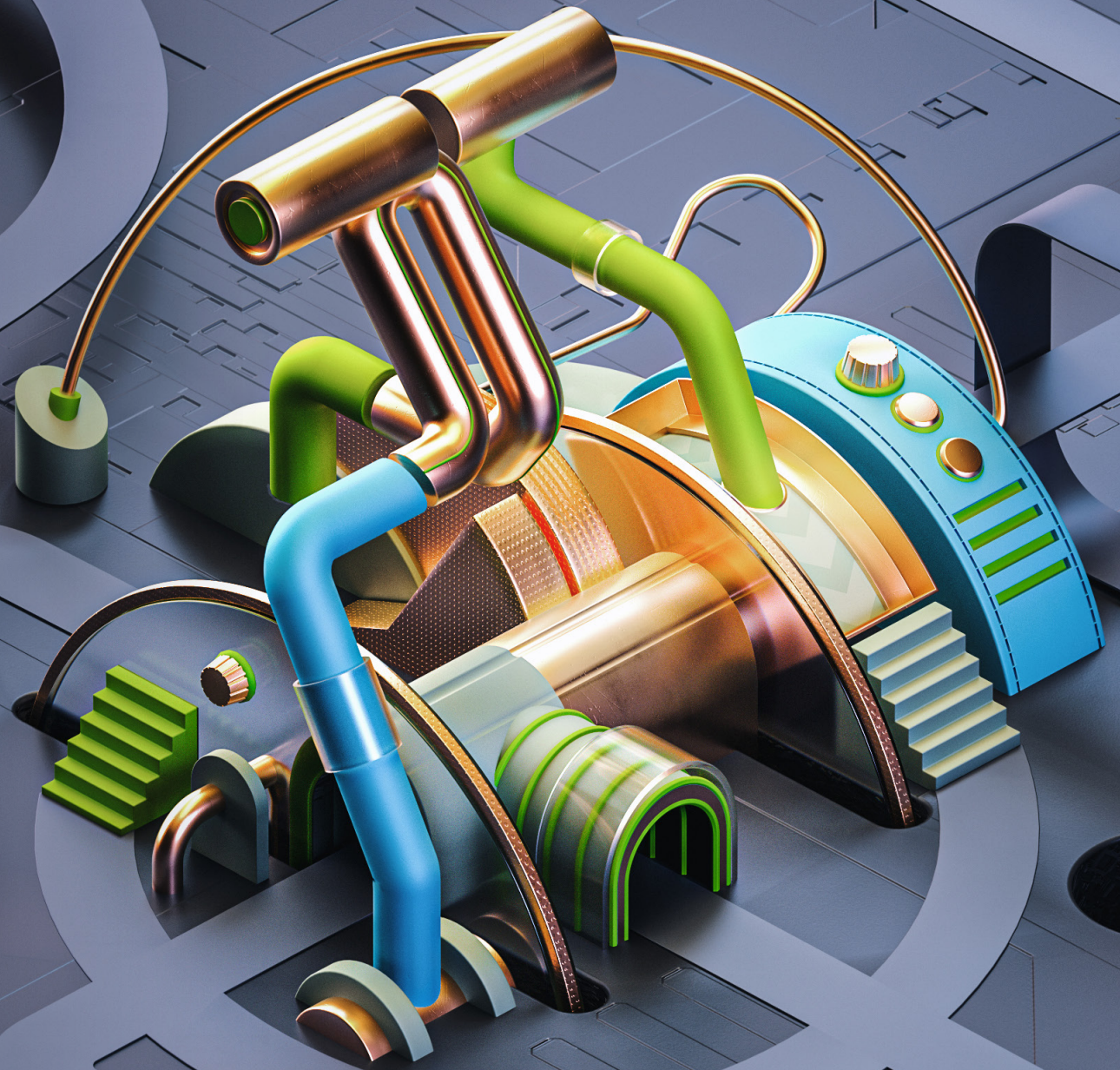


Deloitte.
Insights

Tech Trends 2021



MLOps: Industrialized AI

AI + DEVOPS PRINCIPLES

Like DevOps, MLOps features automated development pipelines, processes, and tools that streamline machine learning model development and operations.



STRENGTH IN NUMBERS

Multitalented teams of technologists and machine learning professionals can help organizations operationalize and scale AI.

OPEN THE BLACK BOX

MLOps can help AI teams promote trust by addressing data management challenges such as accountability and transparency, regulation and compliance, and ethics.



TREND 4

MLOps: Industrialized AI

Scaling model development and operations with a dose of engineering and operational discipline

Sophisticated machine learning models help organizations efficiently discover patterns, reveal anomalies, make predictions and decisions, and generate insights; Forrester reports that more than half of global data and analytics technology decision-makers have implemented or are in the process of implementing some form of AI.¹ As machine learning and AI increasingly become key drivers of organizational performance, enterprises are realizing the need to shift from personal heroics to engineered performance to more efficiently move ML models from development through to production and management.

Despite growing ML adoption, many organizations are hamstrung in their efforts by

clunky, brittle development and deployment processes that stifle experimentation and hinder collaboration between product teams, operational staff, and data scientists. In one survey of nearly 750 business decision-makers, only 8% considered their companies' ML programs to be sophisticated. And deployment happens too slowly: Twenty-two percent said it takes between one and three months to deploy a newly developed ML model into production—where it can deliver business value—with another 18% saying that it takes more than three months.²

As a result, IDC reports, 28% of AI/machine learning projects fail, with lack of necessary expertise, production-ready data, and integrated development environments cited as

the primary reasons for failure.³ Many more projects (47%) fail to even make it out of the experimental phase and into production.⁴

Many organizations are constrained by artisanal development and deployment techniques, with star data scientists frequently treated as virtuosos and given considerable creative control. Typically, these models are developed and deployed using manual, customized processes that, however clever, aren't terribly scalable. And enterprise data infrastructure is not designed to support rapid, consistent, streamlined development of machine learning models, as the chapter [Machine data revolution](#) discusses.

Organizations may need to rethink cultural norms, organizational structures, and governance mechanisms to more efficiently leverage AI resources, according to Jeff Butler, director of research databases at the Internal Revenue Service. “AI and machine learning can transform the way business is done, but only if organizations can fundamentally reshape organization structures, cultures, and governance frameworks to support AI,” he says. “Scaling AI across the IRS means that we are thinking differently about how models are created and managed, how to get the skills and talent we need, and how to hold ourselves accountable to taxpayers.”⁵

Indeed, as we noted two years ago in the *Tech Trends* chapter [AI-fueled organizations](#), to integrate AI and machine learning into every process and system, businesses must be able to deploy them consistently and at scale.⁶ To realize the broader, transformative benefits of AI and machine learning, the

era of artisanal AI must give way to one of automated, industrialized insights. Enter MLOps, also known as ML CI/CD, ModelOps, and ML DevOps: the application of DevOps approaches and tools to model development and delivery to industrialize and scale machine learning.

MLOps optimizes development, deployment, and management

Twenty years ago, similar development and operational challenges faced in software development led to the birth of DevOps. By standardizing and automating application development, deployment, and management, DevOps transformed the way many IT teams release and manage software, enabling them to dramatically improve development efficiency, delivery schedules, and software quality.

Today, it’s AI’s turn for the DevOps treatment. MLOps is an approach that marries and automates ML model development and operations, aiming to accelerate the entire model life cycle process. MLOps helps drive business value by fast-tracking the experimentation process and development pipeline, improving the quality of model production—and makes it easier to monitor and maintain production models and manage regulatory requirements. The MLOps market is expected to expand to nearly US\$4 billion by 2025.⁷

The DevOps approach recognizes that improving software operations warrants attention, just as improving software development does. Like DevOps, MLOps features automated pipelines, processes, and tools that streamline all steps of model construction. Through continuous development, testing, deployment, monitoring, and retraining, MLOps can

improve collaboration among teams and shorten development life cycles, thereby enabling faster, more reliable, and more efficient model deployment, operations, and maintenance as well.

With automation and standardized processes, MLOps can encourage experimentation and rapid delivery, helping enterprises industrialize machine learning. For example, new techniques and approaches, supported by better data organization for use by machines, can reduce to days or even hours the process of customizing and adjusting the way models learn to generate the most accurate outcomes, known as model tuning. To help ensure that the best processes are industrialized, productionized, and scaled, teams can reevaluate and automate existing processes for creating, managing, and curating the data, algorithms, and models at the heart of machine-driven decision-making.

Once models have been deployed to production and begin encountering more data, monitoring their performance can help ensure they continue to deliver business value. If unchecked in production, unexpected bugs could be introduced into the pipeline. And as the data used to train and validate models ages, predictive accuracy can deteriorate.

MLOps can encourage experimentation and rapid delivery, helping enterprises industrialize machine learning.

This concept, known as model drift, is one of the leading reasons that models miss performance targets. For example, COVID-19 disrupted many supply chains because

demand planning models weren't updated frequently enough to account for the quickly emerging "new normal" as the pandemic began. As discussed in the chapter [Supply unchained](#), many businesses had either too much or too little supply, in large part because their demand planning models were operating on data and assumptions that became outdated nearly overnight.

MLOps helps organizations monitor model performance and manage model drift's predictive inaccuracies by helping standardize processes for maintaining alignment of AI models with evolving business and customer data. Human ML experts can monitor production models, observe how they change and behave as they scale, and decide when they need to be retrained or replaced. As a result of this planning and monitoring, model drift is diminished, and development and deployment become more flexible and responsive.

Development focus shifts from exceptionalism to professionalism

Bringing the discipline of DevOps to machine learning can help AI adopters scale model development and deployment, but they must also tackle a significant skills gap. In a recent Deloitte study, 68% of executives surveyed described their organization's skills gap as "moderate-to-extreme," with 27% rating it as "major" or "extreme."⁸

Typically, enterprises rely on a small number of highly skilled data scientists and analysts to develop and test complex ML models and then deploy them to a production setting. With expertise in statistical analysis and experience in determining appropriate ML approaches, developing models, making prototypes, and ensuring the models' predictive accuracy, these data scientists are in high demand.

But relying on a few experts has limits, chiefly related to scalability and repeatability. Every data Jedi typically prefers their own set of model development and deployment workflows, based on education, experience, and personal preferences. They then often build models with bespoke data extracts that can require significant effort to recreate when later brought into a production setting using real-world, large-scale data. As machine learning permeates the enterprise, a more scalable, efficient, and faster approach is needed to improve development resilience, reduce production bottlenecks, and increase the reach of ML projects.

Organizations need supporting teams of multitalented technology and ML professionals to help with activities such as data management, model deployment, and postdeployment monitoring and management. MLOps practices encourage communication between expanded development and production teams; like DevOps, it's a deeply

collaborative approach, enabling a broader and larger team of professionals to work together more efficiently to get more done in a standardized manner. Tools can help too: Automated machine learning, or AutoML, can accelerate model development by helping data scientists quickly test different models and variants.

These new players can help data scientists test and fine-tune their creations, deploy models to production, manage production models, address issues related to security and governance, and remove impediments to AI and ML initiatives associated with outdated data infrastructures. Together with MLOps, data engineers and technologists can expand the focus of AI teams from model building to operationalizing. By lightening the load on the still-critical data scientists, the new supporting cast and crew can help ensure that the entire production is as Oscar-worthy as the lead actor's performance.

MLOps helps address emerging challenges associated with data use

Despite the many similarities between DevOps and MLOps, machine learning spawns complex, data-related issues not commonly faced in the software development process, such as accountability and transparency, regulation and compliance, and AI ethics.

For example, ML models often make predictions that drive decisions related to medical diagnoses, loan applications, prison sentencing, and other consequential matters. These require model and algorithm transparency to shed light on how and why these decisions are made. There may also be privacy and consent issues related to both training and production data sets. And because ML systems often use sensitive

personal information, data protection may further need to meet regulatory compliance standards, such as HIPAA, PCI, or GDPR. Another challenge: the use of biased data that reinforces and amplifies societal prejudices—sometimes overt but often implicit. And it's not enough to simply retrain models with unbiased data, because developers can unintentionally build their own biases into algorithms and models.

MLOps can help organizations manage such dilemmas by establishing and enforcing program-level guardrails that can drive accountability as a baseline requirement. Within a robust MLOps framework, development and deployment teams will find it easier to adhere to governance and compliance protocols and privacy and security regulations. Similarly, programmatic traceability standards can help ensure that model transparency—and to a degree, fairness—are standard ingredients in any

model's design and implementation. MLOps tools can automatically record and store information about how data is used, when models were deployed and recalibrated and by whom, and why changes were made.

Another challenge: the use of biased data that reinforces and amplifies societal prejudices—sometimes overt but often implicit.

Without MLOps procedures in place, it would be infeasible, if not impossible, to prove proper data handling or use in response to an external inquiry.

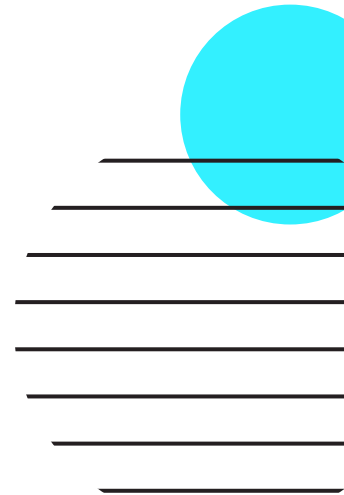


As model development and deployment is standardized and automated—and becomes a team sport—accountability is diffused and shared throughout the process. The responsibility, then, sits at the process level, with the baseline requirement to produce more auditable, accountable AI. Cracking open the black box of machine learning can result in transparency that enables stakeholders to more easily interpret, understand, and trust the data and logic upon which decisions are founded.

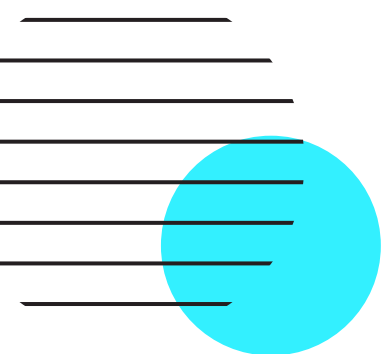
The way forward

As enterprises seek to scale AI development capacity from dozens to hundreds or even thousands of ML models, they can benefit from the same engineering and operational discipline that DevOps brought to software development. MLOps can help automate manual, inefficient workflows and

streamline all steps of model construction and management, but organizations likely will also need to infuse AI teams with fresh talent whose capabilities complement those of highly skilled data scientists, further extending teams' focus from model building to operationalization. When armed with MLOps tools and processes, these expanded AI teams likely will be better able to address challenges related to accountability and transparency, regulation and compliance, AI ethics, and other issues related to managing and organizing data for machine-driven decision-making. As a bonus, this approach enables data scientists to focus on experimenting and innovating with new AI technologies that go beyond core techniques, enabling organizations not only to scale ML initiatives but to be more operationally resilient and agile in the face of technological change.



LESSONS FROM THE FRONT LINES



The next wave of AI research

Researchers at the National Oceanic and Atmospheric Administration (NOAA) are increasingly leveraging AI and machine learning to better understand the environment and make potentially life-saving predictions. With an extensive network of environmental satellites and observation systems that collect real-time weather, climate, and ocean data, the federal agency currently uses AI to interpret earth, ocean, and atmospheric observations, improve weather forecasting, monitor marine mammal and fish populations, and aid many other applications.

As NOAA seeks to expand its use of AI and ML to every mission area, it recently launched an effort to improve the efficiency and coordination of AI development and use across the agency. Historically, NOAA scientists have undertaken AI initiatives and machine learning models independently, with every researcher potentially having a different idea about how to leverage AI for a specific project; development happens organically. As a result, line offices, made up of multiple research centers and divisions, are each at a different stage of maturity in the AI journey.

“To create truly transformational products, we need a more consistent, synchronized approach to AI across the agency,” says Sid-Ahmed Boukabara, principal scientist for strategic initiatives at NOAA’s Center for Satellite Applications and Research, the research arm of the National Environmental Satellite, Data, and Information Service.⁹ “We aim to dramatically expand the application of AI in every NOAA mission area by improving the efficiency, effectiveness, and coordination of AI development and usage across the agency.”

NOAA developed a bold strategy focused on achieving five strategic goals.¹⁰ One of those entails the establishment of a virtual AI center, allowing line offices to share best practices and integrate efforts when appropriate. The NOAA AI Center was proposed in the latest presidential budget request and is being discussed on Capitol Hill.

Regardless of where a line office, division, or center sits on the maturity curve, the NOAA AI Center is envisioned to work with those scientists and researchers to help them effectively transition AI projects from idea to operations. Initially, the agency aims to increase the use of small-scale demonstration projects related to specific areas such as weather forecasting,



which can serve as proofs of concept for larger-scale efforts. Another objective of NOAA's AI strategy has been to strengthen and expand partnerships in order to enhance the use of AI to achieve the NOAA mission.¹¹

In addition to partnerships and coordinating AI research, the NOAA AI Center is expected to be responsible for making NOAA's data AI-ready and available to the agency and public, promoting ML algorithm development, AI labeling, application development, information exchange, and general AI awareness generation and workforce training. Technical specialists from the NOAA AI Center, embedded in the line offices, will provide researchers with the know-how, tools, and support to execute their ideas. "We'll make sure to not stifle scientists' creativity and instead help them conserve resources and enhance their use of AI when needed," Boukabara says. "By cross-fertilizing knowledge across the agency, we'll be able to

benefit all line offices by efficiently leveraging the newest machine learning techniques when scientifically appropriate."

Scaling to thousands of models in financial services

AI and machine learning technologies are helping financial services firm Morgan Stanley use decades of data to supplement human insight with accurate models for fraud detection and prevention, sales and marketing automation, and personalized wealth management, among others. With an AI practice that's poised to grow, the firm is leveraging MLOps principles to scale AI and ML.¹²

"We need to be able to scale from hundreds of models to thousands," says Shailesh Gavankar, who heads the analytics and machine learning practice in Morgan Stanley's Wealth

Management Technology department. "There are limitations to doing everything manually as long as data scientists and data analysts are working on their own 'island' without the ability to collaborate or share data."

Currently, the practice is using common platforms for managing data and developing, deploying, and monitoring ML models. To build and test models, people created a sandbox with access to a centralized data lake that contains a copy of the data used in the production system, a technique that makes it easier to bring models from development into production.

In the development environment, data scientists, business analysts, and data engineers across the practice can access the same standardized data in near-real time, enabling them to efficiently and collaboratively explore, prototype, build, test, and deliver ML models. Advanced techniques mask

personally identifiable information so the teams can generate insights without exposing sensitive data. “Across our AI practice, processes are built around data accuracy and privacy,” Gavankar says. “Applying the highest standards to the training system ensures that we meet data compliance and regulatory requirements.”

For good model governance, transparency, and accountability, an independent, in-house model risk management team was established. With years of experience deploying trading models, the team is responsible for assessing risk and validating the quality of ML models before they go to production. The team evaluates the accuracy of the models and works to identify sources of bias or other unintended consequences. They also review data lineage as well as plans for production monitoring and intervention should the model start to drift.

As its AI practice evolves, Morgan Stanley Wealth Management will be focusing on continuing to improve speed to market by further automating the model risk management process and integrating the sandbox and production systems. “As MLOps tools and processes enable us to operationalize models more efficiently,” Gavankar says, “we can continue to increase the number of models in production and more fully leverage AI’s ability to drive better business decisions.”

One-stop shop for model development and deployment

As AI and machine learning transform health care, health insurer Anthem, an industry leader in the use of clinical, customer-facing AI applications, is increasingly leveraging AI

to reimagine and reinvent critical back-end business processes. About two years ago, the company embarked on an AI-supported journey to streamline claims management. As part of that process, leaders built a platform that consolidates model development and deployment across the enterprise.

Anthem initially built several ML models that revealed patterns in claims data, made predictions to speed processing, and identified and corrected errors. The models were successful—and leaders realized they needed to scale. “As the models began to deliver business value, we realized we needed infrastructure that could help us develop and operationalize machine learning more efficiently,” says Harsha Arcot, senior director of enterprise data science.¹³ “To address this challenge, we decided to build a single interface for all AI and ML solutions across the Anthem ecosystem.”

The company built an integrated development environment and an end-to-end platform that serves as a one-stop shop where developers and data scientists prepare and store training data, build and validate models via easy-to-use interfaces, and deploy them at scale. A feedback mechanism allows models to continuously learn and improve while a separate platform monitors the performance of production models.

Simultaneously, the company has been working on an initiative that consolidates data from seven systems into a single repository. With most of that work complete, the process of finding the data to build, train, and operationalize models is much more efficient.

The platform also provides Anthem with the flexibility to duplicate models for multiple use cases. For example, if a pipeline is already built out into the legacy claims system for a commercial use case, it can also be easily

deployed on the consumer side. “It’s much more efficient than when we used to develop a model for each use case from scratch,” Arcot says.

Using the platform, Anthem data scientists have developed a number of models, including those that fast-track the processing of pre-approval claims, identify and automatically reject duplicate claims, and determine whether a medical procedure needs preauthorization. Previously, a human claims examiner or clinician needed to manually review and process all of these claims.

Arcot says the platform has dramatically increased model deployment speed. “Before we developed the platform, it took about six months to deploy very simple models,” he says. “Now we are able to develop much more complex initiatives in half the time.”

MY TAKE

Swami Sivasubramanian

Vice president, Amazon
Machine Learning, AWS



We are entering the golden age of machine learning, with adoption increasing across all customer segments.

Once considered peripheral, ML technology is becoming a core part of many business strategies around the world. From health care to agriculture, fintech to media and entertainment, ML holds great promise for many industries. Driven by the wide availability of cloud-based computing power, storage capacity, and easy-to-use AI toolsets, the normalization of AI and ML continues at a rapid pace. However, before enterprises can scale from dozens to thousands of ML models and make machine learning an integral part of their strategy, they need to address the AI skills gap and integrate ML practices into individual lines of business. They must also get their data strategy in order, tackle governance issues, and streamline model production. Let's look at each of these gaps.

Organizations must have a strategy to contend with the global shortage of AI skills—one of the biggest barriers to adoption. Across

the lines of business, from engineering to product teams, people need a broader understanding of AI and ML concepts and tools to help identify relevant business opportunities and understand the potential of this technology for customers and other key stakeholders. At Amazon, we addressed this skills gap by building a Machine Learning University in 2014.¹⁴ Available to anyone interested in machine learning, the university helps AI professionals keep their skills sharp while giving product managers, program managers, and other novices the opportunity to learn the basics of AI and ML.

Armed with an understanding of AI fundamentals, business stakeholders can play a collaborative role in developing strong business cases for ML initiatives and develop ML-driven solutions that matter to their customers and business. When data scientists and business stakeholders team up to identify strategic problems to which AI might

be applied, they can meaningfully move the needle for the business. Without collaboration, AI teams risk building impressive prototypes that never get business buy-in or have real-world customer impact.

Armed with an understanding of AI fundamentals, business stakeholders can play a collaborative role in developing strong business cases for ML initiatives and develop ML-driven solutions that matter to their customers and business.

When it comes to ML adoption, data is often cited as the No. 1 challenge. In our experience, more than half of the time spent building ML models can involve data wrangling, data cleanup, and pre-processing stages. If you don't invest in establishing a strong data strategy, ML talent will be forced to spend a significant portion of their time dealing with data cleanup and management instead of inventing new algorithms. Specifically, poor data and model governance are also significant challenges to widespread AI adoption. Driven by concern that data will be used inappropriately, many business divisions tend to hoard data into silos and are reluctant to share it with others. Good data governance can give business partners confidence that their data will be used properly, thereby encouraging sharing and typically leading to more accurate models. Similarly, strong model governance mechanisms and monitoring processes can help AI adopters maintain accuracy once models are in production. Automated monitoring tools can

provide feedback on how the model is changing and alert human developers when the models need to be retrained and recalibrated.

In addition, a solid strategy for managing and storing data can help optimize data scientists' skills and time. Automating time-consuming data management tasks can help free up these professionals to focus on what they do best: developing algorithms and building models. By simplifying the process of classifying data and controlling access, automated data management can help address data governance challenges.

Finally, as businesses scale their ML practices, it is important for builders to focus on what is meaningful for the business instead of worrying about developing ML infrastructure—an undifferentiated but heavy workload. Streamlining model production can help organizations use their talent and other resources more wisely. For example, many

companies invest in developing, deploying, and managing models. This undifferentiated heavy lifting can distract talent from value-driving tasks such as solving critical business problems and building customer-focused solutions. For many companies, a more efficient solution might be to leverage existing platforms and tools, such as Amazon SageMaker, that expedite and simplify the model production process, drawing humans into the loop for critical decision-making. Similarly, organizations nowadays do not have to spend time building an automatic speech recognition model for transcribing contact center calls—instead, they can use cloud AI APIs, such as Amazon Transcribe, or fully packaged AI products, such as Contact Lens for Amazon Connect, that modernize contact centers.

Removing these and other roadblocks standing in the way of efficient ML adoption can help industrialize and scale AI across the

enterprise, enabling organizations to efficiently ingrain machine learning into business processes and embed it into new products and services.

EXECUTIVE PERSPECTIVES



STRATEGY // With ML adoption growing across industries, CEOs—particularly those whose companies operate in low-growth sectors—are exploring how to use machine learning to grow market share and lower costs. CEOs may want to speak to their CIOs and IT teams about their vision for applying AI/ML to boost the bottom line. For example, if they hope to increase earnings per share by 10 points, CEOs should make their priorities clear and spend time understanding what can be achieved and/or what investments are needed. As the organization hires AI/ML talent to scale capabilities, leaders should provide a clear mandate to these new teams for how and when technology should augment human decision-making.



FINANCE // As organizations are increasingly pressed to make good decisions faster and develop better models for demand forecasting, finance leaders are quickly realizing that their organizations need machine learning at scale. Assuming that technology speed and capability will continue to increase exponentially, making a machine-based decision in the future will cost a fraction of a nonscalable human decision today. Indeed, 67% of executives in Deloitte’s State of AI survey are already leveraging ML for efficiency gains, such as faster account reconciliation or more accurate accruals.¹⁵ To ready their organizations for this change, CFOs can choose between becoming more technically savvy or buying financial planning and analysis as a service. Whether they sponsor data officers or take on the task themselves, finance leaders may soon rely on the power of machine-driven insights for their regular updates to analysts and shareholders.



RISK // ML deployments are quickly scaling up and enabling algorithms to make key decisions for the organization. Yet trust remains an issue: Humans are undeniably prone to bias, but the press and the public often take particular notice of biases in machines and biased outcomes of ML models.¹⁶ CROs can work with their CIOs, CDOs, and other IT leaders to anticipate potential brand risks and suggest design workarounds. They can also make purposeful choices with AI and ML algorithms not only to help maintain public trust in their organizations but to position risk management protocols for AI/ML as a competitive differentiator.

ARE YOU READY?



KEY QUESTIONS

Do you have the skill sets and organizational structure needed to meet your AI goals today? In two years?

How can you improve the time to market of models and improve their performance in production?

How can you improve models' governance, accountability, and transparency? What precautions can reduce developer and data bias? How can you better protect sensitive data?

LEARN MORE



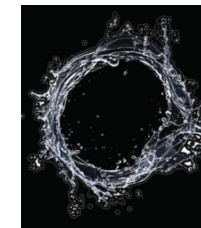
Thriving in the era of pervasive AI

[See](#) how companies are managing and getting ahead of the rise in AI adoption.



AI & cognitive technologies collection

[Learn](#) how cognitive technologies can augment manual tasks and decision-making.



Leverage MLOps to scale AI/ML to the enterprise

[Listen](#) to a podcast on the ways MLOps can integrate AI/ML models into business processes.

AUTHORS

Our insights can help you take advantage of emerging trends. If you're looking for fresh ideas to address your challenges, let's talk.

Beena Ammanath

Executive director, Deloitte's
AI Institute
Deloitte Consulting LLP
bammanath@deloitte.com

Frank Farrall

AI Ecosystems leader
Deloitte Consulting LLP
frfarrall@deloitte.com

David Kuder

US AI Insights and Engagement
Market offering leader
Deloitte Consulting LLP
dkuder@deloitte.com

Nitin Mittal

US AI Strategic Growth offering leader
Deloitte Consulting LLP
nmittal@deloitte.com

SENIOR CONTRIBUTORS

Paul Phillips

Managing director,
Deloitte Consulting LLP

James Ray

Senior manager,
Deloitte Consulting LLP

Paulo Maurício

Senior manager, Deloitte &
Associados, SROC S.A.

ENDNOTES

1. Srividya Sridharan, Gene Leganza, and Jeremy Vale, "[Research overview: Artificial intelligence](#)," Forrester, May 20, 2020.
2. Algorithmia, [2020 state of enterprise machine learning](#), 2019.
3. IDC, "[IDC survey finds artificial intelligence adoption being driven by improved customer experience, greater employee efficiency, and accelerated innovation](#)," June 10, 2020.
4. Jessica Davis, "[Getting machine learning into production: MLOps](#)," *Information Week*, June 26, 2019.
5. Jeff Butler (director of research databases at the Internal Revenue Service), phone interview with authors, October 16, 2020.
6. Nitin Mittal, Dave Kuder, and Samir Hans, [AI-fueled organizations: Reaching AI's full potential in the enterprise](#), Deloitte Insights, January 16, 2019.
7. Cognilytica, "[The rapid growth of MLOps](#)," April 2, 2020.
8. Susanne Hupfer, [Talent and workforce effects in the age of AI: Insights from Deloitte's State of AI in the Enterprise, 2nd Edition survey](#), Deloitte Insights, March 3, 2020.
9. Sid-Ahmed Boukabara (principal scientist for strategic initiatives, NOAA's Center for Satellite Applications and Research), phone interview with authors, October 14, 2020.
10. National Oceanic and Atmospheric Administration, [NOAA artificial intelligence strategy](#), February 2020.
11. National Oceanic and Atmospheric Administration, "[AI agreement to enhance environmental monitoring, weather prediction](#)," October 27, 2020.
12. Shailesh Gavankar (head of Analytics and Machine Learning practice, Morgan Stanley), phone interview with authors, October 16, 2020.
13. Harsha Arcot (senior director of enterprise data science, Anthem), phone interview with authors, October 23, 2020.
14. Amazon, "[Machine Learning](#)," accessed November 23, 2020.
15. Deloitte, [Why CFOs should have artificial intelligence on their minds](#), 2020.
16. Craig S. Smith, "[Dealing with bias in artificial intelligence](#)," *New York Times*, November 19, 2019.

Deloitte.

Insights

Sign up for Deloitte Insights updates at www.deloitte.com/insights.

www.deloitte.com/us/TechTrends



Follow @DeloitteInsight



Follow @DeloitteOnTech

Deloitte Insights contributors

Editorial: Matthew Budman, Blythe Hurley, Abrar Khan, Rupesh Bhat, and Nairita Gangopadhyay

Creative: Alexis Werbeck, Dana Kublin, Tristen Click, and Victoria Lee

Promotion: Hannah Rapp

Cover artwork: Vault49

About Deloitte Insights

Deloitte Insights publishes original articles, reports and periodicals that provide insights for businesses, the public sector and NGOs. Our goal is to draw upon research and experience from throughout our professional services organization, and that of coauthors in academia and business, to advance the conversation on a broad spectrum of topics of interest to executives and government leaders.

Deloitte Insights is an imprint of Deloitte Development LLC.

About this publication

This publication contains general information only, and none of Deloitte Touche Tohmatsu Limited, its member firms, or its and their affiliates are, by means of this publication, rendering accounting, business, financial, investment, legal, tax, or other professional advice or services. This publication is not a substitute for such professional advice or services, nor should it be used as a basis for any decision or action that may affect your finances or your business. Before making any decision or taking any action that may affect your finances or your business, you should consult a qualified professional adviser.

None of Deloitte Touche Tohmatsu Limited, its member firms, or its and their respective affiliates shall be responsible for any loss whatsoever sustained by any person who relies on this publication.

About Deloitte

Deloitte refers to one or more of Deloitte Touche Tohmatsu Limited, a UK private company limited by guarantee (“DTTL”), its network of member firms, and their related entities. DTTL and each of its member firms are legally separate and independent entities. DTTL (also referred to as “Deloitte Global”) does not provide services to clients. In the United States, Deloitte refers to one or more of the US member firms of DTTL, their related entities that operate using the “Deloitte” name in the United States and their respective affiliates. Certain services may not be available to attest clients under the rules and regulations of public accounting. Please see www.deloitte.com/about to learn more about our global network of member firms.