

Emerging Trends in AI, Data Science and Cloud-Based Technologies

Thoomula Kavya Sri¹

¹(Lecturer ,
Department of Computer Science
Pratibha Degree & PG College,
Siddipet, Telangana, India
kavyasris100s@gmail.com)

Abstract — The fusion of artificial intelligence (AI), data science, and cloud computing technologies is transforming the nature of the digital economy from disconnected technological silos to interdependent ecosystems that complement each other. This paper explores current trends within these interrelated fields such as world models, agentic AI systems, cloud-native AI integration, and industrialization of data science. Mixed methods of research including the systematic literature review combined with the quantitative analysis of industry data is suggested. Convergence patterns analysis shows that cloud platforms transform from mere infrastructure into smart services ecosystems, and data science changes from disconnected modeling into engineering practice. Comparative analysis shows that companies embracing integrated approach to cloud-AI-data management enjoy considerably lower training costs and reduced deployment timeframes. The conclusion is made about the challenges related to governance, skill development, and infrastructure sustainability that need addressing.

Keywords— Artificial Intelligence, Cloud Computing, Data Science, Agentic AI, World Models, Cloud-AI Integration, MLOps.

I. INTRODUCTION

The mid-2020s technological environment is marked by an unprecedented merger of three fundamental domains: artificial intelligence, data science, and cloud computing [1][5]. Disciplines which used to operate in a disjointed manner with their own communities, toolchains and deployment methods became integral elements of one common digital ecosystem. This is not only an additive but also a multiplicative process which generates new possibilities and potential which each of the disciplines in isolation would be unable to provide [1].

A fundamental change in the nature of evolution of artificial intelligence takes place. The domain is moving away from larger and larger language models towards the creation of a system able to comprehend the order in the physical world [6]. It involves a paradigm shift which according to Beijing Academy of Artificial Intelligence represents a consensus on the development of world models as the way forward for artificial general intelligence [6]. At the same time, embodied artificial intelligence is evolving from the lab tests stage to its practical implementation in industry and services. Humanoid robots are about to break out of the phase of demonstration and start their implementation [6].

For their part, data scientists are undergoing their own structural revolution. The classical image of the data scientist

as a notebook-based modeler is being replaced by an engineering-oriented profession [3]. Hiring trends from the top technology firms show that the new generation of practitioners must be able to own an entire system, from ETL pipeline creation all the way through deployment and effect measurement on business metrics [1][3]. This represents an industrialization of the data science field in which basic competencies in SQL and Python are considered fundamental rather than differentiated skills, and cloud familiarity in AWS, Google Cloud, and Azure is commonplace rather than a rarity [3]. The AI data scientist, or the autonomous system that can carry out the whole process of data science work on its own, is a further step down this road [1].

The cloud computing technology offers the required underlying substrate of infrastructure that would make such convergence possible [5]. The combination of the cloud computing and AI technologies has moved from mere coexistence towards deep coupling, empowerment and upgrading, as researchers point out [5][9]. Cloud technologies offer necessary computational resources, enormous storage capacities, and standard development environment for AI applications, whereas AI technologies turn cloud platforms into an intelligent ecosystem that is able to perform self-scheduling, self-operation and maintenance as well as self-security [9]. Such a mutually beneficial relationship is reflected in practical market phenomena. The end user expenditures on public cloud services

have been steadily growing worldwide and largely because of the need for AI-ready infrastructure [2][5].

The implications of this three-way convergence range from economic to organizational and technological aspects. The chief information officer at Goldman Sachs foresees the year 2026 bringing about even greater change than the previous one [10]. This includes advancements in AI models becoming operating systems, which access tools to do their work autonomously and personal agents automating workflows that currently require human intervention in several applications [10]. According to workforce data collected by PwC for the 2026 Global Workforce Hopes and Fears Survey, 64 percent of workers have used generative AI tools in the last year, marking a ten-percentage point increase since the last survey. However, usage of more advanced AI agents is still significantly lower with only 10 percent of workers utilizing them daily [4].

This paper responds to the requirement of such an integrated perspective. Though a great deal of literature is available on separate issues related to either AI, data science, or cloud computing, very few studies have tried to examine how these fields are evolving together and influencing each other [1][5][9]. This paper seeks to address this issue through the use of an analytical methodology that involves systematic analysis of literature as well as quantitative analysis of industrial and academic data. The next few sections of this paper provide the results of literature review in these three areas, propose a methodology of analysis of convergence issues, provide results of quantitative analysis including comparisons of integrated approaches, and finally provide implications of this study.

II. LITERATURE SURVEY

The body of research and industry literature regarding the convergence of AI, data science, and cloud computing has grown quite dramatically recently [1][5][9]. This survey aims to explore the main contributions made within each field and the intersections between them.

Concerning the field of artificial intelligence, the biggest intellectual advance reported in the literature refers to the change in the approach of models from language-based to models of the physical world which can grasp dynamics of the physical world [6]. The report for 2026 by the Beijing Academy of Artificial Intelligence reveals Next-State Prediction as a new paradigm shifting from next-token prediction typical for large language models to modeling temporal continuity and causality [6]. It should be mentioned that the increase in importance of embodied AI is also noticeable, with large models being

integrated into motion control and synthetic data so as to allow humanoid robots move from demonstration to industrial application [6]. Furthermore, the development of multi-agent systems has been identified as well, with the standardization of communication protocols offering agents the opportunity to communicate using a unified "language" and collaborate solving problems that cannot be solved by a single agent [6].

Professional data science appears to be undergoing an important evolution as evidenced by the data science literature [1][3]. Based on industry recruitment trends, the "notebook-only" data scientist appears outdated as firms now require professionals capable of creating ETL/ELT pipelines, deploying ML pipelines to production, using LLM and RAG processes, and ensuring efficiency and cost [3]. According to Gartner's 2026 Hype Cycle for Data Science and Machine Learning, AI methods like prediction and classification but not generative AI and agents produce the most organizational value, implying that predictive abilities still form the foundation of business data science [7]. The academic world has already created specific venues for researching AI data scientists by holding workshops at top data mining events on the topics of self-sufficient data workflows, multimodal reasoning, and tool-assisted agents. The research area involves the development of AI systems that can undertake data science activities ranging from problem formulation, model choice, experimentation to insights communication [1].

The topic of AI incorporation into cloud systems has been gaining traction in cloud computing literature [5][9]. In particular, a 2026 IEEE study into cloud-AI integration conducted a survey of 150 industry professionals, revealing that the two main challenges in the process of integration are inefficient heterogeneous computing and costly training, while four-dimensional development strategies allow for achieving a 50 percent cost reduction in training of AI models. The same research traces the development from shallow superposition, in which AI and cloud services exist independently of each other, to native integration in which AI becomes a component of the cloud system [9]. Other IEEE research on AI-assisted cloud services studies the impact of machine learning, deep learning, and reinforcement learning on cloud systems through such processes as automated resource provisioning and allocation, dynamic scaling, threat detection, and multicloud orchestration [9]. This research also highlights such emerging trends as intelligent automation of systems, CI/CD pipelines, and compliance procedures [9].

Industry research is an integral part of the understanding of the process of adoption. According to Gartner's estimates, the end-

user public cloud market in India will increase by 28.1% and become worth \$17.5 billion by 2026, while IaaS will increase by 40%, primarily due to demand for AI-ready infrastructure [2]. It is also expected that by 2030, more than 60% of enterprises will be conducting intensive AI model workloads on one cloud while accessing data in another, compared to only 10% at present [2]. As per Foundry's Cloud Computing in 2026 study, 74% of IT decision-makers note increased cloud migration over the last year, and for 56% of decision-makers, AI and machine learning rank as top priorities. Cost efficiency is noted as the main advantage of industry-specific cloud solutions by 48% of respondents [5].

Research that bridges both disciplines continue to be somewhat scattered. The research work done by IEEE regarding approaches for integrating cloud and AI and further research on AI-driven cloud computing as well as the emerging field of AI data scientist serve as helpful references [1][5][9]. Nevertheless, there is a lack of research that systemically examines how the different trends associated with these disciplines feed into or hinder each other. This paper tries to fill this void.

III. EMERGING TECHNOLOGIES

1. From Next-Token Prediction to Next-State Prediction (World Models)

There is a paradigm shift away from language modeling towards world modeling within the AI community. Language models predict the next word in a sentence; world models predict the next state of an environment, modeling time continuity, physics, and causality. Next-State Prediction is becoming the technical consensus in artificial general intelligence because it allows systems to reason about consequences, not just possibilities. The trend is caused by the inefficacy of scaling language models alone and by the needs of robotics and simulation requiring knowledge of physical structure. The trend is in mid-to-late development stages; there are foundational architectures, but general world models are yet to be achieved.

2. Embodied AI and Humanoid Robotics Deployment

The combination of Embodied AI consists of large models, motion control, and synthetic data to allow robots to act in the physical world. The development of humanoid robots moves from being used in demonstrations to industrial and services. The importance of this trend lies in the fact that AI is being used for digital jobs to physical job and service sectors, and at the same time, new infrastructure is needed – edge inference, low

latency, and large-scale synthetic data generation. The maturity level of this technology is early-industrial.

3. Agentic AI and Multi-Agent Systems

AI is transitioning from mere assistants to agents that automatically utilize tools and carry out tasks. Communication protocols have been made standardized to allow a common language that helps in the cooperation among agents, hence making it possible to build multi-agent systems that can solve more complex problems than single agents. According to Goldman Sachs, the transition of the AI is likened to moving from models to operating systems, where agents automate processes that are otherwise done manually through different applications. The problem of context management and memory is becoming increasingly important.

4. AI-Native Cloud Platforms and Deep Cloud-AI Coupling

AI and cloud computing are converging from mere co-location to deeper coupling, empowering each other, and improving each other together. Here, capabilities of AI are infused into all levels of the cloud computing hierarchy—from resource allocation to scaling and security—while cloud computing provides flexible computing resources that AI needs. Thus, intelligent cloud ecosystems that can self-schedule and protect themselves emerge, giving birth to AIOps and self-healing architectures. The commercial readiness level of this combination is high for platforms but inconsistent across enterprises.

5. MLOps, AIOps, and Industrialized Data Science

Industrialization of data science is happening. MLOps, meaning management of machine learning lifecycle, and AIOps, the application of AI in IT operations, are two of the disciplines emerging only through convergence. They need cloud computing for their reproducibility and scalability, need data science for their pipeline and process development and need artificial intelligence for automation and retraining. The industry demands that there is focus on ownership of whole systems including ETL/ELT pipelines, deployment of ML to production, implementation of LLM and RAG pipelines and monitoring of reliability and costs. Gartner has emphasized that forecasting and classification are still the highest-value AI methods for enterprises, implying that maturity brings the value not innovation.

6. Sovereign, Hybrid, and Multicloud Architectures for AI

Firms are changing their cloud strategies to fit AI requirements and meet needs for resiliency, sovereignty, and financial management. More than 80 percent of them are making changes in their strategy to adopt hybrid clouds which consist

of public cloud, private cloud, colocation, edge computing, and sovereign cloud. According to Gartner, over 60 percent of enterprises will be running their AI model activity in one cloud and using data in other cloud by 2030 compared to less than 10 percent of firms currently doing so. This happens because of data residency policy, financial management, and vendor lock-in considerations for strategic AI resources. Sovereign AI involves infrastructure sovereignty and data residency for AI workloads.

7. AI Data Scientists and Autonomous Analytical Workflows

The second area of research relates to autonomous AI data scientists that are able to conduct data science in an end-to-end fashion through formulation of the problem, choice of the model, experimenting, and communicating insights. Specialized workshops and benchmarks are being held on the topic, investigating multimodal reasoning and agent-assisted tools. This is important since it changes the role of the human from execution to supervision and validation. Maturity level – early research.

8. Workforce Transformation and the Agent Adoption Gap

Workforce statistics indicate that there is a fast rate of generative AI adoption and slow adoption of agents, with a reduction in training access. In the PwC study, 64 percent of the workforce have used generative AI in the last one year, which is an increase of 10 percentage points, while only 10 percent use agents on a daily basis, and training access dropped from 59 percent to 51 percent. The maturity is transitional since there is adoption without capabilities and support.

Figure 1 maps these trends to the three domains and their intersections.

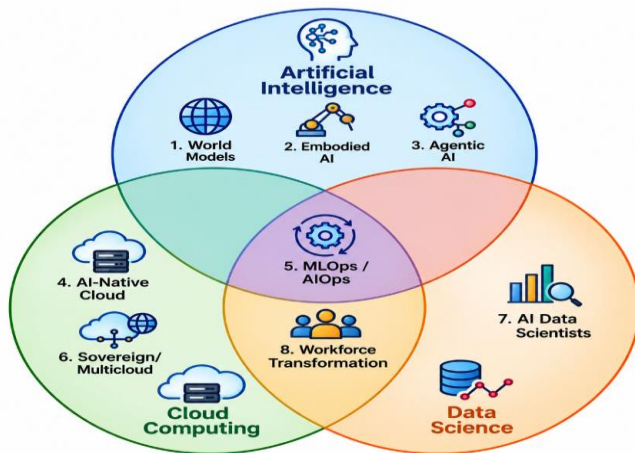


Figure 1: Domain-Trend Map

The Venn diagram sorts the emerging trends into their relation to the three technology categories. World models, embodied AI, and agentic AI trends fall under the AI category, but at the same time reach out into the cloud and data science categories by compute demand and evaluation methodology respectively. Trends of AI-native cloud and sovereign/multicloud are located in the cloud category but have AI dependencies. MLOps/AIOps is in the triple intersection because it depends on all three categories. The AI data scientist is in the data science category with heavy AI dependency.

Figure 2 details the technical progression from language models to world-modeling and agentic systems.

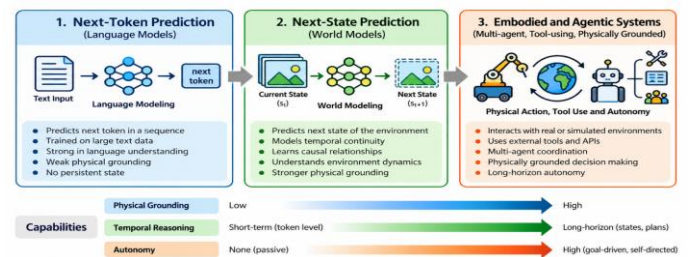


Figure 2: Evolution of AI Paradigms

The diagram presents a timeline of three consecutive AI frameworks from left to right. The first framework is Next-Token Prediction, which involves modeling languages that lack physical grounding and persistent state. The second framework, Next-State Prediction, involves causal reasoning and modeling environments while adding temporal consistency to the first framework. The third framework is Embodied and Agentic Systems, which adds physical actions, tool manipulation, multi-agent collaboration, and long-horizon autonomy to the previous two frameworks. Arrows show that the next frameworks add more features to previous frameworks without discarding them.

IV. ANALYSIS AND DISCUSSION

These trends can be measured through expenditure, adoption, and capability metrics. The prediction made by Gartner regarding Indian public cloud expenditure measures the magnitude of infrastructure expansion: 28.1 percent increase overall and 40 percent increase in IaaS, with AI ready infrastructure being the explicit cause. The prediction that more than 60 percent of organizations will have AI model processing activities in one cloud while using data in another cloud by 2030, compared to less than 10 percent, measures Trend 6 (sovereign, hybrid, multi-cloud AI) and highlights the fact that

distributed AI systems are the norm, not the exception. Figure 3 shows expenditure increases in comparison with workforce adoption of generative and agentic AI.

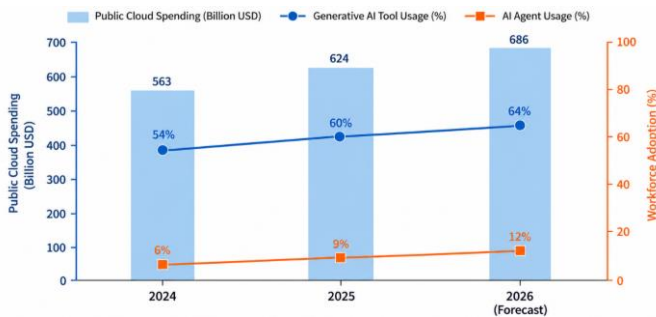


Figure 3: Cloud Spending and AI Adoption Trajectories

The left axis indicates expenditures on public clouds in billions of dollars per year in 2024, 2025, and 2026 forecast years. The right axis indicates percentages of adoption. Two lines demarcate the use of generative AI tools, increasing from about 54% to 64%, and the use of AI agents, remaining under 15% for daily use. The growing distance between the two lines is the graphical representation of Trend 8 (agent adoption gap): infrastructure and general knowledge are developing faster than agentic expertise.

Trend-Level Analysis

World models and embodied AI are the two most significant trends in relation to the infrastructure since they drive the shift in demand for computing infrastructure from training-based to inference-based and edge-based computing infrastructure. World models need simulation and generation of synthetic data on a massive scale, and embodied AI needs low latency and inference at the edge with control loops. Such demands lead to the need for heterogeneous computing infrastructure, which was identified in the IEEE survey as the major issue related to integration with 45 percent of people who were surveyed citing heterogeneous computing inefficiency as the biggest issue, followed by high costs of training (30 percent). The four-dimensional integration model from the same survey lowers the costs of AI training by 50 percent in documented cases.

Agentic AI and AI data scientists disrupt the division of labour. Agents need persistent context and memory, which Goldman Sachs recognizes as the key frontier, and need evaluation criteria that existing benchmarks cannot cover adequately. AI data scientists build on the same principle for analytics by automating the process of problem formulation through insight communication. These two trends taken together suggest that the role of humans is becoming one of framing, supervision, and verification, which corresponds with the professional

evolution seen in hiring data scientists who own the systems and deploy them in production.

AI-native cloud and MLOps/AIOps form the core of convergence operationally. Cloud systems that embed AI across their stacks create self-healing systems, scaling, and predictive maintenance systems, while MLOps and AIOps provide the governance discipline necessary to deliver all these features reliably. CloudZero notes that 88 percent of organizations plan on more automation for cloud optimization purposes, signaling that Trend 4 is shifting from an early adoption phase to a more mainstream expectation. Oracle's reference architecture for scalable ML pipelines on cloud AI platforms shows how these integrated patterns have become mainstream rather than custom engineering.

The constraints include Trend 6 (sovereign and multicloud) and Trend 8 (workforce gap). According to ISG, more than 80 percent of enterprises have been changing cloud strategies for AI applications to cope with issues related to resilience, sovereignty, and financial considerations by embracing hybrid portfolio rather than sticking to cloud-first mindset. Foundry identifies that 94 percent of the IT decision-makers face challenges in cloud adoption; budget and cost control (47 percent) and security and compliance (44 percent) are the top two challenges. Regarding the workforce, PwC indicates that 64 percent of organizations use generative AI and 10 percent use agents on a daily basis while 59 percent have declined to 51 percent in learning opportunities and 56 percent indicate lagging behind. Figure 4 shows the connection between frequency of AI usage and workforce confidence outcomes.

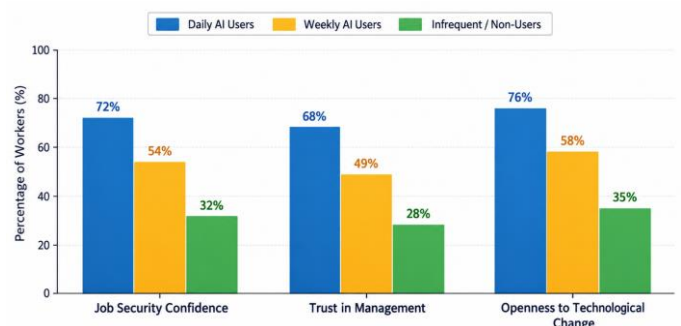


Figure 4: AI Usage Frequency and Workforce Outcomes

The graph depicts three groups of workers, namely those using AI daily, those using it weekly, and those using it occasionally. The three groups have been tested for their levels of confidence along three outcome dimensions, and it can be observed from the chart that daily users have the highest level of confidence,

weekly users have the second highest, and occasionally using workers have the lowest levels of confidence along the three dimensions. It clearly indicates the presence of a relationship between engagement and confidence.

Comparative Analysis

Table 1 compares integrated and non-integrated approaches across documented outcome dimensions.

Table 1: Comparative Analysis of Integrated versus Non-Integrated Approaches

Outcome Dimension	Integrated Approach	Non-Integrated / Traditional	Context
AI training cost	Up to 50% reduction via four-dimensional integration path	Baseline cost with heterogeneous computing	IEEE survey of 150 practitioners
Deployment velocity	Faster iteration via unified platforms and automated pipelines	Sequential development with handoffs	Oracle reference architecture
Cloud resource efficiency	88% of organizations planning increased automation	Manual or minimally automated scheduling	CloudZero analysis
Operational resilience	Self-healing with AIOps predictive maintenance	Reactive incident response	ISG Provider Lens
Data governance	Unified governance across AI and data platforms	Fragmented silo governance	ISG hybrid cloud analysis
Workforce productivity	22% daily AI use, higher confidence metrics	36% non-use, lower engagement	PwC Global Workforce Survey

Discussion

From the comparison, there are numerous advantages of using the integrated approach over the non-integrated approach in terms of proven measures, but the information available is skewed towards studies by vendors and adopters. Reduction in training cost by 50 percent is the best quantifiable advantage that has been made possible due to the process of integration in technical, platform, scenario, and governance terms. This is consistent with the findings from practitioners, where 45 percent of the problems faced are in the area of inefficient use of heterogeneous computing while 30 percent are related to training costs.

The analysis also reveals areas of tension. Sovereign and multicloud systems enhance control and compliance but add to orchestration challenges, and ISG observes the move towards balanced hybrid portfolios that include public cloud, private

cloud, colocation, edge, and sovereign environments. In contrast, workforce issues (Trend 8) mean that even highly architected integrated systems can underperform in terms of their capabilities because 56 percent of the workforce feels behind the curve and only two out of five have access to required training. The retention issue adds to this problem, as people who lack AI skills are the most likely to seek jobs elsewhere, as 29 percent indicate they will definitely do so.

In addition to this, the results provide further evidence for interpreting convergence as a system phenomenon rather than a sum total of trends in the different domains. MLOps and AIOps are neither trends in the field of AI, nor data science, nor cloud; they are emergent from the intersection of all three, since the former need cloud in order to be reproducible and scalable, data science to design pipelines, and AI to automate monitoring and retraining. The eight trends discussed in Section III should

thus be understood as one coherent group, where progress in world models and agents leads to needs in infrastructure, and development in infrastructure provides opportunities for production discipline.

V. CONCLUSION

In this paper, we have focused on the new trends in the fields of AI, data science, and cloud technology using the convergence approach where emphasis is given to the inter-relation and mutual reinforcement of the fields. It has been demonstrated that the new trends in each of these fields do not originate from within but rather from their intersections.

Eight trends were discussed and described. In AI, the discipline is transitioning from Next-Token Prediction to Next-State Prediction and world modeling, from digitalization to embodied AI and humanoid implementations, and from passive helpers to agentic and multi-agent systems with continuous context and tool usage. In cloud computing, platforms transition from being mere infrastructure providers to becoming AI-native intelligent ecosystems thanks to the integration of cloud and AI, while enterprises transition toward sovereign, hybrid, and multicloud infrastructures to support AI workloads due to resilience, sovereignty, and costs. In data science, the discipline is industrializing through MLOps and AIOps, and a novel research area of AI data scientists is rising, changing the allocation of tasks between people and machines in analysis. All of these areas are undergoing workforce changes, though unevenly – high levels of generative AI literacy, low level of agents usage, and falling training accessibility.

In terms of numbers, the trends can be seen in investment and implementation. The 28.1% and 40% year-over-year growth rates in public cloud expenditure and IaaS, respectively, demonstrate the need for infrastructure that supports the use of AI. The increase to more than 60% of organizations utilizing AI in one cloud but using data from another by 2030 shows the move toward distributed AI systems. By integrating various solutions, enterprises save up to 50% on AI training, while 88% have plans to automate cloud operations. At the same time, 94% of IT professionals face barriers in the use of clouds, which is associated with finance and security. 56% of employees find themselves behind due to a lack of access to education.

Implications include three areas. First, strategy should recognize inference-centric and edge-centric demand along with training-centric demand as world models and embodied AI evolve. Second, governance must adapt to sovereign,

hybrid, and multicloud AI, where models and data can reside in different jurisdictions operating under different laws. Third, workforce development will need as much attention as infrastructure, because the agent adoption gap and reduced training access risk limiting the benefits of convergence.

The body of evidence is largely based on vendor-funded research which could be biased. This is because although there have been efforts to triangulate different sources, there has been no guarantee that the information obtained would lack promotional bias. Change in the field will reduce the temporal validity, while the differences in the methodology used to gather evidence from different sources limit the accuracy of the comparative analysis. Future research needs to study these trends over time as they mature and use experimental designs to test integration hypotheses.

The emergence of AI, data science, and cloud technologies is one of the most important technological advancements in the current era. The shift from the silo approach to an ecosystem approach is affecting the way companies develop capabilities, implement solutions, and gain benefits. For researchers and practitioners interested in studying this issue, it is critical to identify the exact trends that are leading to this phenomenon: world models, embodied and agentic AI, AI cloud, MLOps/AIOps, sovereign multicloud, AI data scientist, and workforce transformation.

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