DataRobot

REPORT

5 LATEST TRENDS

in Enterprise Machine Learning

ALGORITHMIA
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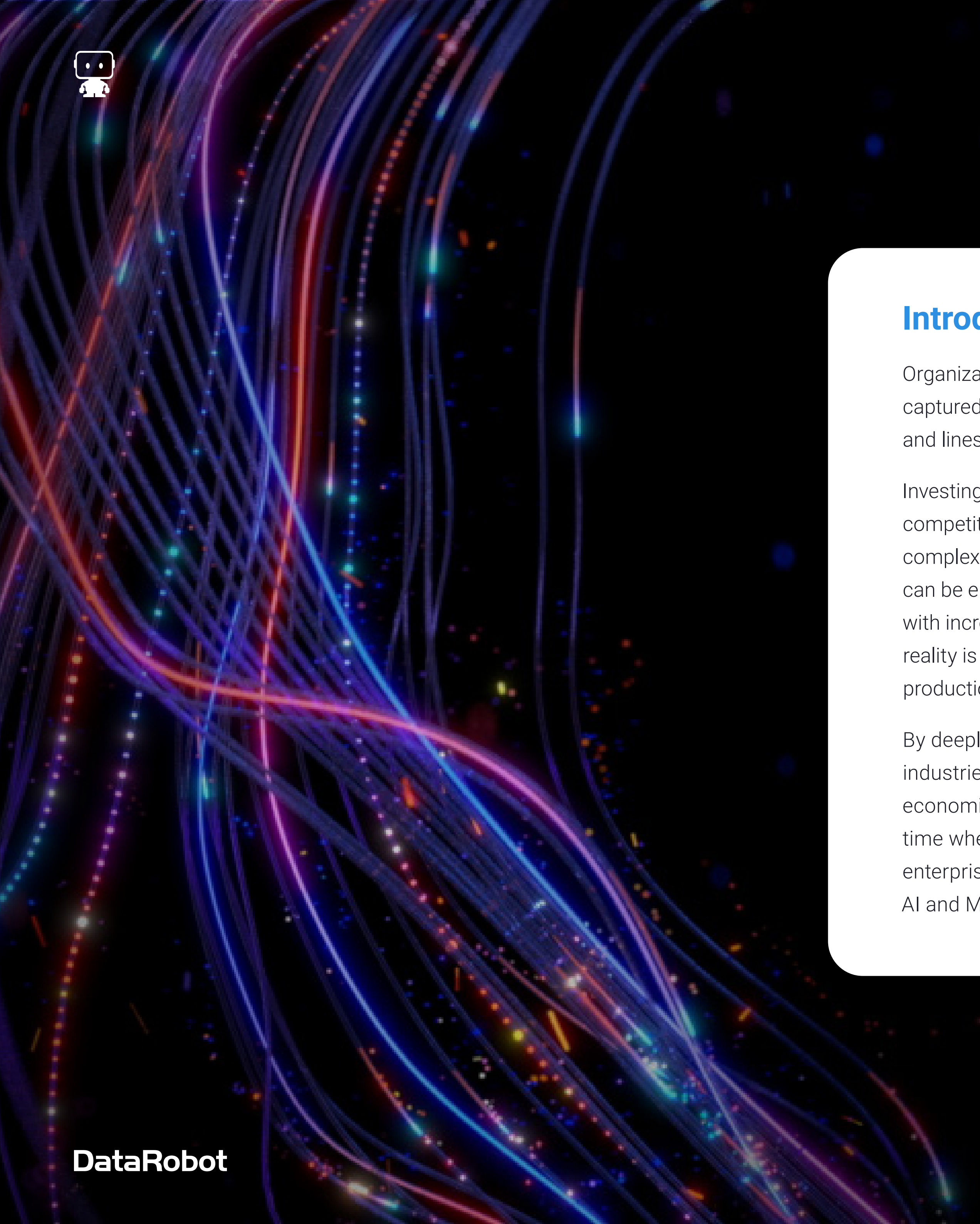


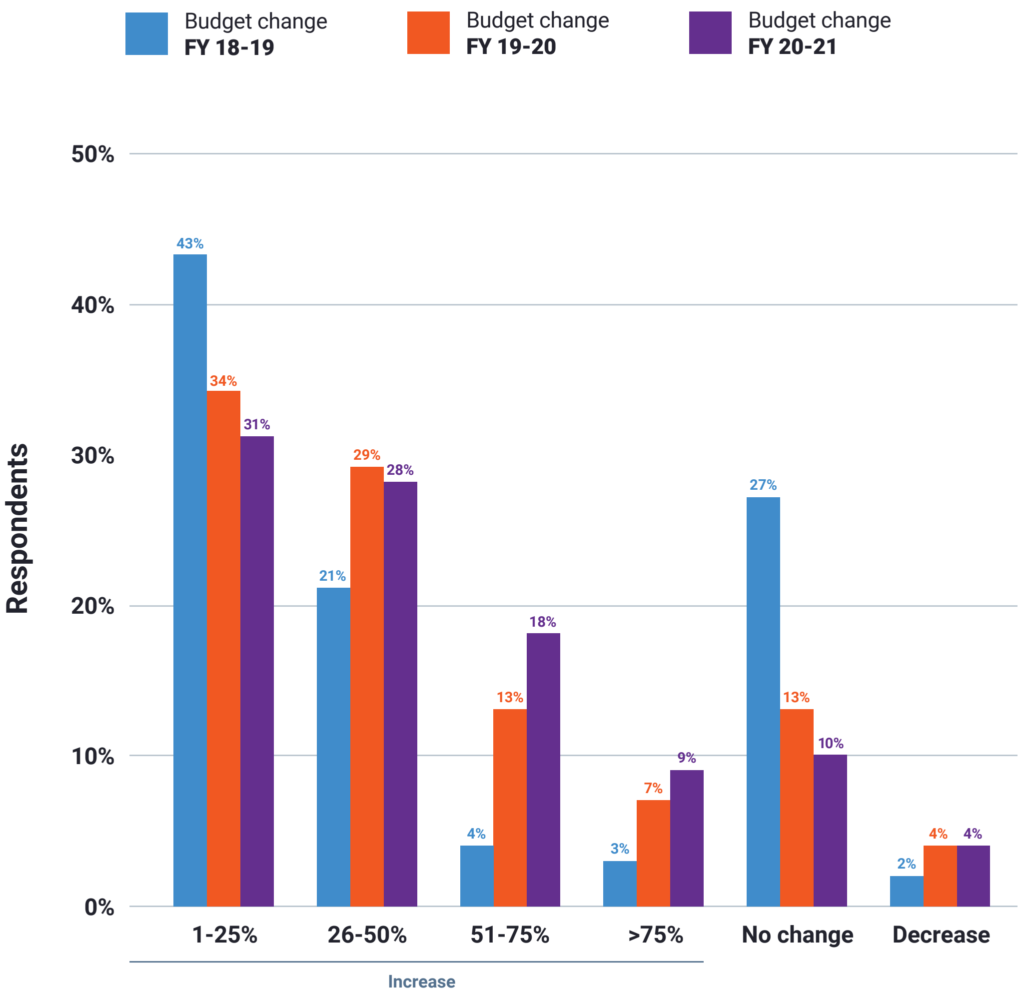
Introduction

Organizations are under growing pressure to transform the volumes of data captured by their systems into valuable insights that drive impact across all levels and lines of business.

Investing in AI/ML is no longer optional, but critical for organizations to remain competitive. Yet, this growing investment also brings challenges. AI remains complex and out of reach for many. Outcomes that drive real business change can be elusive. And as investments in AI/ML grow, many are left contending with increasingly challenging operational concerns and technical debt. The reality is that the vast majority of organizations still struggle to bring models into production and maximize their business impact.

By deeply exploring the AI/ML strategies of over 400 organizations across industries, DataRobot has gained unique insights into how AI is unlocking economic growth, as well as the common hurdles facing organizations, at a time when this has never been more critical. This report explores the latest enterprise AI/ML trends unfolding in 2021, and how organizations are turning to AI and ML to drive business value and gain a competitive advantage.

86% of Organizations Have Increased Machine Learning Budgets for 2021

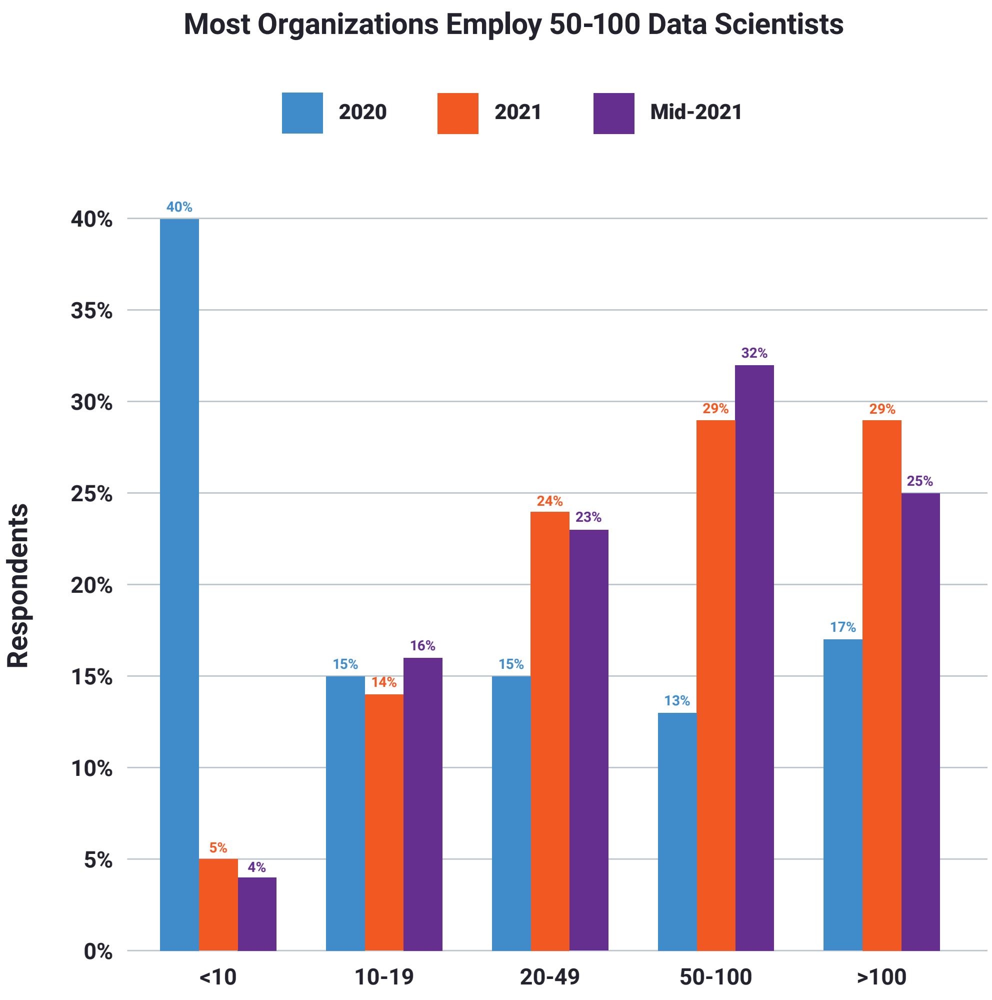


2021: Enterprise AI/ML Investments Accelerate

Our latest research points to sustained, long-term investments in machine learning spurred in part by the economic disruptions of the pandemic. AI/ML budgets, staffing, and prioritization all grew year-over-year in 2020, and this wasn't a temporary surge.

In 2021, budgets and prioritization continue to increase for ML. 86% of organizations have increased their AI/ML budgets from FY20 to FY21, a higher rate than in our previous studies.

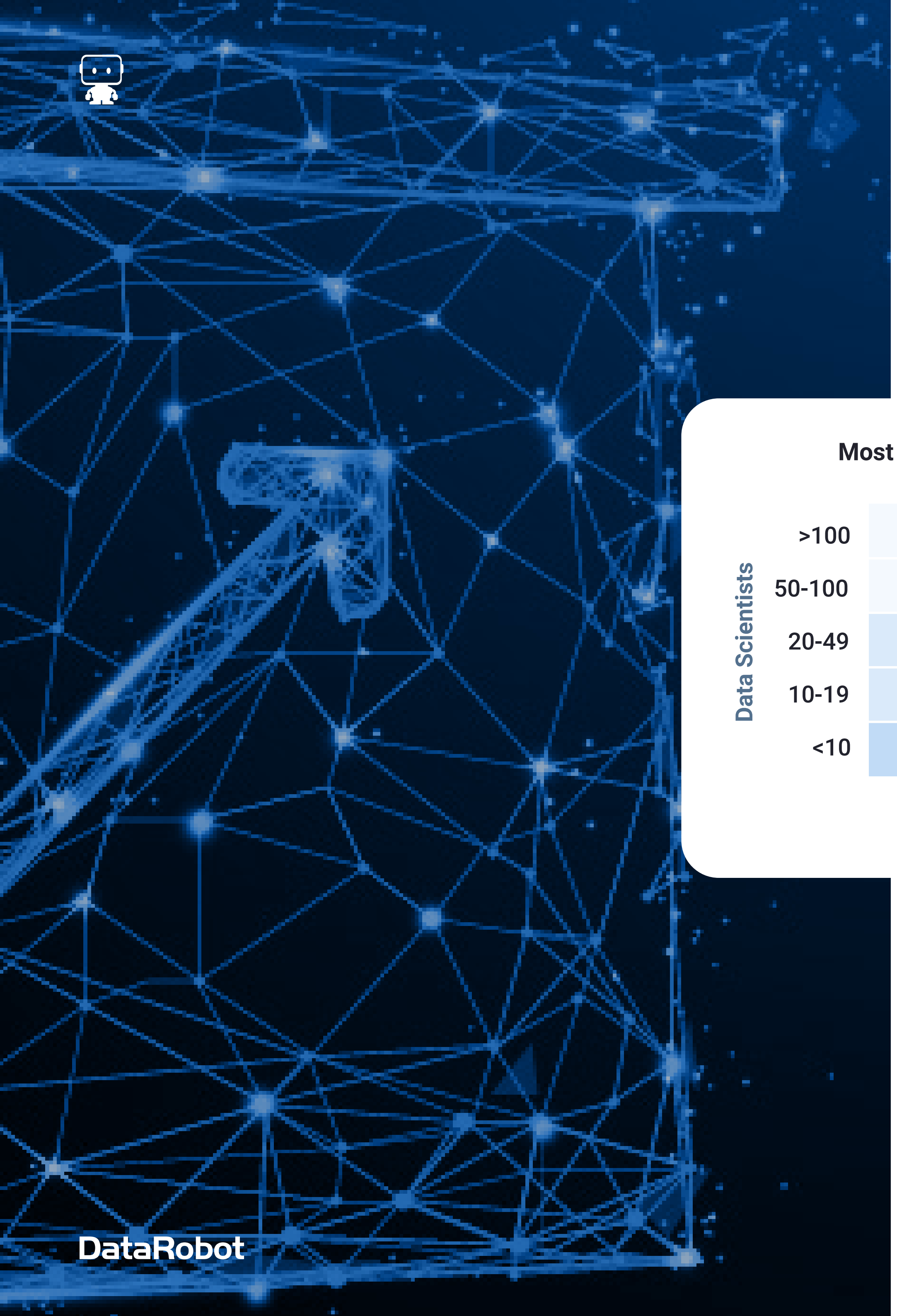
The size of these budget increases has grown as well: More companies report increases of greater than 50% than in the past, signaling their growing recognition of the transformative business value of AI/ML.



In 2020, respondents were asked to indicate the number of data scientists employed at their organizations through a free-form response field. In all subsequent surveys, respondents were given the predefined ranges shown in this chart. 2020 data has been aggregated into the same ranges for comparability.

What's more, AI/ML continues to move to the top of many organizations' strategic roadmaps. 86% of companies rank AI/ML over other IT initiatives in terms of strategic importance, meaning it's either their top priority or a high priority relative to other IT initiatives. 42% list it as their top priority.

Hiring also continues to grow, with 57% of organizations now employing 50 or more data scientists. Companies employing 50-100 data scientists represent the largest single range in terms of staff size. This reflects the continued maturation of enterprise AI/ML as it moves into the mainstream.



Another sign of the market's maturation is the diversification of skill sets and users engaged in AI/ML across the enterprise. Collaboration is critical to aligning resources and bringing diverse expertise to AI/ML projects. And today, organizations tend to employ about the same number of data scientists as AI/ML engineers.

Most Organizations Employ the Same Number of Data Scientists as ML Engineers

Data Scientists \ ML Engineers	<10	10-19	20-49	50-100	>100
>100	0%	0%	1%	6%	19%
50-100	0%	1%	8%	19%	3%
20-49	1%	4%	12%	4%	1%
10-19	1%	7%	5%	2%	1%
<10	2%	1%	1%	0%	0%

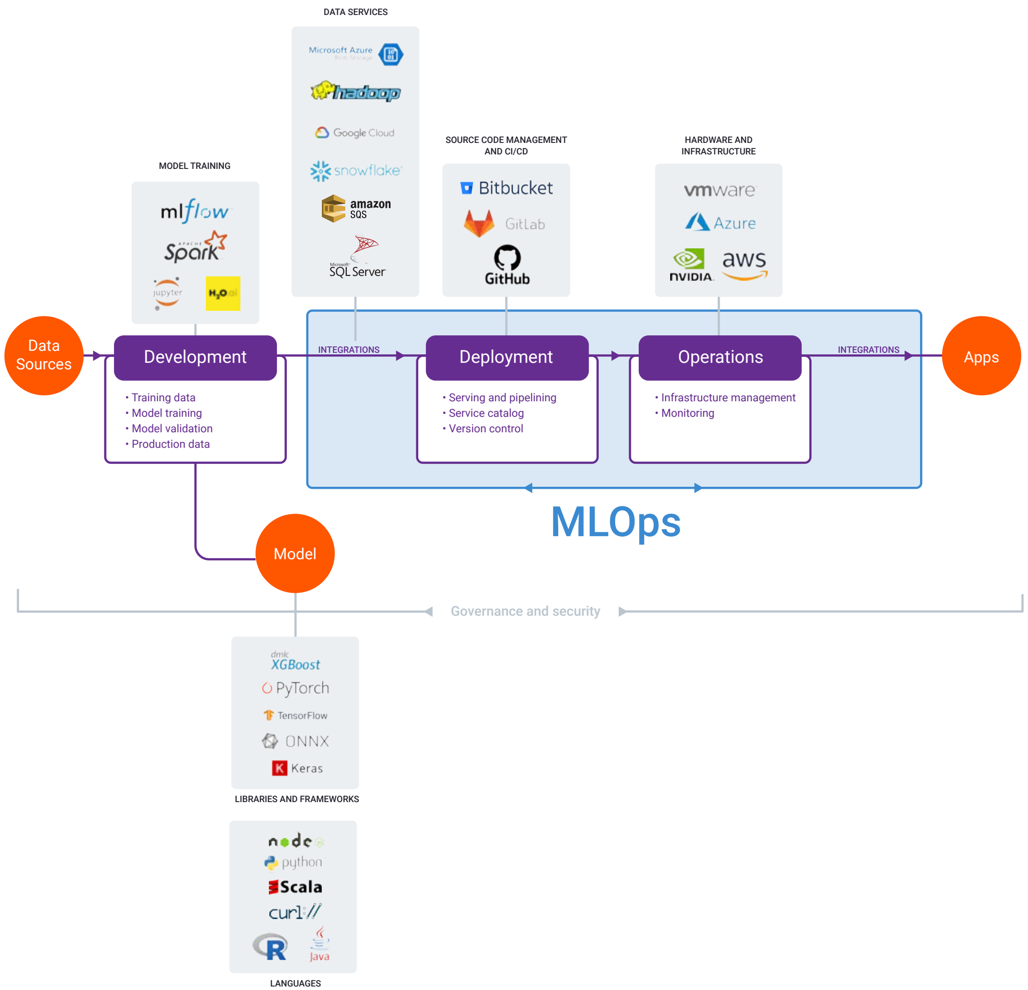
Indeed, the second wave of enterprise machine learning adoption is not slowing but rather speeding up. But with this momentum also comes challenges and increased complexity for many organizations.

This report explores the top five machine learning trends in the enterprise—and how you can position yourself for AI/ML success through the rest of 2021 and beyond.

#1 MACHINE LEARNING TREND

INFRASTRUCTURE, TOOLING, AND WORKLOAD NEEDS BECOME UNMANAGEABLE AND INCREASINGLY COMPLEX

The Machine Learning Ecosystem



The AI/ML ecosystem is complex and consists of a wide range of components across the AI/ML lifecycle, from development tools to data services, deployment tools, hardware, and infrastructure. MLOps provides the core operational components of the lifecycle and the ability to integrate with the rest.

Infrastructure, Tooling, and Workload Needs Become Unmanageable and Increasingly Complex

Every enterprise has a growing, diverse, and often disconnected combination of infrastructure, tooling, and specific use cases and requirements for AI/ML. In 2021, that unique blend has become unsustainably complex.

As they navigate the journey from AI/ML model development to production, organizations must choose from a dizzying array of tools, services, and environments—and each company ends up with its own unique patchwork of components.

This is where an end-to-end AI/ML platform with enterprise-grade machine learning operations (MLOps) comes in. The unified platform provides a center of excellence for production AI, giving organizations a central place to deploy, monitor, manage, and govern any machine learning model in production, regardless of how it was created or when and where it was deployed.

Indeed, our research shows that most enterprises require a complex infrastructure to support development and production needs across the AI/ML lifecycle. As just one example, 37% have a hybrid environment for model deployment, combining both cloud and on-premises solutions, while 28% have a multi-cloud environment.

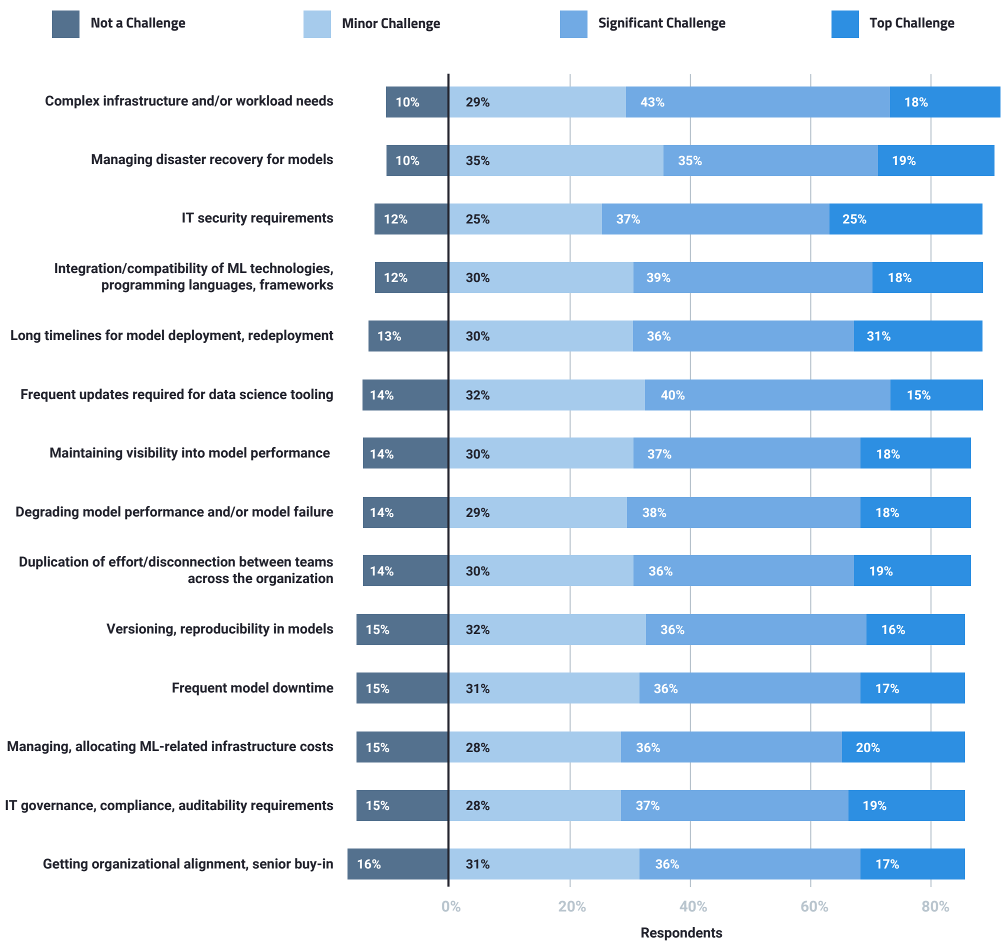
In our own conversations with companies, we also see similar complexity in terms of data services, development and CI/CD tools, libraries and frameworks, and much more.

#1 MACHINE LEARNING TREND

"The need to leverage machine learning for better and faster insights is clear. Only organizations that are able to rein in the complexities around infrastructure, tooling, operations, and workloads will be able to deliver on the value of those insights. The explosion of AI/ML technologies across the data science ecosystem simultaneously provides broader choice for users and increases integration overhead between systems that erodes data governance. To tackle this complexity, one strategy is to think in terms of your data being a gravity center, and decide if the various tools, platforms, and analytics capabilities can be organized around it. In doing so, you can determine the essential AI/ML components that orbit around your data and minimize friction between tools."

—Paul Zhao
Principal Product Manager,
Data Science and Machine Learning, Snowflake

Enterprises Struggle With a Wide Range of Machine Learning Challenges



Respondents were asked to rank the significance of each challenge. The total percentage of respondents struggling with each challenge was calculated by adding up all responses across “Our top challenge”, “Significant challenge”, and “Minor challenge” with the underlying data before rounding to the nearest percentage point. Categories do not all add up to 100% because they have been rounded to the nearest percentage point.

Reflecting this trend, organizations need to support a diverse range of workloads for their AI/ML, from the simple to the complex. 69% need to support real-time inference, 55% need to support batch jobs, 54% need to support event-driven jobs, and 41% need to support cron jobs. The vast majority (73%) need to support more than one of these needs, which adds complexity.

Given this complexity, many organizations have a difficult time keeping up. 90% of organizations struggle with complex infrastructure or workload needs—a tie for the #1 overall challenge reported by organizations—while 88% struggle with integration and compatibility of AI/ML technologies, and 86% struggle with the frequent updates required for data science tooling.

Flexible integrations between tools in unique environments is essential to AI/ML success, yet many organizations are trying to manage AI/ML with their own in-house MLOps solution.

"It's telling that 86% of organizations struggle with frequent tooling updates. The most common alternative to a single integrated AI/ML lifecycle solution is a build-your-own solution, frequently built from open-source components. Organizations that take the BYO route put in a lot of effort up front to create an integrated solution, but often neglect to account for the maintenance and upgrades as the various components in their tool chain release security patches and new editions (and all at different times). These continual changes can create mismatches—resulting in different components needing to be substituted in, causing rework, or some features getting dropped altogether. This should be factored into calculations for total cost of ownership, as should be the time that AI/ML engineers spend away from business-value work on the AI/ML applications themselves."

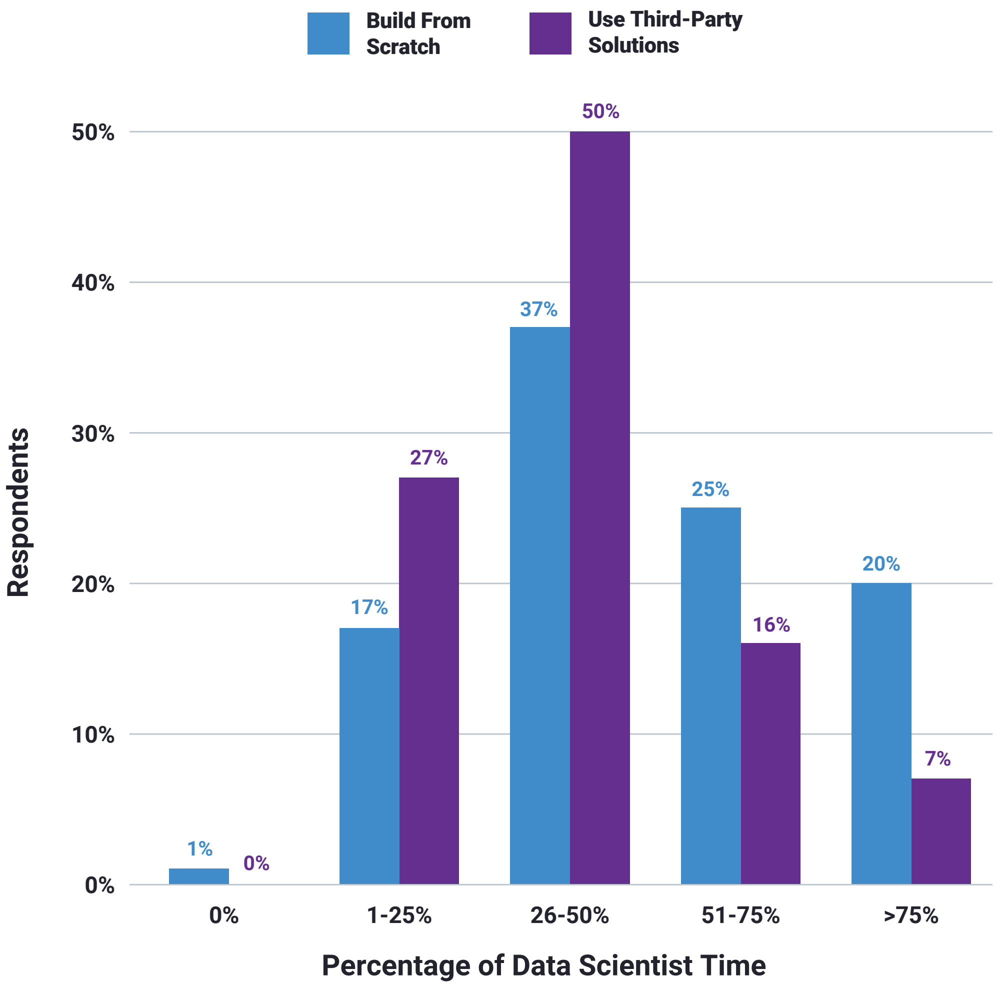
—Michael Azoff
Consulting Analyst,
GigaOm

When asked how they approach model deployment and management infrastructure, most organizations (63%) indicated that they're using third-party tools—either by relying on them entirely or using them in combination with in-house tools. However, more than one third (37%) said that they're building and maintaining their own system entirely in-house, meaning that they're taking a completely do-it-yourself (DIY) approach.

This is where an end-to-end AI platform can help. Commercial AI platform solutions lead to improved outcomes by enabling the automation of AI/ML pipelines, driving efficiency, and eliminating unnecessary manual work and complexity. Their benefits include:

1. **Lower infrastructure costs**
2. **Reduced time to deployment**
3. **Streamlined integrations and compatibility with other tools**
4. **Stronger security, compliance, and governance**
5. **Greater organizational efficiency and more effective use of data scientists' time**

Data Scientists Spend Less Time On Model Deployment at Organizations That Use Third-Party Solutions



Respondents were asked to indicate how they approach model deployment and management infrastructure. The "Use third-party solutions" category refers to respondents who selected either "We rely entirely on third-party tool(s)" or "We use a combination of in-house and third-party tools", whereas the "Build from scratch" category refers to respondents who selected "We build and maintain our own system entirely in-house".

These improved outcomes have compounding effects as AI/ML initiatives scale. For example, respondents were asked to indicate the approximate percentage of their data scientists' time that's spent deploying models, where "deploying models" refers to "prepping trained models and deploying them where they can be consumed by apps or used with other models".

At organizations using third-party solutions, data scientists spend a smaller percentage of their time on these deployment tasks—freeing them to instead focus on producing business results.

#2 MACHINE LEARNING TREND

ORGANIZATIONS USE A WIDE RANGE OF KUBERNETES DISTRIBUTIONS FOR ML SERVING

Every Kubernetes Distribution is Being Used in the Enterprise

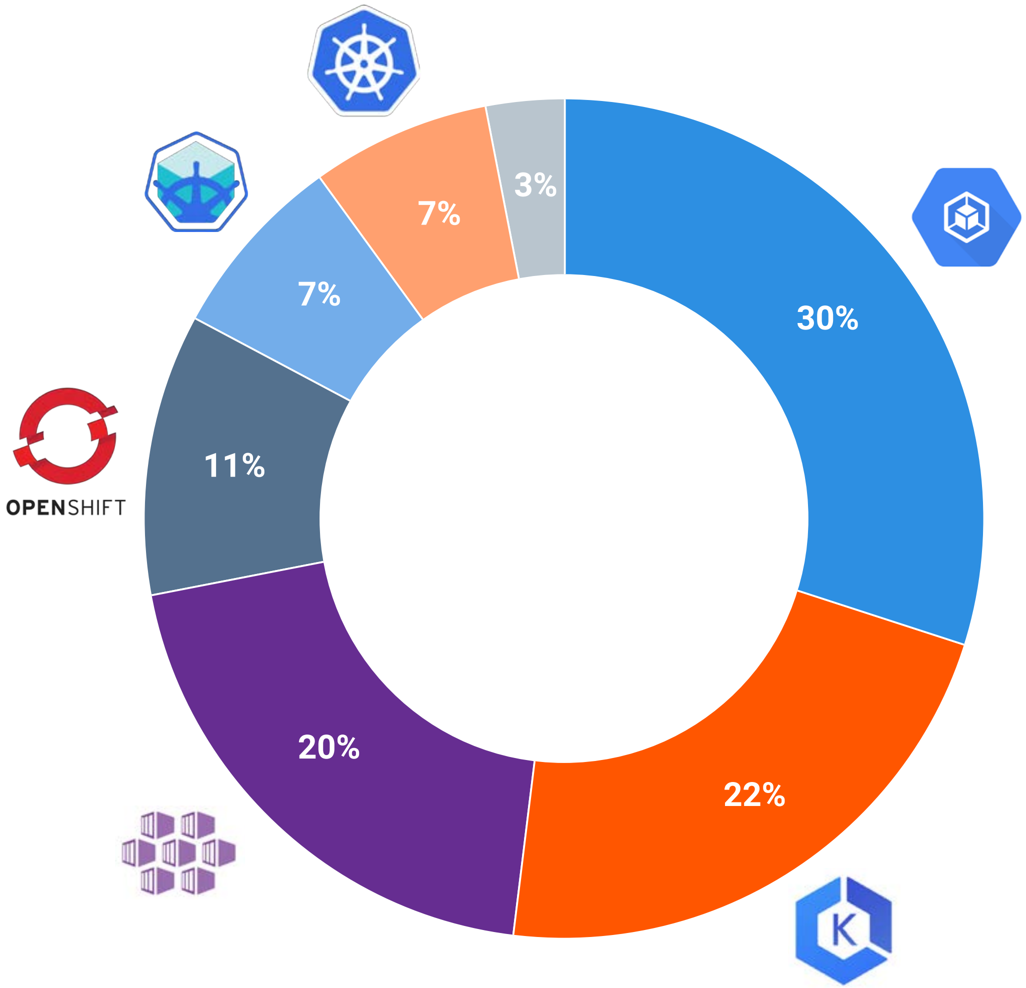


Chart doesn't show respondents who selected "Other" (less than 1%). Respondents who selected "None of the above" were assumed to not be using Kubernetes for ML serving.

Organizations Use a Wide Range of Kubernetes Distributions for ML Serving

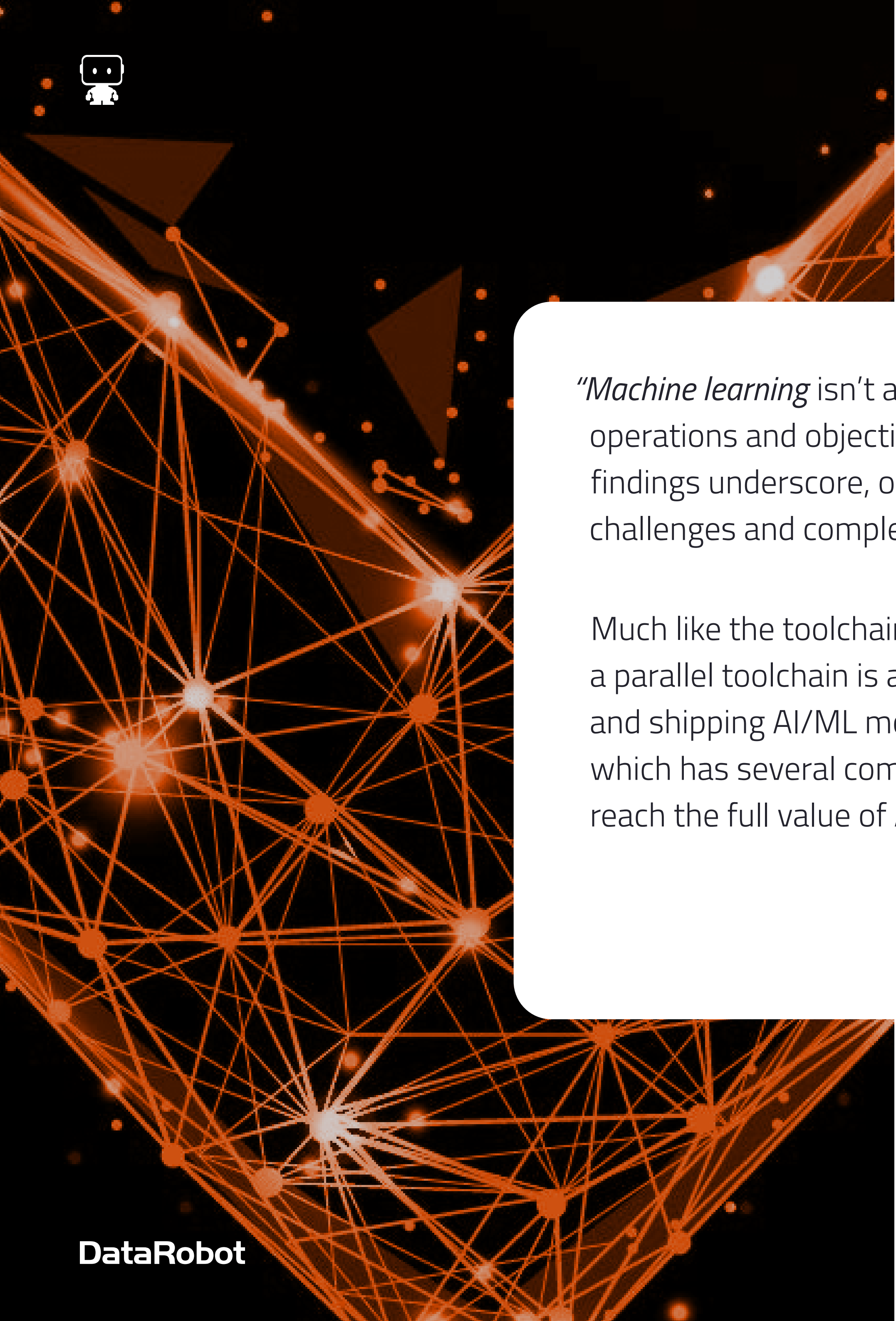
Kubernetes has become a tool of choice for operating modern software applications at scale. It's especially popular for deploying and managing AI/ML workloads in production—nearly every organization (97%) is using some form of Kubernetes for ML serving.

While Kubernetes itself is virtually a consensus choice for enterprise machine learning, there's significant variance in the particular distribution that's used. Kubernetes comes in a variety of different flavors and organizations are using essentially all of them.

30% of organizations use Google Kubernetes Engine for ML serving, for example, while 22% use Amazon Elastic Kubernetes Service. Another 11% use Red Hat OpenShift, and 7% are running the open-source version out of the box.

The diversity of the Kubernetes ecosystem further illustrates the enormous importance of investing in MLOps to enable compatibility between a wide range of tools.

- Google Kubernetes Engine
- Amazon EKS
- Azure Kubernetes Service (AKS)
- Red Hat OpenShift
- Minikube
- Kubernetes
- None



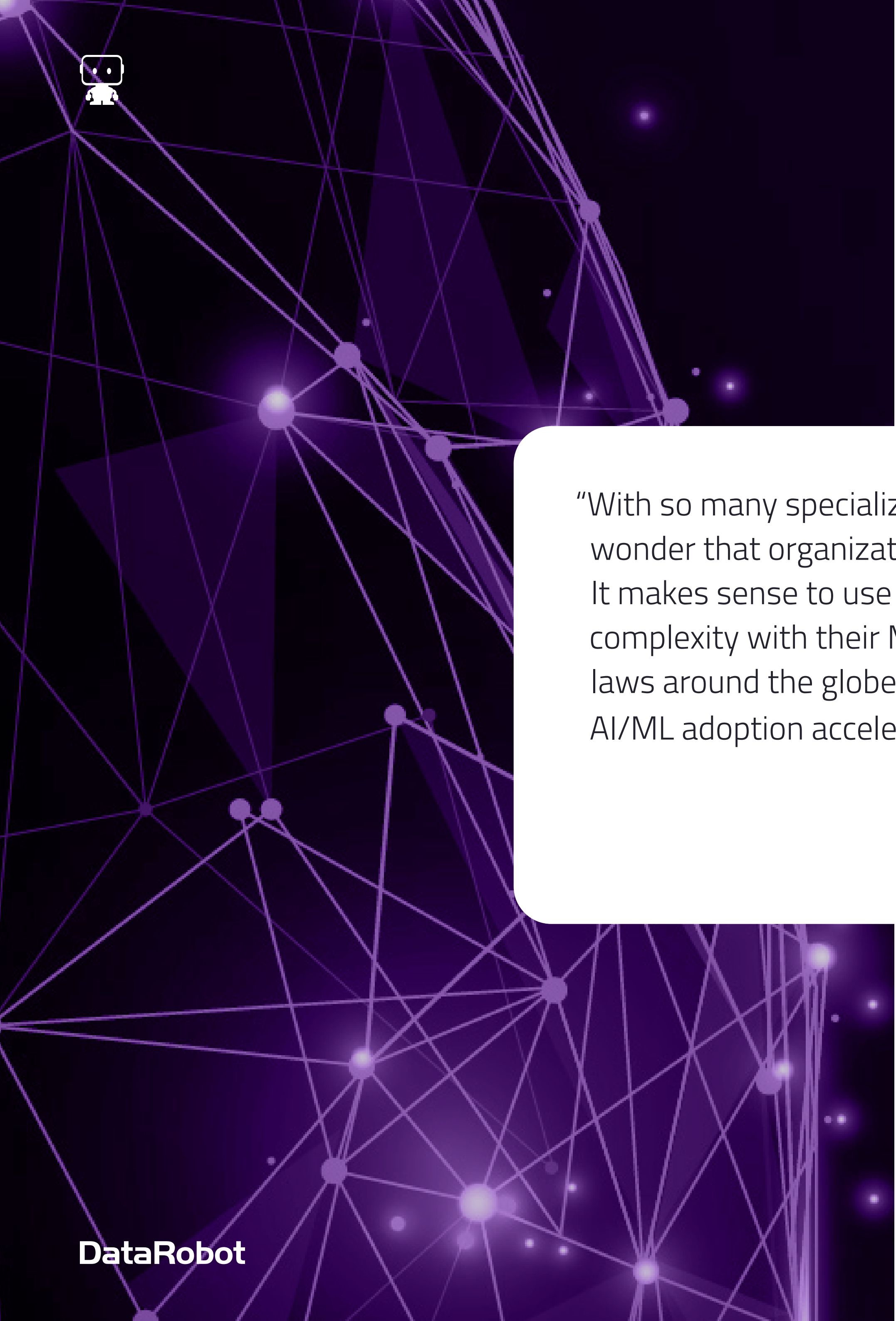
"*Machine learning* isn't a buzzword: this technology is already powering business-critical operations and objectives for many companies across all industries. Yet, as the survey findings underscore, organizations are struggling to wrap their arms around the challenges and complexities that come with every AI/ML initiative.

Much like the toolchain we saw emerge for software development in the last 20 years, a parallel toolchain is arising to tackle the distinct needs of AI/ML practitioners building and shipping AI/ML models into production. A critical piece of this toolchain is MLOps, which has several components—deployment, serving, observability, etc. In order to reach the full value of AI/ML in organizations, MLOps must become a priority."

—Aparna Dhinakaran
Co-Founder & Chief Product Officer,
Arize AI

#3 MACHINE LEARNING TREND

MOST ORGANIZATIONS RUN MACHINE LEARNING ACROSS GEOGRAPHIC REGIONS



Most Organizations Run Machine Learning Across Geographic Regions

Similarly, the diverse and distributed nature of infrastructure and environments for AI/ML adds complexity—in terms of where AI is deployed as well as how it's managed, secured, and governed.

> "With so many specialized and niche applications for data science development, it's no wonder that organizations are combining so many tools with hybrid environments. It makes sense to use the best tool for the job. It's going to be up to IT to tackle this complexity with their MLOps strategy. And given the complexity of data and privacy laws around the globe, the need to run AI/ML across multiple geographic regions as AI/ML adoption accelerates will only increase the urgency of this challenge."
>
> **—Demetrios Brinkmann**
> Head of Community,
> MLOps Community

Nearly all organizations deploy and serve models in a widely geographically distributed environment. In fact, a clear majority (64%) of respondents need to support more than 10 regions for their models and data, and 22% need to support more than 20. Only 2% limit their operations to a single region.

Not only does this distributed serving add to the diversity of business environments today, but it also has major performance, compliance, and security implications.

Most organizations (83%) said they have SLA requirements for model latency, but this significant geographic distribution can present performance challenges.

Similarly, 84% of organizations must comply with regulatory or security requirements with the data centers or cloud environments they use.

Organizations need tools that enable them to meet these needs, as we expect the geographic distribution of AI/ML models—and the complexity of compliance and security requirements—to only increase.

"Organizations need to run their models close to the data and applications that need them most—and increasingly, this means running those models across geographic and regulatory boundaries. This underscores the need for an end-to-end AI platform with MLOps that supports distributed serving. With distributed serving, organizations with high-security, high-availability, or high-performance workloads can easily deploy and serve models where they need to and in the environment that works best for them without compromising security or governance."

—Kenny Daniel
CTO of MLOps,
DataRobot

#4 MACHINE LEARNING TREND

SECURITY AND REGULATORY REQUIREMENTS GET MORE COMPLEX

Most Organizations Run Machine Learning Across Geographic Regions

As the complexity of an ever-changing regulatory and security landscape intensifies, meeting these needs is becoming an enormous challenge.

In fact, IT security is the #1 challenge for many enterprises as they grow their AI/ML initiatives. 88% of respondents ranked it as a challenge, while 25%—the largest percentage for any single challenge—named it their “top challenge”.

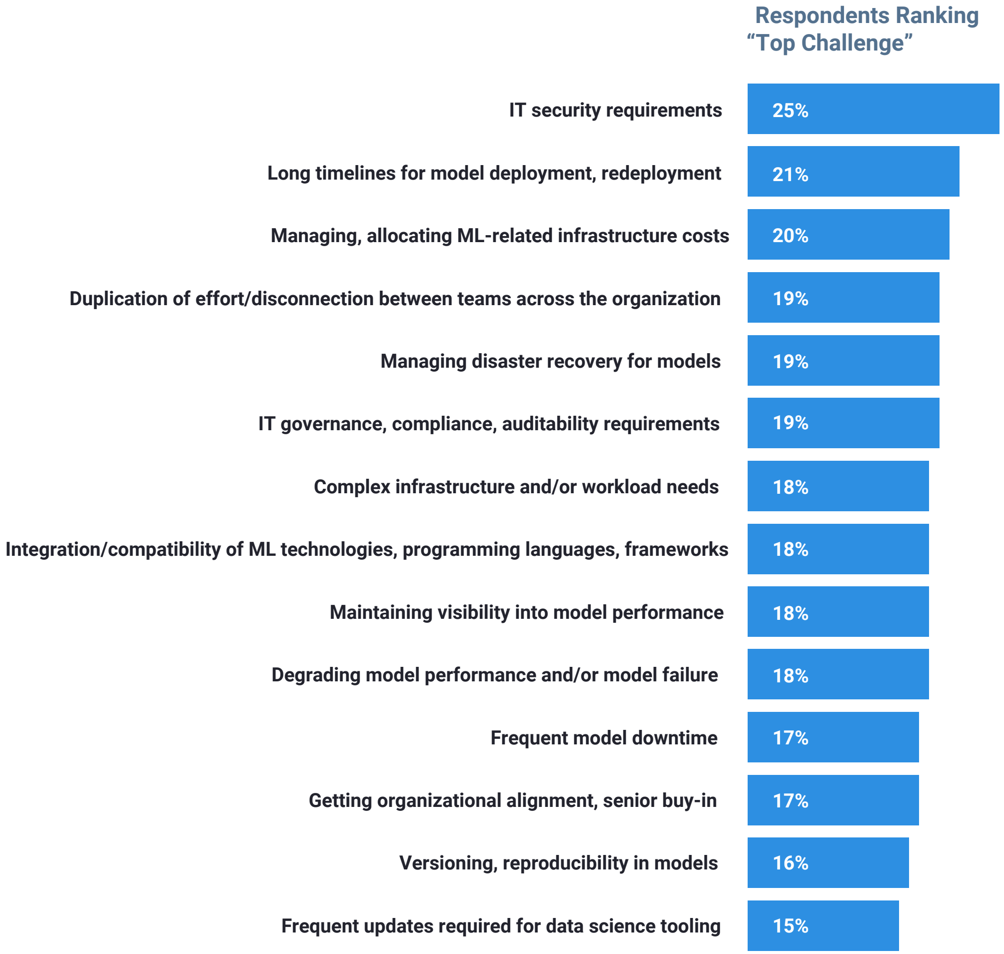
85% also struggle with IT governance, compliance, and auditability requirements.

“The COVID pandemic has really brought MLOps front and center for business applications of AI/ML. With the world changing rapidly around models, it became critical to be able to detect changes in near real time and to be able to deploy refreshed models rapidly into production. The biggest challenges to speed in MLOps relate to the ever-growing requirements around security and controls. The most successful products in this space will have extensive security and controls built-in.”

—Dave Castillo

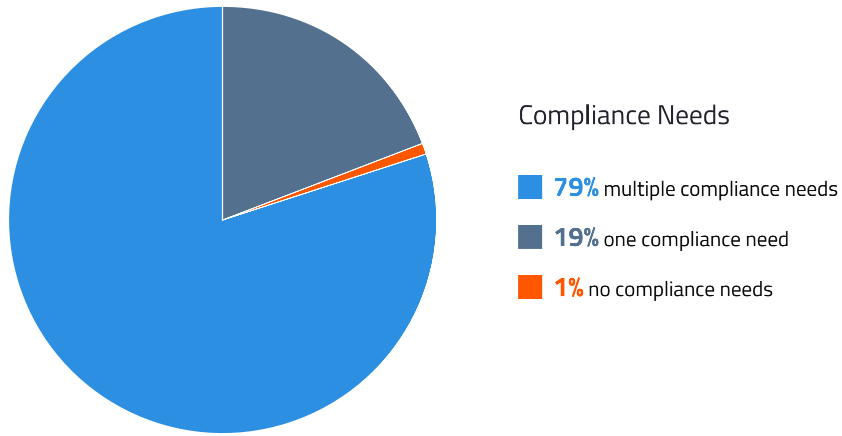
PhD, Firmwide Head of AI/ML Technology,
JPMorgan Chase

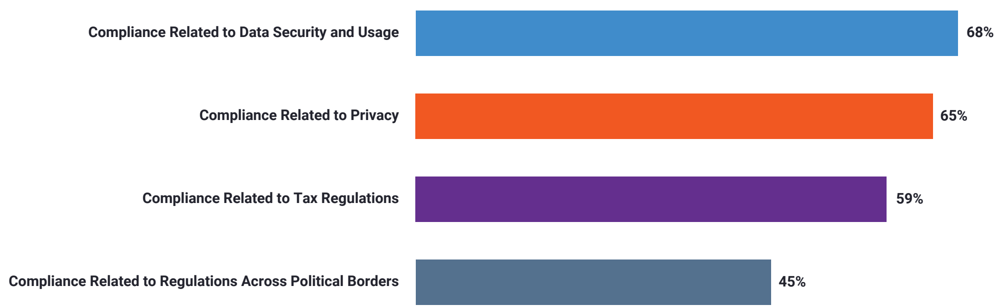
IT Security is the #1 Machine Learning Challenge at 25% of Enterprises



When asked about their specific compliance needs, organizations reported compliance related to data security and usage (68%) as their top requirement, followed by privacy (65%), tax regulations (59%), and regulations across political borders (45%). The vast majority of enterprises (79%) must meet more than one of these needs, and only 1% have no compliance needs at all.

79% of Organizations Have Multiple Compliance Needs





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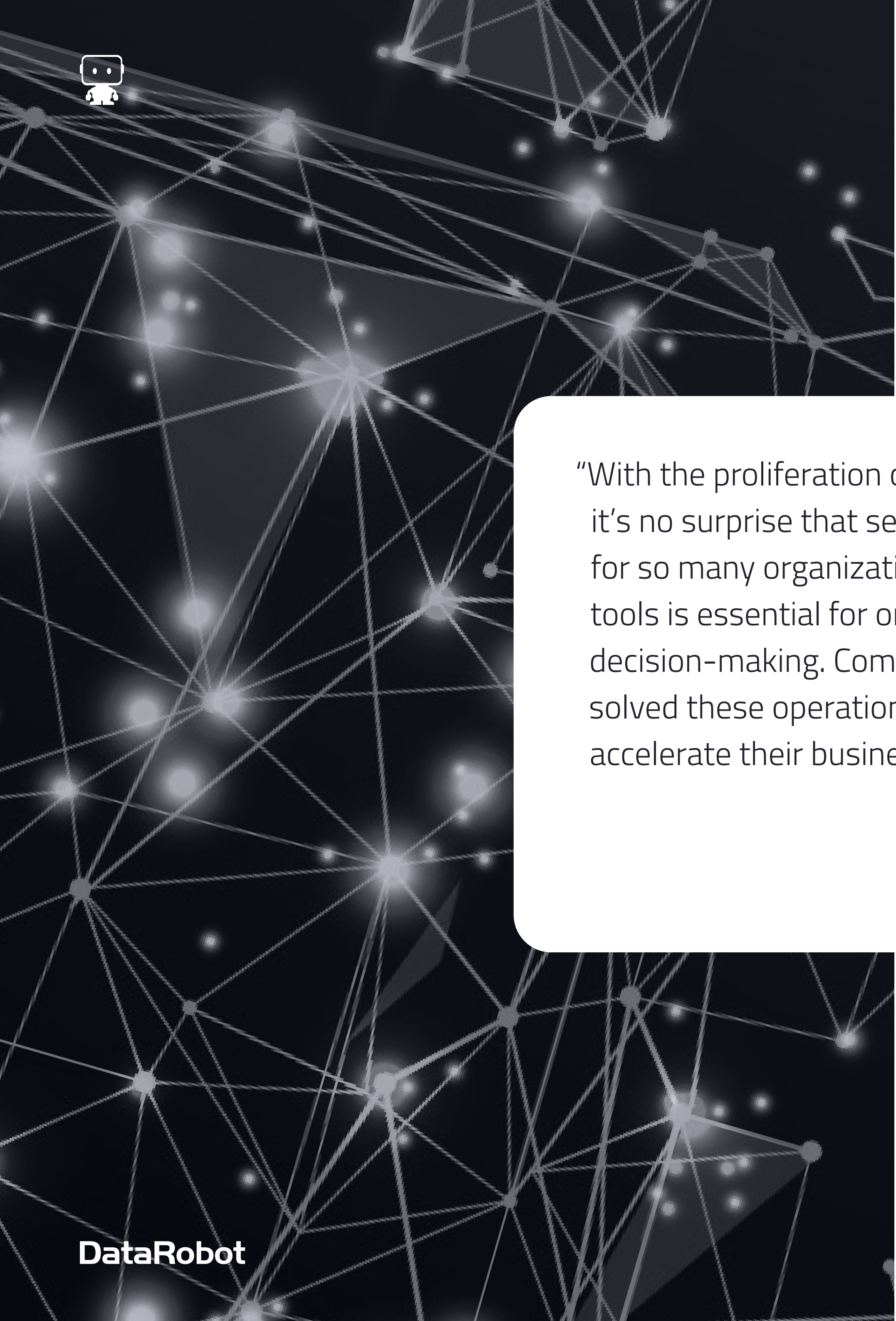


Organizations are already struggling with compliance, and we expect the landscape will become even more complex. Companies that try to meet these needs with a DIY solution take on significant technical debt and risk critical gaps in coverage.

> "With the proliferation of a wide range of data sources and tools for machine learning, it's no surprise that security, compliance, and governance are top AI/ML challenges for so many organizations. Secure interoperability and integration between data and tools is essential for organizations to tap into actionable insights that inform better decision-making. Companies that turn to platforms and tools that have already solved these operational issues will unlock significant time to value and dramatically accelerate their business impact from AI/ML."

—Mohan Rajagopalan

Senior Director of Product Management, AI/ML, Splunk

#5 MACHINE LEARNING TREND

THERE'S AN URGENT NEED TO AUTOMATE ML PIPELINES FOR COMPLEX, HIGHLY PERFORMANT USE CASES

There's an Urgent Need to Automate ML Pipelines for Complex, Highly Performant Use Cases

"As AI/ML budgets and the number of data scientists employed by companies increase in 2021, organizations tackle increasingly sophisticated use cases that take advantage of complex combinations of models. The maintenance of these applications rapidly becomes prohibitive when tackled manually—driving up cost and latency, and reducing ROI. Organizations that use MLOps for efficient pipeline maintenance will shorten their time to market, increase the value their apps can deliver, and improve their competitiveness."

—Anna Patterson
Founder & Managing Partner,
Gradient Ventures at Google

As the market continues to mature and complexity increases, enterprises are also expanding into more sophisticated AI/ML use cases and trying to maximize the performance of the models they have in production. This is evident in several of our findings:

83%

Companies that have SLAs for model latency

69%

Companies that need to support real-time inference

94%

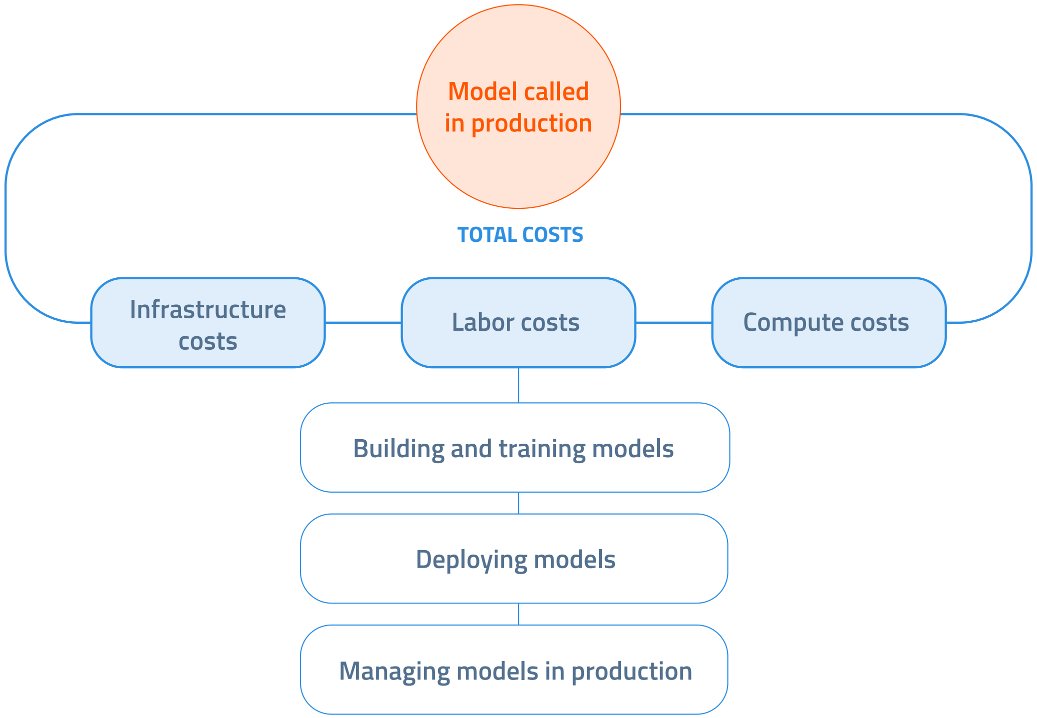
Companies that report having visibility into the performance of their models in production—yet 86% also report challenges with maintaining that visibility

"It's exciting to see that most organizations are monitoring the performance of their models in production. However, many are still reliant on manual processes to do so. As companies expand into more complex use cases for AI/ML, full-stack ML application observability needs to be a focus—and they need the right tools to automate this process and maximize performance."

—Guy Fighel

GVP Product Engineering & General Manager Applied Intelligence, New Relic

The Total Cost of Calling Machine Learning Models



Every time a model is called in production, you're paying not only for the resources it takes to run the model but also the resources it took to build and maintain that model—costs that might have been incurred a long time ago.

To optimize ROI, organizations must consider not just infrastructure and compute costs, but also the total cost embodied in *every single call of a model*.

The "cost per call" of a model includes not only infrastructure and compute costs, but also the labor required to build, deploy, and manage models. And this can add up to a surprisingly large amount if your team is doing any manual work that could be automated.

Organizations must automate their AI/ML pipelines to optimize performance and ROI. An automated AI/ML pipeline not only delivers models to production, but also monitors their performance, triggers alerts, and kicks off model retraining jobs once in production—enabling high-performance AI/ML that continuously tunes models and minimizes downtime.

This reduces the cost per call by eliminating unnecessary manual deployment and management work, enabling teams to focus on building innovative models that maximize business impact.

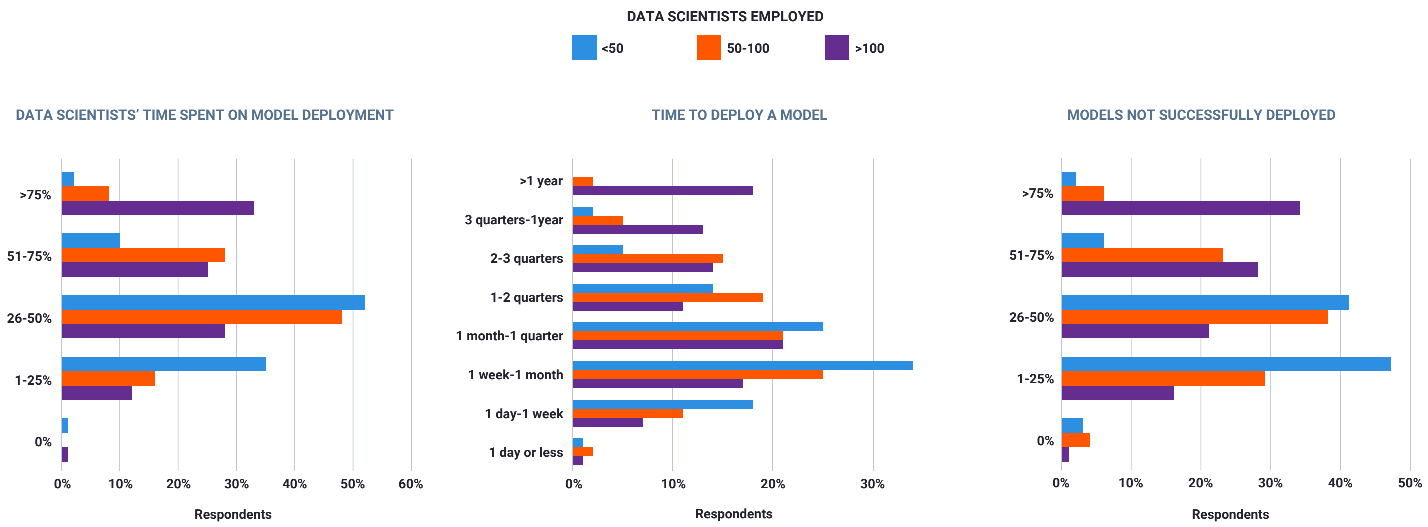
"There is a big gulf between experimenting with AI and actually gaining significant value from AI in high-leverage use cases. Crossing that gulf requires proper investment in MLOps maturity—building the right organization and infrastructure to manage AI at scale. Automating AI/ML pipelines and providing end-to-end monitoring and observability to your data science operations team is the only way to unlock that value and protect against risks from deployments that aren't monitored closely. The good news is the rewards for getting it right are huge—the companies who successfully cross the gulf to AI transformation first will be leaders in their verticals for years to come!"

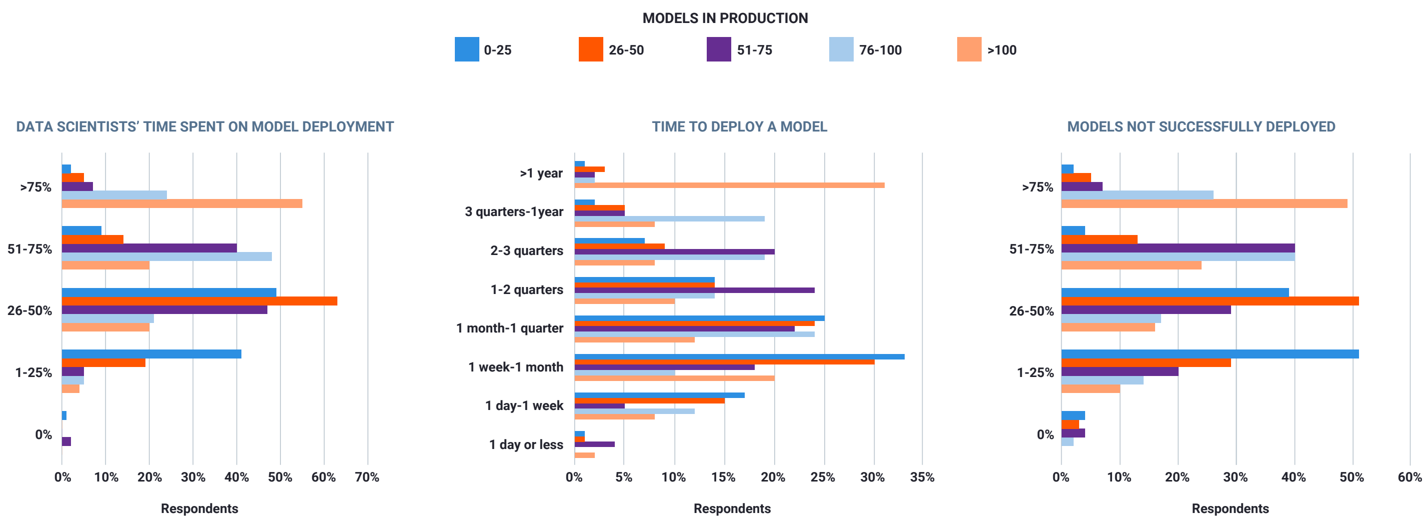
—Adam Wenchel
CEO & Co-Founder,
Arthur

You might logically assume that organizations with the greatest AI/ML resources and scale today have already built fully automated pipelines. In fact, the opposite is true. Organizations that employ more data scientists and have more models in production actually tend to:

- **Spend a greater percentage of their data scientists' time on model deployment.**
- **Take longer to deploy trained models to production.**
- **Have a greater percentage of models that aren't able to be deployed successfully (defined as models that an organization develops that don't get deployed to production within at least a year).**

Manual Scaling Efforts Lead to Lowered Outcomes





"Data scientist time spent on model deployment" is defined as the average percentage of an organization's data scientists' time that's spent deploying models. "Time to deploy a model" is defined as the average time required to put a trained model into production once it's been developed. "Models not successfully deployed" is defined as the average percentage of models that an organization develops that don't get deployed to production within at least a year.

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Automating pipelines is an urgent need for all organizations, and can help with the following challenges reported by respondents:

87% struggle with long model deployment timelines, and at 59% of organizations, it takes at least one month to deploy a trained model to production.

At 31% of companies, data scientists spend more than half of their time on model deployment.

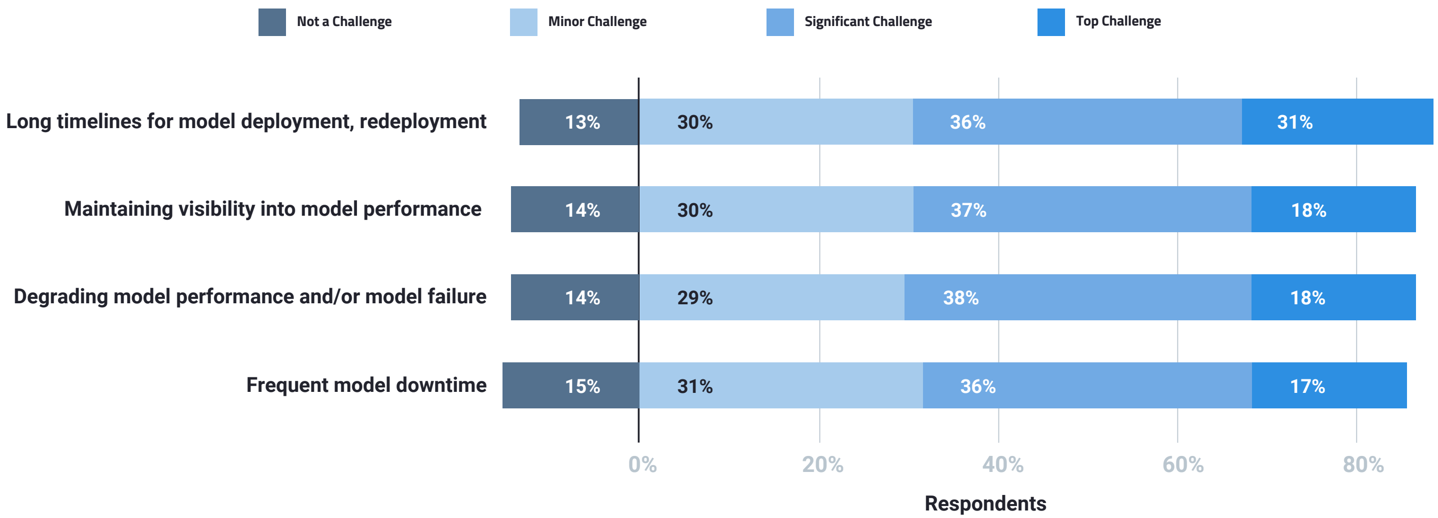
At most organizations (64%), more than a quarter of all developed models are not successfully deployed (meaning they're developed but not deployed within at least a year).

86% experience challenges maintaining visibility into model performance, 86% suffer from degrading model performance, and 85% deal with frequent model downtime.

This suggests that enterprises with the most resources for AI/ML are also the least efficient at using them. Rather than automating their pipelines, we believe they're taking on more manual work to achieve greater scale.

This is unsustainable.

Common Challenges That Can Be Improved with Automated Pipelines



Respondents were asked to rank the significance of each challenge. The total percentage of respondents struggling with each challenge was calculated by adding up all responses across "Our top challenge", "Significant challenge", and "Minor challenge" with the underlying data before rounding to the nearest percentage point. Categories do not all add up to 100% because they have been rounded to the nearest percentage point.

Clearly, enterprises must focus on automating their AI/ML pipelines to resolve these issues. When they do, they will achieve greater efficiency and improve their ROI.

> "As the field of enterprise AI has matured, we've experienced a phase shift wherein post-deployment maintenance has eclipsed model deployment as the number one challenge enterprises face. However, with the MLOps movement now racing to create a new software category, enterprises of all sizes can look forward to new solutions that will make their models more transparent, robust, and reliable."
>
> **—Alessya Visnjic**
> CEO & Co-Founder,
> WhyLabs

As AI/ML requirements become increasingly complex, tools that reduce the operational burden on your team are a must. As our research shows, when organizations use third-party tools for model deployment and management, their data scientists spend a smaller percentage of their time on manual deployment work. This reduces the cost per call and sharpens the team's focus on high-performing use cases that deliver maximum business value.

You don't just need AI/ML—you need high-performance AI/ML. And that's what an end-to-end AI platform with enterprise-grade MLOps helps you achieve.

NEXT STEPS:

ACCELERATE YOUR ENTERPRISE MACHINE LEARNING

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Next Steps: Accelerate Your Enterprise Machine Learning

The clear trend in this report is that machine learning in the enterprise is more important than ever. Staying competitive in this new normal requires investing in AI/ML now. That's why we're hearing from enterprises like CEMEX that are revolutionizing their own decades-old industries with AI/ML.

But investing in AI/ML is only the first step.

In a time of ever-increasing complexity, AI/ML alone won't ensure success. Your organization's competitive advantage depends on high-performance machine learning made possible by an AI platform with MLOps.

"The past year and a half of global pandemic and economic uncertainty have continued to cause rapid change in many areas, but especially in artificial intelligence and machine learning. The steadily increasing investment in AI is driving the industrialization of MLOps. As more organizations realize the importance of AI/ML to drive revenue and efficiency, they're beginning to run into more complex operational concerns: corporate governance, IT security, risk management, and multinational regulation.

"This increasing complexity is making the scale and efficiency of MLOps a first-order concern. Organizations that get MLOps right are the ones that are going to be able to scale effectively and apply AI/ML in ways that make real impacts for their business.

"We are encouraged that the question is no longer *if* or *when* an organization will pursue its AI/ML strategy, but *how quickly* it can scale its efforts to apply AI/ML to mission-critical apps and drive business outcomes."

—Diego Oppenheimer
EVP of MLOps,
DataRobot

METHODOLOGY

Methodology

*** In July 2021, DataRobot acquired Algorithmia. The survey was conducted by Algorithmia prior to the acquisition.***

The purpose of the enterprise machine learning trends research is to report on the latest developments and trends in enterprise machine learning. This report is based on data collected in May 2021 in a survey effort that returned more than 400 responses. The survey asked 29 questions about AI/ML initiatives, challenges, infrastructure, company demographics, and more. The survey questions were developed by Algorithmia (now DataRobot) employees, and an independent third-party company conducted the survey on our behalf to ensure survey attribution anonymity and remove bias on the part of the respondents. Respondents voluntarily participated in the survey in exchange for access to content or a service, such as free Wi-Fi. Respondents received no monetary payment for their participation. The third party screened participants using the following questions:

What is your company's annual revenue?
(Only respondents at companies with $100M+ in revenue were included.)

Which best describes your role?
(Respondents with roles of "Consultant" or "Student" were excluded.)

Are you involved with artificial intelligence (AI) and/or machine learning (ML) projects at your company?
(Only respondents who answered "Yes" were included.)

In this way, we amassed a group of more than 400 individuals with a level of insight into the machine learning efforts of their companies across a random sampling of industries and machine learning maturity levels.

This research is an evolving project and we seek to make improvements every time we publish new findings. The findings in this report are more comparable with previous findings than they have been in the past because we limited the survey to respondents at companies with $100M or more in revenue, a change we made in our last report to improve the relevance of results to enterprise IT environments. (Note that we made a slight change to the wording of this screening question to improve its accuracy, and plan to maintain that change in subsequent reports.)

There are a few important details to note about this report's findings:

- In all charts and analysis, percentages have been rounded to the nearest percentage point.
- A small number of respondents didn't answer all questions, and charts and analysis only include respondents who answered the relevant question(s). In cases where we analyze the responses of multiple questions, we only included respondents who answered all of the questions.
- For simplicity, we assumed that every respondent represents a different company, and we use the words "company", "organization", and "enterprise" interchangeably.
- Our analysis of organizations with multi-cloud and hybrid environments for model deployment was based on a question in which respondents were asked to indicate which infrastructure their organization uses for deploying models (AWS, Azure, Google Cloud Platform, VMware-based, or Other). The percentages of respondents with multi-cloud and hybrid environments were calculated based on those responses. Respondents who selected "Other" (less than 1%) were excluded from this analysis.

This is a special biannual edition of the report due to the volatility of 2021. We will continue to run regular reports on the state of the industry to share our insights into how the industry is evolving and help business leaders make decisions in a timely manner with the latest data. As we continue to build on this work in subsequent reports, we aim to reach ever more relevant and applicable insights to help AI/ML leaders drive innovation in this space.

View previous annual reports for 2021, 2020, and 2018.

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