Strategy For and With AI

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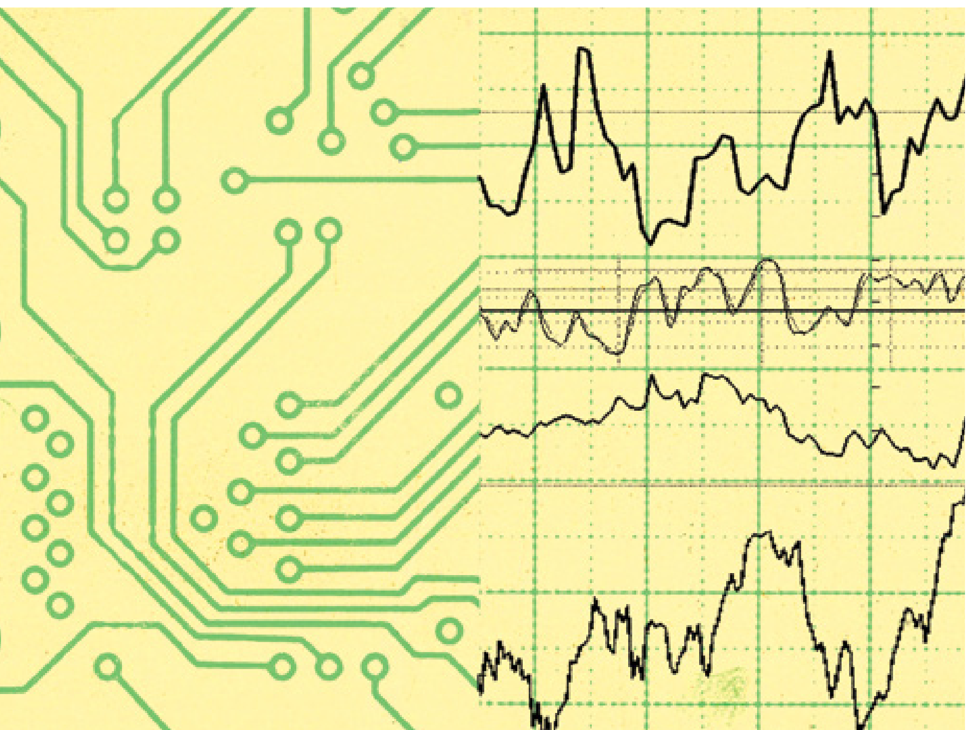
A company's strategy is defined by its key performance indicators. Artificial intelligence can help determine which outcomes to measure, how to measure them, and how to prioritize them.

BY DAVID KIRON AND MICHAEL SCHRAGE

Many executives, intent on understanding and exploiting AI for their companies, travel to Silicon Valley to acquaint themselves with the technology and its many promises. These pilgrimages have grown so common that tours now exist to facilitate inside peeks at innovative startups. Buoyed by hype and smatterings of algorithmic knowledge, returning executives share a common goal: determining what products, services, and processes AI can enhance or inspire to sharpen competitive edges. They believe a comprehensive strategy for AI is essential for success.

That well-intentioned belief is off the mark. A strategy *for* AI is not enough. Creating strategy *with* AI matters as much — or even more — in terms of exploring and exploiting strategic opportunity. This distinction is not semantic gamesmanship; it's at the core of how algorithmic innovation truly works in organizations. Real-world success requires making these strategies both complementary and interdependent. Strategies *for* novel capabilities demand different managerial skills and emphases than strategies *with* them.



Machine learning pioneers — Amazon, Google, Alibaba, and Netflix come to mind — have learned that separating strategies *for* developing disruptive capabilities from strategies deployed *with* those capabilities invariably leads to diminished returns and misalignments. Not incidentally, these organizations are intensely data- and analytics-driven. Their leaders rely heavily on metrics to define, communicate, and drive strategy. This reliance on quantitative measures has increased right along with their growing investment in AI capabilities.

Our research strongly suggests that in a machine learning era, enterprise strategy is defined by the key performance indicators (KPIs) leaders choose to optimize. (See "About the Analysis," p. 32.) These KPIs can be customer centric or cost driven, process specific or investor oriented. These are the measures organizations use to create value, accountability, and competitive advantage. Bluntly: Leadership teams that can't

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clearly identify and justify their strategic KPI portfolios have no strategy.

In data-rich, digitally instrumented, and algorithmically informed markets, AI plays a critical role in determining what KPIs are measured, how they are measured, and how best to optimize them. Optimizing carefully selected KPIs becomes AI's strategic purpose. Understanding the business value of optimization is key to aligning and integrating strategies for and with AI and machine learning. KPIs create accountability for optimizing strategic aspirations. Strategic KPIs are what smart machines learn to optimize. We see this with Amazon, Alibaba, Facebook, Uber, and assorted legacy enterprises seeking to transform themselves.

These principles have sweeping and disruptive implications. As "accountable optimization" becomes an AI-enabled business norm, there is no escaping analytically enhanced oversight. Boards of directors and members of the C-suite will have a greater fiduciary responsibility to articulate which KPIs matter most — and why — to shareholders and stakeholders alike. Transformative capabilities transform responsibilities. You are what your KPIs say you are.

Distinct Complements

Historical context and precedent are important: Blending strategy *for* and strategy *with* is hardly unique to AI and machine learning. John D. Rockefeller's Standard Oil, for example, dominated the petroleum market not just because the company had an effective strategy for capitalizing on the nascent railroad industry's emerging capabilities but also because it allowed those capabilities — logistical powers of transport and delivery — to shape its broader strategy. By ruthlessly exploiting scale and acquiring and designing fuel tank cars, Standard Oil consistently reaped disproportionate returns from a rapidly expanding physical network.[1]

More recently, incumbents grasped that they urgently needed a strategy for the internet to compete with disruptive born-digital startups. But those organizations discovered — sooner or later — that their strategies for the internet were contingent upon the success of their strategies with the internet. Retailers, for example, commonly use internet-based omnichannel strategies to compete on customer experience. They might start by building strong relationships with shoppers online, for example, but when those same customers go to physical store locations, geofencing apps alert the company to their imminent arrival. Staff is then primed to help facilitate customer pickups. These seamless experiences blend strategy with and for the internet.

Creating an enterprise strategy for developing or applying a capability is not organizationally, culturally, or operationally the same as cultivating a strategy *with* that capability. These activities are complements. A strategy for sustainability (such as lowering one's carbon footprint or reducing waste) should not be divorced from having a sustainable overall strategy enabling the business to operate in thriving communities. Similarly, a strategy for AI shouldn't be viewed as a substitute for creating a strategy with AI.

Where Opportunity Lies

What, then, does strategy *with* AI pragmatically mean? Like any corporate strategy, it expresses what enterprise leaders deliberately seek to emphasize and prioritize over a given time frame. Strategies articulate how and why an organization expects to succeed in its chosen market. These aspirations might involve, for example, superior customer experience and satisfaction, increased growth or profitability, greater market share, or agile fast-followership when rivals out-innovate the company.

Whatever the specific strategy, virtually all organizations create corresponding measures to characterize and communicate desirable strategic outcomes. Those metrics — be they KPIs, objectives and key results (OKRs), or a Balanced Scorecard — are how organizations hold humans and algorithms accountable. For public companies, strategic KPIs typically respect and reflect investor concerns; for private equity, strategic KPIs might be calibrated to maximize a sale price or facilitate an IPO. Data-driven systems, enhanced by machine learning, convert these aspirations into computation. World-class organizations can no longer meaningfully discuss optimizing strategic KPIs without embracing machine learning (ML) capabilities.

Uber, for example, runs hundreds of ML models to optimize its ride-sharing platform and food-delivery

THE LEADING QUESTION
What does creating strategy with AI involve?

- **Organizations must first realize that their key performance indicator (KPI) portfolio represents their strategy.**
- **They can then use machine learning applications to choose, measure, and optimize their KPIs.**
- **They must manage their data as an asset in order to enhance their KPIs and help their machines learn.**

ABOUT THE ANALYSIS

This article draws on results from a 2018 survey of 3,225 business executives, managers, and analysts from companies based in 107 countries and 20 industries. To complement our survey analysis, we conducted 30- to 60-minute interviews with 17 executives and academics about the role of KPIs as a leadership tool. Some related findings were published in the 2018 *MIT SMR* report "Leading With Next-Generation Key Performance Indicators." This article extends that discussion by drawing out the implications of machine learning and AI for both identifying and optimizing strategic metrics.

business. Uber has made enormous investments in its machine learning capabilities and implementations. Whether it enjoys an abundance of available cars on call or relies on relatively few, its ability to estimate accurate arrival times for customer and driver alike is essential to how it competes in the marketplace.

"Accurate ETAs are critical to a positive user experience," observes Jeremy Hermann, who heads Uber's machine learning platform, "and these metrics are fed into myriad other internal systems to help determine pricing and routing. However, ETAs are notoriously difficult to get right."[2]

Yet, so many critical outcomes are dependent on robust ETA analytics — rider and driver expectations, fares, food pickup and delivery — that ETA is a core Uber metric. Hermann notes, "Uber's Map Services team developed a sophisticated segment-by-segment routing system that is used to calculate base ETA values. These base ETAs have consistent patterns of errors. The Map Services team discovered they could use a machine learning model to predict these errors and then use the predicted error to make a correction. As this model was rolled out city by city (and then globally …), we have seen a dramatic increase in the accuracy of the ETAs, *in some cases reducing average ETA error by more than 50%*."[3] [emphasis added]

Simply celebrating effective and globally scalable machine learning models misses the larger point. Uber cannot deliver on operational or strategic aspirations without reliably delivering on its ETA KPI. Chaotic ETA outcomes would prevent Uber from being a "low cost" or "best value" provider of mobility/delivery services. Technical, organizational, or operational changes that might threaten ETA outcomes are counterproductive. Uber must marginalize or minimize KPIs that might conflict or compete with effective ETA prediction.

Clarifying those constraints is crucial. In the words of Harvard Business School's Michael Porter, "The essence of strategy is choosing what not to do."[4] Once those guardrails are established, identifying and minimizing unwelcome consequences becomes as important as promoting the outcomes you want. The essential takeaway here is that prioritizing KPIs — ranking them according to what matters most and what the organization must learn the best — is essential to enterprise strategy. In an always-on big data world, your system of measurement is your strategy.

Determining the optimal "metrics mix" for key enterprise stakeholders becomes an executive imperative. Are customer-centric strategies, for example, better optimized via customer lifetime value (CLV) or balanced blends of earnings before interest, taxes, depreciation, and amortization (EBITDA) and net promoter score? For what customer segments should profitability be privileged over satisfaction or loyalty? As algorithms get smarter, leaders must have the courage to explore how best to answer these questions. AI makes that feasible, affordable, and desirable.[5]

This optimization imperative, our research suggests, demands a rigorous rethinking of the metrics chosen to define desirable (and undesirable) strategic outcomes. When machine learning measures management and manages measurement, metrics don't just reflect strategy but drive it. Achieving KPI outcomes (and suggesting new KPIs) is what smart machines need to do — and *need to learn to do*.

AI is not just about building products, services, or processes. Leaders need to recognize that AI must be primarily about enhancing the formulation and execution of strategy. To the extent that KPIs are essential to formulating and communicating strategy, strategy is quintessentially a system of measurement. Our research shows that AI transforms the strategist's choices about which KPIs to optimize and how to optimize them. Strategy is about optimizing KPIs with AI/ML.

Looking Forward and Backward

Machine learning profoundly changes how to approach optimizing leading and lagging KPIs. McDonald's has a multipart growth plan explicitly combining the two types of indicators. A key strategic aspiration is to once again be a family destination that appeals to parents. A lagging indicator is more visits by families with kids under the age of 13. A leading indicator is any evidence of becoming "a place I'm happy to bring my children," says McDonald's global chief marketing officer Silvia Lagnado.

Reliably measuring "happy place to bring my children" is methodologically challenging. Customer surveys are limited to those who fill them out, a source of selection bias. Machine learning-based sentiment analysis improves on this approach: It can classify large volumes of geotagged Twitter data and other data sets to correlate neighborhood-level well-being with comments about fast-food locations. A group of University of Utah academics developed a blueprint for this type of ML application.[6] Such machine learning mashups are becoming standard practice in academic and business research.

With machine learning, McDonald's can more effectively pursue high-priority KPIs. Marketers exploring in-store promotions with family-oriented advertising and menu options might improve family traffic but will fail if those promotions produce store conditions that annoy parents. Maximizing sales or revenues cannot come at that cost. Striking a productive balance between those measures is what optimization means. That's what McDonald's machines need to learn to serve up.

Not coincidentally, in March 2019, McDonald's announced its $300 million acquisition of Israel-based Dynamic Yield, which uses machine learning and big data to make personalized recommendations. McDonald's says it intends to use the company's tools to customize the drive-thru experience by creating dynamic digital menu boards that recommend menu items based on local demographics, previous orders, weather, and time of day, among other factors.

GoDaddy, the multibillion-dollar web-hosting and internet registry innovator, is also embracing leading as well as lagging data-driven KPIs. Since 2016, the Scottsdale, Arizona-based company's market value has grown more than 2.5X in no small part due to its dual commitment to strategic KPIs and machine learning. "We're very excited about the prospect of using the large data sets that we have," observes GoDaddy COO Andrew Low Ah Kee, "[to] train a model to solve and optimize against [customer] lifetime value as opposed to solving for transactional period revenue."[7]

Low Ah Kee's essential insight is that leaders have the duty and responsibility to pick which time horizons and "objective functions" to optimize. GoDaddy's emphasis on customer lifetime value (which anticipates future revenues, costs, and loyalty in addition to capturing past purchase behavior) reduces short-termism and threats to customer experience quality, he asserts. "We see in our customer base, when we help our customers succeed, the lifetime value it brings to us is significantly higher than for people whom we approach with just a transactional view," he notes. "As you start to extend the time horizon, I think the degree of [organizational] misalignment tends to go down." It's easier to miss long-term goals if the focus is on short-term tactics.

Making Smarter Trade-Offs

We argue that strategy is best understood and experienced as how the business invests in, manages, and prioritizes its KPI portfolio. KPIs and the relationships between them are the critical strategic units of

LEARNING WHAT TO OPTIMIZE

Optimizing known KPIs is important but not strategically sufficient. When appropriately trained, machine learning models can learn to identify and recommend novel or emergent KPIs. That is, machines can "learn to discover" enterprise KPIs on their own, without expert guidance. This is the difference between supervised and unsupervised learning. GE Healthcare CMO Glenn Thomas explains that his data science teams are "actually boiling out the KPIs from the data rather than setting the KPIs to be measured."

While Thomas declines to disclose emergent KPIs produced this way, an important irony cannot be overlooked: Thomas and his marketing/data team increasingly use machine learning to find KPIs they might never have discovered on their own. In marketing, promotion, interaction, and engagement domains, technology can go beyond "learning to optimize" to suggest what can and should be optimized.

analysis. Strategic success means the company's machines learn to optimize KPI portfolio returns.

To be clear, optimization in this context does not mean maximization. On the contrary, it means computationally learning to advance toward desired strategic outcomes through carefully calculated and calibrated KPI trade-offs. Understanding trade-offs among and between competing — and complementary — KPIs is essential. Simply optimizing individual KPIs by priority or rank ignores their inherent interdependence. For any KPI portfolio, identifying and calculating how best to weight and balance individual KPIs becomes the strategic optimization challenge. (See "Key Performance Indicators and Ethical Strategy.")

Even as "yield management" machine learning models for airlines, hotels, and other travel-related businesses algorithmically improve, strategic challenges sharpen: How can revenue-enhancement KPIs be optimized in the context of customer satisfaction and net promoter score KPIs? Do loyal customers deserve preferential rates or service bundles relative to typical customers? Learning to optimize for "best customers" draws on different data sets and expectations than learning to optimize for typical or average customers. What does an optimal balance between loyal customers and asset monetization margins look like? Smart machines can learn to strike that balance, but preemptively minimizing human insight and oversight seems foolish.

Similarly, high-frequency algorithmic traders may seek to maximize the frequency of profitable trades and/or maximize hourly, daily, or weekly profits. Yet, at the same time, they may wish to avoid or minimize the risk of regulatory intervention. One KPI maximizes profit (or "profits per trade" or "profits per trading strategy") while another signals that the company's trading patterns are unlikely to trigger an external review. Again, smart machines can learn to strike that balance. What is the risk appetite, not for particular trades but for particular regulators?

Every organization confronts this clash and conflict of strategic prioritization. No right answer exists. That said, some KPIs deliver disproportionate value and insight into helping company leaders better — or more optimally — achieve their strategic aspirations. Weighting these measures and metrics lends itself to machine learning applications. They facilitate alignment between local optima and the desired global optimum. Consequently, there can be no meaningful discussion about "optimal" strategic trade-offs in a KPI portfolio without a machine learning/AI capability.

The Essential Role of Data

There is no enterprise strategy for or with AI without an enterprise strategy for — and with — data. It is the essential ingredient for machine learning and dynamic optimization. As the Uber, McDonald's, and GoDaddy examples affirm, optimizing strategic KPIs — ETAs, happy families, CLV — is contingent upon data volume, velocity, variety, and quality.

That makes data governance key. Organizations must invest in recognizing which data might enhance or elevate their KPIs — and which data will help their machines learn. Digital processes and platforms that combine and analyze data, siloed and scattered, empower the company's artificial intelligentsia.

Technology titans and a growing number of legacy companies embrace comprehensive data strategies and practices. They explicitly, ruthlessly, and relentlessly manage data as an asset. This, as much as their technical prowess, sets them apart operationally and culturally. They employ chief data officers, data scientists, and data wranglers,

KEY PERFORMANCE INDICATORS AND ETHICAL STRATEGY

Google's YouTube division introduced two new internal metrics in the past two years for gauging how well videos are performing, according to people familiar with the company's plans. One tracks the total time people spend on YouTube, including comments they post and read (not just the clips they watch). The other is a measurement called "quality watch time," a squishier statistic with a noble goal: to spot content that achieves something more constructive than just keeping users glued to their phones.

The changes are supposed to reward videos that are more palatable to advertisers and the broader public, and to help YouTube ward off criticism that its service is addictive and socially corrosive. Creating the right metric for success could help marginalize videos that are inappropriate or popular among small but active communities with extreme views. It could also help YouTube make up for previous failures in curbing the spread of toxic content.

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holding people and processes accountable for getting value from data. Increasingly, much of that value comes from how quickly, accurately, and reliably that data trains machines.

Unfortunately, crisp and clear alignment between enterprise data governance and strategic AI initiatives remains elusive. A recent *Forbes Insights* CXO survey on AI and machine learning revealed that three out of four top executives declared AI a core component of their digital transformation plans. However, only 11% of the surveyed executives said their companies have begun implementing an enterprisewide data strategy, and only 2% said they have a serious "data governance" process in place.[8]

These findings, unhappily consistent with our own, suggest that successful and sustainable implementations of AI/ML-enabled optimization strategies are unlikely until data is explicitly treated as an asset. Organizations need effective data platforms and processes to enable effective machine learning platforms and processes. Ironically (even perversely), many companies have enormous amounts of timely, relevant, and valuable data for strategic AI efforts but lack the commitment and competence to harness it. Their data doesn't inform their KPIs or their strategy. An unwillingness or inability to use strategic KPIs to prioritize or align data assets with strategic outcomes further undermines their AI aspirations. These gaps render strategies for/with AI impotent.

LIKE ROCKEFELLER'S RAILROADS and the internet, artificial intelligence and machine learning represent enormously powerful strategic capabilities. They computationally transform the economics of optimization for business. Appropriately developed and deployed, they can literally learn how to create more value for more customers at lower cost and with greater speed. A strategy *for* AI matters less than clearly articulating the strategic aspirations, goals, and outcomes that leaders wish to optimize. Machine learning, like transportation and communication, is a means to an end. What needs to be transported? What needs to be communicated? What needs to be optimized? Artificial intelligence and machine learning can, in principle and practice, offer actionable answers to these questions. The true strategic opportunity and impact of these technologies is the chance to rethink and redefine how the enterprise optimizes value for itself and its customers.

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