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Chapter 6: Artificial Intelligence Integration with Cloud Platforms: A Focus on Azure, AWS, and GCP AI Ecosystems

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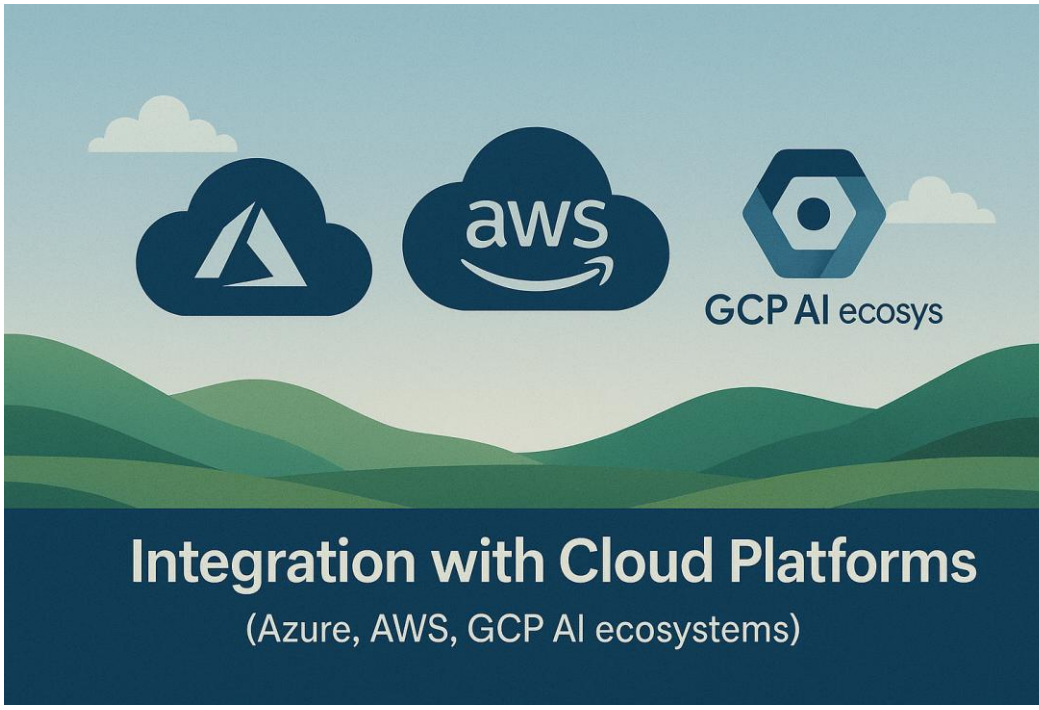
1. Introduction to AI Integration

Artificial Intelligence (AI) has emerged as one of the most transformative forces in business in this century. As companies combine datasets, AI infrastructure, and powerful AI algorithms to produce smarter and more generalized AI models, business leaders in every industry must be prepared to fundamentally reorganize their operations around models and products created with the help of this new technology. Generic AI assistants will affect the way knowledge workers do research, draft documents, analyze information, and create visual aids.

While most of the AI hype today is around these large-based AI services, in the corporate world it is the added-value, specialized AI integration that will change the nature of products and services, and how they are created and delivered [1-2]. Today's large model development is being built around next-generation cores that create domain-specific models. In effect, the domain-specific models act like adapters, playing the same role that certain data formats do with web objects, or photos do with certain applications, and called on by corporations to customize AI services to their business-specific data and processes. Product and service firms will harness these domain-specific models to leverage their own data to create customized models.



Cloud service companies are expected to have accelerated this capability through the new hardware engines they have created to power AI visual capabilities, and the software services they have created to support integration and especially retrieval-augmented generation. The offering of these capabilities, on a pay-as-you-go basis, will democratize the power of AI elsewhere to niche players with focused platforms.

2. Overview of Cloud Platforms

Accessible via the internet, cloud platforms provide an assortment of on-demand services. These on-demand services, which are based on a shared infrastructure, can be further categorized as IaaS, PaaS, or SaaS. Thus, rather than investing in their own infrastructure, customers may save both time and money by taking advantage of a third party [2-4]. The cloud allows users to store and access applications and data, regardless of location. Coupled with automation and virtualization, clients can gain significant advantages in terms of efficiency.

The majority of cloud providers allow customers to pay for only the services and resources utilized, charging fees in units. This ensures that customers pay only

for what they use—a potential boon to budget-conscious companies. Cloud computing also allows customers to access a potentially limitless pool of computing resources. Providing speedy access to resources can give potential clients an edge over their competitors when dealing with seasonal demand spikes. Cloud computing can also allow clients to balance demand by using resources located remotely in the cloud. Most cloud providers also offer software tools to streamline development, testing, deployment, and maintenance. These combined advantages have resulted in more and more businesses turning to cloud integration, a testimony to the advantages of cloud services.

2.1. Understanding Cloud Computing

Cloud computing has transformed the way organizations think about IT. Gone are the days of organizations trying to determine the amount of IT infrastructure they need to have in place to support their applications and services. IT resources such as servers, storage, and databases can now be deployed as needed from an extensive pool of resources owned, maintained, and supported by a third-party service provider [5-6]. These resources can be shared between many organizations—referred to as a "multi-tenant" environment—reducing the cost of providing those resources. In addition to pay-as-you-go provisioning, cloud service providers also add the ability to quickly deploy large amounts of IT resources for peak demand times. The scope of cloud computing goes beyond the delivery of IT resources, however. Cloud computing describes a complete model for offering IT services to customers, and includes how those resources are provisioned and governed. Although the technical foundations of cloud computing existed for many years, it wasn't until companies began offering full-blown computing services based on these ideas that the term cloud computing started to gain traction. Sure, technical solutions that resemble the key tenets of cloud computing existed before. Managed service providers and outsourced computing companies were performing similar IT outsourcing tasks. So were companies who offered dedicated hosting. What's different now is how a cloud service provider leverages the tenets of cloud computing to create a far simpler and more economical model for IT service delivery for a much broader set of organizations. It is these aspects that make many of the exciting possibilities using cloud computing available for everyone.

2.2. Key Benefits of Cloud Integration

Many enterprises are foregoing capitalizing and deploying on-premises infrastructures; these days, they are increasingly adopting cloud-based services.

Cost and availability are two of the most attractive advantages of cloud computing. At a high level, by leveraging cloud services, organizations can significantly reduce the capital and operating costs to acquire and support IT infrastructure [7,8]. With commodity use-based pricing and an always-on service availability model, organizations can get started with little investment and manage financial outlay to what they actually consume. Enterprises can also scale the IT infrastructure and services on demand in response to business needs. For example, if you are an online retailer, your infrastructure needs fluctuate wildly during peak times such as the holiday season. Cloud services address this kind of scenario easily. And cloud services help you scale rapidly, because all it takes is a few clicks to deploy thousands of machines.

Another benefit of cloud computing is that it moves IT service requirements from the IT organization to the service provider. That moves the burden of raising and provisioning requests with an internal IT group to the cloud services provider and shifts the responsibility for monitoring and managing service levels to the provider as well. The cloud services provider offers predefined templates for provisioning basic services. With these templates, a user can provision popular services quickly in a self-service manner with few clicks. The services are delivered at enterprise-grade quality levels, yet the user can provision the service in minutes and for a fraction of the cost of an on-premises solution. Self-service provisioning allows users in organizations to get IT services without going through the lengthy process of raising requests with the IT organization and waiting for them to fulfill the requests. Organizations can achieve faster time to results for key projects when business-focused people can provision the services they need to get the job done.

3. Microsoft Azure AI Ecosystem

Microsoft's investment in AI is a strategic play to create a new wave of applications across consumer and enterprise-driven opportunities. By augmenting its existing products and services, Microsoft aims to drive growth and engagement through enhanced Search, productivity, communications, and security experiences [9-12]. However, Microsoft is most likely to witness incremental adoption of next-gen enterprise apps built on Azure's Generative AI capabilities. Microsoft is likely to see strong adoption of LLM-based services that will help developers quickly build and deploy enterprise applications ranging

from automating customer support to generating insights from internal documents. Developers have recently gained access to Microsoft Azure services. Azure provides pre-trained models across speech, language, and vision that can be further fine-tuned on proprietary data.

Microsoft Azure AI services are a collection of tools, services, and responsible AI guidelines to help an individual or organization in their AI journey, either through building or accessing Azure AI. Azure AI includes components such as Azure Machine Learning, Azure Applied AI Services, Azure AI Infrastructure, and Azure AI Service tooling and Integration. Azure Machine Learning is a cloud-based service to train, evaluate, and deploy machine learning models. Azure Applied AI Services are pre-built models in domains such as natural language processing, speech, and bioinformatics, designed to work right out of the box while being customizable for your specific workflow. Azure AI infrastructure includes virtual machines, managed Kubernetes clusters, and data storage services, built for AI workloads. Azure AI service tooling and integration includes Visual Studio Code, Azure AI Studio, Power Platform, and Windows Desktop.

3.1. Azure AI Services Overview

Microsoft's stated mission is to empower every person and every organization on the planet to achieve more. This includes a strong focus on democratizing AI and we believe that two aspects of Microsoft's implementations of Cloud AI technologies are especially relevant for practical AI: the focus on providing ready-to-use AI capabilities through Azure AI services; the focus on providing a continuum of AI technology usage that enables virtually any person or organization to use and implement AI capabilities of sufficient sophistication for their needs [7,13-15].

In this section, we will provide an overview of Azure AI services and outline the various aspects of AI integration with Azure, with the more generic purpose of making Azure the best place to do AI. Then, in the next sections, we will delve more deeply into Azure AI services and practical AI implementations that leverage Azure, focusing on Integration with Azure Machine Learning and Azure Cognitive Services, which are essential for most practical AI implementations. Finally, we will illustrate some unique advantages of Azure for practical AI, through a couple of case studies of AI integrations with Azure that we have been involved with.

At the highest possible level, AI capabilities can be categorized on the basis of whether they are primarily designed for use by knowledgeable individuals; ready-to-use by non-specialized individuals with little or no technical AI knowledge; powered with some technical knowledge of Azure technologies; or built by AI developers specializing in model building or specialized solutions.

3.2. Integrating AI with Azure Machine Learning

As the key AI service from Microsoft Azure ecosystem, Azure Machine Learning provides a breadth of tools and capabilities for building and integrating AI into different applications and operations [9,16-18]. Although its core capability is operationalizing custom machine learning models created with different libraries, it also provides drag-and-drop tools for using pre-built components for quickly operationalizing models from developers with different skill levels. These capabilities enable organizations to deploy their own custom and pre-built AI models easily at scale. Azure Machine Learning also specializes in making sure models are trustworthy, through bias detection and mitigation, model interpretability and explainability, and a broader approach to responsible AI. The Azure Machine Learning portfolio of capabilities is focused on each step of the processes of creating, deploying, and managing AI model. Azure machine learning pipelines enable the most technical data scientists to build complex workflows for large-scale training, testing, and deploying models using automated machine learning, hyper-parameter tuning using reinforcement learning, distributed training and inferencing, and model-metadata integrations. The myriad of pre-built capabilities can be integrated with tools for a range of programming languages including R, Python, and SDKs for .NET languages, as well as with tools from third parties. Each of these tools allows developers to use AutoML or manual tools for computer vision, reinforcement learning, time-series forecasting, natural language understanding and conversing, and a range of other well-defined areas for using machine learning.

3.3. Azure Cognitive Services

Cognitive services are designed for individualized products and economies of scale. Therefore, Microsoft has created the Azure AI converts complex algorithms into straightforward APIs that help AI Engineer customers easily integrate smart into applications, websites, and developers [2,19-20]. The assembly is an integration of APIs that ease intelligent and smart decision-making in various manners, including natural language processing, automation learning, and machine vision. The services are structured mainly in four

categories: vision, language, speech, and decision. Below is the perspective of each service.

The Computer Vision service can extract information from images to generate the Intelligent Media Exploration and Search solution. It classifies content in images, determines color association in images, and extracts texts. The Custom Vision uses a model to classify specific contents in images. The Face service is able to identify and analyze faces. The Ink Recognizer connects handwritten with typed user input. The Form Recognizer is useful to identify data information contained in documents and forms structure. The Face service identifies and analyses human faces.

The Language service has the ability to understand what a human being thinks and uses the Text Analytics. The Personalizer is crucial to improve user experiences across multiple application channels [9,21-23]. The Speech service offers multiple technologies to process voice communications by recognition and synthesis, set up classification, and author dialogues through conversation. Textile offers both conversation and dialogue predictions. The Decision service provides general analytics and/or recommendations for specific products. The Anomaly Detector detects data abnormality. The Personalizer service helps for user experience personalization. The Metrics Advisor is fundamental for optimized user experience through business metrics.

3.4. Case Studies of Azure AI Implementations

In this section, we illustrate organizations and companies that have integrated AI with Azure's services. For example, Real Madrid, one of the most prestigious soccer clubs in the world, is using Azure-based AI to address how to keep and enhance the connectivity with their over 500 million fans across the world. They created a digital platform and mobile application that improves their global fans' online experiences through customized services and value-added features. Their new solutions, based on the combination of mobile and social media, suggest fans' events, merchandise, services, etc., based on their individual preferences and needs as well as the events of their favorite sport's team. The new mobile app provides real-time notifications and enables digital ticket management and purchases for soccer matches and events, along with personalized content such as live broadcasts, videos, news, and alerts [24-26]. To deliver must-have digital experiences, Real Madrid's Club believes it’s vital to leverage Fan Experience through data and analytics to make better business decisions while gaining

insights, feedback, and individual preferences at a whole new level. Therefore, machine learning capabilities are essential to help Real Madrid predict fan activity, ranking the club's most passionate fans according to variable ticket prices.

Another example is how Heineken has focused its engagement with consumers, suppliers, fans, and local communities since COVID-19 caused the new normal epidemic, with the use of intelligent and secure personalization and connected experiences. Beyond focusing on values like advocating for bars and pubs while keeping people connected, entertaining, and safe, and being the best for people, it is focused on something bigger by building a more sustainable future together. Heineken transformed its marketing channel strategies, using a data-driven solution for analyzing its consumers' behavior in the different markets, mainly during the period of COVID-19 financial impact.

4. Amazon Web Services (AWS) AI Ecosystem

The vendor with the largest cloud hosting market share provides the broadest and deepest set of machine learning (ML) and artificial intelligence (AI) services to address different customer needs – from pre-built solutions to end-to-end platforms for data scientists and developers – all of which are responsible for making ML and AI usable, efficient, and compliant. Their AI services support four ML- and AI-based personas. First, data engineers need help preparing and transforming data for ML [8,27-30]. They build and automate data pipelines that make it easy to clean, aggregate, label, and visualize data. Second, ML engineers develop algorithms and models that productionize ML throughout their company. They build, train, and deploy ML models and integrate ML into business processes. Third, developers, researchers, and data scientists explore methods and build models for a wide variety of AI and expressive generation tasks. Fourth, they want to help every customer develop AI/ML skills so every company becomes an AI company.

In this chapter, we first describe AI and ML services designed for different personas. We then provide a heavy emphasis on SageMaker. This is the main platform service designed to be used primarily by two of the above personas – ML operators and data scientists. After describing the importance of SageMaker and how the AI services connect to it and simplify its operation, we then turn our

attention to the tasks SageMaker is designed to support. Finally, we overview the AI models and frameworks that can be either built, customized, or used from the SageMaker platform, including example case studies which utilize these capabilities.

4.1. AWS AI Services Overview

Amazon Web Services is currently at the forefront of all major Cloud Platform vendors in terms of Ecosystem of AI Service offerings from the Cloud Platform itself or from Service Partners [9,31-33]. In a short period of time from inception, AWS has now launched hundreds of AI, Machine Learning Services, Tools, Frameworks, and SDKs/toolkits in several diverse functional areas of Business. Through its partnership network, AWS has integrated various AI Libraries and Ecosystems. Most AI frameworks are integrated into the AWS Ecosystem providing a toolset for customers that can work seamlessly with the AWS Cloud Solutions.

AWS has launched an extensive set of AI Services and Tools to cover all customer use cases across industries and sectors in a myriad of Machine Learning areas such as Automated ML or AutoML, MLOps, Deep Learning Model Training, and Inference, Computer Vision, Natural Language Processing, Reinforcement Learning, Recommendation Engines, Fraud Detection, Autonomous Driving, Speech, Chatbots, and Conversational AI, Datasets Management, Ground Truth Creation, Analytics, and Observability. Advanced Service Integrations are available with Services for such specific Customer Needs and Use Cases such as Retail Inventory Management, Customer engaged, Contactless Virtual Queuing, 3D Vision for Predicting Occupancy Quality, Custom Visual Language, 3D Model Generation for Merchandising and online Retail Best Practices, Advanced Services for Data Annotation. These Services can seamlessly integrate with a Customer using the Power of Data Lakes, Visualization Service, Voice, Video Services, Business Intelligence API, and SaaS Tools, Security Services, and Database Services to provide a complete Business or Functional Area solution.

4.2. Integrating AI with AWS SageMaker

Amazon SageMaker is a fully managed, cloud machine learning service that is the backbone of the AWS AI/ML ecosystem and helps customers build, train, and deploy scalable AI solutions [34-36]. As a fundamental service within the AWS ecosystem, Commerce services can be tightly integrated with SageMaker

to manage, enable, and enhance the Amazon AI model training, deployment, and management process. Amazon SageMaker enables Developers to quickly integrate a wide range of capabilities within their applications, from pre-built solutions to customized model training and delivery. SageMaker Studio is the first fully integrated development environment for machine learning. With SageMaker Studio, developers can quickly prepare their data, analyze, visualize and explore the data, and construct the ML pipeline using code while being assisted by pre-defined notebooks and have debugging capabilities. Customers can then easily provision model training jobs on demand or in parallel, tuning the models, and evaluate the performance. On Model deployment, developers can quickly publish the Inference endpoint(s) or use our Serverless Inference capability to manage the scaling of Inference request demand up and down so that they are only billed on the processing time [3,37-39]. For customers who train models that are frequently retrained with low-latency demands, SageMaker offers the Model Registry to manage their intermediaries and final model artifacts. Developers can configure the Model Deployment service so users can update their Inference requests with the latest retrained models automatically, enabling automation for their low-latency Model Inference demand, while the older models are archived in the Model Registry.

4.3. AWS Deep Learning Frameworks

Although AWS AI Services and AWS SageMaker provide a lot of prebuilt and pretrained capabilities for the customers who want to build customized DL/DL-based ML models, there are numerous open source frameworks available on AWS. The customers can use them either directly on the public AWS infrastructure or within the AWS SageMaker environment. These frameworks are based on the most popular general purpose and ML-focused programming languages, that is, Python and R, respectively. These frameworks also help the researchers, educators, and scientists who want to use AWS resources for DLE and have worked on them in their own local environments. The open source software in recent years is amazing and very useful for ongoing DLE research as well as for teaching DLE to students.

The support for TensorFlow, Keras, PyTorch, MXNet, Chainer, OpenFace, DeepStream SDK, Scikit Learn, nGraph, and others is really extensive and impressive. Various organizations have developed an extensive set of DL frameworks, which are based on the discussed programming languages. AWS has utilized the large software developer community that has created these

frameworks. These frameworks are baseline or building blocks on which specialized DLE systems are built to solve DLE-focused problems. Some of these specialized DLE systems are developing systems for facial recognition, drive autonomous vehicles, and bring AI to edge for retail applications.

4.4. Case Studies of AWS AI Implementations

It is indeed exciting to see the value these institutions have created by implementing some of these AI services. The Wiltshire Police are addressing two problems using a real-time facial recognition system. Firstly, the review of footage of public crowds for specific people is slow, laborious, and not time-optimized. By integrating a facial recognition solution, they expect to be able to filter crowds for specific people in real time, thereby creating alerts. This would enable them to quickly capitalize on incidents such as a missing child. Secondly, the data analytics potential of such a tool means they can learn more about repetition, locations, time of day, etc., of faces at public events and use that information for preventing future incidents. The Viettel Cyber Security Center of Viettel Group in Vietnam has two business areas. One is to respond to spam, predict spam, and block spam. The other is to research and develop AI solutions to help their partners improve their services. Currently, because the amount of spam messages in Vietnam is large and mostly sourced from Western numbers, VCC is developing two AI systems for spam classification. One system predicts the likelihood that the sending number sends spam by developing a model that detects spam content. The other system analyzes delivered spam messages and develops a model to classify sending numbers based on similarities in content to develop a message classification model. These two models will be integrated to help VCC's partners better filter for spam and predict which messages have the potential to be spam.

5. Google Cloud Platform (GCP) AI Ecosystem

5. Google Cloud Platform AI Ecosystem Google Cloud Platform is widely recognized as the industry leader in AI infrastructure. With its focus on machine learning services and sharing of innovations, it ranks closely with Microsoft Azure among enterprise leaders that are looking for comprehensive cloud AI solutions. Both the AI ecosystem and search are influenced by the idiosyncrasies of the product portfolio structure. We summarize the AI services available for

developers and data scientists in Section 5.1. Then, in Sections 5.2 and 5.3 we explore how it facilitates the development of custom AI products and services using its predefined services and shared open source software, libraries, frameworks, and developer toolset. Finally, Section 5.4 provides a few brief examples of companies that have incorporated AI services into their products and business practices.

5.1. AI Services Overview The AI services available to enterprise and business users can be grouped into five categories: • Built AI building blocks • Hosted ML and AI platform services • Popular software libraries in combination with hardware • Popular AI developer tools and libraries available under an open API • Research software package releases The AI building blocks provide completely predefined services for text processing, image and video analysis, speech recognition and synthesis, translation, and conversation and dialogue processing. For developers looking to customize functionality, the next category consists of ML and AI hosted services. These managed services include AutoML Cloud (for translation, image classification and object detection), Cloud ML Engine (TensorFlow training and prediction), Human-in-the-loop AI, Document Understanding AI, BigQuery ML (for SQL users), Cloud AI Platform Notebooks (managed Jupyter notebooks), Cloud AI Platform Pipelines (Kubernetes Pipelines), and AI Explanations (to explain model predictions).

5.1. GCP AI Services Overview

Google Cloud AI provides a comprehensive AI platform. It offers services for hardware accelerated AI infrastructure, pre-trained AI APIs custom model development, and expert services to help customers accelerate successful AI delivery. Google Cloud AI's pre-trained APIs are the easiest way for developers and companies to leverage state-of-the-art AI in their applications with just a few lines of code, less than an hour, and no machine learning expertise. Customers can also leverage Google Cloud AI's training and inference services with AutoML for computer vision, natural language and translation, and video intelligence, allowing companies to create custom models.

GCP is the only cloud offering differentiated hardware accelerators, including both TPUs and GPUs, with advanced infrastructure optimization like the scaling out of TPUs, and per second billing for GPU clusters. Google Cloud AI also provides MLOps services with MLOps partners to help customers manage their custom ML models and model pipelines throughout their lifecycle, allowing them

to manage the entire AI development and production lifecycle. Google Cloud AI's expert services provide access to Google Cloud AI experts at all stages, from strategy to implementation. Google Cloud AI works closely with partners, from system integrators and consulting firms, to vertical SaaS providers and AI-enabled marketplace companies.

Google Cloud AI offers integrated solutions and services. Google Cloud AI provides customers with packaged and solution-driven offerings for industry use-cases, ranging from specific challenges such as product search, to larger initiatives like enterprise-wide document digitization. Google Cloud AI invests in specialized niche partners with highly differentiated offerings powered by pre-trained and custom developed GCP AI models. Google Cloud AI is also making this expertise available through partner networks for channel sales, hire a partner grouping for Access, and SaaS/ISV programs for partners with built on GCP offerings.

5.2. Integrating AI with Google Cloud ML Engine

A broad variety of pre-built ML solutions, as well as pre-trained APIs, are provided by Google Cloud. With these solutions, a user can execute innovative deep-learning-based tasks without creating or training any ML models. If a user wants to create a custom model in a service manner, GCP provides BigQuery ML for analytics users that wish to use standard SQL. Users can create custom ML models in a notebook experience with Google Colab or with TensorFlow, Keras, or PyTorch, which are natively supported and managed by Google Cloud AI Platform. For advanced/deep ML users who have data engineering or data science backgrounds and wish to develop ML with their own programmatic steps, Google Cloud's AI Platform provides an end-to-end environment, covering model building, management, deployment, and monitoring. Google Cloud AI Platform provides a PaaS-type ML platform, whereas Google Cloud's managed ML APIs and BigQuery ML provide a SaaS-type ML platform. Users looking for SaaS options can take advantage of Google Cloud's managed ML APIs and BigQuery ML, and users looking for a PaaS option can leverage Google Cloud AI Platform [36,40-42]. While GCP's managed ML APIs can handle most of the business use-cases for companies looking for fast and efficient solutions, those wishing to build a custom model that requires a slightly different architecture can utilize Google Cloud AI Platform, together with AI tools and libraries like TensorFlow and AutoML, to build and manage the solution for their needs. For custom solutions that require flexibility or bring business logic pruning or

training inferences close to on-prem or other data processing, Google Cloud also provides a powerful Hybrid-ML solution to cover these use-cases. GCP has recently focused on bringing local solutions closer to users by combining its AI Platform with Anthos.

5.3. Google AI Tools and Frameworks

Google AI has created a range of tools to help you either improve upon or integrate AI capabilities into your project. Each of the tools listed below has a clear way to integrate them into your existing solutions, whether they be browsers or applications.

TensorFlow is an open-source library for machine learning and neural networks, originally developed for internal use. It is now perhaps the most established and popular deep learning framework. TensorFlow can be installed on a variety of platforms such as Windows, macOS, and Linux devices. It also has the capability to utilize both CPU and GPUs for processing, a number of which are supported for use [40,43-44].

DeepMind Lab is an open-source 3D game engine built for research in AI, particularly reinforcement learning. It uses the same rendering library as Quake III Arena, as well as some additional features for the rendering. DeepMind Lab has capabilities not present in traditional game engines, such as a global visual system to create semi-3D-like renderings to be used in guidance tasks. It is built for use in a variety of tasks, including navigation, memory, and social interaction.

Cloud TPUs are specialized chips for AI computations, originally designed to accelerate the training of deep learning models. Since we first launched them, we added Cloud TPUs to Cloud and have scaled them in response to our customers' needs. You can now access the most powerful available TPU, which contains 256 chips, offers 4 petaflops of performance, and is available in Cloud for a much lower price than other clouds that offer GPUs.

5.4. Case Studies of GCP AI Implementations

Google Cloud offers a bevy of tools and frameworks to implement projects that use AI or ML, and many organizations have already harnessed these to great success. Here are a few case studies of companies from all sectors of business that have creatively implemented AI using GCP and its AI services.

Coca-Cola had a problem with its supplier relationships. It had lots of suppliers that spanned the globe and lacked a way to create a cohesive strategy for these

groups. To combat this problem, it created a Global Business Services team to set a single principle for how they were going to work with their suppliers. The team consolidated sellers and created support functions capable of working together across markets to create a more efficient and effective strategy. Still, Coca-Cola had so many suppliers that within the glucose business, there could still be 15 or more suppliers competing for a single source of supply. The supplier consolidation process, therefore, was key to developing relationships with the few selected suppliers and keeping them happy. By implementing analytics and GCP tools, Coca-Cola's model could simulate efforts across buying power consolidation and blending stream using models, allowing the team to follow a more complete process.

Another creative GCP AI implementeer is Johnson & Johnson. Johnson & Johnson is known for their medical devices, consumer health, and pharmaceutical products. Over the last 25 years, they have invested billions of dollars in numerous digital health technology startups that have eventually exited via initial public offerings and mergers and acquisitions. They have also partnered with various companies, but their overall strategy still remains unknown. However, in recent years, J&J has ramped up efforts to leverage machine learning, virtual reality, and artificial intelligence algorithms. With the help of a specific application, the company is able to utilize AI and the capabilities around it for its computer vision projects.

6. Comparative Analysis of AI Ecosystems

The three major hyperscalers, AWS, Azure, and GCP, have developed unique strengths and weaknesses in their respective cloud AI ecosystems through their unique product portfolios. One of the main differences between these platforms is accessibility. Many AWS AI services are low-hanging fruits. For example, certain APIs allow many developers, even without engineering experiences, to experiment with large-scale AI in their applications within minutes. GCP greatly invests in democratizing ML too, with AutoML and many major covered APIs, including Vision and Natural Language. On the contrary, Azure has invested heavily in tooling and MLOps for data scientists and ML engineers [3,45-47]. Many Azure AI products are also low-hanging fruits as they tackle the problems of experimentation, deployment, and scaling ML today. While there is much tooling around Python for data science, there is no good production tooling

around either Java used for big data processing or C++ used for the inference speed at scale for AI practitioners who work for enterprises or places where ML is deployed today. Azure is clearly the best choice when the priority is to develop and deploy production ML workloads at scale in enterprises.

The second difference between these cloud AI ecosystems is their ability to serve specialized vertical AI. On the one hand, Google has committed decades of research in core Computer Vision, NLP, Speech, and Video areas [5,19,]. GCP's footing in these verticals is very strong based on its open-source leadership, its research in public Speech and Translation benchmarks, or its pioneering achievements in open-sourcing linear model for broadening the understanding of ground truth generation for picture tasks, among many others.

6.1. Strengths and Weaknesses of Azure, AWS, and GCP

Cloud platforms are today the basis of several AI services and solutions. Now, we compare different cloud platforms to see their advantages and disadvantages. In particular, we focus on the comparison of the AI services and solutions provided by Azure, AWS, and GCP. Although the major cloud service vendors do not reveal their total costs of providing the services in their cloud platforms, considering the fact that these three cloud platforms host a major portion of all worldwide available AI services, we will highlight their strengths and weaknesses so that the customers can choose the most appropriate cloud platform to provide their AI services.

Microsoft Azure provides a high-quality set of machine learning and AI services and solutions. Its integration with the Microsoft software stack is another major strength of Azure. GCP is also a leader in many cutting-edge AI technologies. It excels in APIs related to language understanding, translation, and the largest models related to language-based generative models. However, GCP is not very active in some AI areas such as vision-based services related to image and video recognition. Also, customers can expect some delays in key enterprise AI trends—multimodal models and enterprise custom tailored models. AWS is primarily a comprehensive cloud platform that offers a wide range of services across virtually all solution spaces. At the same time, it also commits a large number of resources to remain a leader in AI services and solutions.

AWS, Azure and GCP compete actively to remain at the top of the AI services and solutions. Their major strengths and weaknesses in AI service areas push them to remain competitive. AWS has the largest number of AI services in total,

as it has been committed to them for a long time. However, AWS does not span across as many major AI services and domains compared to Azure and GCP. Overall, we see that Azure, GCP, and AWS remain the leaders in deploying and improving the AI services on their respective cloud platforms.

6.2. Cost Analysis of AI Services

Cost-analysis of AI cloud services is essential for both enterprise architects and executive management to ensure that the selected services are financially sound. It is quite common for enterprise cloud bills to be excessively high due to inefficient services selection and configuration. Some of the factors affecting costs are:

• Resource used and time taken – there are typically different types of resources and the charges are different based on the amount and duration of resource use.

• Infrastructure – billing is not the same for on-demand resource use versus pre-selected reserved resources. Some services allow for greater cost efficiency through batch processing or spot instances.

• Models used – While the cloud platforms offer pre-trained models, ready-to-use AI services are not available for all use cases. Custom solutions using pre-trained open-source models or tools may result in lower costs.

• Upkeep of deployed services – post-deployment monitoring and upkeep of the deployed services may also incur costs due to need of scheduled VMs, or the enterprise may need to resort to development of a custom solution on the cloud infra.

6.3. Performance Metrics and Benchmarks

We strongly believe that performance benchmarks along with publicly available task results and model cards should be the primary way to evaluate and compare products for cloud AI. These comparisons should be done for a specific business problem of interest, using the provider's help for any integration and support. Other metrics like scalability, general support, data preparation tools, and packaging are all secondary.

The only reason to use performance metrics other than specific problem benchmarks is to evaluate unknown problems. First, cloud AI providers should be developing and advertising task-wise semantic benchmarking for their major cloud AI services packaging actual deployed products, or better – no task-wise

semantic major differences amongst similar products. Secondly, model cards should accompany every major offering to at least partially disclose how the product fared in multiple benchmarks across many datasets and how it was trained. Model cards should also note all expected limitations of the released model and its corresponding datasets, and any major additional considerations needed when utilizing the models.

Public web service support for major deployed models should be done within the bounds of the model cards, and abide by 3rd party approval to ensure provisioning of only use-approved sensitive datasets. Major companies allow their cloud AI services to also provide links to task common benchmark datasets, and some have curated public model cards, possibly due to the huge interest in AI/NLP on common datasets.

7. Challenges in AI Integration with Cloud Platforms

Cloud platforms today are uniquely positioned to enable improved AI adoption and delivery through convenience, scalability, and availability of diverse workloads and stakeholders. However, a number of challenges hinder deeper AI integration with cloud platforms. Here we describe some of the more prominent such challenges.

7.1. Data Privacy and Security Concerns

Numerous legal and compliance requirements exist around data privacy and security that limit AI integration with cloud platforms, which are often inherently shared concepts. Data must be kept secure and private, while providing access to multi-party workloads for training and use of AI systems. Multi-party workloads by their very nature involve several entities sharing and processing the same data without visibility into the inner workings of each other's AI models, nor should they be allowed to see or modify each other's data. These concerns are exacerbated for moderation use cases, e.g., moderation of healthcare-related worker search queries, which may contain sensitive and personally identifiable information. Model confidentiality and data privacy on the cloud are critical requirements when attempted to be met by the cloud service provider — and

when they are not, reduced trust among organizations leads to a bottleneck to AI adoption.

Though cloud computing has become a pervasive element of business today and offers a wealth of potential for companies throughout every industry, there remain a number of challenges that can impede the successful integration of AI models with the cloud. Security is chief among these problems. The ability for cloud operators and customers alike to store and share confidential data is at the very core of cloud computing's promise for businesses and consumers. However, this usage raises several gravely important security and privacy considerations, especially when it comes to the development and deployment of machine learning models.

The problems associated with privacy on cloud platforms is more urgent than with traditional database storage. In a cloud implementation, the client simply transmits its data into the cloud via the network and it usually can retrieve the results after processing. However, the cloud model can easily allow the cloud provider full access to the content of the data, thus raising significant privacy concerns, especially for sensitive information such as images, healthcare, financial, or personal information subject to regulations. More specifically, during the training phase, the cloud provider has access to the sensitive training data and possesses the ability to leak this information back to anyone, perhaps by maliciously reprocessing the data and returning it encrypted and memorizing the neural network. In inference mode, privacy can be breached even when the cloud provider does not get access to the actual images triggering the model. Data sharing agreements need to be established and contracts for security and privacy defined between the parties. While such problems exist for all cloud vendor clients, companies in certain sensitive domains, such as banking and finance, observe these precautions to avoid compromising their customers' sensitive data.

7.2. Scalability Issues

Cloud platforms have provided services and tools to cater to machine learning and AI model development built on the concept of auto scaling, simple pay-as-you-go pricing and the power of APIs. Machine learning workloads have several unique characteristics when compared to traditional software workloads. For example, it requires a frictionless model development environment. A large number of developers work on research problems associated with the development of machine learning models using a variety of algorithms.

Additionally, the time it takes for training machine learning models is an order of magnitude longer than traditional software workloads, ranging from seconds to hours and days, depending mainly on data volume and model complexity. In addition to training, scoring or generating inferences from the model to test if it is learning is also a task that could take time, especially during the first few iterations. Every machine learning developer usually runs through a cycle of trials with variation in the algorithms used before arriving at a working model that can take hundreds and thousands of hours for large-scale problems. Naturally, the model that is developed needs to be built for scalability that allows hundreds of operations to work in parallel in the production phase where it could actually draw inferences on business impacting problems.

Cloud platform providers have worked to provide tools and services that expose the capabilities for parallelization when building models as well as the capability to support technologies such as transfer learning and federated learning to efficiently train models at scale. However, cloud has limits on scaling compute resources both in the multi-tenant nature of the service as well as the core limits in each underlying node. For some very specialized problems, this limit could be hit. Cloud providers also have inherent limits on scaling technologies mainly due to risk mitigation strategies related to security, reliability and stability, as they build the services in a shared manner. Some of the popular limitations are associated with pricing quotas for burstable nodes, limits on concurrent requests per instance, limits on the number of operations that can be executed in batch mode as well as other limits associated with pipelined operation durations.

7.3. Integration Complexity

Traditionally, working with machine learning and AI required a great deal of knowledge and expertise in areas such as computer science, statistics, and mathematics. However, the increased demand for AI has resulted in the development of several cloud-based products and services that can be used by both professionals as well as amateurs. All three cloud giants have products and services that literally cover the entire lifecycle of AI.

Even so, the availability of sophisticated tools does not automatically make it easy for client organizations to integrate AI pipelines within their applications or the cloud platforms themselves. By virtue of their elaborate structure and architecture, AI pipelines are not easy for the average tech teams in companies to implement. An AI pipeline is more than just a machine learning pipeline,

comprising stages such as creating a model, validating it, and deploying it. Typically, an AI pipeline integrates different data sources, combining data engineering tasks, and various other business systems throughout an organization that may already be in place. It might also interface with various third-party vendors of data and services, especially in the area of natural language processing, machine vision, and generative models, that are growing at a heady pace.

In addition, ML and AI do not always provide tangible business benefits at the end of the day. One of the major needs for implementing machine learning models is to purposefully define goals for them at the start, and keep track of the right metrics to monitor for throughout their lifetime. Organizations must also be prepared for the drama of deploying imperfect models that might serve to deliver business benefit, perhaps in phases, instead of waiting for the proverbial day when the fully-fledged 'perfect' AI model goes live, as that might never happen.

8. Future Trends in AI and Cloud Integration

Artificial Intelligence is expected to witness remarkable growth in the upcoming years. By 2030, AI is predicted to become a cumulative more than $15 trillion industry, outperforming both the Industrial Revolution and the invention of the steam engine in terms of economic growth rates. Several emerging technologies, such as neuromorphic computing, quantum computing, generative models, foundation models, and natural language programming, are expected to boost the performance of AI-based solutions. In the upcoming years, the combination of IoT, AI, and edge computing is predicted to streamline business operations in industries such as retail, manufacturing, healthcare, and smart cities. Edge ecosystems are not only expected to improve the efficiency of businesses across these industries, but also better employee experiences, consumer experiences, and patient outcomes.

Portfolio vendors are investing significantly in AI, specifically for edge computing. They are working on integrating next-gen infrastructure components at the edge with cloud ecosystems. By 2026, 75% of enterprise-generated data is predicted to be processed at the edge of networks, compared to less than 10% today. Currently, enterprises are in the early stages of realizing the potential of AI. AI can improve revenue by enhancing consumer experiences through

personalization, augmenting employees by reducing time and effort to perform tasks, and increasing the efficiency of existing business processes and operations. Thanks to advancements in cloud ecosystems, the costs and time taken to implement enterprise-grade generative conversational applications will come down significantly. By 2025, the number of organizations using AI tools to create new products will triple compared to today. The democratization of AI has just begun, but it is expected to accelerate rapidly.

8.1. Emerging Technologies in AI

As discussed earlier, the AI revolution demonstrates huge technological investment across the world, with significant contributions from almost all private software and technology companies. As a result of their AI priorities, we see quality products and models from various companies. While LLMs have grown into a standard AI interface, the AI research ecosystem continues to work on novel AI models and architectures that boast better alignment, higher capabilities, or better training paradigms. In a world with a multiple chatbot scenario, users want to select the one that suits their needs best. Some companies have taken this a step further by allowing users to create personalized chatbots with their favorite voices. A video messaging software also debuted a similar AI character capability in its product library.

A major tech company, since its early days, has foreshadowed novel architectures, whether it be attention-based transformer models, neural style transfer models, or prompting techniques that include few-shot learning and in-context learning. This legacy carries on, where, leveraging Large Language Models, their research team created LLM powered multimodal models capable of text-to-image synthesis and text-to-video creation. These models have emerged with either competitive capabilities or better efficiencies and alignments than their predecessors. Such an unprecedented improvement in alignment and capabilities has led to novel uses of AI, with many people across demographics using its APIs from websites, mobile applications, and even within video games, to name a few. Products for coding, video editing, and image generation have made using Generative AI for hobbies more accessible than ever.

8.2. The Role of Edge Computing

Edge computing is a distributed computing framework that brings the computation and data storage closer to where the actual need is. In other words, in edge computing, data processing takes place closer to the devices collecting

data rather than relying solely on a central data center that is usually located miles away from the source of the data. While Cloud computing relies on centralized data centers, edge computing relies on numerous smaller distributed data centers. It is the deployment of localized resources such as switches, routers, gateways, servers, and storage.

Edge computing employs the basic geographical proximity principle of how people naturally prefer to rely on products, services, retail outlets, and facilities that are physically closer to them than to those situated at great distances. Over the years, we have become accustomed to how production facilities are built closer to where customers are located. Products are shipped to their customers from these facilities rather than from central production locations that may be in a different continent.

The current leader in the public Cloud space offers solutions that enable customers to run workloads at the edge. Its IoT solutions allow the billions of devices worldwide to gather data. These devices communicate with the rest of the world via Edge Gateways and Edge Devices that leverage hardware acceleration technologies. There is collaboration with third-party hardware manufacturers to improve existing edge capabilities. Other platforms also offer a variety of Cloud and edge services targeted at different market segments.

8.3. Predictions for Cloud AI Ecosystems

We are more likely to see new innovations in the form of combining the existing techniques in a novel way, rather than creating generic new algorithms. There are discussions regarding AI Windows; Moving Away from Labeled Data; AI for Richer Interaction; Generalist/Multimodal Models; Prompt Engineering; AI Helps with AI; Using AI in Every Step; Diffusion New Technologies and more recently support for AI for Graph data and Generative Transformers are some of the predictions for Computer Vision. Getting AI-ready Enterprises; Cloud First Approach for AI; Open-source models from Cloud Providers; MLOps Best Practice of the Industry; Cloud Support for Finding AI Initiatives; New Cloud Services for GPU for Model training; Improved Cloud Providers Hardware On-Premise; Growing Portfolio of First-party Connector with Industry-Specific App; Privacy Preservation by Cloud Offerings; Putting more power into the hands of Non-Data Scientist; More and more Companies Offering SaaS out of AI in the Cloud are some other experts' opinion for collaboration of Cloud and AI. PaaS and SaaS AI Services: make Your Life Easier. As an industry, we will see new

business models emerging; enterprise AI will get deployed at scale; with 'AI Factory' models and Cloud Powering Internal Enterprise AI. For developer roles, the developer machine will tend to get redefined with hosted IDEs; while mission-critical applications will reside in the cloud; and helping Cloud Companies with Business Models will Help AI-Providing Enterprise. Data Garage will Drive Composable Data; Future SaaS Apps will Leverage LLMs; along with Revenue Growth and more advanced deep learning; using AI to Discover AI Models; Al Discovery; people will be rewarded by pushing the AI frontier; Cloud Providers Will Improve Discovery of Models; many More Medical Services will Leverage AI; and Accurate Models, and running Behind the Scenes for You, and AI-Default will put the "I" back in AI. These predictions and redefine the relationships between business, technology, human activity and nature in the civilization in the next 10 years.

9. Best Practices for Successful AI Integration

In order to get desired business results, organizations need to focus on certain guidelines as best practices for the successful adoption and integration of AI initiatives into their enterprise cloud platforms and data landscape. Below we discuss such practices in detail. In any organization, having a clear vision for AI as part of a digital strategy across the enterprise is important. The organization should understand what substantive processes or situations should be augmented or improved by applying AI, as well as the business problem(s) being solved. This understanding can both drive AI integration into production, as well as enable close alignment between AI data practitioners and business stakeholders. Failure to align an AI project with a business objective can result in building and deploying algorithms that do not have the potential to create significant business value.

After establishing return on investment, it is important to invest resources in developing a solid data architecture plus a data governance and management policy, with an emphasis on the accessibility, accuracy, and organization of data, to facilitate the data tasks required to maximize the usefulness of data for the business. Monitoring is essential to ensure that the AI system continues to function as intended and evolves gracefully as new business challenges arise and as data and models evolve. Transparency and good documentation of the AI system throughout the development and deployment process are important. In

addition, the AI team should empower users to ask questions and even experiment with the system, either through formalized user-testing sessions to the enterprise data team.

9.1. Planning and Strategy Development

Much has been said regarding the impact of AI in organizations, concerning technology, business areas, employees, tasks, and results. However, it all begins with the decision to apply some level of AI in projects and the definition of the way AI can have positive impacts. Prior to funding or allocating personnel to actual project execution, such decisions and definitions need careful and broad discussion within the organization. These need to address issues such as the following, in no particular order: the definition of guidelines and AI policy at a level required by the organization for such new technology; the alignment of the AI-enabled projects with the organization's strategy and goals, and the prioritization of the AI-enabled project pipeline; the allocation of the right level of executive sponsors and stakeholders for the AI-enabled projects; the organization responsible for the AI strategy and policy, project portfolio definition, monitoring and special support, if required; the methods and tools that will be followed and used by the AI-enabled projects, encompassing both technical and non-technical recommendations; the type of support the organization wishes to provide at the project execution level, including education, development, and infrastructure; the ethical issues that need to be addressed during AI project execution; the level of AI project monitoring and oversight, among other issues.

These above-mentioned definitions will vary according to the organization's characteristics, guidelines, and decisions. In any case, the need to carefully define the strategy and the best practices to be followed by AI-enabled projects is of the utmost importance for successful project execution, pre-and post-deployment, as well as for realizing the expected. In anticipation of the exemptions raised during AI project execution, as one size does not fit all, when the cloud platforms package available services as engineering building blocks to speed up AI solutions for organizations without the need to go from scratch, human resources are still required to understand AI challenges, communicate with AI developers, connect the different technological components, validate, and deploy the AI solutions.

9.2. Monitoring and Evaluation

The success of AI projects, perhaps even more so than in traditional software projects, is dependent on careful ongoing monitoring and evaluation of the models and their predictions. Concepts like data drift, model drift, and AI accuracy drift should be on the top of every AI team member's mind as they integrate the models and put them into production — and then every single day of those models' lifecycles thereafter. The concept of observability is a top-of-mind cornerstone in the software development community — how do you expose not just the status but the operation of your software systems to outside inspection. AI monitoring is a distillation of that software observability concept to explicitly address the challenges in monitoring AI models exposed to implementation and usage drift.

Model Monitoring Model monitoring is the most basic type of AI model monitoring. Model monitoring constantly keeps track of prediction results. In the case of models that produce discrete labels as predictions, model monitoring keeps track of prediction counts over time per output category, or label. Monitoring of regression outputs would track the range, variance, and distribution of continuous prediction results. Model monitoring reports when results go outside of previously defined ranges or statistical distributions.

Model Performance Monitoring Model performance monitoring tracks a model's performance with respect to a performance metric during production that was defined as an integral part of the testing and deployment schedule. In supervised learning tasks where the target data is unseen and not subjected to active change, this can often simply be a redetection of the test set. In real-world deployment of production models where ground truth is not known, monitoring input and output data becomes the major method for assessing overall model performance.

9.3. Collaboration and Team Dynamics

Collaboration is a significant part of AI integration because it's so unlikely that a single person has all the skills needed to work on a complex AI project. Many aspects of such a project rely more on general software engineering than on unique AI knowledge, but expert input is needed in many areas, such as concept definition, data sourcing and treatment, model selection, and annotating and evaluating results. Other areas need different types of experts—most importantly, good UX designers and researchers. An AI research scientist can come up with a great model that solves a specific business problem, but simply integrating those

results into a product is often not sufficient for success. In the end, at least some users must interact with the resulting program enough to see concrete business value, so it needs to look and behave a certain way. The quality of the users' interaction beats the quality of the AI math nearly every time in terms of overall project success.

Thus, a collaborative team-problem approach is usually needed, especially in the UX area. Strong-loop or continuous UX testing needs to be done through the whole life cycle of an AI product. During the modeling phase and beyond, a small group of representative users can collaborate on use definition and data labeling. Simple tinker toys can be made for them to use in evaluating intermediate AI results. Samples of the data being processed by the AI can be used for quick tests on the UX with relatively easy evaluations and feedback. Such collaboration keeps the users involved but doesn't overburden them.

10. Conclusion

Cloud Platform adoption has been rapid and has enabled organizations to readily access and consume infrastructure, platform, and software resources over the Internet. These resources provided by Cloud Providers are currently the backbone of AI Integration as AI models and inferences require massive compute resources and storage, data engineering and data integration tools, modeling and development, DevOps pipelines for regular testing and deployment, tracking of performance and behavior, and finally monitoring and observability tools for analyzing performance issues. Cloud Providers are rapidly expanding their AI ecosystem with required services and tools so that organizations can quickly develop and deploy new AI Model powered applications created by Model developers or curated by business users.

Organizations can reduce the time and cost needed to create new capabilities leveraging AI with these tools, and seamlessly integrate it within their existing process and Data Pipelines which run on the Cloud Provider ecosystem. Once integrated, organizations require proper observability of the AI powered process so that they can monitor the AI models deployed and take preemptive action on model drifts that need retraining and/or validation of their results. Cloud Provider tools enable organizations to track the models that are creating business value or failing to do so. But it is advised to adopt a multi-cloud AI strategy for critical

processes that require high availability and response times. Normalization of AI Model results across various platforms with their own approaches to training and deployment and addressing latency concerns are important challenges to be tackled.

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