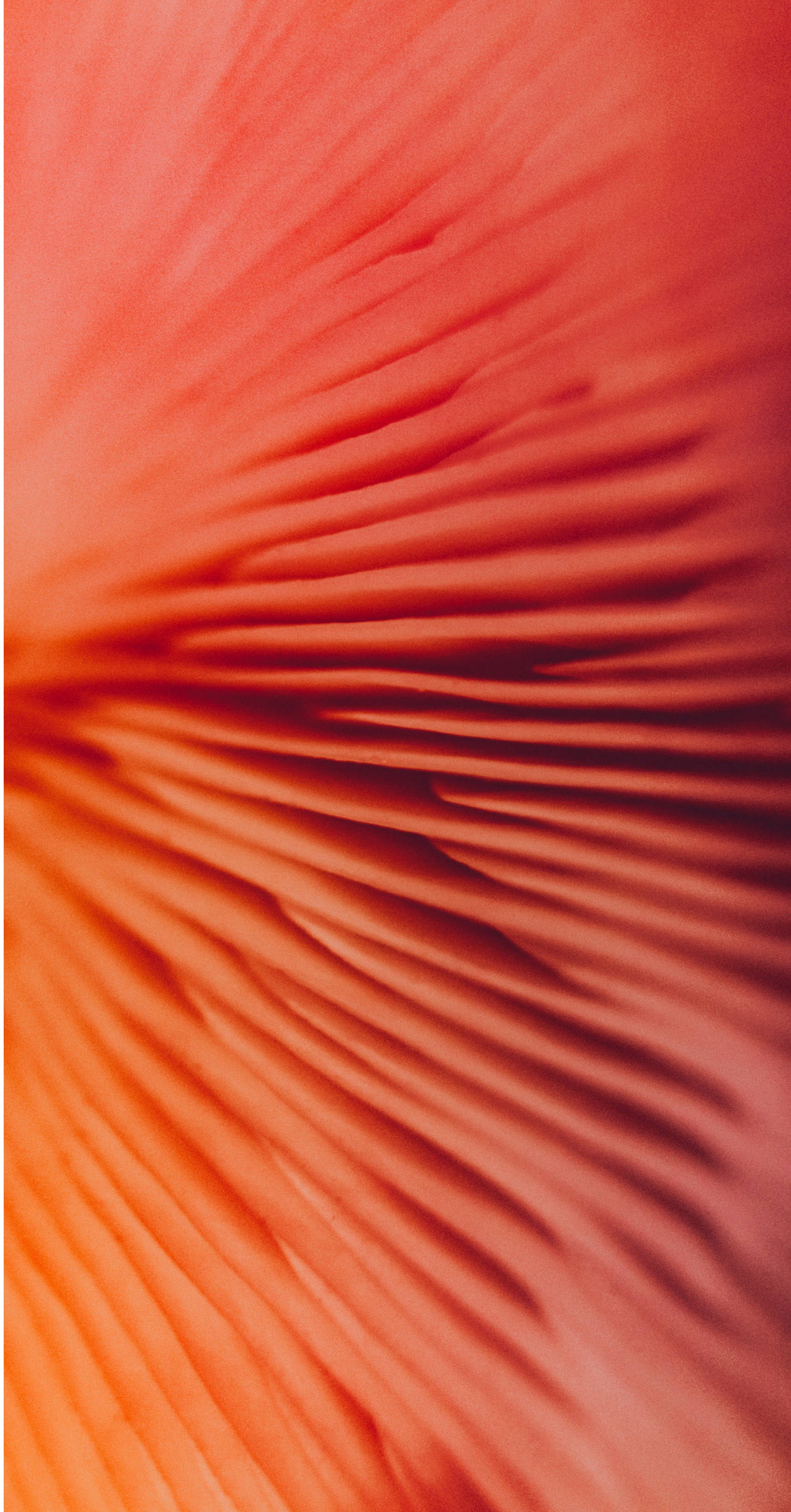
Putting Customer Risk Management Tools in Place

Organizations looking to implement effective tools for managing customer risk might hesitate because the task seems resource intensive. Fortunately, it's possible to approach the transformation in stages. As a starting point, testing data sets against the objective of predicting customer perspectives yields insights on your approach to the customer journey. Even if you don't go all the way to a full predictive model, this kind of testing very accurately test the value of the data you do collect. If it's not predictive, after all, then why are you collecting it?

Keep top of mind these key ideas about predicting and managing customer risk:

- Effective tools in this area improve human judgement, and vice versa. Capitalize on the complementary nature of human and machine insights.
- The goal of predicting customer risk is to manage it, that is, to act on insights in time to change the predicted outcomes. To do that, attributing customer experience to specific operational factors is critical.
- Iterative success is a hallmark of customer risk management. Insights spring from the ongoing interactions between predictive account scoring, the data-driven customer journey framework, and customer-optimal performance indicators.

Explore our other publications for more about the data science and approaches that make it possible to predict and manage customer risk.



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