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EXECUTIVE GUIDE

The AI & Machine Learning Imperative

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EXECUTIVE GUIDE

The AI & Machine Learning Imperative

Redefining AI Leadership in the C-Suite

CFOs who step up to take ownership of AI technology are positioning themselves and their organizations for the future.

BY THOMAS H. DAVENPORT AND BEENA AMMANATH

Who makes decisions within organizations about investments in artificial intelligence tools? Who *should*? The company CEO and CIO (or other senior technology leaders), of course, but who else?

We contend that while CFOs may not think of themselves as leaders of artificial intelligence for their companies, they can make a bigger leadership impact when it comes to AI strategy and adoption.

There are two key reasons. The first is that CFOs are heads of the finance function, and many finance processes and tasks can be performed by AI. One survey of U.S. organizations found that 24% of finance managers are currently using AI, and another 50% expect to use it within three to five years.

The second reason is that CFOs are usually the primary custodians of "value for money" appraisals and as such should provide oversight on AI investments. A 2018 Deloitte survey on trends in CIO reporting relationships found that 28% of CIOs report to the CFO. This is significant in terms of AI because a 2020 survey of global AI adopters from Deloitte found that IT is the single most likely area (with 47% listing it as a "top two" application domain, and cybersecurity in second place, with 22%) where companies will apply AI and automation to tasks and processes frequently repeated activities. These include rebooting servers, monitoring networks, supplying user passwords, and capturing and monitoring trouble tickets, or initiatives like helping to validate and prioritize cybersecurity threats. When CIOs make the case for AI investments, CFOs should be alongside the effort, integrating financial evaluations with technology strategy.

While AI is likely to dramatically affect business practices in the future across the C-suite, it's already having an impact today. In other words, the time for CFOs to step up to AI leadership is now.

Opportunities for AI Within Finance Functions

The finance function offers many areas for using AI, and it's worth ticking through some of them. One of the primary areas to deploy robotic process automation (RPA) is the financial period close, where reporting typically involves the extraction of data from multiple systems, consolidation and reconciliation of journals across the organization, and data transfers from internal groups and to regulators. Invoicing, too, involves structured, repeatable activities and information access. RPA is perfectly suited for these types of work — it can reduce the burden on human workers, improve cycle times, and reduce mistakes.

Tax, audit, and compliance functions are also well suited for AI. AI can extract supplier contract terms and match them to goods and services delivered. Employee expense report information can be checked against corporate policies. The speed and constant work of AI systems typically means that 100% of transactions can be audited rather than just a sample. Other forms of AI can be used for forecasting, estimating demand (typically using external data), and assessing risks, including conducting appraisals of brand damage from problems such as security breaches.

The use of AI for finance functions is taking root. In the 2020 global AI adopter survey, 8% of respondents put finance in the top two application domains. But in a 2018 Deloitte survey of enterprise AI, 37% of large U.S. organizations were pursuing use cases with AI involving risk management, 29% on cases involving forecasting applications, and 23% on cases addressing tax, audit, and compliance issues — all of which touch on finance.

Admittedly, AI applications in finance thus far have been relatively pedestrian. However, the future of intelligent financial applications is likely to be much more dramatic. Most transactions will be automated, replacing outsourcing as a way to achieve productivity. Finance functions will likely be staffed by substantially fewer people, all of whom understand AI and how to add value to it. Budgets, forecasts, financial analysis, and approaches to improving financial performance will likely be based on machine learning models trained by internal and external data.

These developments will be particularly important in the COVID-19 economy; some AI companies, for example, have already developed approaches to using AI to minimize accounts payable cash outflows. Some companies are basing rapidly changing demand predictions on external data such as surveys, mobile phone data on consumer movement away from home, and even sensor data from consumer thermometers.

Many of the external services offered to finance functions — auditing, consulting, and tax advice — will also be automated and substantially more intelligent; Deloitte, for example, is rolling out AI-supported audits now. In 10 to 20 years, we expect that CFOs will oversee a stable of algorithms and AI applications that will make their function more successful and efficient than it has ever been.

Opportunities for AI Within Finance-Related Functions

CFOs who lead business functions such as IT and procurement may be responsible for sponsoring and overseeing AI applications in these areas. AI, of course, can ultimately can lead to substantially greater productivity in IT functions, especially in industries where IT is becoming the "factory" for financial services and e-commerce businesses and others. However, Deloitte's 2020 enterprise AI survey found that 62% of executives view cybersecurity as one of their top three concerns about AI, so CFOs may want to play a leadership role there.

A variety of AI applications can be employed in the procurement domain, including spend classifications, supplier risk assessments, automated contract reviews, and chatbots for routine supply ordering. Even when procurement does not report to the CFO, it may be wise for finance chiefs to pay attention to this area and insist on some of these capabilities because of the implications they could have on the financial health of the business.

Oversight of AI Investments

CFOs usually have the oversight role for their companies' spending and investing activities. Many businesses are spending significant amounts on AI — 53% of respondents to the Deloitte 2020 survey said their companies had spent more than $20 million annually on AI technology and talent, and 71% report that they will spend more on AI in the coming year.

The Deloitte survey data also suggests a large majority — 81% — of the longer-term users of AI have seen returns on their AI investments, with a payback period of less than two years. CFOs can help ensure that high levels of value from AI continue to be achieved by creating systems and processes for reviewing investment proposals, moving AI systems toward production deployment, and assessing the value of systems post-implementation. These moves are particularly important in the difficult economic climate we are likely entering.

Despite the fact that AI is a relatively new technology, each investment should be intended to deliver financial value to the organization — even though not all of them will pay off. CFOs can play a role similar to that of a venture capital partner, doing whatever is necessary to clear the way for AI initiatives to succeed and creating a higher likelihood that they will provide a high return on investment.

The AI-Oriented C-Suite Exec: Key Tactics

CFOs and other C-suite executives who focus on AI technology today will begin to reshape the divisions they lead. There are five specific tactics to move toward this goal:

- **Set personal examples for other senior executives.** CFOs can explore the different types of AI technologies and learn which ones are most relevant to specific use cases. In team meetings of the finance function, CFOs might use their AI knowledge to suggest particular projects and technologies. In gatherings of senior management teams, CFOs can motivate other leaders to adopt AI within their own business functions and units.

- **Meet with AI companies.** Taking meetings, especially with companies of finance-oriented AI applications, will help CFOs learn what's possible. It will also help prioritize which companies to work with.

- **Select AI projects to advocate for as executive sponsor.** For a CFO, the executive sponsor role might mean overseeing projects that are particularly relevant to the finance function, or those that need more focus on achieving returns on investment.

- **Create specific roles to advance AI in the function — and even consider adding a small center of excellence.** At least some practitioners with deep understanding of both AI and finance would be needed to staff these positions. Such roles could also be part of a centralized center of excellence on AI if the company has created one.

- **Establish an educational initiative for team members to learn more about AI.** The goal here would be to help all finance employees understand how to add value to AI in finance, accounting, and other specialized topics.

Together, these activities can make the CFO one of the most important executives in a company's journey to effective use of AI. If an organization is to transform its finance function with AI capabilities, or to employ a wise investing approach to AI in general, leadership from the CFO is essential.

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Leading the Intelligent Enterprise

To prepare for the next phase of AI, leaders must prioritize assembling the right talent pipeline and technology infrastructure.

BY JOSEPH BYRUM

Artificial intelligence (AI) and machine learning offer new ways to boost productivity, develop talent, and drive organizational change by enhancing managers' ability to make the right calls in complex situations.

Augmented intelligence tools have already made an impact for many companies, but the next revolution will happen when every aspect of a business, from top to bottom, is designed with AI in mind. Call this new construct *the intelligent enterprise*. Like other major revolutions in management, it's poised to transform industries and organizations for decades to come. To prepare for this next phase, leaders will need to harness machine intelligence for decision-making across the business, assemble the right talent, and recognize the benefits and limitations of AI to shape organizational strategy.

Understanding the AI Advantage

It's not hard to find examples of the amazing things we can do with artificial intelligence. AI and analytics have changed the centuries-old techniques of plant breeding, helped advance cutting-edge research into disease, and even been used to decipher damaged ancient Greek tablets.

What these achievements have in common is that they are discrete, structured tasks. In each example, algorithms are used to absorb available data, recognize patterns therein, simulate outcomes, and select moves or produce results based on the statistical likelihood of success. In plant breeding, for example, the simple step of designing a trial to see whether your breeding effort has succeeded or failed requires choosing from a set of 1.16×10^{12} possible combinations. Yet, increasing efficiency in this highly complex process through data analytics can save millions of dollars.[1]

If improving one aspect of one process through data analytics can have a massive payoff, imagine what can happen when an organization takes advantage of AI's ability to learn, analyze, and optimize across all processes and business functions.

The next revolution will happen when every aspect of a business, from top to bottom, is designed with AI in mind. Call this new construct *the intelligent enterprise.*

How AI Can Accelerate Leadership

Businesses, particularly large corporations with a global footprint, are complex adaptive systems. No one person, or even one group of managers, can know what's going on at all levels of an organization consisting of thousands of employees. Even so, the CEO is responsible for keeping the board and shareholders happy, positioning the company for the future, maintaining employee morale, and developing an advantage over the competition — all while turning a profit. Although the CEO relies on an executive team for support across these different functions, he or she ultimately shoulders the blame for bad choices. No wonder most CEOs at large-cap companies don't last more than five years.[2]

With so much responsibility, the CEO's scarcest resource becomes time, and that's where AI brings the most value to the top job. AI is an ideal tool for observing and gathering the available information touching on business operations. This includes internal reporting data as well as relevant external news stories and analysis relevant to the industry, digested and categorized by natural language processing algorithms. The Reuters news service, for example, uses AI to sift through 700 million daily tweets to spot breaking news that can be handed to a journalist for further investigation.[3]

The intelligent enterprise must similarly process a mountain of data, prioritizing items according to relevance, which helps to avoid information overload for the leaders reviewing the reports. This gives the CEO maximum awareness of what's happening throughout the business and the industry so that more of his or her time can be spent addressing issues likely to have an impact on the bottom line.

Moreover, the intelligent enterprise imagines AI systems in every division, department, unit, and group in the organization — human resources, IT, marketing, finance, operations, and so on — so that each of these operations can be optimized with augmented intelligence systems that provide decision support to human employees.

Many HR departments already use a simple form of textual analytics — keyword scoring — to sort through unwieldy stacks of résumés that accumulate whenever a new job is posted. Applications for an accountant position that don't mention, for example, the required academic credential or license can be tossed out right away. NASA's AI system performs a deeper analysis that evaluates the context in which the keywords are used.[4]

In the intelligent enterprise, more-advanced expert systems would use cognitive engines to understand the applications. Moreover, they would not focus narrowly on making the HR manager's life easier. Each corporate unit's and division's systems would exchange information automatically, so the HR system would know when new talent might be needed. It could review past applications and have potential candidates lined up for consideration as soon as any new hiring was approved. In this way, the system would become a key part in advancing the CEO's goals by ensuring that the company had the talent it needs to execute the overall mission.

The interconnection between business divisions would also give the CEO a real-time look into company performance. Data from each business unit wouldn't be filtered by preconceived ideas about what the numbers ought to look like or shaded by department heads putting the best face on the results. The numbers would speak for themselves.

With a clear view of what's happening, the CEO could swiftly reorient the company, as needed, to remedy problems or take advantage of favorable conditions. Armed with solid information and options weighed by AI simulations, the CEO could formulate multiple potential strategies to deal with the situations that arise. Instead of being based on hunches, emotions, or guesswork, these strategies would be fully informed by the best available data.

Know AI's Limits

While innovation in AI systems continues to rapidly evolve, it's not all-knowing — in fact, artificial general intelligence exists only in science fiction. For now, it still falls to the human CEO and executive team to pick the strategy and execute it. But machines and AI systems are incredibly valuable for presenting data and providing options for leaders to consider based on different real-world contexts and goals. For example, sometimes the CEO will want to take a long-shot risk. Or perhaps it's important to spend money on an initiative that won't hit certain strategic targets but will improve employee morale. Reality is far too complex for a statistical algorithm to imagine every possibility that leaders might take into consideration.

Experienced CEOs are needed to consider the intangible factors a machine will miss. While the CEO's primary job is making decisions, the role doesn't end once a choice has been made. Here, AI tools are essential for monitoring results and evaluating whether the strategy is producing the intended effect. When bad choices are made, it's important to change course quickly. The continuous cycle of acting and reviewing results is critical for updating or abandoning strategies when necessary to achieve the organization's goals.

Constant reevaluation of the company's direction, in matters big and small, may seem like a waste of time, but it's an effective insurance policy against complacency. Adaptability allows a business to stay ahead of customer and market needs and avoid becoming the next BlackBerry, Blockbuster, or Borders.

What AI does is enforce discipline on corporate strategies. It continuously, and automatically, evaluates questions like, "Is the plan working?" or "How are the forecasts and projections?" It plots out alternatives — what happens if the company pivots in this direction or that direction? The intelligent enterprise also provides clarity about the goals and objectives of the organization, aligning every business division toward the overall strategy by setting goals (for instance, by having the talent on hand to accomplish the next mission) and tracking progress toward those goals and the end results.

Sometimes overall change is needed, and sometimes it's not. The intelligent enterprise is a system designed to be ready for either possibility. In a complex market environment, success comes to the companies best able to adapt to fast-changing circumstances. By building adaptability into the structure of the company, AI helps the CEO manage challenges as varied as the disruptions of a global pandemic or the discovery of new technologies.

Companies are investing in AI today, but to achieve the ultimate strategic goals of this investment, organizations must broaden their sights beyond creating augmented intelligence tools for limited tasks. In order to turn this broader vision into reality, leaders must prioritize assembling the right talent pipeline and technology infrastructure to enable the intelligent enterprise of tomorrow.

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The Building Blocks of an AI Strategy

Organizations need to transition from opportunitistic and tactical AI decision-making to a more strategic orientation.

BY AMIT JOSHI AND MICHAEL WADE

As the popularity of artificial intelligence waxes and wanes, it feels like we are at a peak. Hardly a day goes by without an organization announcing "a pivot toward AI" or an aspiration to "become AI-driven." Banks and fintechs are using facial recognition to support know-your-customer guidelines; marketing companies are deploying unsupervised learning to capture new consumer insights; and retailers are experimenting with AI-fueled sentiment analysis, natural language processing, and gamification.

A close examination of the activities undertaken by these organizations reveals that AI is mainly being used for tactical rather than strategic purposes — in fact, finding a cohesive long-term AI strategic vision is rare. Even in well-funded companies, AI capabilities are mostly siloed or unevenly distributed.

Organizations need to transition from opportunistic and tactical AI decision-making to a more strategic orientation. We propose an AI strategy built upon three pillars.

1. AI needs a robust and reliable technology infrastructure. Given AI's popularity, it is easy to forget that it is not a self-contained technology. Without the support of well-functioning data and infrastructure, it is useless. Stripped of the marketing hype, artificial intelligence is little more than an amalgamation of mathematical, statistical, and computer science techniques that rely heavily on a stable infrastructure and usable data.

This infrastructure must include support for the entire data value chain — from data capture to cleaning, storage, governance, security, analysis, and dissemination of results — all in close to real time. It is not surprising, then, that the AI infrastructure market is expected to grow from $14.6 billion in 2019 to $50.6 billion by 2025.

A good infrastructure allows for the establishment of feedback loops, whereby successes and failures can be quickly flagged, analyzed, and acted upon. For instance, when Ticketmaster wanted to tackle the growing problem of opportunists — people who buy event tickets ahead of genuine customers, only to resell them at a premium — it turned to machine learning algorithms. The company created a system that incorporated real-time ticket sales data along with a holistic view of buyer activity to reward legitimate customers with a smoother process and block out resellers. As the company soon realized, resellers adapted their strategies and tools in response to the new system. Ticketmaster then modified its infrastructure to include feedback loops, allowing its algorithms to keep up with the resellers' evolving techniques.

2. New business models will bring the largest AI benefits. AI has the potential to offer new sources of revenue and profit, either through massive improvements over the current way of doing things or by enabling new processes that were not previously possible. But incremental thinking about how AI can be used will most likely lead to modest results. Significant benefits are unlikely to be achieved without a new business model mindset, or a so-called intelligence transformation.

AI allows for improvements that far surpass human capabilities. For example, OrangeShark, a Singapore-based digital marketing startup, uses machine learning for programmatic advertising, thus automating the process of media selection, ad placement, click-through monitoring and conversions, and even minor ad copy changes. Because of the efficiency offered by its system, OrangeShark is able to offer a pay-for-performance business model, whereby clients only pay a percentage of the difference between customer acquisition costs from a standard advertising model and the OrangeShark model. By completely automating a previously semi-automated task, the company has created a new business model that makes monetization of massive efficiency gains possible.

At the other end of the spectrum, Affectiva, which calls itself an "emotion measurement" company, houses the world's largest image database of sentiment-analyzed human faces. The company analyzes and classifies a range of human emotions using deep learning models that can then be made available to clients. Some applications study emotional responses to ad campaigns, while others help people relearn emotional responses after a stroke. Affectiva has built a business model based on providing intelligence as a service in an area where nonhuman intervention was previously impractical.

These examples merely scratch the surface of possible AI-enabled business models. We will soon have smart cameras that facilitate franchising contracts and employee compensation schemes. Machine learning on granular data will allow for customization of products and services across time. As these and similar developments open up new sources of revenue and profit, new business models should therefore be considered as a foundation of any AI strategy.

3. AI without ethics is a recipe for disaster. The final AI strategy pillar is ethics, which is not necessarily a common component of technology strategy. However, the use of AI raises many potentially thorny ethical issues, such as incorrect insights and inherent biases due to poorly constructed algorithms, and an upswing in unemployment due to the substitution of human labor with machine output.

Take, for example, facial recognition, one of the most common AI use cases today. While the technology has proved to be effective in a number of areas, such as catching criminals, finding missing people, and even monitoring blood pressure, it also raises a number of ethical concerns, such as the right to avoid surveillance and the accuracy of the algorithms used to identify individuals and groups. For example, most AI systems are better at accurately identifying people who are white than people of other ethnicities, and at identifying men's faces rather than women's; indeed, some systems misidentify gender in up to 35% of darker-skinned females.

In December 2018, Google announced that it would suspend sales of its facial recognition software, citing concerns over ethics and reliability.

Google's competitors, in contrast, took an additional 18 months to reach the same decision. Only in early June 2020, in response to the Black Lives Matter movement, did IBM halt the sale of facial recognition software to police forces in the United States. Two days later, Amazon announced a one-year moratorium on sales of its facial recognition software to police, followed by Microsoft the very next day. For these organizations, the reputational damage of producing systems that systematically misidentified minorities, and selling the technology to police forces to identify criminals, had already been done. Google was proactive, while IBM, Amazon, and Microsoft were reactive, demonstrating that compliance with today's ethical standards is insufficient; instead, organizations must also anticipate future ethical issues.

The need for a responsible approach to AI is likely to increase even further, for three reasons. First, as organizations scale up their use of AI, the ease of capturing sensitive, personal data about individuals will increase. Already, we are faced with the prospect of social networks and internet giants knowing significantly more about our day-to-day habits than our loved ones (and perhaps even we ourselves) know.

Second, as organizations transition into newer business models, the marginal value of collecting and using data will increase. Organizations will be able to assign a dollar value to each bit of data collected and accurately calculate the risk-reward ratio associated with each data point. Under these circumstances, the temptation to extract additional value from the data they have collected or purchased may push organizations to overstep ethical boundaries, such as by repackaging and selling data without consent.

Third, despite the importance of ethics, there is a general lack of overarching guidelines or benchmarks for responsible AI practices. Without a single established ethical arbiter, each organization and industry will have to determine its own standards and limits.

Unfortunately, the fragmented approach to AI will only exacerbate this problem. Unless organizations take a coordinated approach to AI ethics, it will be too easy for a rogue team to breach ethical guidelines. It is possible that an AI ethics office will need to be created within organizations to oversee AI activities, establish and implement ethical AI guidelines, and hold the organization accountable for its ethical practices. Companies that consider the ethics function as a branding and trust-building mechanism will come out ahead of those that deem it merely a regulatory issue. In addition to efforts within organizations to manage AI ethical practices, industry associations, governments, and multinational nongovernmental organizations can also play a role by setting out clear guidelines governing the responsible use of AI technologies.

Because AI is not a regular technology, the AI strategy needs to be approached differently than regular technology strategy. The power of AI to fuel the extremes of corporate performance, both positive and negative, requires a purposeful approach built on three pillars: a robust and reliable technology infrastructure, a specific focus on new business models, and a thoughtful approach to ethics. An AI strategy needs to be built on a solid foundation to survive the strong winds of change.

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Modern Business Models Will Drive the Post-Pandemic World

To remain relevant and resilient, companies and leaders must strive to build business models using three key components for growth.

BY LANHAM NAPIER, JIM CURRY, BARRY LIBERT, AND K.D. DE VRIES

In the face of a global health and economic crisis, many traditional companies have suffered tremendous losses, and some have shuttered their doors. Those that heavily rely on physical capital (for example, stores, goods) and human capital (for example, services) were already vulnerable in economic downturns. The pandemic has exacerbated the lack of resilience in these business models, which have struggled to compete against digitally centric companies that can leverage data and machine learning to create valuable insights, intelligence, and capabilities across the organization.

For instance, compare companies whose products are *like air* (customers rely on them all day long for business, personal or financial use) with those that are *like haircuts* (customers use them sporadically; they are nice to have but are not critical to their needs). Those in the former category that are being used constantly with little effort have proved to be resilient even in times of crisis. We typically know these as software-as-a-service (SaaS) products, such as Salesforce for business or Amazon Prime for consumers. In addition, those companies that combine SaaS with multisided platforms (like marketplaces) to fulfill their customers' needs through a network of partners (such as Apple's developer network) have an added advantage. These new, three-pronged models go far beyond SaaS and include the following:

1. A community of active B2B and B2C users that creates a network effect due to their interactions.
2. A marketplace that delivers offers from sellers and suppliers to meet customers' needs.
3. A secured data lake powered by AI that enables customized offers and insights.

We call this new winning combination a *modern business model* (MBM). In fact, MBMs occupy four of the top 10 spots of the S&P 500's most valuable companies: Apple, Amazon, Alphabet (Google), and Microsoft. And they are not alone — Shopify, Spotify, and others have adopted this new AI-powered, subscription-based model with marketplaces.

Based on our own machine learning analysis of the Russell 3000 Index (see "Comparing the Resilience of Modern vs. Legacy Business Models"), we found that SaaS, marketplace, and modern business models have proved to be more resilient than their legacy business model counterparts in times of disruption.

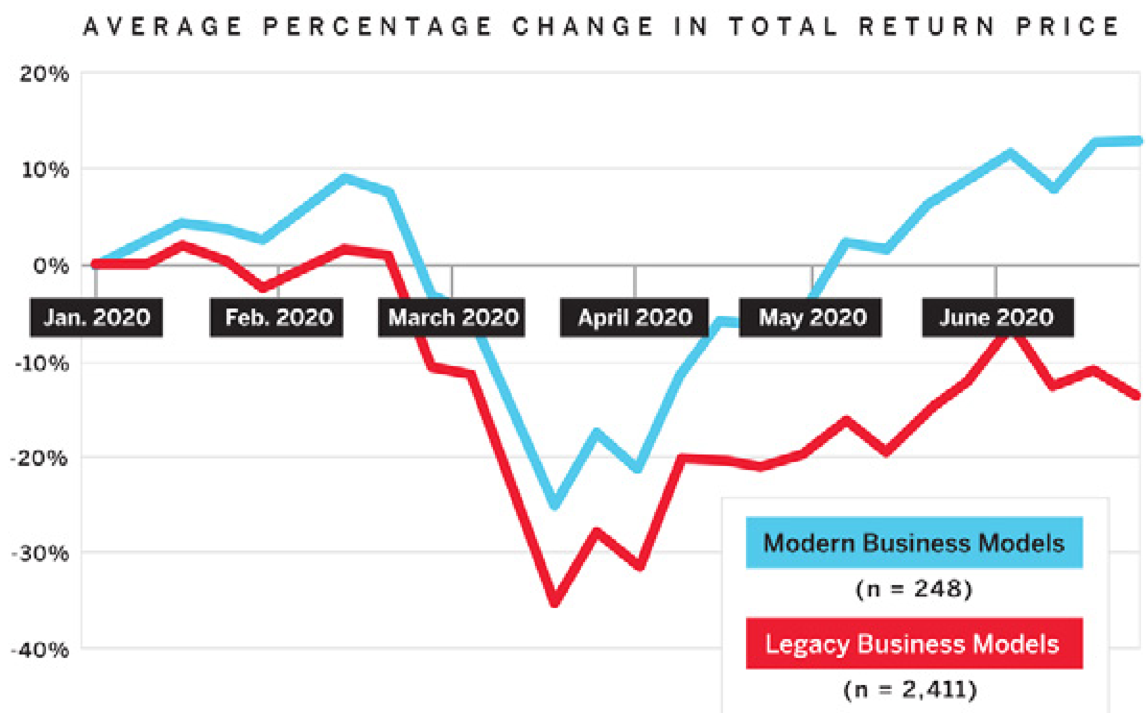
While adopting a full MBM is not possible for many legacy companies (which rely on physical and human capital), SaaS companies are well positioned to add AI-powered data lakes and marketplaces of sellers and partners. (Our team has also created an assessment model for SaaS companies to determine whether they have MBM potential.) And if your company is a marketplace, it may also be primed to achieve the modern status; the question you need to ask yourself is, can you create a subscription service that is critical (like air) to your buyers' and sellers' offers? By adding these key components to your growth strategy, you can begin to move from laggard to leader.

Product-Led Growth Is the Future of SaaS Growth

To put a fine point on the power of the "like air" SaaS solution, product-led growth is a growth model that

COMPARING THE RESILIENCE OF MODERN VS. LEGACY BUSINESS MODELS

In times of disruption, modern business models prove more resilient than legacy business models based on the change in total return price.



Source: Authors' analysis of the Russell 3000 Index focuses on the product itself to drive customer acquisition, retention, and expansion.

With a modern business model, companies must provide a valuable B2B or B2C software solution that becomes critical for users as they perform their daily functions. To do that, MBMs use AI to generate and present data, to both business and consumer customers, that's used in combination with SaaS tools to create greater value. Machine learning enables valuable insights that drive action for a business's ecosystem of product users. For example, one of our portfolio companies, Fiix, is a cloud-based maintenance management system and emerging marketplace. AI tracks and analyzes parts and inventories and alerts users if a critical part is projected to run low, allowing the customer — or even the machine — to solve the issue by ordering the required part.

Imagine a marketplace that matches salons and clients. Before this marketplace scales to critical mass, it's very easy to disrupt. However, if we add a SaaS solution that allows owners to keep track of operational data like appointments, payments, inventory, and client profiles, and power it with AI, the value increases. In this example, AI can facilitate personalized offers from sellers to buyers. Based on their observed wants, needs, and purchase behaviors, clients are sent reminders to schedule their next appointment, and buyers receive alerts for low inventory or the need to place orders. A good example of this is Mindbody, an online marketplace and AI-driven software solution for boutique gyms, salons, spas, and their clients. The private software maker, which was acquired in 2019 for $1.9 billion, has a successful MBM that is integral to a user's daily workflow.

Network Growth Is Critical to AI and Data Generation

In today's digitally centric world, increased access to people and their data have made offer personalization possible, and even expected by users. Business and consumer customers want to feel especially important, regardless of how fast your company is growing. However, many organizations focus on themselves — their internal processes, people, and products — and spend little time or effort on customer engagement and loyalty other than social media likes. Profitable growth begins with creating more promoters and fewer detractors. MBMs use AI and machine learning to increase customer loyalty by recognizing and serving the needs of customers with an almost human-level degree of understanding and personalization — or empathy at scale. Given that empathy is the ability to understand and share the feelings of another person, our belief is that AI, when used with care and compassion, enables companies that are data-, machine-, and network-centric to begin understanding the feelings of their customers and suppliers. It even enables the sharing of those feelings among their network participants so that their partners can meet their needs with offers of goods and services. An example of this is DigniFi, which uses machine learning and data to match consumers who need car repair financing with lenders that want to reach those consumers with myriad offers.

> AI, when used with care and compassion, enables companies that are data-, machine-, and network-centric to begin understanding the feelings of their customers and suppliers.

In the marketplace environment, this means better matching to users' needs and creating a tailored experience, by surfacing the information and features that are most relevant to them. The value scales with each additional participant, which drives community development and growth. As more matches take place, the data and insights expand in exponential fashion, leading to improved user experience, more features, and more value. This growth attracts more users, which continues the flywheel cycle of more data to improve the community experience. As the network grows, it becomes harder for community members to leave for a competitor, especially if this is where everyone is. Eventually, the marketplace grows to an impassable data lake — competitors in the industry will struggle to cross it. In this way, AI is an essential component for MBM businesses to foster customer empathy and create supplier value on an unprecedented scale.

What gives MBMs absolute advantage over traditional and SaaS business models is that MBMs actually become stronger as they get bigger. AI and machine learning allow MBMs to see greater returns instead of the decreasing value of investment that many companies see as they expand.

Failing to Prepare Is Preparing to Fail

You've probably heard the classic advice to start with the end in mind. Another way of saying it: Failing to prepare your business for success in today's modern environment is preparing to fail. There are three factors of success in a pre- and post-COVID-19 world:

1. A data- and AI-centric strategy that drives insights from every interaction and helps match customers' wants and needs with suppliers' products and services at scale.
2. A SaaS product that is as critical as air, providing a reason for both customers and suppliers to interact with your company all the time.
3. A marketplace that goes far beyond your own offers, in which your sellers and partners meet each and every need of your customers.

Companies that neglect these three critical ingredients will mistakenly think that somehow the products and services they market, make, and sell will suffice in a world in which customers can get whatever they want, wherever they want it, from whomever they want it. To remain relevant and resilient, companies and leaders must strive to build business models in a way that ensures that these three components are working together: AI that enables and powers a centralized data lake of enterprise data, a marketplace of sellers and partners that make individualized offers based on the intelligence of the data collected and powered by AI, and a SaaS platform that is essential for users.

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Reskilling Talent to Shrink Technology Gaps

Leaders must focus on managing the gaps in AI skills and processes within the organization.

BY SAM RANSBOTHAM

Frustrated with artificial intelligence efforts, the CIO at a large pharma company characterized the products and services from AI vendors as bright but “very young children” requiring tons of effort from internal staff members to reach the maturity to solve practical business problems. The company could buy AI-enabled products and services, but purchasing alone was not enough. Acquiring sophisticated AI technology still left the organization far from achieving strategic goals and increasing business value.

This company’s dilemma isn’t an isolated case. Despite the growing prevalence of AI technology and copious data within companies, getting value from AI isn’t easy. Even with AI technology increasingly easier to acquire, 40% of organizations making significant investments in AI still do not report business gains from AI. As with technology advances in the past, technology alone isn’t the answer to value.

Instead, getting value from AI requires investment beyond technology, notably in data infrastructure and talent. AI talent can be a particularly difficult limitation. Once armed with technology and infrastructure, many organizations find that they don’t have the AI skills they need.

Technology creates an inevitable gap — a gap between the sophisticated solutions an organization produces with a given technology and what portion of that production the organization can use. Spiffy models don’t help if people in the organization don’t know what the results mean or what they should do differently based on the results. The problem for managers, therefore, is less about managing the technology itself and more about managing the skills and processes needed by people and teams.

To illustrate, consider the relationship between the maturity of an organization with a particular technology and the sophistication of its use of that technology. As an organization matures, the technical sophistication likely improves in general. But this technical sophistication isn't distributed evenly throughout the organization. Some employees have greater technical skills than others do. Some organizational roles (such as AI and IT teams working on the production and development side of the technology) are likely more technically sophisticated than those of employees who consume those results (such as upper management or customer service teams). Compounding the difficulty, as the organization matures, the skill levels among employee groups develop at different rates.

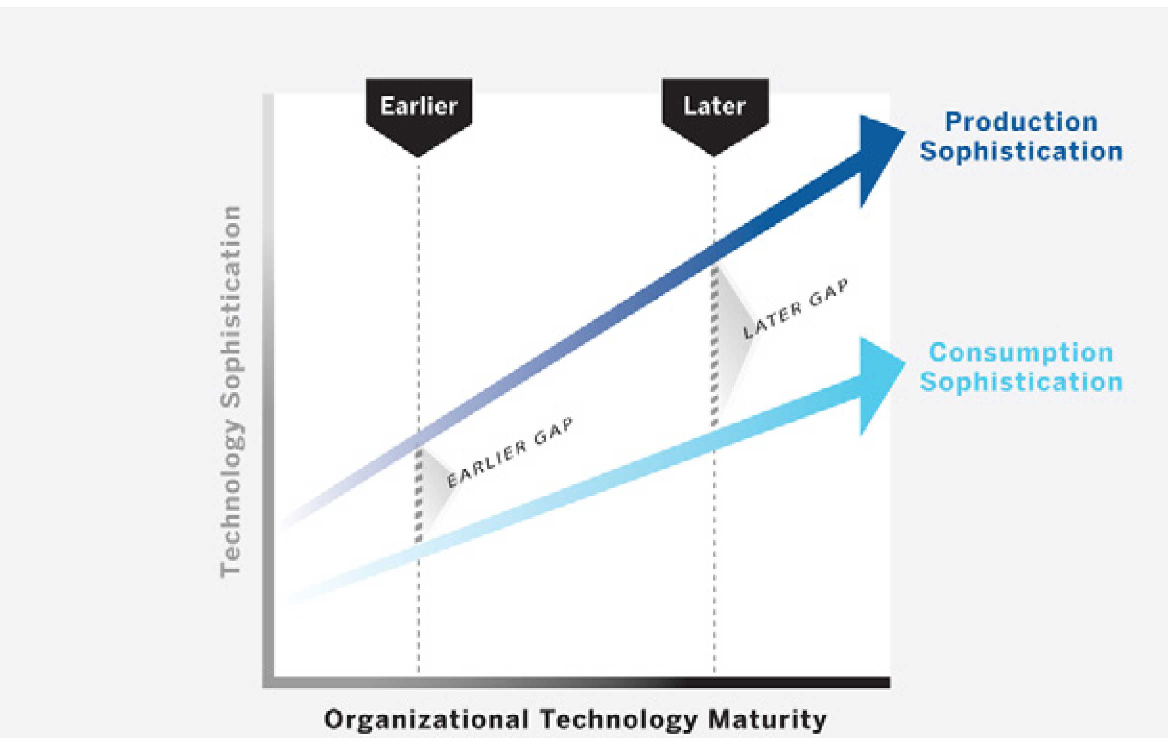
As organizations put more resources into a general-purpose technology such as AI, they can produce more sophisticated results with the technology. (See "Maturation of Technology Sophistication.") Employees working directly with AI will gain experience. For example, customer churn models can boost prediction through more sophisticated algorithms, fraud detection can better discern legitimate from nefarious transactions, or inventory logistics can continuously refine routing and stock replenishment. All of these applications benefit significantly from recent improvements in AI, increasing the sophistication of AI-based results that the organization has at its disposal.

Fortunately, the rate of increase in production sophistication can improve sharply. Ecosystems scramble to offer products and services to help organizations make the most of technology advances. For example, when an organization doesn't have the necessary talent to produce results with a technology like AI, it can look outside for help. Unfortunately, outsourcing delivers AI-related value to only 12% of organizations that report using this approach.

This bleak statistic doesn't necessarily mean that outsourcing doesn't work. External talent can help organizations improve productivity and results with new technology. Organizations can quickly benefit from the hard-won experience of others without the hardship of winning it themselves. But, as the disappointed pharma executive

MATURATION OF TECHNOLOGY SOPHISTICATION

Producers and consumers of technology mature at different rates, leading to growing, not shrinking, gaps between what organizations can create with technology and what they can use.



found, expertise about the specific business context is necessary, particularly as organizations try to apply AI to core, unique processes.

The difficulty is that producing results with AI systems alone isn't enough. The organization must be able to use these results to further business goals. Salespeople need to understand how to use the customer churn predictions and what they mean to their organization. Customer service agents need to understand why the system flagged a customer's transaction as fraudulent. Supply chain managers need to know why a system recommends a particular production level or logistics plan. It asks a lot of experienced workers to trust algorithmic results that they don't yet understand.

Yes, organizations can increase their consumption of new technology results and data. And companies and managers can help employees improve their ability to work alongside machines. Consumption improvements are necessary for companies to see the benefits of new, sophisticated AI systems. Otherwise, the advances in production go to waste.

But the rate of improvement of AI consumption results is slower than the rate of improvement of AI production. Relatively few people produce AI models themselves. Most employees are consumers of the results of those models. Increasing the sophistication of a larger group of users of technology moves slowly, particularly when (by definition) this group of employees isn't focused on the technology but rather on their business role.

Consumption is necessary because technologies like AI do not work in vacuums. Technology requires business context — which is organization-specific. This context, unsurprisingly, is more difficult to outsource. Instead, many organizations find that it is easier to add technical skills to knowledgeable businesspeople than to add business acumen to knowledgeable technical people. Helping these businesspeople improve their ability to work with AI creates value. According to the 2019 *MIT SMR*-BCG Artificial Intelligence Global Executive Study and Research Report, organizations that actively help their existing workforces gain AI skills are more likely, by 40 percentage points, to generate value from AI than companies that have not focused on reskilling.

Because improvements in consumption increase more slowly than advances in production, the gap between what an organization can produce and consume can increase rather than decrease as the organization improves its use of technology. While the organization matures in its use of AI in general, consumption still lags production, potentially leading to greater discomfort for the technology users. Ironically, as the organization matures, it faces a growing gap.

Organizations must therefore encourage employees to use their new skills. To improve employees' comfort with new technologies, Roche Diagnostics uses "innovation theaters" to provide accessible examples of how the organization can use AI. Siemens' annual internal conference on AI highlights ways that employees can use AI. Both of these examples build on extensive AI skill training. These companies recognize the importance not only of making AI technologies available in their organizations but of reskilling employees to consume them well.

Acquiring the right AI technology and producing results, while critical, aren't enough. Instead, to gain value from technologies like AI, the company needs to focus on those employees who will consume the AI results that the organization produces.

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How Managers Can Enable AI Talent in Organizations

Leading a successful AI-enabled workforce requires key hiring, training, and risk management considerations.

BY DANIEL ROCK

Recent progress on the technical side of machine learning, particularly within deep learning, has followed an accelerating trend of businesses adopting AI technologies into their processes and workflows in the past decade.[1] Some of these advances, such as Google DeepMind's AlphaGo and OpenAI's GPT-2 and GPT-3 models, have demonstrated expert-level performance in domains previously held up as examples of areas where bots would be incapable of challenging human abilities.[2]

With respect to business outcomes, most of the exciting developments involve using deep learning for supervised learning problems. Supervised learning is a form of machine learning where you have input and output variables and use an algorithm to learn the function that relates input to output. The algorithm is "supervised" because it learns from training data where input and output are known in advance. These deep learning algorithms enable a different kind of software development — where instead of explicitly writing a recipe in code to complete a task, a model is trained with data to learn how to complete the task on its own. These types of algorithms are also especially useful for different types of prediction.[3]

Finding and enabling talented individuals to succeed in engineering these kinds of AI systems can be a daunting challenge for companies. Building organizational AI/machine learning capabilities requires a fundamental reengineering of existing business processes. These efforts naturally include hiring or training technical talent.[4] Effective AI management, however, is perhaps even more critical. Ultimately, managers are responsible for shaping the design and direction of the organization's strategy to maximize the returns of any new technology. With this comes the responsibility to manage the associated risks of building AI systems. Done properly, effective AI management can drive faster productivity growth and provide companies with a competitive advantage.

Hiring and Training Considerations for Managers

The first requirement for leaders in building a successful AI system is hiring and training the right talent. An AI team is effectively a type of data science team, but it builds a different suite of products. For example, instead of running experiments to determine the effect of a new ad campaign, an AI team might build a product image classifier to determine how store shelves are organized. These teams use many of the same tools, including common programming languages like Python and R, cloud-based computing environments, and database technologies. Provisioning a team to build machine learning models involves familiarity and knowledge of the organization's technological hierarchy. Questions for leaders and teams to keep in mind include the following:

- **Is there a way to access a lot of computational power quickly?** Running production-quality AI systems is often best handled with cloud services, but building out a data center can be a better option for some companies. Either way, AI engineers are going to need access to the right machines.

- **Is there technical talent supporting the stability of the computational systems?** Stability of data infrastructure and computational resources is key to building out systems that scale. That means hiring IT talent that can make it easy for data science and AI engineers to produce reliable models.

- **Is data collected, cleaned, and accessed in a reliable and compliant way?** Professional data engineers can make sure that the raw data inputs are available in the format and quality needed to maximize AI value while minimizing risks.

AI, like other forms of IT, requires a lot of preexisting investment in various other assets, such as technical expertise, businesses processes, data, and culture, to be productive and provide value in a new context.[5] Early on, all of this additional complementary investment and change management can make it seem like AI (and data science as well) is a drag on productivity. After all, more resources are committed to generate some of the same outcomes. However, in time, what may have looked like initial dips in measured productivity will pay off with real returns. My research colleagues and I refer to this phenomenon as the Productivity J-Curve, and our research supports the idea that these up-front investments help organizations move toward the objectives stakeholders want to reach.[6]

In my own work partnering with LinkedIn's Economic Graph Research and Insights team, I found that a major portion of the business value of AI talent is reflected in these complementary assets. This makes sense given that many of these intangible assets, such as new processes, provide more value when AI skills become easier to acquire.

New tooling and platforms, such as Google's TensorFlow and PyTorch open-source machine learning libraries, have made it easier to train deep learning models and build skills more quickly on AI teams. In my research, I used LinkedIn data to track the prevalence of AI skills across companies and found that the market value of publicly traded companies that were already using AI increased by as much as 3% to 7% after TensorFlow came into the market at the end of 2015.[7]

These types of open-source solutions allow companies to accelerate machine learning initiatives without undertaking the cost of building out new development frameworks themselves. Meanwhile, the technical requirements needed to support production systems written with TensorFlow or PyTorch are already integrated into the major cloud providers. For managers, the best bet is to hire people who either know one or more of these frameworks or can learn them quickly. On the training side, these frameworks emphasize concepts over difficult programming syntax. That means existing employees in software engineer and data analyst roles can quickly learn the skills they need to be AI engineers. Programs such as Deeplearning.ai and Fast.ai offer ways to pick up these additional frameworks through online instruction.

Developing Effective AI Management

Even with a strong technical team in place, every AI-powered organization needs to successfully invest in organizational complements to maximize the return of AI. There are many perils and pitfalls to using AI systems. Managing these risks requires designing an effective management and reporting structure.[8] Organizational design choices play an important role here. For instance, are the AI engineers developing products for internal clients, or are they part of those client teams? Some companies prefer a hub-and-spoke model, where a core analytics team supports many different internal groups, while others might embed data scientists within each of those groups. The same organizational models can be applied to AI. When AI developers aren't embedded within internal groups, some of those clients might be worried about AI replacing them or challenging their position in the company. They might stand in the way of implementing a new process if it's perceived to be a threat.[9] In these instances, managers need to prioritize buy-in. Effective communication and education about AI is therefore paramount. AI is only (very) useful for a subset of the tasks that people do in the workforce.[10] Managers can assuage internal fears about AI with clear planning for how work will change with the adoption of the new technology.

Even with a strong technical team in place, every AI-powered organization needs to successfully invest in organizational complements to maximize the return of AI.

Another technique involves arming senior management with enough information to motivate subordinates to be data-driven. With AI training for senior executives and information pipelines giving these executives a granular view of their businesses, others in the organization will need to get on board with the new technology to keep up. If the organization is forecasting sales using a new technique, for instance, AI leaders should send those reports to the top of the organization for executives to reference in their meetings with midlevel managers. In the scenario where AI teams are spread out throughout the business, management is more responsible for the big-picture view of where new technology investments should happen. In either case, the organization is better off if decision makers understand which problems AI can solve and which problems are better tackled with other tools.

Another area that managers must handle aggressively involves bias. With machine learning, it can be difficult to interpret the "why" beyond certain predictive capabilities. For instance, with black-box models, determining the reasons someone's credit score went up or down can be tough to do. This goes beyond biased data sets leading to ineffective and inappropriate model outputs in production contexts. Algorithms are designed by humans; choices made by biased human designers or within complex social systems can also lead to outcomes in conflict with the organization's goals and values.[11] Managers need to closely monitor how their organization ingests, processes, and exports data. Whenever possible, systems should be proactively audited to make sure they serve the right purposes.

Lastly, managing the risks of AI systems requires the ability to recognize the difference between correlation and causation. Machine learning is most often used for predictive purposes in supervised learning. What is the model meant to do? It might not matter why a cat is recognized in a picture — that's a prediction (effectively, a correlation). It does matter why a given product line's customer acquisition costs are going up. That's a question about cause and effect. Managers in both cases need to think like social scientists: Develop a hypothesis, find the right tool kit and data to make an assessment, and then make decisions armed with better information.

Incorporating AI and machine learning into organizational workflows is risky, yet the returns are potentially very high if the right complementary investments are made. As with previous waves of information technology, AI requires management to grow with the new capabilities of the organization. AI talent is becoming more abundant across the globe. It is up to a new breed of managers with complementary managerial talent to bring out the best from their technical engineering and research teammates.

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Machine Learning and Your Business: The Journey From Concept to Reality

As vice president of the Machine Learning Solutions Lab at AWS, **Michelle K. Lee** leads a global business focused on helping AWS customers identify high-value machine learning use cases and guiding them to implementation. Previously, she was the under secretary of commerce for intellectual property and director of the United States Patent and Trademark Office, an executive at Google, a partner at the law firm Fenwick & West, and a computer scientist at Hewlett-Packard Research Laboratories and the MIT Artificial Intelligence Laboratory. She received bachelor's and master's degrees in electrical engineering from MIT and a J.D. from Stanford Law School.

aws machine learning

In this Q&A, Michelle K. Lee, vice president of the Amazon Web Services (AWS) Machine Learning Solutions Lab, shares real-world examples of machine learning in action, describes four key implementation challenges, and offers other advice.

This conversation has been condensed and edited for clarity, length, and editorial style.

Q: Can you provide an overview of how artificial intelligence (AI) and machine learning (ML) are driving digital transformation?

Lee: AI and machine learning went from being aspirational technology to mainstream extremely fast. For a long time, that technology was limited to a few major tech companies and hardcore academic researchers. But this began to change with three primary advances in technology.

First is the increase in the power of computers. Second: the decrease in storage price. And third is cloud computing. Machine learning requires extremely powerful computers to pore over large amounts of data that is easily accessible. Through cloud services pioneered by AWS, the powerful computers and access to the large amounts of data necessary for ML are now readily available to all, not just a few major tech companies and academic researchers.

As a result, almost every industry – finance, retail, agriculture, health care, manufacturing, and, really, every business – has the opportunity to take advantage of the recent advances in machine learning. When I talk to executives now, they are no longer asking, "*Why* should I be looking to employ machine learning in my business?" but instead, "*How* should I go about doing so, and how can I be successful in that?"

Q: Could you provide examples of businesses using ML for forecasting, prediction, and decision-making?

Lee: Domino's Pizza is using Amazon Personalize to predict purchasing behavior and then delivering personalized promotions and notifications to their customers via digital channels, including their popular mobile application. So instead of sending the same SMS [text] promotions to everyone, they can send them at times that suit the customer with the content that is most likely to result in a conversion of a purchase.

Intuit has employed ML-driven forecasting capabilities to predict call-center demand on a particular day or time to make sure that their customer service agents are adequately staffed.

In the health care space, we are helping companies to make better, faster decisions. We're seeing a shift from reactive to predictive care, including the use of predictive models to accelerate research and discovery of new drugs and treatment. Cerner, one of the largest publicly traded health care IT companies, used Amazon SageMaker to build a solution that enables researchers to query anonymized patient data records to predict congestive heart failure up to 15 months before clinical manifestation. They're also using Amazon's Transcribe Medical to free physicians from the tedious task of note-taking by providing a virtual [voice-to-text] scribe so the doctor can focus more on the patient interaction.

"I believe that every organization has a machine learning opportunity. What business wouldn't benefit from improved data-driven forecasting of customer demand, or enhanced forecasting of supply chain and inventory needs? What business wouldn't benefit from enhanced personalization of services and products offered to customers to help drive revenue?"

Convoy, a Seattle-based logistics company, is disrupting the trucking industry by using machine learning to more efficiently match truck drivers wanting to drive loads with shippers needing to transport loads, resulting in lower costs and faster deliveries. As a result, truck drivers are driving more often, according to the schedules they want, and those who need their goods transported are able to connect with drivers more easily through the machine learning solution.

Another example, from a completely different industry, involves the National Football League. The NFL developed a set of next-generation stats and ML models using its historical data on, for example, pass completions. Then, when the fan is watching the game on TV, the NFL provides stats about the probability that the player will actually catch the football for a completion as the play is unfolding. These almost instantaneous predictions enhance the fan viewing experience and are enabled by the ML models combined with real-time data from the field.

Q: Those are great examples. But how do companies with less experience know whether they need ML in the first place?

Lee: I believe that every organization has a machine learning opportunity.

What business wouldn't benefit from improved data-driven forecasting of customer demand, or enhanced forecasting of supply chain and inventory needs? What business wouldn't benefit from enhanced personalization of services and products offered to customers to help drive revenue? What business wouldn't benefit from automation in the very labor-intensive customer-call centers? Or from a quick assessment of the customer sentiment about the company, its performance, or its product offerings through online reviews, social media, or even by recordings from customer call centers?

I had the privilege of leading the U.S. Patent and Trademark Office, a governmental agency that has been examining patent applications pretty much the same way for over 200 years. Because I have this artificial intelligence and computer science background, I recognized that I could use data and data analytics to improve the quality and consistency of the patents issued, so I implemented that at the USPTO. I'd say if a 200-year-old governmental agency has a machine learning opportunity, I would imagine most businesses probably do, too. It's just a matter of finding it.

Q: Are there misconceptions about ML from a business standpoint?

Lee: Probably the biggest one is that the only thing standing between you and your dream ML application is a team of data scientists. In actuality, a number of factors need to come together in order to achieve a successful machine learning implementation.

Yes, you do need data scientists, either on your team or as consultants. But, equally important, you need to identify and tackle the right machine learning use case for your company – one that solves a real and significant problem that has measurable return on investment. You also need to have the data required to support the building, training, and testing of your machine learning model. And it certainly helps to have senior-level business buy-in for the project so that it is not simply a science experiment but something that solves a real business problem and is incorporated into the fiber of the business.

Q: What kinds of ML specialists do companies need today?

Lee: Particular roles that are necessary include data scientists, data engineers, software developers, and technical program managers. A variety of skills are needed, and the key for a company is to do a skills analysis to identify the gaps up front. Data analytics and machine learning, at least in their current forms, are relatively new disciplines, so there is a shortage of people with these skills. This means that a company probably isn't going to be able to hire all of them, so perhaps it ought to focus on training its current workforce.

At Amazon, we took an approach to both hire new talent and develop existing talent. Amazon developed a machine learning university that we have used for over six years to train our engineers. Last year, we made a lot of this content available for free to our customers – and, actually, to the public too. We have seen well over 100,000 developers start their machine learning journeys using this content.

Q: What are some common challenges that companies may face in adopting ML?

Lee: We've learned four key challenges that leaders need to address for successful adoption of machine learning: data strategy, getting started, the ML skills gap, and spending time on undifferentiated heavy lifting. That last challenge refers to activities such as building their own infrastructure and tools for data aggregation, access, and cleanup and modeling, rather than taking advantage of existing services such as Amazon's data lake offering, SageMaker for helping with ML model building and deployment, Rekognition for computer vision, Translate for language translation, or Comprehend for natural language processing.

Data is often cited as the No. 1 challenge in adopting machine learning. To be successful in machine learning, a company needs to have a data strategy that identifies the data it has, where it's located, who controls it, and where it needs to be to support its full and optimal use by the company. A company also needs to ask, "What data don't I have today that I want to have in the future?" and then begin developing a plan to gather such data.

"You do need data scientists, either on your team or as consultants. But, equally important, you need to identify and tackle the right machine learning use case for your company — one that solves a real and significant problem that has measurable return on investment."

Without a data strategy, the ML scientists a company hires will spend an inordinate amount of time dealing with data-management access and cleanup or, worse, get bogged down and frustrated because they lack what they need to solve the larger problem. So companies need to enable the IT team to break down any data silos and to collect the right data in a safe and compliant way.

A second challenge is, how do I get started? Although every business has a machine learning opportunity, not every business problem is solvable by machine learning. So identifying that high-value use case whose results are measurable is key. But that's not always easy. There is a lot of hype around what machine learning can do. That's why AWS created the Machine Learning Solutions Lab, which allows us to work side by side with our customers, to listen to their business problems, to identify their highest-value ML use cases, and to help guide them to implementation. To each of our engagements, we bring tremendous depth and breadth of experience and expertise based on our engagements across a wide range of industries and use cases.

The third challenge is the skills gap. Again, the growth in artificial intelligence has led to a shortage of data scientists and machine learning experts. You may not be able to hire all the data scientists you need, so you should probably focus your energy on upskilling the level of your current workforce and/or leveraging outside resources.

And a fourth challenge is the tendency to think you have to develop everything on your own from scratch, when a cloud platform like AWS can provide many of the necessary tools and infrastructure needed for data access and machine learning model development, testing, and deployment. By taking advantage of these existing tools and services, you can focus on bringing your differentiated, value-added contributions, such as your domain and industry expertise and any special insights that

> **"As a leader, it's important to articulate the priority of machine learning to the company and to encourage team members to continually ask themselves whether a business problem might be better solved with machine learning. Again, not every business problem is best solved by machine learning. But constantly asking that question is critical."**

you have, to solve the problem at hand.

Q: What kind of culture do organizations need to succeed with ML?

Lee: Machine learning requires a cultural shift that's most successfully driven from the top. As a leader, it's important to articulate the priority of machine learning to the company and to encourage team members to continually ask themselves whether a business problem might be better solved with machine learning. Again, not every business problem is best solved by machine learning. But constantly asking that question is critical.

Ten years ago, the Amazon leadership team asked every business leader at Amazon – regardless of whether they were running a research team, a fulfillment center, an HR organization, or the legal department – how they planned to leverage machine learning in their business. "We don't plan to" was not an acceptable answer. This forced every part of the organization to think about how ML could improve some aspect of their business and to develop a plan to achieve it. Today, I would say there's not a single business function at Amazon that isn't made better through machine learning.

But this didn't happen overnight. It took a cultural and a technological shift.

Q: What else would you like business leaders to know about ML?

Lee: Machine learning is still in its infancy, but it's not entirely new. Still, the path to machine learning success is not always straightforward, so many organizations need a partner to help them along the journey.

We have successfully helped so many organizations, from Domino's Pizza, to the NFL, Cerner, and NASA, achieve machine learning successes.

While we always aim to help our customers identify and deploy their high-value ML use cases, our goal is also to teach our customers "how to fish." To this end, we offer a program called AWS Machine Learning Embark, which not only provides workshops and ideation sessions to help identify their best use cases, but also machine learning training for both technical and business leaders for the precise reason I mentioned earlier: You want people within your organization, at every level, to be thinking, "How might machine learning improve or solve the business problem at hand?"

ABOUT AWS

AWS offers a broad and deep set of machine learning and AI services for your business. On behalf of our customers, we are focused on solving some of the toughest challenges that hold back machine learning from being in the hands of every developer.You can choose from pretrained AI services for computer vision, language, recommendations, and forecasting, or Amazon SageMaker to quickly build, train, and deploy machine learning models at scale. Customers can also build custom models with support for all the popular open-source frameworks. Our capabilities are built on the most comprehensive cloud platform, optimized for machine learning with high-performance compute and no compromises on security and analytics.

Learn more at aws.ai.