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Leadership's role in fixing the analytics models that COVID-19 broke

COVID-19 has upended life as we knew it, and our new behaviors are wreaking similar havoc on some analytics models that rely on historical data. How can leaders enable teams to get analytics back on track?

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The COVID-19 crisis has put a spotlight on the power and potential of analytics and artificial intelligence. We have heard from leaders across industries and geographies about the many ways analytics have enabled them to more effectively handle the challenges presented by these unprecedented times, from supporting and protecting workers to engaging increasingly digital customers and managing fragile supply chains.

But the crisis has also revealed the technology's Achilles' heel. One of the most widely used advanced-analytics techniques—machine learning—relies on the principle that patterns and behaviors from the past will likely repeat in the future. Algorithmic models expose these patterns in data and draw on them to predict what will happen (such as whether a particular customer will cancel a service) and even recommend what the business should do (for example, identifying which offer will most likely change a customer's mind). This was effective until the pandemic transformed the way we live and work.

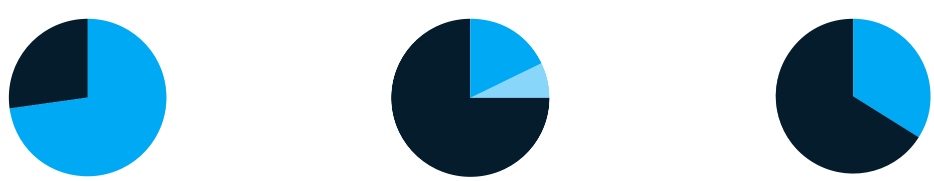
Lockdowns, travel bans, physical distancing, and widespread furloughs have altered how we shop, where we perform our jobs, how—and if—we travel, and more. Even as communities reopen, we're a far cry from business as usual (Exhibit 1).

These shifts are reflected in the data feeding into some algorithmic models built before the crisis, reducing their predictive powers and, in some cases, sending them completely off the rails. One energy company, for example, struggled with trading decisions when crude-oil prices crossed into negative numbers, because data scientists built existing models on the assumption that barrel prices would never fall below zero.

Even once the next normal emerges, organizations won't be out of the woods. Some patterns in data captured during the COVID-19 crisis (for example, extraordinarily high demand for hygiene products) will become irrelevant. New lasting patterns, such as higher consumer spending on digital channels, will emerge, invalidating or reducing the predictive power of pre-COVID-19 data as well.

Exhibit 1

COVID-19 is profoundly shifting consumer behavior—and these changes are reflected in the data feeding many analytical models, causing some to go awry.



73%

of US consumers are uncomfortable with returning to "regular" out-of-home activities

18–25%

of European consumers expect to reduce attendance at movies, concerts, and other events, as well as international travel

1/3

of consumers in China, India, and Indonesia intend to spend less

Source: "Survey: US consumer sentiment during the coronavirus crisis," August 2020, McKinsey.com; David Chinn, Pal Erik Sjatil, Sebastian Stern, Sahil Tesfu, and Eckart Windhagen, "Navigating the post-COVID-19 era: A strategic framework for European recovery," June 2020, McKinsey.com; Stephanie Chan, Mahima Chugh, Felix Poh, and Simon Wintels, "An early view of post-COVID-19 discretionary spending in Asia," June 2020, McKinsey.com.

Despite these issues, pre-COVID-19 models have tremendous capacity to give executives important insights to help them navigate the crisis and the next normal—if leaders are prepared to take the steps needed to shore up those models. The challenge here is not simply a technical one for data scientists to solve. While analytics professionals will play an important role, successfully stabilizing critical models will depend equally on efforts from leadership to recalibrate business strategies for the changing landscape, forge new data partnerships, convene interdisciplinary teams with sufficient diversity, and more.

Where should leaders start? In this article, we share a framework that leaders can use to prioritize their efforts, evaluate and resolve the risks, and ready their organizations for the future.

Reassessing business priorities to focus model-assessment efforts

At its most basic level, advanced analytics is designed to improve decision making. As a result, before leaders evaluate which models they can trust today and which require adjustments, they should first reassess which models they actually *need* during this profound transition.

The economic repercussions of the pandemic have been wide-ranging and world changing. All industries and companies have been affected—albeit in different ways. Telecommunications companies struggled to keep up with dramatically higher broadband demand, while oil and gas companies watched prices shrivel as automobiles and airplanes sat idle. Consumer-packaged-goods companies raced to ramp up production of essentials, such as hygiene products, while clothing retailers shut stores down.

While this quick-shifting environment affected the accuracy of models built before the crisis, it also led to the need for wholly new analytics capabilities to help leaders tackle these fast-emerging challenges. Executives at one mining company, for instance, created in just a few weeks a global cash-flow tool that integrated and analyzed data from 20 different mines so they could effectively strengthen the company's solvency during the crisis.

Conversely, in some instances, previously business-critical models have been temporarily benched due to changing priorities during COVID-19 lockdowns. Such was the case at most banks across one European country as they redirected outbound sales representatives from branches and call centers to offer support to their customers (for example, helping customers shift to online banking or secure emergency loans). This temporarily erased the need for a tool that these sales representatives had been using daily to recommend products and identify cross-selling opportunities.

Determining where to focus model assessments requires identifying the new, or newly important, business strategies the pandemic has demanded. This exercise should occur at regular intervals (typically every few weeks) among business and analytics leaders until a relatively more stable next normal establishes itself.

For organizations with hundreds or thousands of models supporting critical business, performing a layered model-triage process can focus limited analytics resources on the most critical models. To identify those models, financial-services organizations, for example, typically consider how a model is used, whether a model is material in financial reporting, to what degree COVID-19 has had an impact (in the next section, we discuss how to determine this), and how direct that impact is on critical business. This has led banks to focus on credit, pricing, valuation, and market-risk models, including high-impact macroeconomic models, over fraud or marketing models. Other considerations include regulatory focus or the potential of upstream models to "contaminate" other critical models.

Reevaluating model risks to identify problematic analytics

In general, no analytics system is immune to faulty predictions or suboptimal recommendations resulting from changing patterns of behavior captured in the data feeding into the models. At the same time, not all systems will face the same level of impact, and companies in different industries will find the most problematic models in different pockets of their organizations (Exhibit 2).

Understanding which models to trust and which to scrutinize for problems requires understanding the factors that influence model performance:

— *How a model is built.* The more complex the model, the more opaque it is, so leaders have more difficulty gauging when its predictive powers may be in question. In cases where the simplest possible model is a complex one, explainability tools can make opaque models more transparent to reduce risk and enable humans to incorporate their expertise and judgment to address highly volatile elements.

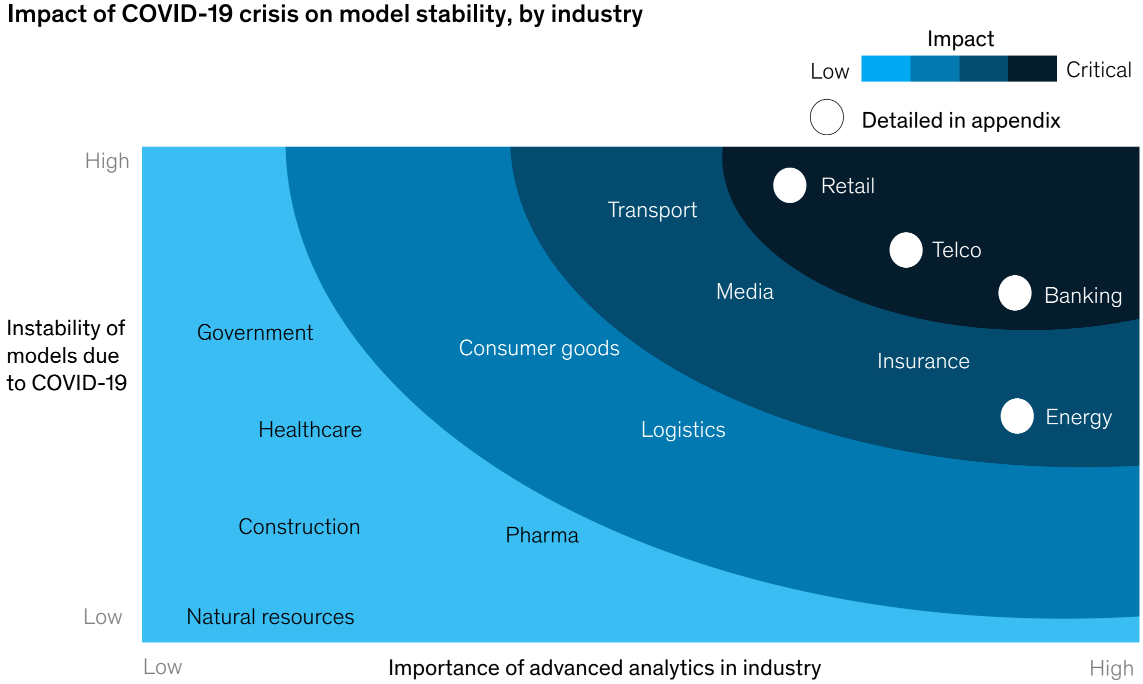
— *What data are used.* Some types of data present more potential problems for the models that rely upon them than others. For example, customer-segmentation and -propensity models can be highly susceptible to performance issues, because they typically rely heavily on individual characteristics and behaviors drawn from years of historical customer data, which might look very different from the data coming in from customers today. Conversely, asset-management models that depend on explicit macro- and microeconomic variables can take into account the impact of COVID-19 by simulating the effect of changes to macroeconomic variables, making them somewhat less at risk.

— *How features are weighted.* Data scientists often shape more accurate predictions by identifying and ranking "features" in the data. Common examples in the case of underwriting would be time to repay and delinquency rates. Data features can be heavily influenced by current events. Bank leaders, for instance, are finding delinquencies occurring significantly less often than expected, given a high unemployment

Exhibit 2

COVID-19-related disruptions to analytics models are most common in industries where organizations rely more heavily on advanced analytics.

Impact of COVID-19 crisis on model stability, by industry



rate, thanks to the direct and indirect effects of government financial-assistance programs. As a result, models using these artificially reduced delinquency rates may offer falsely optimistic guidance after the government interventions end, and that guidance would affect a broad range of underwriting, customer-service, and capital decisions.

— *What assumptions were made during the model build.* The energy company mentioned earlier was using analytic models that didn't account for crude-oil prices reaching –$30 per barrel. Many banks' models don't account for negative interest rates. Retailers' logistics and demand-forecasting models didn't account for having to move their entire operations to digital. Logistics companies' forecasting applications didn't account for the collapse of passenger air travel, which is closely intertwined with air-freight availability and costs. Indeed, all of these were reasonable assumptions before COVID-19 but are no longer accurate today, and that can have tremendous implications for model predictions.

While analytics professionals should handle the actual evaluation of these elements, senior executives and business-unit heads need to understand what they are and how they affect model performance. Only then will they know what to prioritize, how to address the underlying business assumptions, and what questions to ask analytics teams to ensure that the factors are properly addressed—all of which will give them renewed confidence in the models, once they have been adjusted.

Just as leaders need to frequently reassess the criticality of business strategies in these turbulent times, they'll need to constantly reevaluate the models that are most at risk. At one North American bank, the head of model risk management convened the chief credit officer and heads of analytics periodically throughout the crisis to consider how evolving customer spending and payment behavior, government response, and business operations (such as store openings or forbearance programs) might affect drivers of model performance. (See sidebar, "Building trust through challenger models," for one approach the organization took to enable more reliable model-based decision making during the crisis.) Initial reviews resulted in a focus on portfolio monitoring, stress testing, and credit models to protect against losses. More recent reviews have broadened the scope to include revenue-projection models, which required a better understanding of what consumers were spending their money on, and how much, during COVID-19 and fed into stress testing and other key business models.

Building trust through challenger models

The North American bank highlighted in this article decided that the best way to determine charge-offs amid artificially low delinquency rates was to provide decision makers with two models, often called challenger models, to draw from.

The first challenger model overlaid current payment and stimulus data onto the original model to understand a customer's credit risk, knowing that predictive accuracy would be reduced, especially in the longer term.

A second, simpler challenger model determined the impact of different scenarios at a higher level (without details on impact to different customer subsegments) to establish overall losses. Bank decision makers using this approach could better forecast the bank's loss-bearing capabilities and the potential operational consequences on, for instance, staffing at call centers.

The bank's use of two modeling approaches (both of which were explainable), the continued vigilance to ensure trust in the models, and the use of a robust review and challenge process increased the comfort level of multiple stakeholders, including the frontline decision makers.

Expanding the organization's data sources

Whether or not a model needs to be rebuilt or retuned, there's a good chance that a problematic model needs new, fresher inputs to provide more accurate insights in this volatile period. While these are clearly unprecedented times, we find that much data exist that can help organizations better understand current trends and customer needs. Business leaders charged with sourcing these data—whether a business head, chief data officer, or other executive—should expand their sources in a few key ways:

— *Incorporate new or previously unused internal data sources.* Examples of such data include web-page navigation and mobile-app usage from new (or enhanced) digital channels, as well as transaction data. The North American bank mentioned earlier, which had been relying on traditional credit scores to assess an individual's credit risk, began analyzing current-customer account data to uncover in real time any gaps in direct deposits or receipt of unemployment checks.

— *Use existing data in new ways.* A major automotive-engine manufacturer began leveraging telematics data from its engines to improve its understanding of traffic patterns as cities reopened and to inform demand forecasts. Previously, the telematics data were used chiefly to support maintenance and warranty work.

— *Increase the frequency of data collection and processing.* Sometimes the challenge is not purely what data you're collecting and processing, but how often you do so. Simply changing the frequency from, say, weeks to days (or even daily) can shorten learning cycles and enable organizations to pivot more quickly as events on the ground occur. One financial-services company moved from monthly to daily liquidity-reporting processes during the crisis, so leaders could immediately identify any funding gaps.

— *Acquire external data.* In some cases, the acquisition of external data might include open-source data, such as public-health and location-specific data to, for instance, anticipate workforce availability and potential supply-chain disruptions. In others, it may necessitate buying data previously considered too expensive or difficult to obtain. Banks hesitant in the past to spend the time and money to obtain customer permission to access banking records from other banks through open-banking regulations can likely justify the cost today. Finally, external data may also come from novel—and potentially even surprising—partnerships, as in the case of several original equipment manufacturers that shared data on geographical product-demand trends. By doing so, these companies were able to build a more holistic view of market demand, so each could ensure it had sufficient inventory.

Promoting faster cycle times for decision making

The benefits of agile are numerous and well documented, and it's easy to see how such an approach helps companies today in their scramble to adapt. The faster an organization can detect unexpected market changes, test new ideas, and adjust, the more successfully it can respond. One telecommunications provider uses agile practices to deploy analytics-driven micro-campaigns daily, evaluates the results immediately, and then fine-tunes campaigns the following day. This rapid-fire approach recently helped the company recognize quickly that one of the models informing the campaigns was not accounting for the spike in remote working. By updating its algorithmic models to account for this shift, it better predicted and responded to the need for additional products, including personal Wi-Fi hotspots—a product area for which it began capturing greater market share.

One critical enabler of this effort was the convening of a multidisciplinary team, a fundamental component of agile delivery practices. We find companies are best served when they build interdisciplinary teams with a diverse set of roles, including domain experts, frontline users, and technical staff, to develop new analytics capabilities for the business. By incorporating these varying perspectives into one team focused on a critical activity and model, leaders can better ensure all aspects of the model's risks—including data-fit issues, the analytical technique employed, and the functioning of a user dashboard—are addressed.

How to ready your company for whatever comes next

Ultimately, a vaccine for COVID-19 will be developed. The next normal will emerge, and leaders will move from survival mode to more solid ground. This will be a time for reimagining the business and for reform. At that point, how can you structure analytics so your organization doesn't face the same model challenges coming out of the pandemic that surfaced going into it? Five steps in particular will help organizations respond more flexibly:

1. *Deploy a digital nerve center.* Digital nerve centers have emerged as a core capability during the COVID-19 response, enabling organizations to mobilize resources, including new data sources and analytics capabilities, to help business teams get a handle on emerging trends quickly, shorten feedback cycles, and gain greater insight into the various scenarios they might face. A retailer with grocery stores in 15 countries is using a digital nerve center to provide critical business functions—supply chain, employee protection, finance, customer and store operations, and digital channel operations—with rapid access to insights about the company, customers, and suppliers during the pandemic. Already, the work has enabled supply-chain leaders to keep store shelves well stocked, even for high-demand items.

2. *Embrace real-time data.* Previous articles have outlined in depth the shifts necessary for building a data architecture to drive innovation. One shift in particular—the move to real-time collection and analysis of website, social-media, clickstream, and app data—has taken on increased urgency in recent months. Leaders no longer can afford to wait days and weeks for the "latest data" to arrive. Technologies such as messaging platforms and stream-processing capabilities enable the processing and analysis of data in real time, allowing decision makers to respond in hours rather than days or weeks.

3. *Prioritize cultural shifts.* Many leaders found during the pandemic that their companies could be more agile during a crisis than they had realized. Interdisciplinary teams, agile ways of working, and data-driven mindsets sprouted overnight and produced highly targeted and fruitful analytics capabilities. Cultivating these shifts—through, for example, reskilling workers—will be paramount to keeping the momentum going. Such work is possible even while employees are working from home. One financial-services company has launched Zoom-based training to upskill senior company leaders on basic artificial-intelligence concepts, possible ways to use the technology, and techniques to drive change, preparing the company for the next normal.

4. *Ensure compliance by design.* Various activities and tools can help teams ensure that critical oversight is baked into the analytics-development process, so risks are continually managed and detected and rapidly addressed. These include documented guidance and checklists on topics such as setting up diverse teams, ethics training, risk metrics to use, and changes to keep an eye out for—for example, changes in laws, regulations, and policies, as well as evolving social norms. Activities include putting in place methods and data tools for detecting and mitigating risk in data and monitoring models.

5. *Invest in diverse teams.* COVID-19 has affected different communities in very different ways. Diverse teams can help organizations predict the changing needs of their customer communities significantly

faster and more accurately. (In fact, an abundance of research shows that diversity is linked to higher financial performance.) We find companies are best served when they build interdisciplinary teams that include gender, ethnic, cultural, and geographical diversity, along with a diverse set of roles and perspectives, to develop new analytics capabilities for the business. From a role-diversity perspective, individuals with translator expertise are increasingly vital during this crisis to bridge the business and analytics realms and effectively link data, models, and insights to the business problem they are meant to solve or the decision they are meant to inform.

While advanced analytics has demonstrated value before and during the COVID-19 pandemic, it has also shown fallibility in the wake of a crisis. Leaders who recognize the sources of fallibility and take steps to strengthen their company's analytics strategy will be better equipped during the present crisis and future extraordinary events.

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Appendix

Exhibit 2a

Banking: COVID-19's impact on advanced-analytics use cases

Risk use cases are the most affected, due to new regulations and behaviors and banks' low capacity to adapt quickly to new circumstances.

Low impact Medium impact High impact

Use case	Business application	Patterns and behaviors	Ability to adapt
Customer segmentation	Some ad hoc segments might need to be defined	Completely new behaviors that affect segmentation directly	Many use cases depend on segmentation output
Propensity models	Some limitations in product catalog; ad hoc campaigns	New trends in product acquisition and transactions	Most product-acquisition models look far into past and future
Retention	Low impact in churn rate; otherwise, business as usual	Strong value reduction in some segments	Churn and value-reduction models look far into past and future
Pricing	Business as usual	Somewhat important change in price sensitivity of some segments	Price-sensitivity models can use less data if necessary
Risk	Government restrictions in collections	New trends across all risk models	Dependent on external bureaus and look far into future
Branch optimization	Use case irrelevant during COVID-19	Quarantine has changed behavioral patterns completely	Model will adapt quickly if problem correctly defined
Trading	Some government restrictions on financial products	Tremendous volatility and unpredictable behaviors	Most trading models can use only recent data

Exhibit 2b

Telecommunications: COVID-19's impact on advanced-analytics use cases

Drastic changes in the behavior of the customer base, together with strong regulations, result in a critical impact on marketing, risk, and retention use cases.

Low impact Medium impact High impact

Use case	Business application	Patterns and behaviors	Ability to adapt
Customer segmentation	Some ad hoc segments might need to be defined	Completely new behaviors that affect segmentation directly	Many use cases depend on segmentation output
Propensity models	Large limitations; cannot target clients from other telcos	Huge impact from regulation	Most product-acquisition models look far into past and future
Retention	Government restrictions in churn	Strong value reduction in some segments	Churn and value-reduction models look far into past and future
Pricing	Pricing potential needs to be oriented to minimize risk	Important change in price sensitivity of some segments	Price-sensitivity models can use less data if necessary
Risk	Government restrictions in collections	New trends across all risk models	Collections models look far into future
Smart capital expenditure	Business as usual	Consumption patterns differ from the ones observed before	Amount of data can be reduced if necessary
Trading	Business as usual	No huge changes in drivers for technical problems	Past drivers are still valid, and time to response should be similar

Exhibit 2c

Energy: COVID-19's impact on advanced-analytics use cases

Use cases targeting customer bases are most affected, while use cases related to asset management and trading are less impacted or have the capacity to adapt quickly to new trends.

Low impact | Medium impact | High impact

Use case	Business application	Patterns and behaviors	Ability to adapt
Segmentation	Some ad hoc segments might need to be defined (Medium impact)	Completely new behaviors that affect segmentation directly (High impact)	Many use cases depend on segmentation output (Medium impact)
Propensity models	Business as usual (Low impact)	Change in the demand of energy of customers (High impact)	Models need to look far into past and future (Medium impact)
Retention	Restrictions in the ability to change utilities supplier (Medium impact)	Not affected (Low impact)	Churn and value-reduction models look far into past and future (High impact)
Pricing	Restrictions in prices (Medium impact)	Changes in price sensitivity of some segments (Medium impact)	Price-sensitivity models can use less data if necessary (Low impact)
Risk	Strong government restrictions in collections actions (High impact)	New patterns and higher collections risk in some segments (High impact)	Risk models look far into past and future (High impact)
Predictive maintenance	Business as usual (Low impact)	Not affected (Low impact)	Models require very long time windows (High impact)
Power trading	Business as usual (Low impact)	Completely new patterns in demand (High impact)	Some trading models need to look far into future (Medium impact)
Demand forecasting	Manual adjustments to adapt to partial shutdown of economy (Medium impact)	Completely new patterns in demand (High impact)	Demand-forecasting models look far into past (Medium impact)
Renewal generation	Business as usual (Low impact)	Not affected (Low impact)	Renewal-generation forecast models look far into past (Medium impact)

Exhibit 2d

Retail: COVID-19's impact on advanced-analytics use cases

The pandemic's strong impact on business models and consumer behaviors, combined with slow reaction times by most models, leaves retail as one of the most impacted industries.

Low impact | Medium impact | High impact

Use case	Business application	Patterns and behaviors	Ability to adapt
Customer segmentation	Some ad hoc segments might need to be defined (Medium impact)	Completely new behaviors that affect segmentation directly (High impact)	Many use cases depend on segmentation output (Medium impact)
Propensity models	Business as usual in digital channels, although sales volumes will be different (Low impact)	Completely new behaviors in customer base (High impact)	Most product-acquisition models look far into past and future (Medium impact)
Retention	Loyalty incentives must be revised (High impact)	Strong value reduction in some segments (Medium impact)	Loyalty programs require involvement of many stakeholders (High impact)
Pricing	Business as usual (Low impact)	Important change in price sensitivity of some segments (Medium impact)	Price-sensitivity models can use less data if necessary (Low impact)
Demand forecasting	Use case irrelevant during COVID-19 (High impact)	Quarantine has changed behavioral patterns completely (High impact)	Demand-forecasting models react poorly to outliers (High impact)
Logistics optimization	Restrictions to mobility affect use case in short term (Medium impact)	Information needs to be included to account for mobility restrictions (Medium impact)	Optimization will adapt quickly if problem correctly defined (Low impact)