OMDIA UNIVERSE

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Selecting an Enterprise MLOps Platform, 2021

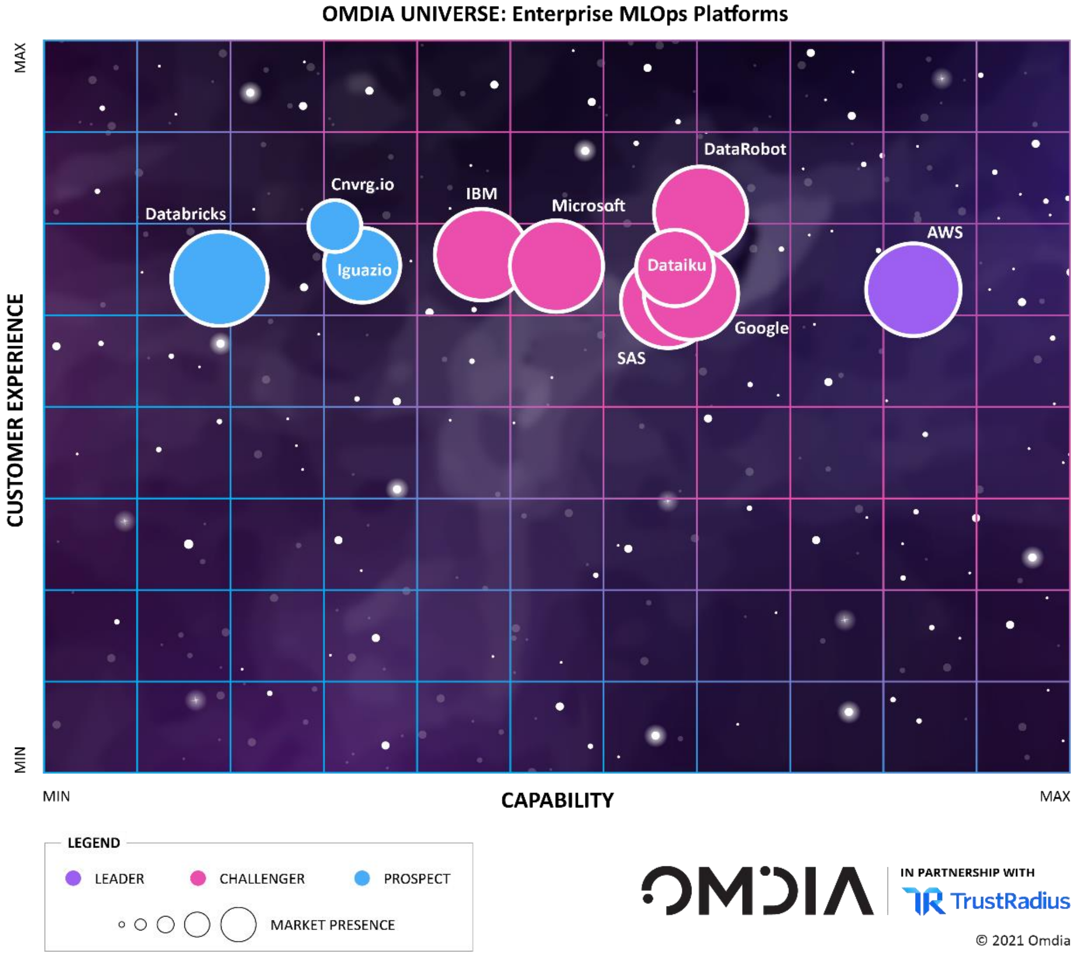
OMDIA

Summary

Catalyst

Machine learning operationalization (MLOps) is a major turning point for a technology marketplace bent on chasing the transformative value of artificial intelligence (AI) but struggling to put that value into practice across the enterprise. MLOps promises to change data science into a pragmatic science of software engineering where machine learning (ML) development projects can run as fully integrated parts of the business, enabling the creation of repeatable, scalable, and trusty AI results.

Figure 1: The Omdia Universe for Selecting an Enterprise MLOps Platform, 2020-21



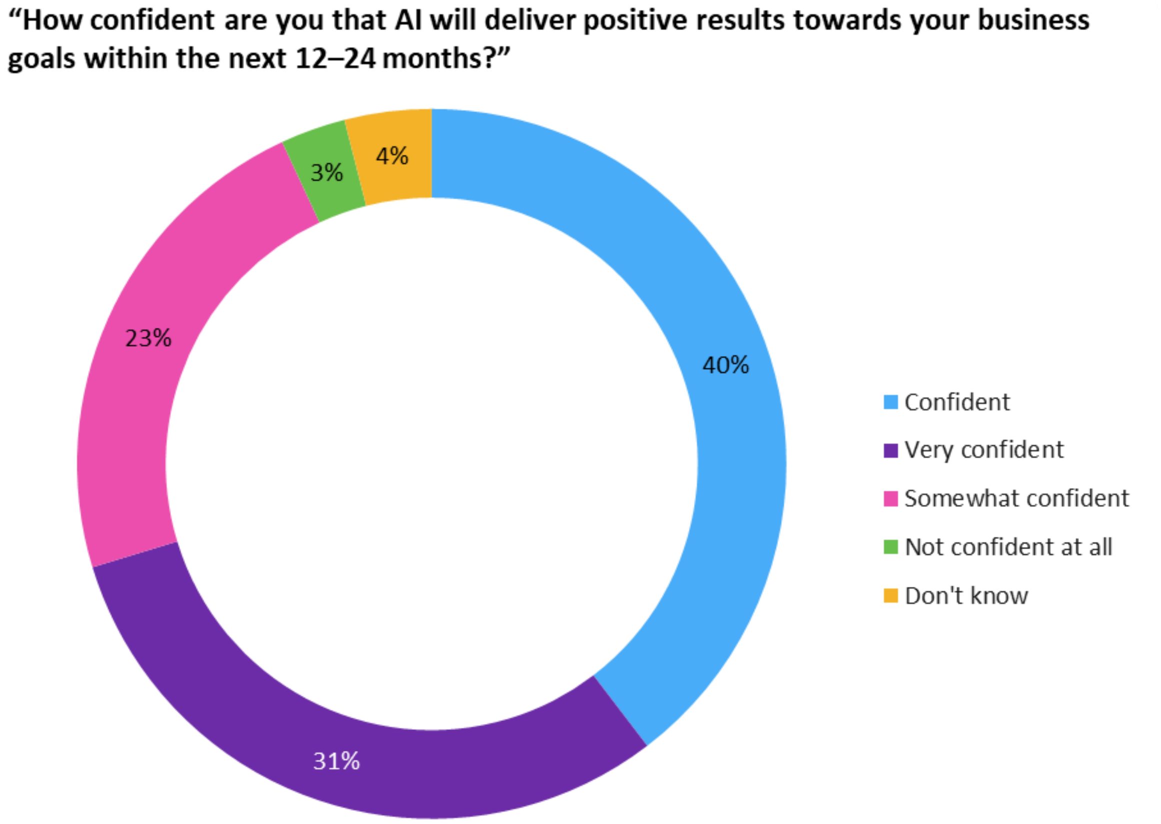
Source: Omdia

Omdia view

In 2011, internet pioneer and creator of the Mosaic web browser, Marc Andreessen, boldly stated that software (intrinsically cloud software) was eating the world and that a battle would rage between aging brick-and-mortar incumbents and software-powered insurgents and that the insurgents were likely to come out on top. The continued meteoric rise of hyperscale cloud platform players Microsoft, Amazon, Google, Salesforce, and others have certainly proven Andreessen right. Yet, it is not software alone that has fueled such tales of market domination. Incumbent market breakers Uber and Netflix are but two examples of companies that have eaten the competition not through software alone but by putting AI to work as a catalyst for both optimization and innovation. For these companies and many others like them (Airbnb and Spotify, for example), AI drives competitive differentiation.

An Omdia study in 2020, *AI Market Maturity* (fielded in May of that same year), reveals that this deep-seated belief in the competitive value of AI extends across the broader enterprise landscape. As an example, a resounding 71% of global enterprise AI practitioners across 12 major industries said they were confident or very confident that AI could deliver positive results (see figure 2). Within the same study, Omdia also asked practitioners if their confidence in AI's ability to add value had changed over the previous 12 months. Of those surveyed, 61% cited an increased level of confidence. Only 3% of respondents claimed a decreased level of confidence.

Figure 2: Near-term confidence in AI



Notes: n = 146
End-user companies were asked, "How confident are you that AI will deliver positive results towards your business goals within the next 12–24 months?"

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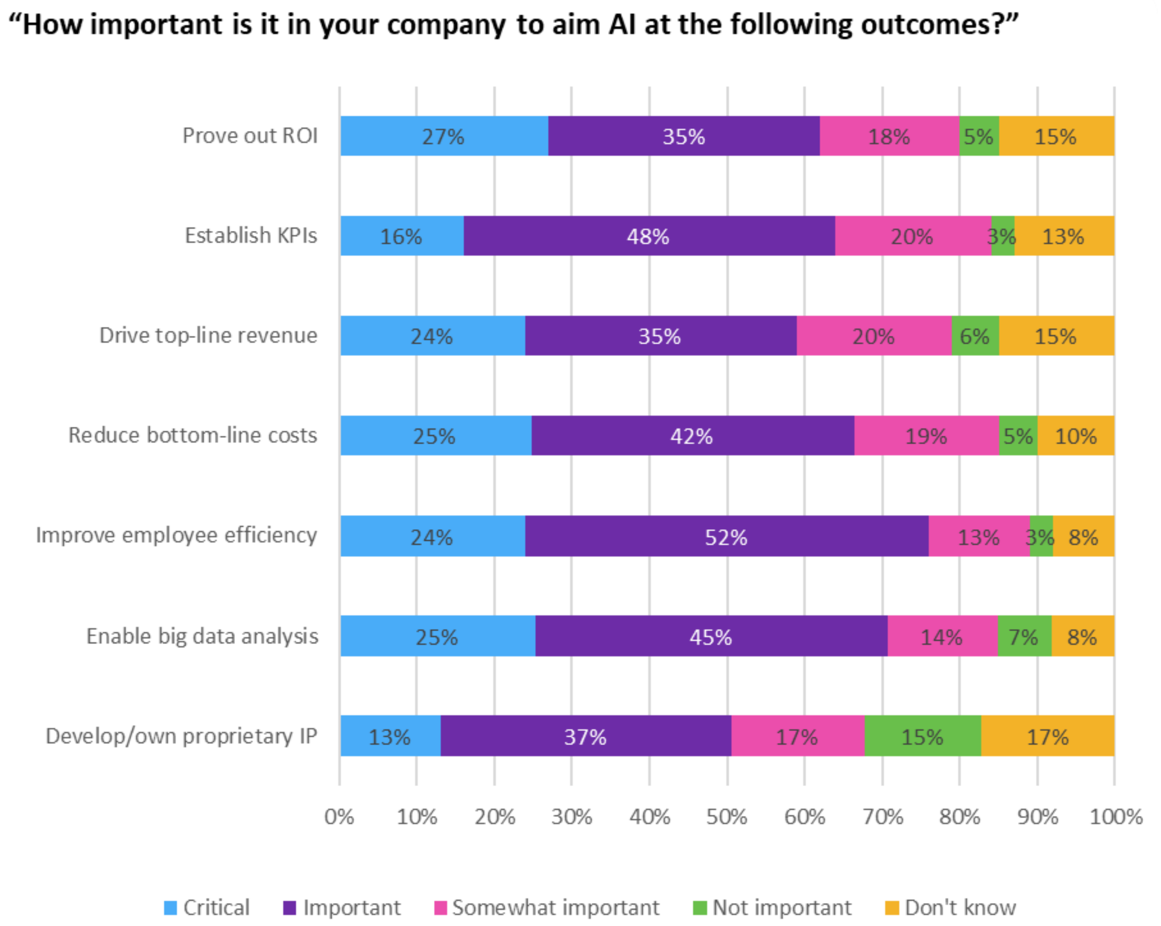
Source: Omdia

Measuring this level of optimism amid a global pandemic (April/May 2020) speaks to the perceived importance of AI. To what end though? Within this same maturity survey, Omdia found that the two most important AI outcomes sought by mainstream enterprise AI practitioners revolve around the act of driving down costs, improving productivity, and creating a solid return on investment (ROI); see figure 3.

Figure 3: Financial and performative returns are top of mind with AI practitioners



Notes: n = 146
End-user companies were asked, "How important is it in your company to aim AI at the following outcomes?"

Source: Omdia

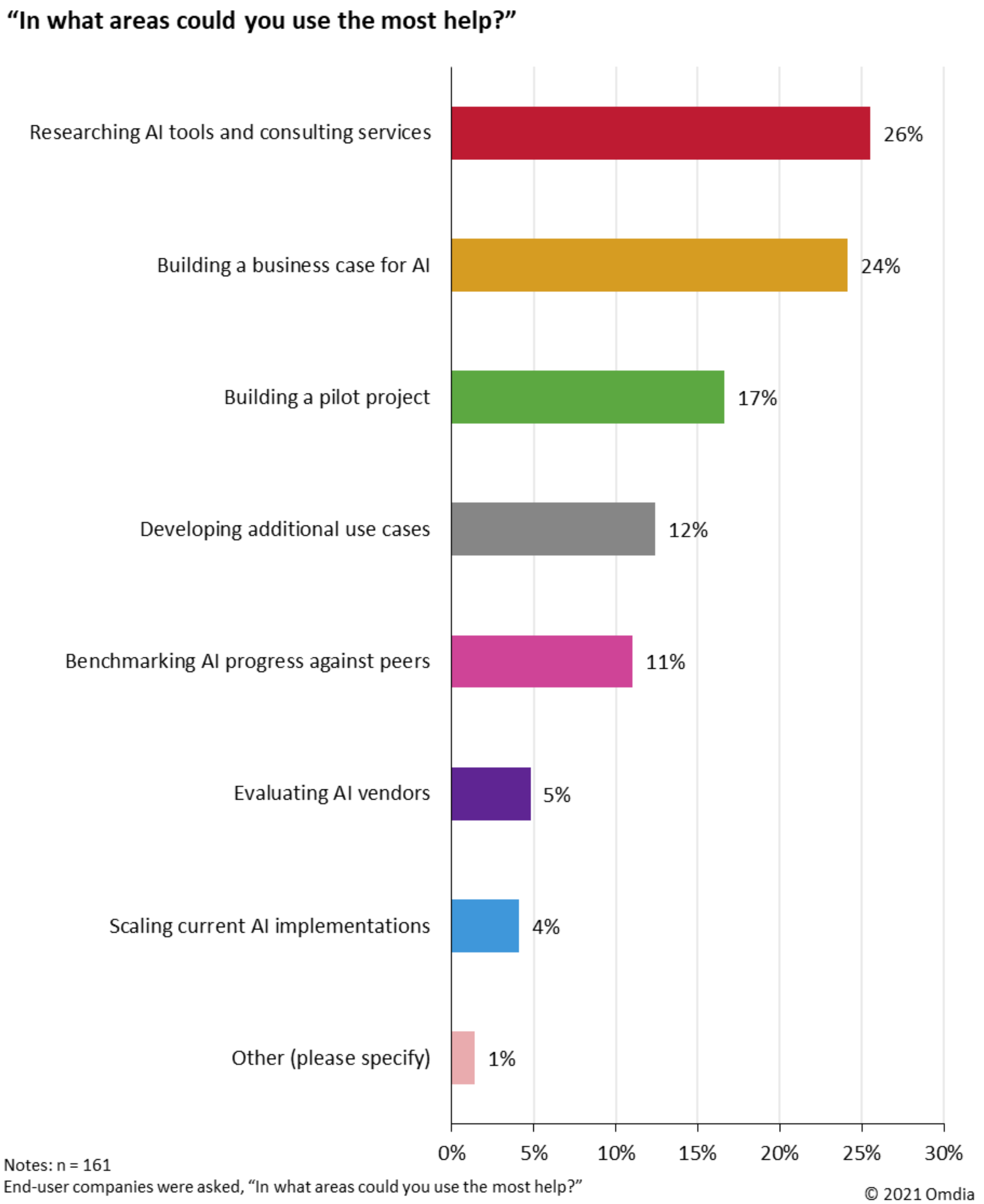
Capitalizing on the abundance of available data and the economies of scale available to store and process that data (often via the cloud), it seems then that enterprises across all major industries have begun remaking their very businesses in the image of those early AI pioneers such as Airbnb, Netflix, and Uber. Reaching the scale of investment in AI that has fueled companies like these, however, is simply not available to the broader enterprise market.

As far back as 2018, Uber, for example, had already invested more than $680 million in data science on its way to embedding AI throughout its business, supporting the entire product lifecycle, spanning product planning, design, engineering, and management. In 2019, Uber managed thousands of ML models in production supporting hundreds of use cases and making millions of predictions each second. To reach this level of maturity and scale, Uber had to invest heavily in data scientists, engineers, product managers, and researchers.

The company also had to invest in an underlying infrastructure capable of supporting millions of predictions per second. Interestingly, this necessitated the development of its ML development and deployment platform, Uber Michelangelo. Begun as a means of democratizing access to AI outcomes and ML tooling across the company in 2015, Uber Michelangelo evolved to tackle several key ML operational challenges such as speeding model development, monitoring, and revising models in production, and supporting low-latency and real-time predictions. To this day, Uber Michelangelo and similar platforms developed by other enterprise AI pioneers Airbnb, Facebook, and Netflix stand as excellent blueprints by which enterprise practitioners can build their ML platforms.

However, building a lifecycle-complete solution demands a level of investment and expertise simply not available to all companies that are seeking to put AI into practice. Enterprise buyers need help from the technology vendor community to help them bring together and harmonize a wide array of tools for use among a highly disparate team of AI practitioners. In the Omdia 2020 *AI Market Maturity* study, when asked to identify their biggest stumbling block in adopting AI, practitioners overwhelmingly cited the complexities of evaluating potential technologies, tools, and services (see figure 4).

Figure 4: AI stumbling blocks in the enterprise



Source: Omdia

Fortunately, enterprise buyers do not have to build their MLOps platforms from scratch. A large, diverse, and rapidly expanding ecosystem of commercial and open source software (OSS) has emerged over the last two years, led by an array of focused startups, vendors from adjacent markets, and hyperscale cloud platform providers. Vendors such as those included in this report have created MLOps-enabled AI development platforms capable of supporting a wide array of use cases across disparate vertical markets.

These platforms espouse the ideals found within in-house solutions like Michelangelo in that they are both open to external technologies, particularly OSS, which informs a great deal of innovation within the realm of data science, and can also be easily integrated into diverse data architectures and make heavy use of cloud-native technologies, especially Kubernetes-managed clusters. The resulting solutions fit effortlessly into existing enterprise environments and can meet customers where they are regardless of their existing levels of investment in AI technologies and expertise.

The adoption of a readily consumable and capable enterprise MLOps platform can pay serious dividends for both inexperienced and experienced enterprises alike. It can help those new to AI rapidly come up to speed by orchestrating what is traditionally a very complex and multifaceted development lifecycle. It can also help experienced practitioners apply the controls necessary to repeat, scale, and most importantly, trust the use of AI outcomes across the enterprise.

Omdia believes, therefore, that investing in MLOps will be necessary for companies that aim to transform their businesses by using AI technologies. Investing in MLOps directly answers what Omdia believes to be the biggest questions facing AI practitioners in the enterprise, namely “How do I move from experimentation to transformation?” Without a solid layer of process integration, automation, and control, even those companies that may have had some limited success with one or two departmental proofs of concept will find it difficult to realize the synergies of employing AI company-wide. Companies unable to use AI at scale may find themselves falling behind better-prepared rivals, unable to competitively optimize processes, reduce cost, and identify new opportunities. Worse, these AI have-nots might fail to adapt to unanticipated and unprecedented market disruptions such as the COVID-19 pandemic.

Key messages

- Deploying ML at scale in the enterprise is a multi-faceted endeavor covering people, process, and platform concerns.
- DevOps practices and technologies show promise in solving many ML operational concerns such as project deployment, testing, and monitoring.
- Enterprise MLOps platform can successfully apply DevOps principles to the task of operationalizing ML, despite numerous ML operational, collaborative, and infrastructure complexities.
- The enterprise MLOps platform marketplace is expanding, and solutions are rapidly evolving to tackle important market challenges such as ML model transparency, explainability, and governance.

- Technology providers are evenly positioned to operationalize the ML lifecycle, particularly across core solution areas such as data preparation, model development, model deployment, and platform implementation. (Omdia weighted these areas comparatively lower in evaluating participants.)
- While approaches and target user roles differ among the solutions reviewed in this report, all will provide a beneficial level of operationalization that's fit for most enterprise practitioners and use cases, both horizontal and vertical.
- Areas where review participants differed in terms of their capability scores revolved around emerging aspects of the ML lifecycle such as collaboration, automation, and governance. (Omdia weighted these areas comparatively higher evaluating participants.)
- Within these emerging areas, technology providers are rapidly maturing their solutions by incorporating differentiated technologies and addressing pressing enterprise concerns such as feature stores and AI governance, respectively.
- Numerous vendors in this report showed a strong ability across both core and emerging solution areas, however, only AWS scored highly across the board, leading and/or matching scores across six of the eight MLOps categories.
- Sitting close behind and poised to pull even with and perhaps overtake the market leader according to Omdia are no fewer than six diverse players including DataRobot, Google, Dataiku, SAS, Microsoft, and IBM.
- Likewise, a small but distinctive set of prospects including Iguazio, cnvrg.io, and Databricks are set to make a stir in the market with their unique approach to distinct market needs and individual approaches to MLOps.
- The close scoring of all Universe participants coupled with the rapidly maturing state of the MLOps marketplace will likely lead to a shuffling of the overall order over the next 12 months, depending on market demands and the speed at which vendors can innovate.

Analyzing the enterprise MLOps platform universe

How to use this report

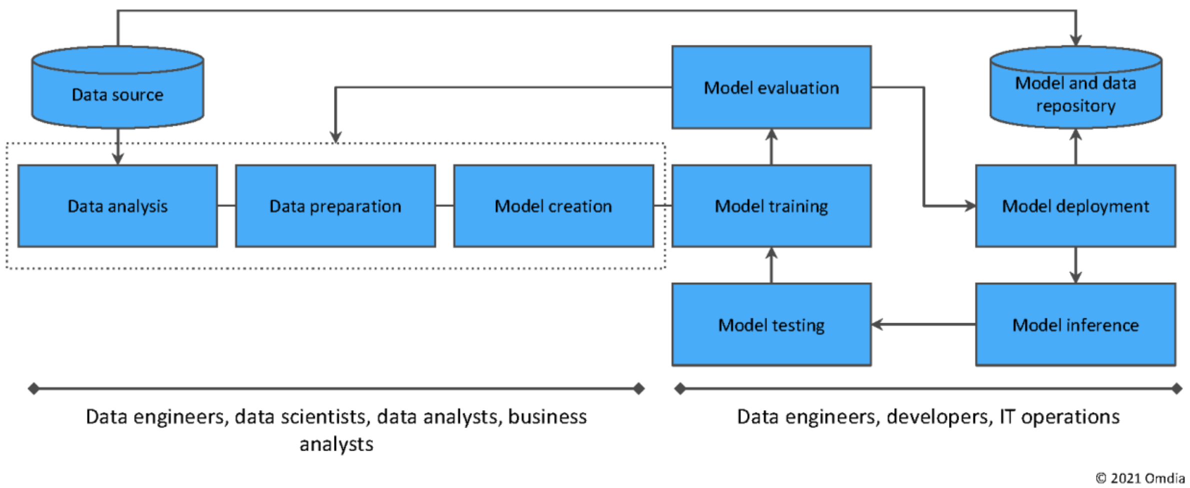
Omdia is a proud advocate of the business benefits derived through technology. Enterprise MLOps platforms are at the forefront of delivering the benefits of AI to businesses and government organizations across the globe. This Omdia Universe report is not intended to advocate an individual vendor but rather to guide and inform the selection process to ensure all relevant options are considered and evaluated efficiently. Using formal selection criteria, Omdia identifies the leading solutions in the market for comparison, so inclusion in the Universe is an accolade. Using in-depth reviews on TrustRadius together with direct interviews with MLOps users to derive insights about the customer experience together with the analyst’s knowledge of the market, the report findings gravitate toward the customer’s perspective and likely requirements. The focus is on those of a medium-to-large multinational enterprise (5,000+ employees). Typically, deployments are considered across the consumer packaged goods (CPG); financial services; manufacturing; retail; technology, media, and telecoms (TMT); and government sectors globally.

Market definition

Omdia defines enterprise MLOps platforms as any conjoined suite of software or services that together enable enterprise AI practitioners to apply MLOps principles to the task of building AI outcomes. The goal of MLOps is to help companies move ML beyond the limits of experimentation to make AI a company-wide core competency and competitive advantage.

Historically, MLOps has been particularly concerned with IT-centric operational issues such as ML model testing, deployment, and monitoring. Omdia believes, however, that MLOps has a much broader and more impactful role to play than simply closing the DevOps gap for data scientists. Omdia asserts that true MLOps solutions are those that address the entire ML lifecycle and in support of all participants, not just IT operations and data scientists (see figure 5).

Figure 5: Enterprise ML lifecycle



Source: Omdia

In practice, building AI outcomes in the enterprise demands a high degree of coordination and collaboration among a wide array of user roles. The tasks performed by each user, furthermore, do not take place in a sequential, one-directional manner. Rather, AI depends upon experimentation, a constant cycle of hypothesis formulation, testing, and revision that continues even after the final product enters production. In this way, Omdia views enterprise MLOps platform market practitioners as those seeking to help enterprise buyers address three major problem areas:

- **Repeatability**: It is difficult for AI practitioners to repeat what is a highly investigational methodology filled with stops and starts, dead ends, and unforeseen avenues of exploration. Unmanaged code, often written in Python and R, lives ungoverned within various Jupyter notebook implementations, making it nearly impossible for anyone but the original author to track and manage the code over time. Add to this the challenge of maintaining versioning across a wide array of libraries and frameworks, which change from project to project, and it is easy to see how lessons learned in one project do not readily carry over into future endeavors.

- **Scalability**: It can be notoriously difficult for companies to effectively manage resource requirements, such as AI acceleration hardware for both development (training) and deployment (inference) because these tasks are themselves dependent on a myriad of malleable conditions. The same holds for all supportive storage and processing resources, such as database instances, data pipeline processing, and inference engine execution. The high degree of entanglement makes it difficult for IT managers and CTOs to predict and, therefore, manage costs, a difficulty that grows exponentially as new AI projects enter development and production.

- **Surety**: It can be difficult to trust AI business outcomes altogether because of a lack of transparency within many deep learning (DL) predictive models, unchecked biases lurking in both data and model alike, poor code documentation across the project lifecycle, and inadequate testing of models before deployment. Even if an organization successfully tackles these and other similar challenges during deployment, maintaining a level of confidence over time demands a high degree of vigilance, monitoring models to ensure that their efficacy does not diminish because of changes in the supporting data or surrounding systems. For highly regulated industries, this kind of monitoring can demand the actual replication of a model's output at a given time. This can be an impossible task for organizations that are unable to fully document the entire ML lifecycle, including data ingestion, data preparation, feature engineering, model selection, parameter tuning, and model testing.

In this report, Omdia evaluated how well several leading AI development platforms that espouse the fundamentals of MLOps (hereafter referred to as MLOps platforms) pursue these three areas and address their associated challenges across the entire ML lifecycle. Given the growing interest in ML development and the consumption of AI outcomes in the enterprise, Omdia could have easily expanded this survey to include what has become a very widespread but somewhat fragmented vendor landscape of AI development platforms, many of which Omdia reviewed in March 2020 (*Omdia Decision Matrix: Selecting an Enterprise ML Development Platform, 2020–21*). AI development tools can be readily had from analytics companies, data platform players, line of business vendors, and AI specialists, including Domino, Anaconda, Samsung, Pachyderm, Oracle, HPE, Seldon, Algorithmia, Comet, OctoML, KNIME, H2O.ai, RapidMiner, Verta, and many others. Instead of attempting to do a deep analysis of such a broad range of providers, Omdia chose to focus on these pure play and platform providers:

- Cloud providers
  - AWS
  - Google
  - IBM
  - Microsoft
- Pure play vendors
  - cnvrg.io
  - Databricks
  - Dataiku
  - DataRobot
  - Iguazio
  - SAS

The goal of combining participants in this way is to understand how these two very different vendor communities are (or are not) evolving toward one another in terms of how they architecture their software, the scope of their MLOps capabilities, and how they support the broad spectrum of user roles necessary to operationalize ML in the enterprise. In doing so, Omdia scored participants across several diverse criteria (see table 1).

Table 1: Enterprise MLOps platform evaluation criteria

Data preparation	Accommodate a broad spectrum of data sources and provide or incorporate a central data repository, encouraging the reliable use and re-use of data both during development (model training) and deployment (inference).
Model development	Support the development of ML outcomes using both proprietary and OSS technologies, incorporating popular ML frameworks, supporting popular languages and other development tools.
Collaboration	Include collaborative services enabling disparate team members (data engineers, data scientists, developers, IT operations specialists, etc.) to work together on ML projects.
Deployment	Enable continuous integration (CI)/continuous delivery (CD) capability for the deployment of ML products, incorporating the ability to monitor and revise models once pushed to production.
Automation	Incorporate or make extensive use of ML automation capabilities, commonly referred to as AutoML, to both speed development and democratize data science among business stakeholders.
Management	Provide or make use of a central repository for the management of ML metadata including training data, models, features, code, as well as other project artifacts.
Governance	Embody several capabilities specific to solving problems of model transparency and explainability, project accountability, regulatory compliance, security, privacy, and bias.
Platform	Employ cloud-native (containerized) technologies and deployment/licensing options and make use of those same technologies/business models in supporting the deployment of ML solutions in the enterprise. Further, the solution should help users provision, orchestrate, and manage supportive system resources, both software and hardware (e.g., AI acceleration hardware).
Go to market	Maintain an active, evolving product portfolio and go-to-market strategy, including (but not limited to) licensing options, global footprints, and developer and user resources.

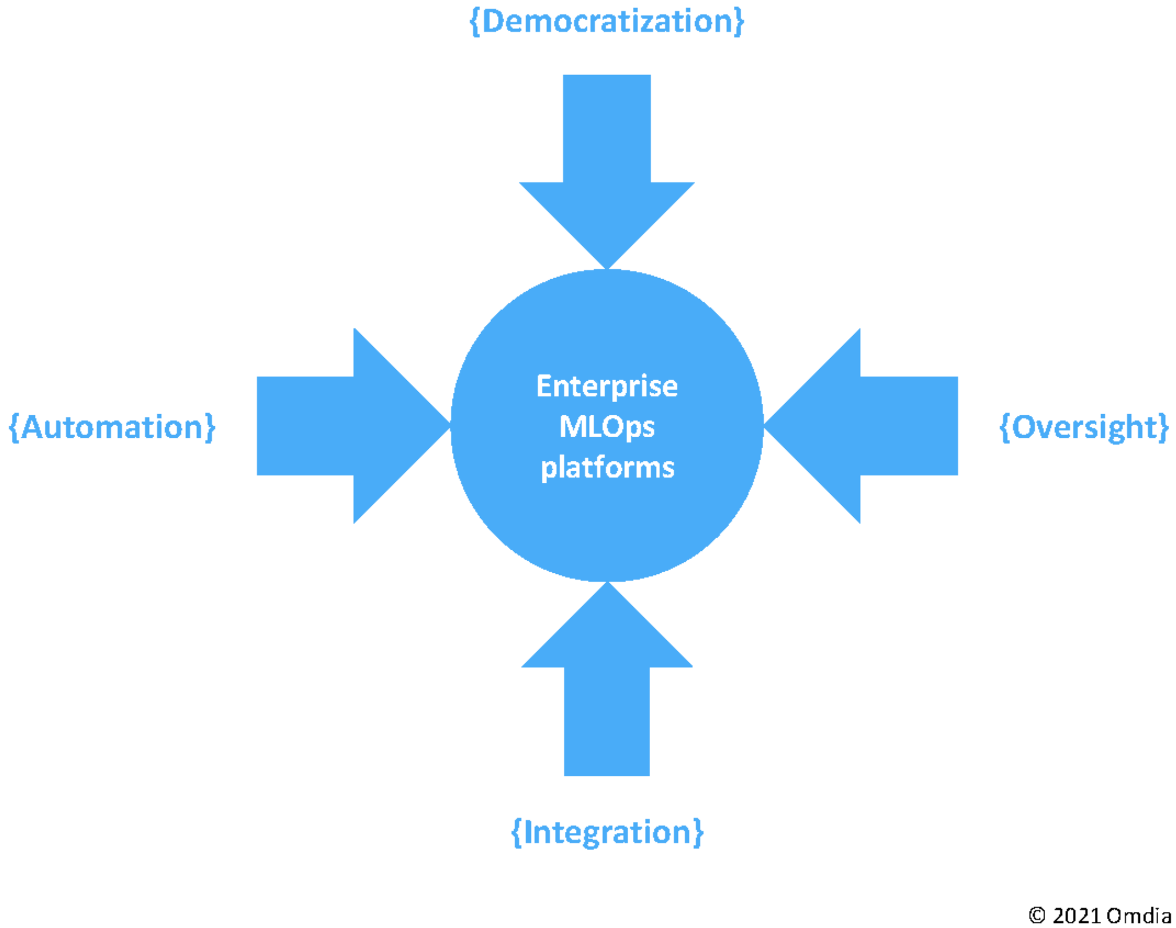
Source: Omdia

Market dynamics

In a word, dynamism defines the current marketplace for enterprise MLOps platforms. Technology providers within this space are rapidly evolving in response to numerous market demands from enterprises such that vendors can help them more efficiently and safely interweave AI throughout their businesses. Early MLOps platforms may have successfully focused on bridging the gap between development and deployment, focusing on the best way to package ML models and move those into production. However, current enterprise AI practitioners building their AI outcomes demand a more holistic view. They are under tremendous pressure, for example, to speed time to market through automation, bring business representatives into the development process through democratization, integrate a wider array of resources, and provide better governance and oversight for running projects.

Looking at these disparate demands, Omdia sees the market evolving across four distinct yet intertwined vectors (see figure 6). Together, these are collectively influencing the very structure and scope of enterprise MLOps platforms with technology providers actively building, buying, and integrating several diverse technologies.

Figure 6: Market vectors influencing the evolution of enterprise MLOps platforms



Source: Omdia

To illustrate, enterprise MLOps platforms are increasingly making use of AutoML as a means of democratizing and automating data science. Popularized by Google in 2018 as a means of speeding up the task of selecting the most appropriate neural network to complete a given DL task, AutoML has grown into a more widely applicable means of automating a wide array of ML tasks including data preparation, model selection, feature selection, and engineering, as well as hyper-parameter tuning. Touted as a means of democratizing data science, AutoML allows non-technical domain experts to participate in the data science process.

True to its roots, AutoML still allows data scientists to speed up and standardize repetitive tasks. However, by consistently documenting these repeatable ML tasks, AutoML can also help companies reuse and extend model resources to achieve both speed and scale in developing additional models. Moreover, the use of AutoML serves to make the process of model construction—and model outputs—more transparent and explainable, which can aid in meeting regulatory compliance requirements and in building trust among project sponsors.

There are many AutoML tools available as OSS development frameworks like Auto-sklearn, Tree-Based Pipeline Optimization Tool (TPOT), and AutoKeras. These basic frameworks can be readily used within commercial enterprise MLOps platforms. More advanced AutoML functionality, however, is emerging within these platforms themselves. Google, for instance, has introduced several AutoML tools targeting specific types of ML use cases such as image detection and language translation. Amazon SageMaker AutoPilot, in comparison, seeks to support a wide swath of the ML lifecycle, starting not with feature engineering but with data preparation.

A second illustrative example of how the market is remaking the MLOps landscape concerns metadata cataloging as a means of responding to market demand for more effective means to understand, disseminate, and manage all of the disparate artifacts and knowledge that comprise a given ML project. Historically, data scientists have struggled to preserve and share valuable information like data transformations, engineered features, and other resources that span both code and data. Software built to cooperatively develop software like Git excel at handling code versioning but stop short of incorporating the underlying data as it moves through a given ML workflow or pipeline. Additionally, publishing a Jupyter notebook in PDF format as a means of preserving and sharing this kind of knowledge is a bit like mistaking a photograph for the subject of the photograph—there is only the representation, not the function.

Such inefficiencies have a huge, cumulative impact. Knowledge remains locked away with a select few practitioners. Projects cannot be readily maintained over time let alone re-used for related requirements. Moreover, crucial insights into the operation and output for those projects exist only within opaque, isolated system log files far from the eyes of those responsible for ensuring the performance, safety, and value of AI within the enterprise.

In response, technology providers have begun incorporating centralized catalogs targeting specific facets of the ML lifecycle, including:

- Data catalogs, describing, validating, and versioning available data sources
- Project directories, describing the current state of all running projects
- Infrastructure libraries, describing and versioning all supportive software and hardware assets belonging to active projects
- Code repositories, describing, validating, and versioning all project software
- Feature catalogs, describing, validating, and versioning features used in training models

Beyond unlocking knowledge and encouraging asset reuse, with these tools, companies can create a common language between business domain experts and data scientists. Commingling business acumen and data literacy, these two groups can effectively communicate and collaborate. More importantly, these centralized metadata repositories together can help companies obtain a single source of truth and through that establish a centralized decision authority with control over all ML assets, all while still enabling diffused centers of excellence to thrive within individual business units.

The vast majority of vendors evaluated within this report provide at least one form of metadata catalog, be that a code repository to version Python code or a feature store to gather, version, collect, and share the artifacts that drive both model training and inference. Of these, the feature store is currently receiving the most attention among technology providers with many vendors beginning to incorporate a repository of ML features into their offerings. However, it should be noted that most of these solutions can certainly make use of external metadata services, integrating with external options such as the OSS framework Feast or best of breed options like Tecton and Hopsworks.

Research findings

Overall, Omdia's evaluation of the enterprise MLOps platform marketplace revealed a vibrant and remarkably close-knit set of competitors, spanning both pure play technology providers and public cloud platform providers. In terms of raw solution capability performance, vendors scored on average 68% out of a perfect 100%. Note that to reach 100%, a given vendor would need to score perfect capability scores across more than 140 specific platform capabilities, spanning seven solution categories listed in table 1. Further, a perfect score for a given capability would require that the vendor's implementation of that capability be not just complete but competitively differentiated. In other words, perfect or near-perfect scores were not seen within this analysis, as no single vendor provided differentiated coverage across the entire capability matrix. In the end, the final analysis from Omdia revealed overall scores that were very close from vendor to vendor with a maximum percentage point spread of only 15%. Such close scoring was even more evident in how well vendors did in providing a positive customer experience with an average score for all players reaching 87%. Deviation within those scores ranged by just more than 1%.

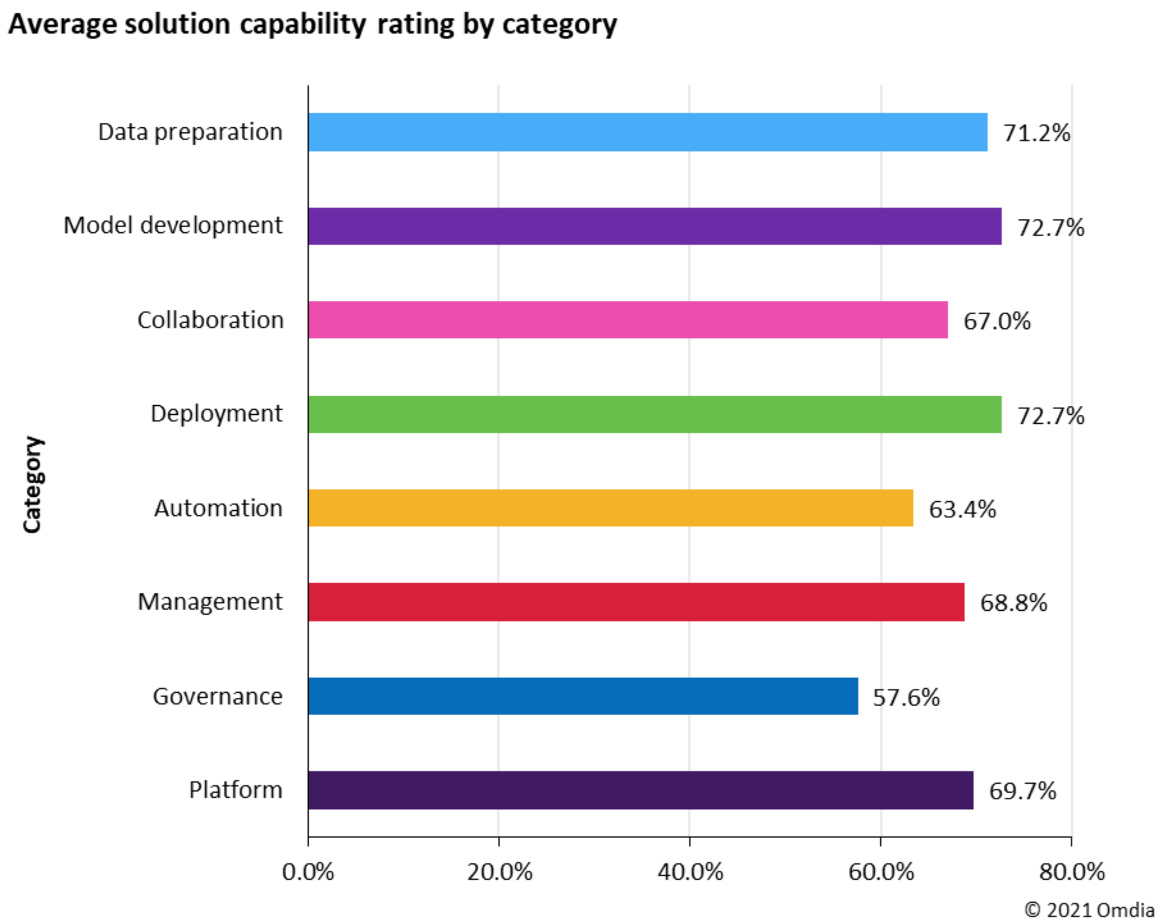
This reflects the fact that all solutions reviewed in this report will provide a beneficial level of ML operationalization that is fit for most enterprise practitioners and use cases, both horizontal and vertical. Within core capability categories like platform (how the vendor deploys its software and manages the deployment of ML models architecturally), scoring across vendors was incredibly even with a standard deviation of only 2.9%. As an example, all the vendors reviewed have built their solutions to run on and deploy to containerized platforms orchestrated by Kubernetes. Similarly, all vendors either work with or depend upon the popular software versioning platform, GitHub, for project versioning.

Such close scoring of all Omdia Universe participants coupled with the rapidly maturing state of the MLOps marketplace will likely lead to a shuffling of the order over the next 12 months. This will depend upon how potentially disruptive technologies such as feature stores, federated learning, and even blockchain influence engineering priorities. The same can be said of enterprise market demands. How those evolve will serve as a signpost to vendors, guiding their research and development (R&D) spending. At the end of the day, the speed at which vendors can innovate in adopting disruptive technologies and in meeting customer needs will most certainly reshape this Omdia Universe going forward.

Future evolution aside, within this report, Omdia recorded several points of diversity among providers that would recommend one solution over the other in terms of matching specific customer preferences and needs. For example, some vendors favor code-first development (such as

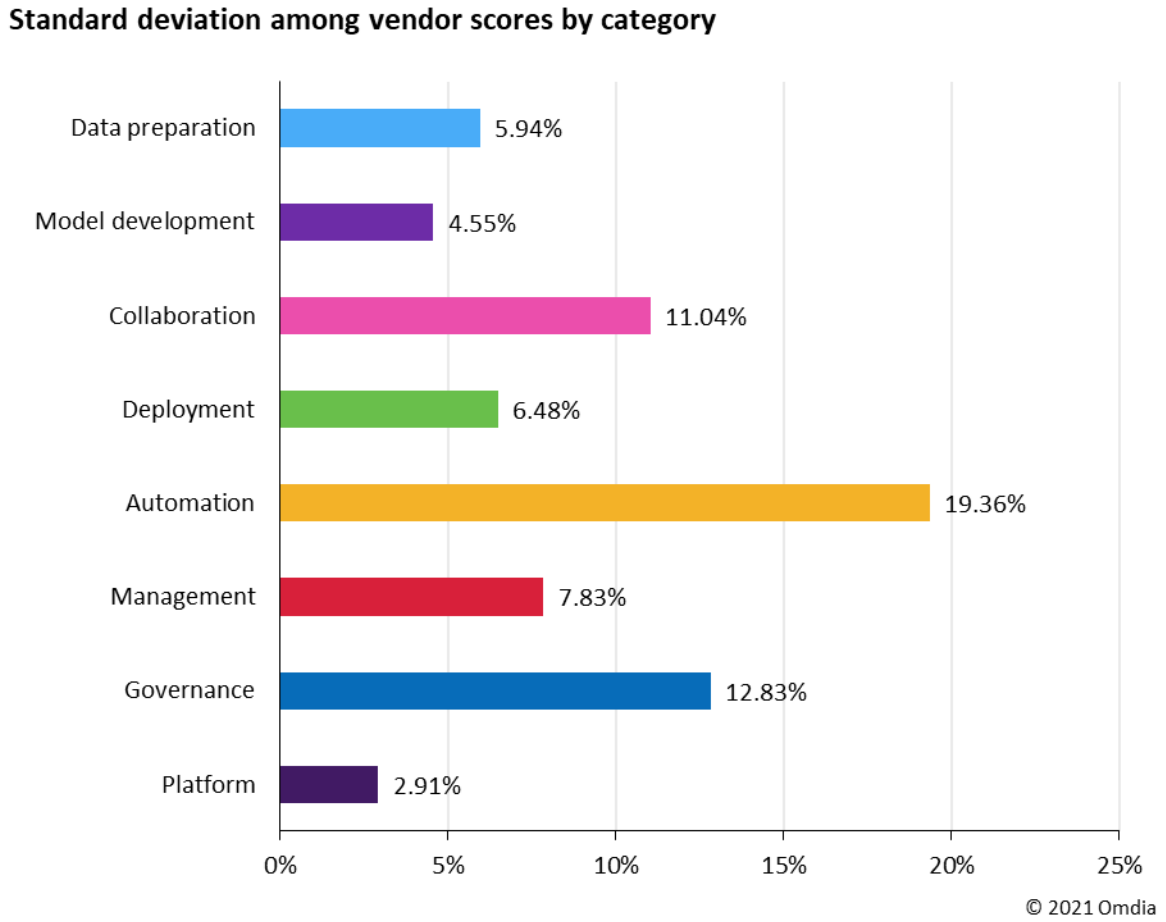
Databricks), while others emphasize a rich user experience (such as SAS). Similarly, some vendors make extensive use of AutoML ideals across the ML lifecycle (such as DataRobot), while others employ AutoML more selectively (such as Iguazio). Omdia has documented many of these notable differences in more detail within the individual solution assessments for all reviewed providers. In evaluating core MLOps fundamentals such as data preparation, model development, model deployment, and platform architectures Omdia found that all participating vendors scored relatively evenly and quite high on the overall solution capability scale, near or above 70% on average (see figure 7). Conversely, within more specialized and emerging areas of concern such as collaboration, automation, and governance, participants scored significantly lower, averaging just more than 62%.

Figure 7: Varying degrees of maturity across the ML lifecycle



Source: Omdia

Figure 8: Emerging areas of interest reveal the greatest diversity



Source: Omdia

This diversity signifies one important fact. The MLOps market is still nascent but very much on the rise with vendors racing one another to adopt differentiating technologies like feature stores and address pressing enterprise challenges such as ML bias, transparency, explainability, and governance. For this reason, Omdia expects the vendors reviewed in this report to come into much closer alignment over time, likely within the next 12 months. In the interim, Omdia research revealed one clear leader among a very tight field of challengers and prospects. This leader (see table 2) was able to consistently deliver across not just core capabilities (platform, development, and deployment) but also across all emerging capabilities (collaboration, automation, and governance).

Table 2: Vendor rankings in the enterprise MLOps platforms Universe

Vendor	Product(s) evaluated	Primary strengths
Leaders		
AWS	Amazon SageMaker, supportive services	Speed and scope of innovation Harmonized hardware for cost/performance balance Multi-pronged focus on trust Outcome-based engineering
Challengers		
Dataiku	Data Science Studio	Rich automation with AutoML Collaboration-complete Out-of-the-box security, privacy, and governance Strong marketplace headstart
DataRobot	DataRobot	Center of excellence in a box Unified administration and collaboration Many any model anywhere Head start with AutoML
Google	AI Platform, supportive services	AI research prowess Supportive communities Purpose-built pricing and flexible usage Responsible AI Full life-cycle metadata management
SAS	Viya, associated services	No assembly required Business-oriented automation High-level, corporate collaboration Top-down trustworthy AI
Microsoft	Azure Machine Learning, supportive services	An exceptionally rich cast of supporting technologies Broad and open ML lifecycle automation Strong community support and influence Building trustworthy AI

Table 2: Vendor rankings in the enterprise MLOps platforms Universe (continued)

Vendor	Product(s) evaluated	Primary strengths
IBM	Watson Studio on Cloud Pak for Data, supportive services	Flexible adoption Building trust, minimizing risk Hybrid cloud deployment, multi-cloud management Cutting edge AI
Dataiku	Data Science Studio	Rich automation with AutoML Collaboration-complete Out-of-the-box security, privacy, and governance Strong marketplace headstart
DataRobot	DataRobot	Center of excellence in a box Unified administration and collaboration Many any model anywhere Head start with AutoML
Prospects		
Iguazio	Data Science Platform	Steeped in solving complex demand Unique serverless functionality Influential technology partnerships ML frameworks as managed hosted services
cnvrg.io	cnvrg.io	Deep hardware integration Straightforward, advantageous pricing Solid data and model versioning Emerging community ecosystem
Databricks	Data Science Workspace	Open yet highly unified Deep integration with host cloud platforms Built for engineers by engineers Embedded business intelligence

Source: Omdia

Market leaders

Market leaders generate an overall solution capability score of 79% or more. Solutions in this category are leading enterprise MLOps platforms that Omdia believes are worthy of a place on most technology selection short lists (see table 2). A vendor in this category has established a commanding market position with its offering, demonstrating a high level of maturity, cohesiveness, innovation, and enterprise fit while having the ability to meet the requirements of a wide range of use cases. Leaders have also executed aggressive product roadmaps to drive enterprise adoption and rapid business growth:

- **Amazon Web Services (AWS) with Amazon SageMaker**. AWS is the outright leader in the Omdia comparative review of enterprise MLOps platforms. Across almost every measure, the company significantly outscored its rivals, delivering consistent value across the entire ML lifecycle. AWS delivers highly differentiated functionality that targets highly impactful areas of concern for enterprise AI practitioners seeking to not just operationalize but also scale AI across the business.

Market challengers

Market challengers each generated overall solution capability scores of between 64% and 79%. This category represents vendors that have good market positions, offer competitive technical functionality, and offer good price/performance propositions, and should be considered as part of the technology selection. Vendors in this category have established substantial customer bases, with their enterprise MLOps platforms demonstrating a good level of maturity and catering to the requirements of a range of process and task automation use cases and continue to execute progressive product and commercial strategies. It should be noted that all challengers within this comparison scored within 1 percentage point of one another. DataRobot, Google, and Dataiku delivered identical solution capabilities scores! This presages an extremely tight race for the lead within this market going forward.

- **DataRobot**. DataRobot has emerged as a convincing challenger amid the top contenders. The company has created a highly unified ML platform, which emphasizes openness, automation, operationalization, collaboration, transparency, explainability, and governance across the entire ML lifecycle and in support of numerous user roles.

- **Google AI Platform**. Google stands as an advanced challenger with a tremendous amount of future potential. Google operates from a position of strength as a global public cloud provider and as a market leader in AI research, engineering, and community building.

- **Dataiku Data Science Studio**. Dataiku is a solid challenger. Punching well above its weight, Dataiku offers enterprise practitioners a full-service platform that revolves around the simple idea that to do AI correctly, companies must view data science as a team sport.

- **SAS Viya**. SAS has garnered the position of a market challenger, offering customers a fully unified and smartly automated analytics platform capable of top-down ML operationalization, governance, and management.

- **Microsoft Azure Machine Learning**. Microsoft stands as a strong market challenger, one poised to take on a more dominant role in supporting the operationalization of AI development in the enterprise, thanks to a global cloud footprint, extensive portfolio of supportive services, and differentiated platform hardware.

- **IBM Watson Studio on Cloud Pak for Data**. IBM operates as a powerful market challenger. With experience spanning more than a century and nearly 350,000 employees operating globally, IBM competes within the enterprise MLOps platform market from a position of strength with a rich portfolio of data science technologies.

Market prospects

Market prospects generate overall solution capability scores below 64% and are characterized as still evolving to meet the full spectrum of enterprise MLOps platform requirements. Prospects provide requisite capabilities in select subcategories while showing weakness in other subcategories. However, Omdia views prospects as having development plans for the evolution of their solutions:

- **Iguazio Data Science Platform**. Iguazio is a dominant market prospect. With strong financial backing and a laser focus on openness and governance, Iguazio delivers an operationalized platform for ML that encourages rapid, collaborative development geared toward handling very complex and highly performant ML use cases in the enterprise.

- **cnvrg.io**. cnvrg.io is a very strong prospect. The vendor placed well against much larger technology providers in operationalizing ML development, scoring very close to global hyperscale cloud solution providers in delivering solid model development and deployment capabilities.

- **Databricks Data Science Workspace**. Databricks is a unique prospect. Databricks is best known for its work in enabling high-performance data processing and storage. However, as the creators of the highly popular open source project, MLFlow, Databricks is uniquely positioned to solve tough data, analytics, and AI problems across cloud platforms using a highly unified architecture built on open source that does not require customers to stitch together multiple tools, technologies, and architectures.

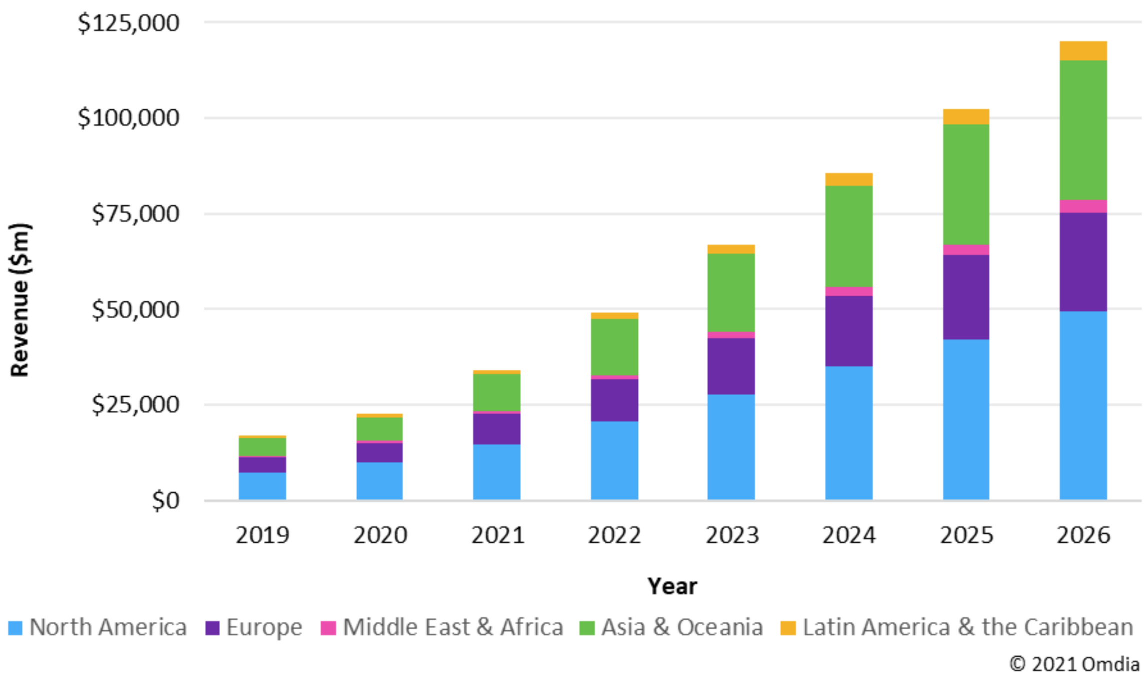
Market outlook

The global COVID-19 pandemic has indelibly altered the technology landscape across all markets, regions, and industries, fundamentally remaking the way businesses look at AI. Before the pandemic, executive discussions revolve around the best way to fail rapidly with AI with rapid experimentation in search of new business opportunities. Widespread disruption to supply chains, staffing, and consumer behavior brought on by COVID-19, however, has since reshaped how executives view the development and use of AI within the enterprise. Discussions now take on a more pragmatic, resilient tone around the ways AI can lower costs, improve efficiencies, and allow for more rapid adaptation to changing market conditions and customer demands.

With this change in emphasis, driven in no small part by COVID-19, Omdia expects the global AI market to continue to grow rapidly. As outlined within the *Artificial Intelligence Software Market*

Forecasts – 4Q20 Analysis, Omdia estimates that global spending will grow to $120 billion annually between 2019 and 2026, a compound annual growth rate (CAGR) of 34.9% (see figure 9).

Figure 9: AI software revenue by region, world markets: 2019–26



Source: Omdia

Vendor analysis

DataRobot (Omdia recommendation: Challenger)

DataRobot should be on your short list if you are looking to speed time to value for AI outcomes across the enterprise.

Founded in 2012 and headquartered in Boston, Massachusetts in the United States, DataRobot specializes in supporting enterprise AI development efforts with DataRobot enterprise AI platform, a lifecycle-complete solution that emphasizes automation, collaboration, and governance. A private firm, DataRobot has reached $750 million in funding, garnering $320 million in series F funding during 2020, led by Altimeter with contributions from strategic investors Snowflake Ventures (Snowflake is a key technology partner for DataRobot), HPE, and Salesforce Ventures. These investments elevate the company's valuation to $2.8 billion, which puts DataRobot on a clear trajectory toward an initial public offering in the future. Over the last four years, DataRobot has put its investment capital to work in building out its platform through several acquisitions, including ParallelM (deployment and monitoring), Nexosis (development), Paxata (data preparation), Nutonian (modeling), and Cursor (cataloging).

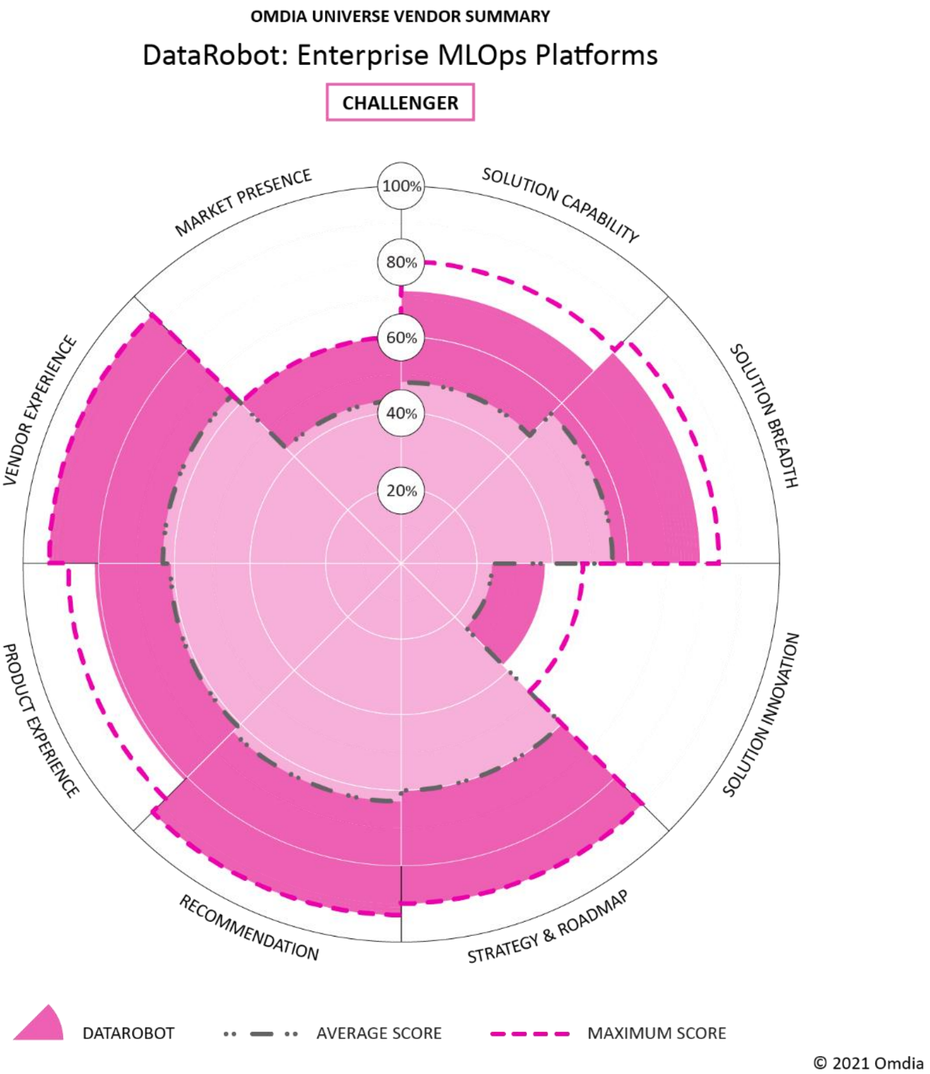
With this financial and technical foundation, DataRobot has created a highly unified ML platform, which emphasizes openness, automation, operationalization, collaboration, transparency, explainability, and governance across the entire ML lifecycle and in support of numerous user roles. In terms of how DataRobot markets this inclusive platform, the company believes it can best deliver value for customers by broadening the pool of users within a company who can gain value from AI and accelerating the time to value for advanced data scientists. It does this by directly supporting creators, operators, and consumers, providing for each the tools necessary to self-provision and self-manage tasks using drag-and-drop, guided, and fully automated capabilities. Architecturally, this inclusiveness translates into a fully model-agnostic framework for managing and monitoring models no matter how they were built or where they are deployed.

Building on these objectives, DataRobot's priorities for the next 12–18 months concern three go-to-market themes:

- Expand the base of AI consumers across the enterprise through persona-centric experiences.
- Grow the number of AI use cases that are trusted and continuously adjust to changing conditions.
- Expand platform capabilities while simultaneously lowering total operating cost.

Since its inception, DataRobot has grown to do business globally in more than 35 countries. It takes a purely horizontal stance, technologically, staying away from productized vertical solutions beyond providing customers and partners with 100+ AI use cases as a starting point. Regardless, the company has seen the most traction within banking, financial services, healthcare, retail, sports, and gaming, as well as manufacturing verticals. Using both direct sales and a reseller channel and marketing to all vertical markets, DataRobot has amassed several hundreds of customers, many of which are Fortune 500. In 2020, the company launched a free trial as a stepping stone for new customers. Since its launch, this program has garnered thousands of sign-ups for the platform, with a high percentage creating projects in their first seven days. In supporting its customer base, DataRobot uses a very hands-on, consultative approach that emphasizes not only integration and deployment but also business transformation through the company-wide adoption of AI. To that end, the company favors long-term contracts coupled with dedicated technical and educational resources designed to help customers both optimize platform usage and maximize ROI. To extend its internal support and integration resources, DataRobot works with several systems integrators including Accenture, Boston Consulting Group, Capgemini, and Cognizant. Key reference customers include Accenture, Boston Red Sox, BlueCross BlueShield, Australian Red Cross Lifeblood, Lenovo, Humana, Tableau, Panasonic, United Airlines, PNC, University of Michigan, and Deloitte.

Figure 11: Omdia Universe ratings – DataRobot



Source: Omdia

Strengths

Center of excellence in a box. One of the biggest challenges facing enterprise AI practitioners has very little to do with writing Python code and ML algorithms. Because of the rise of AutoML tools, MLOps practices, and managed hosted services, companies can stand up working on projects in relatively little time. What must come later, namely a means of governing not only effectiveness but also addressing ethical concerns such as fairness, inclusivity, transparency, and explainability, demands an investment in human expertise. In response, most enterprise MLOps platform vendors have begun creating tools specific to the challenge of rooting out issues such as machine- and human-introduced bias. These tools, which often employ purely mathematical constructs such as

SHapley Additive exPlanations (SHAP) to identify and explain the relative importance of given features in determining the outcome of a given model. DataRobot uses this same approach as well, allowing users to modify features using a what-if tool to better understand how changes in input values might impact model output. However, whereas many rival solutions only focus on models during the development phase, DataRobot seeks to extend its bias-mitigating and transparency tools to models running in production. First, with Humble AI as an example, the company has built into its platform the ability to set running guardrails for model outputs that can, for instance, override in real-time an “uncertain” prediction, defaulting to a safe value. A second example involves the company’s ability to generate pre-built, no-code, user-facing apps, which can incorporate several human-in-the-loop tools to help domain experts (e.g., a loan officer or insurance adjuster) understand how a model arrived at a given output, live in the field. In both cases, DataRobot expertly employs automation and augmentation as a means of building trust in AI both during development and in production.

Unified administration and collaboration. As a highly unified environment, DataRobot can provide its customers with a single pane of glass for the management of all DataRobot projects and project assets, whether under development or in production. This is of value for running projects. From this single interface, business owners can see at a glance important measures such as the service health, amount of model drift, and running accuracy of any given model—regardless of deployment target (local server, third-party public cloud, edge device, etc.), model type (batch, real-time), or interface (app, API call). If a model appears to be drifting out of its predefined range of operation because of accuracy issues, for example, a business user can readily drill into a model dashboard that visually shows accuracy over time according to several measures (including RMSE, MAE, Gamma Deviance, Tweedie Deviance, and R Squared). Users can constrain results to specific periods or even compare results over time with a set of “hot standby” challenger models to determine, for instance, if a poorly performing champion model should be swapped out for a challenger. If this is the case, the business user can kick off an approval-based workflow that notifies the data scientist internally and via Slack integration of the need to consider the swap. If the data scientist recommends a swap and if that request is approved, DataRobot can make the change in real-time with no downtime, since it performs constant operational testing on challenger models. This same flow applies to many operational issues, including model drift, service health (e.g., cluster performance or data integration issues), and application integrations. This same, highly collaborative environment applies to earlier phases in the ML lifecycle. At every step, participants can tag and discuss, tag, and comment on assets, kick off managed workflows, etc. These in-product options, coupled with tight integration with external asset repositories (notably GitHub and Bitbucket, as well as BitBucket Server, GitHub Enterprise, and S3), analytics tools (Tableau and Qlik), and collaboration services (Slack), make DataRobot a solution exceptionally apt at supporting enterprise customers seeking to scale their AI efforts across disparate departments.

Any model anywhere. DataRobot, as a pure play AI development vendor, approaches the concept of openness very differently than its larger rivals that are equipped with their own global public cloud platforms. While most public cloud players are just beginning to address the management and monitoring of models residing “off platform” as seen with IBM’s efforts with Satellite, DataRobot has prioritized this notion for more than a year. As a fully containerized platform, DataRobot itself can run on Kubernetes, Docker, Kubeflow, GCP, AWS, Microsoft Azure, and Cloudera Hadoop. These efforts led to the December 2020 introduction of Portable Prediction Servers (PPS), which is available in the DataRobot MLOps version 6.3. In short, this new service provides a set of Kubernetes containerized RESTful APIs, which allow customers to flexibly deploy models written in any language on any containerized platform or service (on-premises, cloud, hybrid, and multi-cloud). This augments the vendor's existing ability (within Datarobot Prime) to create linear model approximations to deploy and monitor models on any platform that can execute Python or Java code (and JAR files). In this way, DataRobot users can manage and deploy models that were created externally, and conversely, they can deploy those models to a wide array of target platforms without compromising basic monitoring capabilities such as service health, model accuracy, and even explainability (with PPS specifically) as well as monitor any remote model via agents. Additionally, with a new feature, MLOps Remote Model Challengers (available with version 7.0 in March 2020), DataRobot users can create challenger models for any model being managed on any remote deployment platform.

Limitations

Room for growth. DataRobot offers a rich suite of highly integrated (e.g., a central data catalog and asset repository) and often highly differentiated (e.g., pre-built user applications and remote model management) services. However, several future technology investments remain on the vendor's product roadmap for the next 18 months. First and foremost, the vendor is in the middle of a disruptive change in terms of supporting code-centric, in-notebook model development. Broadly, DataRobot feels that current open source technologies (particularly notebook-based development) do not lend themselves to operationalization. For that reason, the vendor removed its existing Jupyter notebook IDE from DataRobot 6.0 in mid-2020. Rather than try to fit Jupyter notebook-based development into its platform, DataRobot instead intends to focus on its internal IDE where it can provide advanced functionality like unit testing, but still allow users to bring their training and inference code into DataRobot. Regardless, DataRobot intends to add support for hosted notebooks and provide advanced functionality for users of JupyterLab (via extensions) before the end of 2021. In the meantime, developers can use their IDE of choice and connect with DataRobot via the company's REST APIs as well as dedicated clients for Python and R. Note also that with the company's June 2020 acquisition of SOURCE AI, DataRobot will accelerate its unique stance on AI development, coupling automation with consultative best practices.

Data labeling. Another key area where DataRobot should invest is in data labeling and annotation services. Right now, the vendor does not connect with any third-party services from CloudFactory, Hive, Google, or AWS, preferring instead to work with data sets that have already been labeled. By acquiring or integrating such functionality, DataRobot could greatly assist customers in identifying and mitigating many forms of bias specific to labeling unstructured data. That said, given the company's willingness to rapidly acquire and integrate required functionality, it is likely that DataRobot will address these opportunities in short order, as it did in 2019 with the acquisition of data prep specialist Paxata and in 2020 with its acquisition of unstructured data specialist Zeff.

Platform cost and commitment. Like most vendors reviewed in this report, DataRobot seeks to lower the bar to adoption for potential customers using freely available software. For DataRobot, this centers on an extended free trial. Launched in July 2020 as a managed service running on AWS (both in the US and in Europe), DataRobot's free trial provides complete functionality limited only to a six-month maximum use of $500 total usage credits, which can be applied according to need (training, data acquisition/prep, etc.). Pricing following the free trial then depends upon the user's modeling capacity and the number of deployed models. Note that even though the company does not publicly disclose its pricing, it has recently adopted a new model that lowers the cost per deployment; thus, lowering the barrier to entry. To date, DataRobot has seen a great deal of interest in its trial service with tens of thousands of signups since launch. Even with this trial, DataRobot's pricing practices strike a chord that is unique compared with broader market pricing trends that employ utility-based pricing to lower the bar to both entry and exit. Comparably, with DataRobot, potential customers are encouraged to commit to a three-year contract to get started. The vendor's reasoning is simple: rather than focus on consumption, DataRobot focuses on success. DataRobot views its customer relationships as long-term investment between provider and buyer, a close relationship that is necessary if buyers want to build a culture of AI-driven insight throughout their entire organization. The company supports this stance through numerous DataRobot investments in customer success, including an AI Success team that works with and educates customer teams until they become self-sufficient. For pricing itself, rather than leave the estimation and administration of pricing to the company itself, DataRobot works closely with customers to right-size and continuously optimize their deployments. Given DataRobot's strength in equally supporting both business users and data scientists through its AutoML philosophy, the company's reluctance to create tiered pricing and/or per-use pricing limits its ability to target a larger pool of potential customers, especially those not ready to commit fully to company-wide AI adoption. (Note that DataRobot has introduced pricing changes that reduce the price-per-model and provide more flexibility across disparate customer needs.) Additionally, rivals can point to DataRobot's high-touch customer engagement model as a limiting factor in terms of the number of customers the company can support, thereby missing out on long-tail market opportunities. Again, however, DataRobot's philosophy of success overconsumption necessitates this approach. Even so, the vendor does offer a self-service option for customers who do not want that level of support.

Opportunities

Head start with AutoML. As the company that pioneered the AutoML category, DataRobot prides itself on prioritizing the use of AutoML as a means of helping data scientists build and manage ML models. Since 2013, the company has invested more than 1.4 million research and engineering hours into the notion of automating as much of the ML lifecycle as possible beyond the traditional scope of AutoML: feature engineering, model selection, hyperparameter tuning, and model evaluation. The result is an AutoML facility that supports disparate user roles (ML engineer, data scientist, and business user), reaches across much of the ML lifecycle (data preparation as well as model development, evaluation, deployment, and monitoring), accommodates multiple data types (tabular, text, temporal, image, and geospatial), and employs hundreds of unique, pre-built pipelines (branded as "blueprints") that marry specific use cases with the most appropriate ML algorithm. On top of this solid foundation, DataRobot provides several unique points of automation. For example, it provides fully automated model explainability and traceability for each step and iteration in the workflow, all tracked within the company's built-in repository and synchronized with external asset repositories such as GitHub. Given the maturity of DataRobot's AutoML capabilities, it is well-positioned opposite many rivals that are just beginning to treat AutoML as a key element within a fully operationalized ML lifecycle. An important next step for DataRobot, therefore, is to create complete synchrony between manual code generation within a notebook-based development and automated code generated within its AutoML facility. To this end, the company has begun working on a way to create bi-directionality between AutoML and notebook code. If DataRobot is successful in this effort, it will be able to not only natively include DataRobot AutoML-generated models in third-party environments but also enable business users and data scientists to seamlessly collaborate in model development.

Threats

Perception of AutoML-centricity. Now in its ninth year, DataRobot stands at an important crossover in terms of determining how it wants to be viewed within the broader AI platform marketplace. From its inception, the company has built its reputation on proving that end-to-end automation (e.g., AutoML) can scale in support of complex, company-wide AI development efforts. Further, it has shown that automation in AI can solve problems along the entire ML lifecycle and across disparate practitioner profiles (creators, operators, and consumers). Yet, despite advances in automating issues such as model transparency both during development and at runtime, the vendor must contend with the enduring market misperception of AutoML itself as nothing more than a way to democratize data science among business domain experts. Though the vendor has certainly demonstrated the value of AutoML within a much broader context—namely automating "everything"—DataRobot depends heavily upon its in-house automation prowess. This leaves DataRobot open to criticism surrounding its ability and desire to incorporate traditional model development practices into its highly unified and governed platform. Slowly this perception should change, owing in no small part to the company's decision in 2019 to completely open up its platform such that it can potentially run and manage any model, no matter how that model was built or where that model has been deployed. In that effort, the company has been highly successful, not only using standards like Kubernetes and ONNX, but also through remote model monitoring services, portable prediction servers (PPS), and support for non-containerized deployments through the use of Java Scoring Code. These efforts, together with new capabilities emerging from the SOURCE AI acquisition, will help the vendor incorporate code written outside of the DataRobot platform. There are more on the table for DataRobot in terms of supporting a wide array of ML development technologies and practices within its platform without sacrificing collaboration, operationalization, and management capabilities.

Methodology

Omdia Universe

The scoring for the Universe is performed by independent analysts against a common maturity model, and the average score for each subcategory and dimension is calculated. The overall position is based on the weighted average score, where each subcategory in a dimension is allocated a significance weighting based on the analyst's assessment of its relative significance in the selection criteria:

- **Market leader**. This category represents the leading solutions that Omdia believes are worthy of a place on most technology selection short lists. The vendor has established a commanding market position with a product that offers the preponderance of differentiated capabilities.
- **Market challenger**. The vendors in this category have a good market positioning and are poised to move into a leadership position. The products offer competitive functionality and good price-performance proposition and should be considered as part of most technology selections.
- **Market prospect**. The solutions in this category provide the majority functionality needed but either lack select, advanced features or suffer from a low customer satisfaction rating. A niche or relatively new vendor with select innovative products and strategy may fall into this category and should be explored as part of the technology selection.

Inclusion criteria

Omdia has closely tracked the evolving enterprise MLOps platform vendor landscape, and we have used these observations as the baseline for inclusion/exclusion in this Omdia Universe. The criteria for inclusion of an enterprise MLOps platform and vendor in this report are as follows:

Table 3: Enterprise MLOps platform inclusion criteria

Area	Required	Nice to have	Desired requirements
General	Yes		The enterprise MLOps platform must be generally available as of January 2019 with at least 50 paying enterprise customers.
	Yes		The solution should focus on the operationalization of MLOps, plying DevOps principles, practices, and technologies.
	Yes		The solution should endeavor to support the entire ML lifecycle with tooling built specifically to the task of orchestrating and automating tasks across all ML project phases and all primary user roles (data engineer, ML engineer, data scientist, developer, IT operations specialist, etc.
		Yes	The solution should directly support ML project development across a wide range of horizontal use cases. Productization of horizontal use cases using pre-built resources is welcome but not required. Similarly, productized vertical solutions are not a requirement for inclusion.
		Yes	Vendors should support or provide professional service engagements but not be exclusively reliant upon those to deliver their solution.
Data preparation	Yes		The solution should accommodate a broad spectrum of data sources and provide or incorporate a central data repository, encouraging the reliable use and re-use of data both during development (model training) and deployment (inference).
Model development	Yes		The solution should support the development of ML outcomes using both proprietary and open source technologies, incorporating popular ML frameworks, supporting popular languages and other development tools.
Collaboration		Yes	The solution should include collaborative services enabling disparate team members (data engineers, data scientists, developers, IT Operations specialists, etc.) to work together on ML projects.
Deployment	Yes		The solution should enable CI/CD capability for the deployment of ML products, incorporating the ability to monitor and revise models once pushed to production.
Automation		Yes	The solution should incorporate or make extensive use of ML automation capabilities, commonly referred to as AutoML, to both speed development and democratize data science among business stakeholders.

Table 3: Enterprise MLOps platform inclusion criteria (continued)

Area	Required	Nice to have	Desired requirements
Management	Yes		The solution should incorporate or fully integrate a central metadata repository for the management of ML data, models, features, code, as well as other project artifacts and metadata.
Governance		Yes	The solution should incorporate several capabilities specific to solving problems of model transparency and explainability, project accountability, regulatory compliance, security, privacy, and bias

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Source: Omdia

Appendix

Further reading

AI Ecosystem Database 2021 (March 2021)

Artificial Intelligence Services – 2020 Report (October 2020)

Artificial Intelligence Software Market Forecasts – 4Q20 Analysis (December 2020)

Enterprise AI Contracts Database – 4Q20 (February 2021)

Omdia Decision Matrix: Selecting an Enterprise ML Development Platform, 2020–21 (March 2020)

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