AI-Powered Cloud Infrastructure Automation

Dimitris Plexousakis
Asst Professor

Abstract

Cloud automation fuels efficiency, resilience, and agility, yet many deployments remain only partially automated, hindering their full potential. A cloud environment evolves with rapid growth or unexpected events, demanding continuous operation. Automation ensures that systems react promptly to changes in workload, performance, cost, availability, or security. AI is poised to take automation a step further by driving operations that adapt in real time with minimal human involvement. AI-driven cloud automation blends machine learning and other artificial intelligence domains into a coherent system of techniques and technologies for improved, automated deployment and operation of cloud-based services and applications.

Automating the entire life cycle of cloud-based solutions—from design to deployment and operation—requires a complete set of automation capabilities and services, spanning the four primary domains of any cloud automation strategy. Clouds typically accommodate a wide variety of resources, each with its own orchestration and management tooling. Delivering an end-to-end integrated solution involves crossing these boundaries and extending automation into the multiple other areas of the cloud environment not directly managed by the underlying orchestration platform. Integrating these capabilities requires addressing the full life cycle of cloud-based services, including networking, security, and governance.

Keywords: Cloud Automation, AI-Driven Cloud Operations, Intelligent Cloud Orchestration, Automated Cloud Lifecycle Management, Machine Learning in Cloud Computing, Self-Adaptive Cloud Systems, Cloud Resource Management, Real-Time Workload Adaptation, Cloud Scalability and Elasticity, Automated Deployment Pipelines, Cloud Infrastructure Orchestration, Cloud Governance and Compliance, Cloud Security Automation, End-to-End Cloud Integration, Multi-Domain Cloud Management, Autonomous Cloud Operations, Cloud Performance Optimization, Resilient Cloud Systems, DevOps and AIOps Integration, Continuous Cloud Optimization.

1. Introduction

Artificial Intelligence (AI), Cloud Computing, and Automation transform enterprise Information Technology (IT) infrastructures, and the interactions among these technologies are the subject of dedicated research. AI-driven Cloud Automation is defined as a solution design that deeply integrates AI and Machine Learning into Cloud Automation to introduce autonomous capabilities, with a focus on Cloud infrastructure (Compute, Network, and Storage). Cloud Automation provides a number of services, including the Automated Integration of heterogeneous Cloud Service Providers, Infrastructure Monitoring, and Governance. AI-driven Cloud Automation can also support orchestration at higher levels of abstraction.

Research investigates what this area of Automation is about, its objectives, the actors involved, and the Value Provided. AI and Machine Learning Architectures can be studied from different perspectives, and an often-overlooked dimension is Automation Indirection, between platform components on the one pass and platform functionalities on the other pass. The Automation Indirection of any layer is a complete, reliable, and non-redundant description of the Services Provided, which precisely describes the elements involved. Since Automation and Orchestration are generally exploited in enterprise IT infrastructures, AI-driven Cloud Automation is indeed the integration of Orchestration and Automation, and its capability, Maturity Assessment, and improvement roadmap can be described. Cloud Automation can be similar to IT Service Management in the broader enterprise context.

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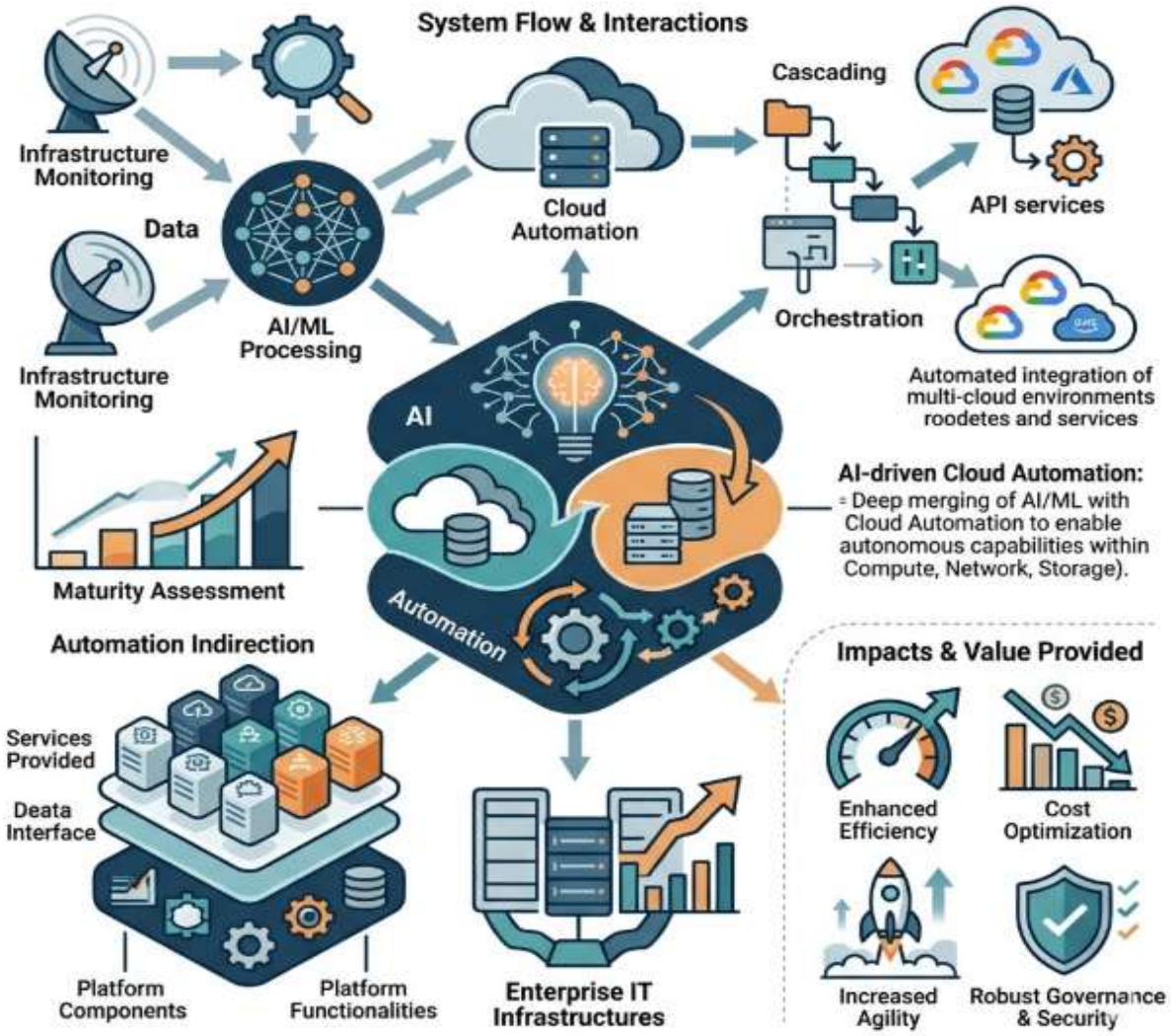

Fig 1: The Nexus of Intelligence and Infrastructure: Characterizing AI-Driven Cloud Automation and its Role in Enterprise IT Transformation

2. Foundations of AI-Driven Cloud Automation

AI-driven cloud automation encompasses processes and functions that eliminate or reduce the need for human intervention in cloud IT infrastructure management, orchestrate multiple heterogeneous automation solutions across multiple layers, and enable the active learning of policies and optimizations. The key actors in the automation ecosystem are cloud consumers, cloud providers, managed services providers (MSPs), and cloud application development teams, and there are value propositions for each group. Cloud consumers seek automation to improve service delivery quality while lowering costs and freeing human resources to focus on activities that add business value. Cloud providers offer automation to address human resource shortages, improve service delivery time and quality, and position themselves to better compete on price, quality, and features. MSPs provide automation to improve operations, reduce the service delivery cycle time, allocate resources more efficiently, and position themselves for greater profitability or reduced price competition. Automation of cloud application development and delivery enables organizations to compete based on speed to market and frequency of feature enhancement.

Automation, orchestration, and optimization are distinct yet interrelated concepts. Automation provides the capability to manage a task or a process without human assistance. Orchestration builds upon automation by cross-coordinating multiple automation efforts that individually span a single layer. Optimization leverages knowledge (data, models, or policies) to improve decision making and resource management. AI-driven cloud automation is broadly defined to include proactive detection of issues and incidents and triggered orchestration actions. The scope is not restricted to cloud services and infrastructure offered by third-party providers but extends to privately owned cloud-like equivalents.

2.1. Definitions and scope

AI-driven cloud automation is defined as the cloud automation technology stack that integrates AI and machine learning in one or more automation layers to achieve automation of all levels—process automation, orchestration and service automation, and full-cycle automation—in one or more functional components, raising automation from the simple execution of scripts to systems engineering and addressing problems that were previously impossible to fully automate, such as continuous compliance and self-healing.

While the system architecture explicitly positions functional components in an enterprise context, the focus of the current study is the capability of the technology itself. Thus, the scope receives additional qualification to define AI-driven cloud automation as the technology stack

that delivers integrated AI-assisted automation of all levels and all activities—process automation, orchestration and service automation, and full-cycle automation—in one or more automation layers, enabling one or more automation components, thereby increasing the capabilities of those components, delivering service assurance and continuous compliance, and continually improving itself. This augmented definition is then tested with a detailed maturity assessment.

2.2. Architectural paradigms

Centralized and decentralized automation architectures are both common in real-world systems, albeit with distinct advantages, limitations, and trade-offs. Centralized architectures are less flexible, since they rely on the automation logic to be implemented in a single controller, but are easier to reason about and diagnose. In contrast, decentralized architectures are better suited for dynamic and large-scale environments. Furthermore, automation can be structured as a set of independent processes, each responsible for a different aspect of the system's management. The internal logic of these processes can be viewed as black boxes, which eases specification, testing, and maintenance.

Automation can also be understood in terms of its layers, namely, the component-specific, functional, capability-based, and performance layers. Automation components are the physical or logical elements of the managed infrastructure, that is, the routers, switches, servers, virtual machines, and so on. Every component provides automation techniques for solving specific management problems. Each technique can be seen as the implementation of a particular management function—monitoring, configuration and provision, control and optimization, quality-of-service assurance, management of network security, detection and recovery from failures, and so on—addressed by the set of requirements for the managed environment. A system implementing all these functions can be said to provide complete capability-level automation. Performance-level automation relates to the use of model-based, machine-learning, or other logic to improve the execution of the functional automation.

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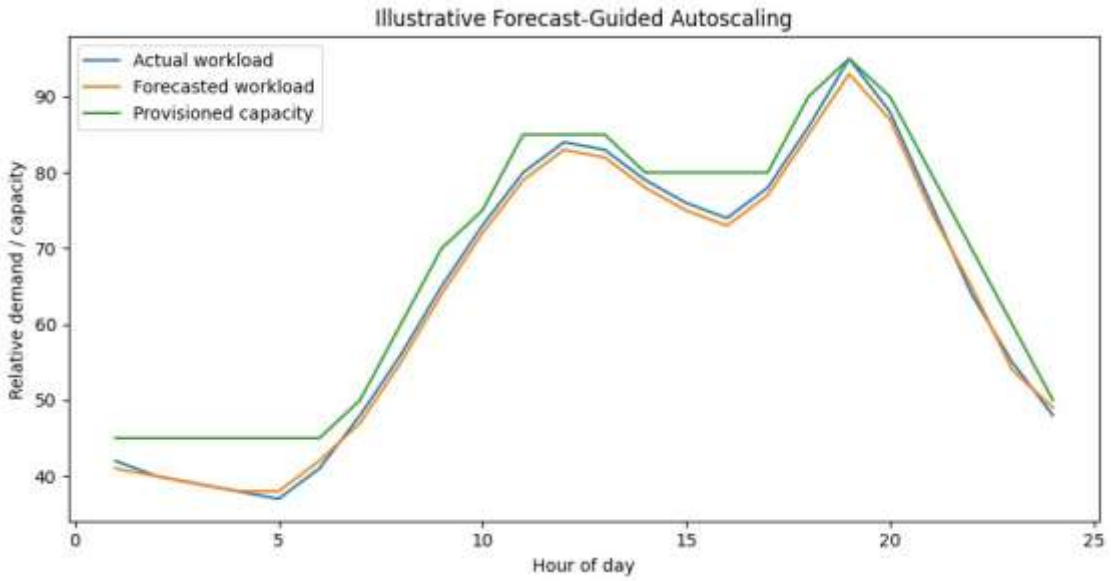

Equation 1) Cost-aware SLA-constrained optimization

- **cost**
- **latency / QoS**
- **SLA objectives**
- **operational risk**

A standard optimization formulation is:

$$\min_{n_t} \quad \alpha\, Cost_t + \beta\, L_t + \gamma\, Risk_t$$

subject to

$$L_t \le L_{\max}, \qquad U_t \le U_{\max}, \qquad n_t \in \mathbb{Z}_{\ge 1}$$

Step-by-step derivation

1. Let cloud cost be proportional to number of instances:

$$Cost_t = c\, n_t$$

2. Latency decreases when more resources are added, so L_t is a decreasing function of n_t.
3. Risk grows if scaling is too aggressive or SLA is near violation.
4. Weighted objective:

$$J_t = \alpha Cost_t + \beta L_t + \gamma Risk_t$$

5. Optimize by choosing n_t:

$$\boxed{\min_{n_t} J_t}$$

3. Methodology

The proposed AI-driven cloud automation model was developed using a design science approach popular in information systems. Initial requirements were derived from a systematic literature overview of AI applications for automation in IT infrastructure management. A comprehensive evaluation design assessed whether the developed model was capable of delivering its intended objectives. Quantitative data were employed to test whether an extensive deployment of these capabilities leads to improved efficiency and effectiveness of IT infrastructure processes. Finally, the AI-driven cloud automation model along with proposed maturity levels and assessment criteria provide the foundation for additional empirical studies. Such studies would use full-scale single-case or multi-case methodologies to establish deeper causal relationships than mere correlations.

The two AI-driven cloud automation case studies highlight the potential of AI-driven cloud automation in addressing specific business needs and provide quantitative outcomes to support the relevance of the AI-driven cloud automation model. The first investigates the autonomous capacity management capability on a public cloud using machine learning methods. Cloud cost efficiency was improved without compromising on SLAs. The second focuses on self-healing in the context of a wider DevSecOps continuity concept. Key performance indicators related to reliability and time to recovery were improved. Both studies draw attention to the natural limitations and risks associated with the use of AI in governance, and the need to address those risks, especially in the area of operational risk.

4. Objective of the Study

The objective of the study is to contribute to the understanding of AI-driven cloud automation mature capability, provide a structured overview of opportunities and challenges, and raise awareness of supporting and hindered factors. Three hypotheses guide the investigation: (1) AI-driven automation in public cloud environments can reach a mature level that creates benefits and addresses challenges from an overall technology-and-business perspective; (2) AI-driven cloud automation supports speculation, optimization, and service-level alignment of IT resources; and (3) AI-driven cloud automation requires modernization of affected processes and underlying data. The findings help organizations understand autonomous technologies and services' maturity and ability to meet modern cloud operations requirements. The study is also relevant for cloud or service providers interested in enhancing the service portfolio or improving quality, resource utilization, and operational costs.

To attain the study's objectives, a series of 13 research questions have been crafted. They address different aspects of an overarching topic and can be organized into three groups: questions that clarify definitions and terminology; questions that examine architectural characteristics of AI-driven cloud automation; and questions that explore mature capability of AI-driven cloud automation, focusing on assessment, advancement, resource operations, and service assurance. The proposed AI-driven cloud automation capability model addresses these aspects. It provides a structured overview that mitigates speculation and guides practitioners who seek development pathways to higher AI-driven cloud automation maturity.

5. Research Summary

Research findings serve several purposes: summarizing empirical investigations on AI-driven automation of IT infrastructure management; integrating insights from preceding chapter sections; and elucidating practical relevance. Examination of literature supported the development of 14 research questions addressing key aspects of automation journey characterization, enabling conditions, and specific use cases. Supporting empirical evidence derived from systematic reviews, original data, and technology engineering.

AI-driven cloud automation fulfills higher-level objectives—automation goals—that extend beyond enabling operator goals. Various stakeholders derive specific value propositions from automation, which can be further delineated into three high-level categories: cost, risk, and business enablement. Commercial interest in automating IT infrastructure for hyperscale

workloads—whether through cloud computing, on-premises resources, or a combination of both—centers around exploiting the economic benefits of increased utilization. However, the traditional quest for minimizing operational expenditure fails to capture the higher-value aspects associated with superior business enablement, such as resilience, security, agility, and speed.

Validation of the research questions revealed crucial support for advancing AI-driven automation in different dimensions. Reports from automation technology vendors and user forms emphasized the pivotal role of data quality, instilled governance supported by C-level advocacy, cultural transformation, and modernization of processes and workflows in enabling elevated maturity on AI-driven automation pathways. Autonomic technology research and roadmap initiatives additionally shed light on enabling enterprise-wide economic optimization by reducing direct operating costs and maximizing automated decision-making in uncertain situations.

6. Automation Maturity in Cloud Environments

Automation capability and maturity models, levels, and assessment criteria are proposed for AI-driven cloud environments. The models and their associated levels form a hierarchy, progressing from basic, foundational automation competencies to more advanced, business-outcome-oriented elements. Defining maturity and creating improvement roadmaps supported by practical assessment criteria enable organizations to invest in and modernize operations intensively. Automation maturity stems from the continuing, multiphase liberalization of cloud-based services. The six-dimension model supports organizational assessment against specific levels and

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overall maturity rating aligned with cloud capabilities.

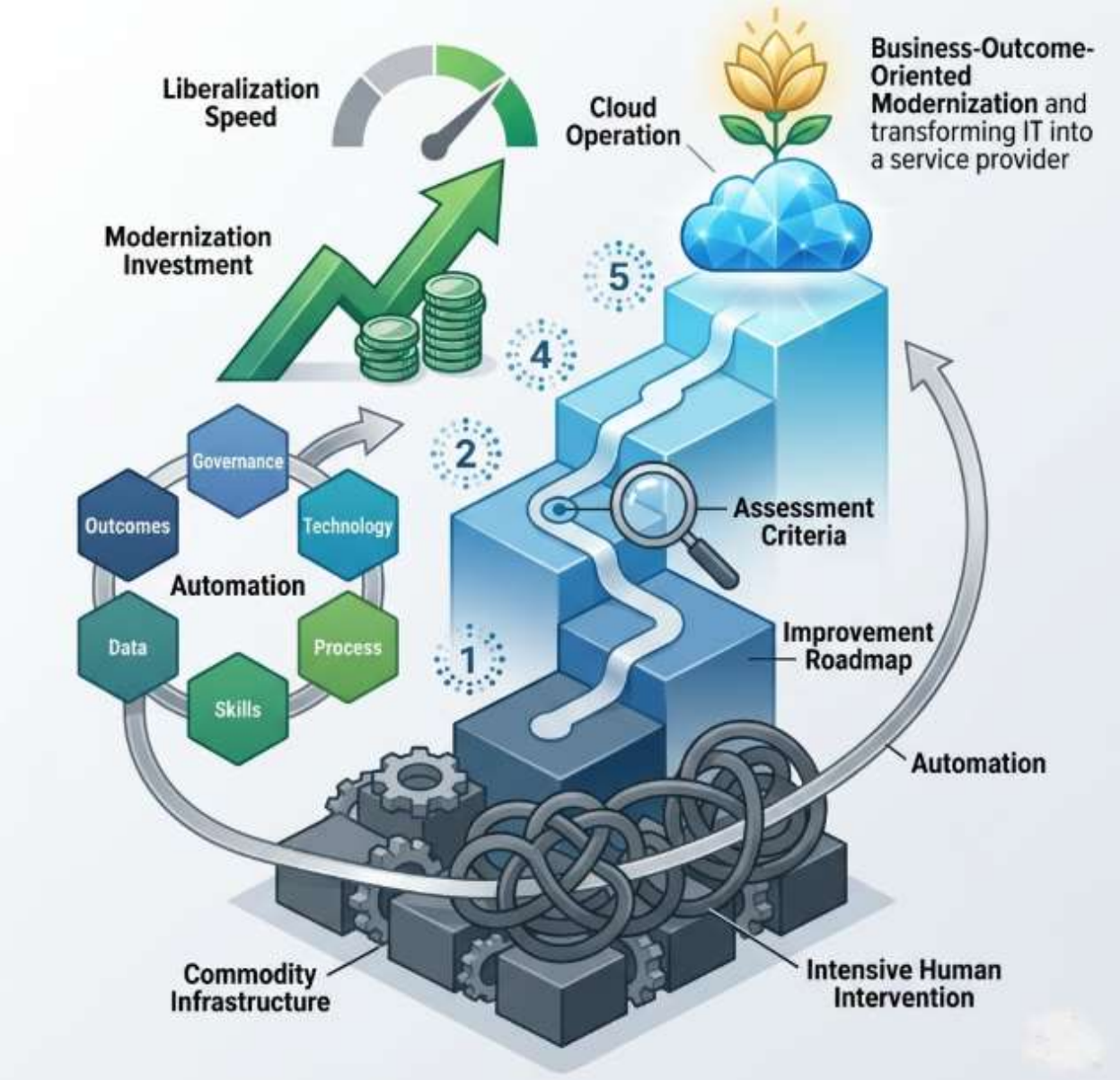

Fig 2: Cloud Autonomous Maturity: A Comprehensive Assessment Framework and Improvement Roadmap for Liberalizing Cloud Operations

From a cloud perspective, automation refers to the acceptance and provision of basic operational tasks to cloud service providers as a way to simplify the management of commodity infrastructure and support the execution of transformation context. Liberalizing cloud services takes this concept further and transforms IT as an enabling function into a service provider for the business. Modernization of these business functions through the use of higher-level cloud services explicitly rests on the organization's capability to use these functions without intensive human intervention through the adoption of, or alignment with, the same higher-level services. Such cloud automation maturity models serve organizations in guiding their investments in modernizing operations. Maturity assessments along these models articulate specific automation requirements and investments at their various organizational sites, thus concretely addressing and improving their liberalization speed.

6.1. Capability models

A capability model for AI-driven cloud automation captures the scope and areas of expertise needed for practical implementation. This framework creates a foundation for maturity assessment, improvement assessment, and roadmap planning for an IT organization. The definition of the areas of excellence is based on the synthesis of relevant literature, practical validations, and the overall objective of automating repetitive cloud-related activities through AI technologies. Capability models specify key functional areas and the needed expertise and technologies within each area.

A formal AI-driven cloud automation capability model consists of five areas: automation enablement, data engineering, policy-as-code implementation, security and compliance automation, and AI for cloud automation. Each area is subdivided into subparts and their corresponding capabilities and technologies. An AI-driven cloud automation capability model is a preliminary step for a subsequent maturity model. Such a model quantifies the level of maturity in the capability areas that profoundly impact operational efficiency, resource consumption, and costs.

The areas explored in the capability model are suitable candidates for measuring the level of AI-driven cloud automation capability maturity within an organization and for building a roadmap that guides progress to a higher level of automation adoption. Automating these aspects

eases the burden of generating and maintaining a production cloud environment and allows cloud administrators to focus on activities that require human intervention.

6.2. Pathways to higher automation

Achieving higher automation requires steering organizations in four directions: improving the quality of existing automated processes, modernizing manual processes with automation, strengthening governance of existing automated processes, and fostering a more automated-friendly culture. These four areas serve as the foundation for a roadmap that identifies a total of eleven milestones toward achieving higher automation.

Successful directions for driving higher automation include improving the quality of existing automated processes, modernizing a subset of manual processes with automation, strengthening governance of existing automation, and fostering a more automation-friendly culture. These four areas form the foundation of a roadmap that pinpoints a total of eleven milestones for attaining higher levels of automation.

In the realm of Operations (particularly Infrastructure Management), organizations that have indeed achieved a high level of automation should no longer only focus on bringing more automation to the remaining set of manual processes. Rather, the attention should shift toward process improvement: ensuring that the quality of the existing automated processes is high enough to truly unleash and yield the expected returns on the time and effort invested in these automation efforts. As process quality improves, the adoption of corporate automation becomes less risky, and their success rates soar. Organizations can therefore start looking for additional candidates to support.

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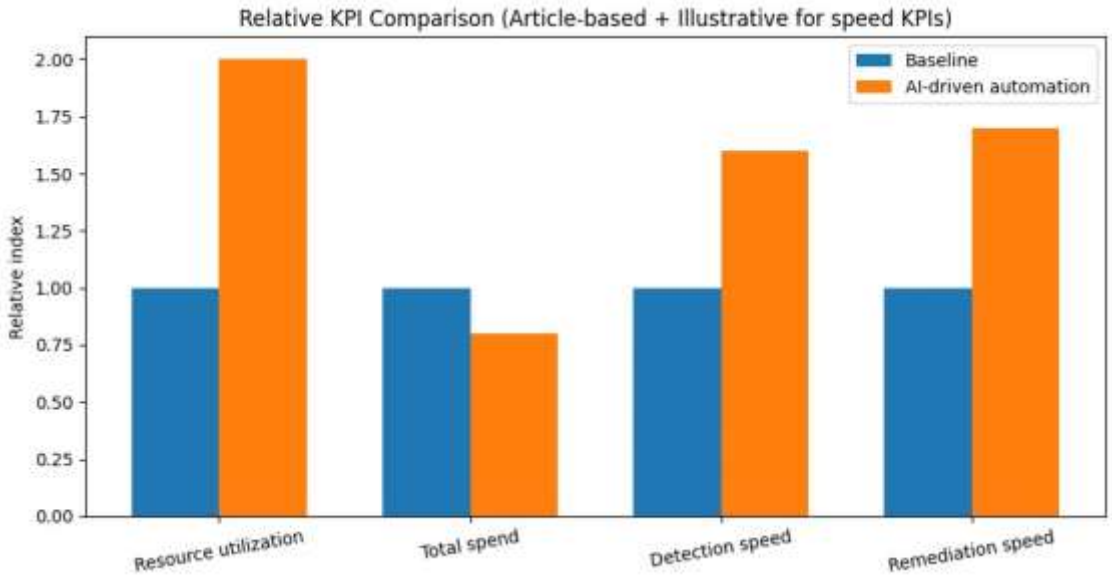

Equation 2) Autoscaling decision equation

Once forecasted demand $\widehat{D}_{t+1}$ is known, required capacity can be chosen as:

$$C_{t+1}^{req} = \widehat{D}_{t+1}(1+m)$$

where m is a safety margin.

Step-by-step derivation

1. Forecast next demand: $\widehat{D}_{t+1}$
2. Add buffer for uncertainty: $m\widehat{D}_{t+1}$
3. Required capacity:

$$\boxed{C_{t+1}^{req} = \widehat{D}_{t+1} + m\widehat{D}_{t+1} = \widehat{D}_{t+1}(1+m)}$$

If each instance provides capacity k, then required instance count is:

$$n_{t+1} = \left\lceil \frac{C_{t+1}^{req}}{k} \right\rceil$$

7. Intelligent IT Infrastructure Components

The design of an intelligent IT infrastructure challenges infrastructure architecture and component automation. Intelligent IT infrastructures are considered cloud-based since a significant portion of compute resources are outsourced, even if these resources are orchestrated, managed, and controlled either directly or by a third party. The automated infrastructure remains responsible for security, availability, performance, and governance by defining correct service-level policies and ensuring that such defined policies are continuously and automatically enforced. In public-cloud service settings, such governance tasks are imposed on the customer by the provider. A significant portion of such automatic and continuous governance can be provided by AI-enabled data-driven automation and closed-loop controls.

Intelligent IT infrastructure automation involves four primary components: (1) the provisioning of compute infrastructure resources, (2) the definition and provisioning of network infrastructure, (3) the automation of network and compute security, and (4) the automation of network and compute equipment malware, firewall, and data quality management. In intelligent IaaS and PaaS solutions, compute resources, including virtual operating system images, are offered as a service and automatically provisioned upon request. The automation of workload placement among IaaS environments possesses significant importance due to possible costs connected to the lack of service levels, service declassifying, or geographical legal considerations. Also, with several resources being provisioned on demand, the goal of achieving the minimum provisioning cost is key. Quality-of-Service (QoS), operational cost, and quality-of-data-data-validation management represent key infrastructures in any data-mining activity.

7.1. Compute and orchestration

Fundamental to every cloud deployment is the provision of fundamental compute resources, yet these resources are not always operating at optimal capacity. The design and deployment of appropriate orchestration methodologies, be it at the infrastructure- or platform-as-a-service level, provide substantial benefits in computing utilization and overall cost. Kubernetes extends the benefits of virtualization within the cloud to the cloud-native applications deployed within the cloud. An operating environment based on containers cannot impose the

level of economic and operational isolation found in virtual machines, yet achieves a level of separation that enhances the quality and cost-effectiveness of development and deployment. Multi-cloud orchestration, service meshes, and the automation of deployment pipelines provide new capabilities to further enhance the quality and cost-effectiveness of cloud-native services.

Autoscaling responds to changes in demand by dynamically creating or destroying compute resources; the optimal number of instances will depend on the anticipated demand, costs, and QoS objectives. The decreasing cost of cloud resources together with the intent to provide a zero-trust network also contributes to a desire to place workloads closer to the callers and hence the higher request rate workloads. Matching demand and supply in terms of proximity adds another level of complexity. Workload placement considers the available resources, any particular QoS associated with each resource, and the resulting cost of the deployment and attempts to minimize costs while meeting QoS objectives.

7.2. Networking and security automation

Automation facilitates the correction of configuration errors that could introduce security breaches, and the constant monitoring of abnormal behavior can support the protection of the environment. Examples include the definition and enforcement of firewall rules (e.g., port timeout, traffic logging, DPI policies) and detection of distribution and usage patterns that diverge from the normal behavior of workloads in the recent past—the critical point is to have these deviations analyzed in near real time and, when plausible, detected automatically. The concept of zero trust prescribes that no user or system should have access permissions set by default; hence the application of least privilege in identity management constitutes another important security discipline. An ideal embedding for Kubernetes-integrated workloads would be AMS services complemented by AdMF. The segmentation of functions and networks, and the definition of policies for network access, also contribute to network security automation.

Security in the scale of hyperscale cloud computing is a huge matter and cannot be solved only by automation. Therefore, the application of the classical security disciplines is mandatory. These disciplines can be made more efficient and consistent by the adoption of automation. Security policy enforcement is critical in multi-cloud environments because it runs on the border between different vendors. For example, some vendors provide equipment that makes a deep packet inspection. Perimeters are usually blurred in cloud computing and the application of the security measure in such environments requires careful study to avoid making those measures

too costly, or missing some critical points. As cloud computing systems reach larger sizes, the adoption of zero trust principles becomes important.

8. AI Techniques for Cloud Automation

Machine learning techniques improve resource-matching and optimization performance by supporting workload forecasting, anomaly detection, and policy decision-making. Forecasting is performed by analyzing resource-specific utilization and demand patterns: metrics related to a workload and its underlying resources are processed through sklearn's Long-Short-Term Memory (LSTM) models, the most effective supervised algorithm for recognizing time series. Anomaly detection allows identifying unusual behavior of key quality indicators (KQIs) of the workloads deployed: resource utilization for VMs, response times for the Active Directory (AD) server, response time and number of transactions for the SQL server, disk queue length for the Tableau server, and the number of FireWall (FW) log events are analyzed through an unsupervised approach based on isolation forests. Reinforcement learning is leveraged to dynamically allocate resources to a service according to its needs: a Deep Q-Network (DQN) is used to determine the optimal set of virtual machine instances assigned to a service, depending on workload latency, cost of VM allocation, and warning levels of involved services.

Support for horizontal and vertical dynamic workload scheduling optimizes infrastructure cost and performance simultaneously, addressing the essential cloud-resource-trading dilemma. The latency-sensitive-portfolio trading configuration addresses the dilemma by testing several implementations for workload-placement-responsiveness tuning. Each portfolio trading configuration is implemented in a specific cloud environment as a Service Level (SLA)-driven workload scheduler able to find the right workload placement for minimizing SLAs and maximizing infra-provisioning profit. A realtime closed-loop system and controller for latency-sensitive workload placement manage the end-to-end process in a continuous infinite loop.

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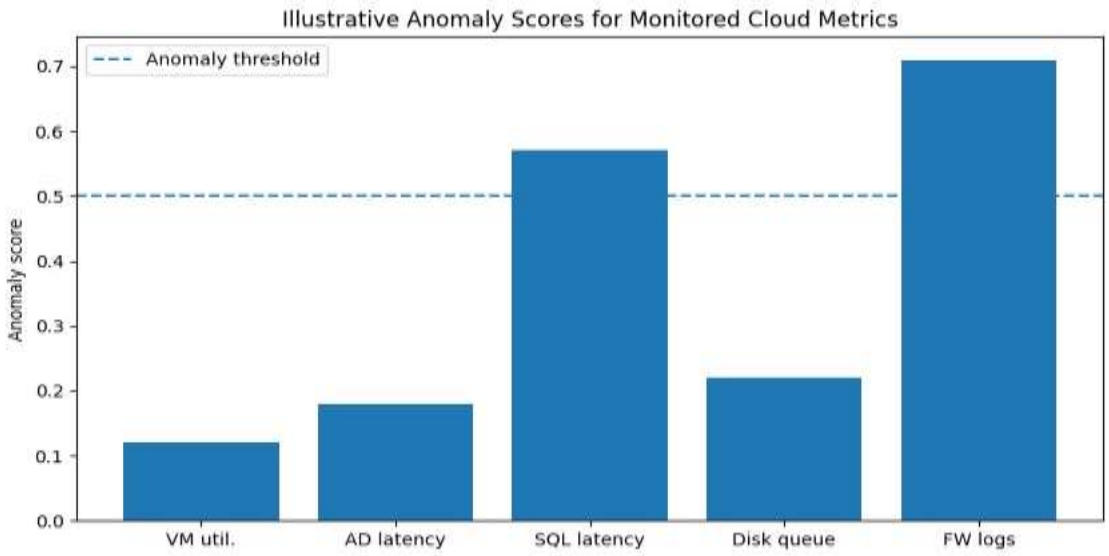

Equation 3) Capacity utilization equation

$$U_t = \frac{D_t}{C_t}$$

Step-by-step derivation

2. Let actual demand be D_t.
3. Let available provisioned capacity be C_t.
4. Utilization is "how much of the available capacity is being used".
5. Therefore:

$$\boxed{U_t = \frac{D_t}{C_t}}$$

Interpretation

- If $U_t < 1$: enough capacity exists.

- If $U_t \approx 1$: system is tightly utilized.
- If $U_t > 1$: demand exceeds capacity; SLA risk appears.

Example

If demand is 70 units and provisioned capacity is 100 units:

$$U_t = \frac{70}{100} = 0.7$$

8.1. Machine learning for optimization

Machine learning can optimize automation-driven IT environments on various levels. At the highest level, machine-learning-based models can enable smarter decisions in resource allocation and workload placement. By learning from historical data, resource utilization anomalies can be automatically detected, helping to define salient thresholds or model expectations for deviant operational behavior. The correlation of different monitored attributes can also be discovered autonomously, helping support change-point detection. In addition, machine-learning techniques from multiple disciplines can be used for process and configuration policy learning. More specifically, predictive models can be built from monitoring history, or even from historical events, to predict future behaviors or resource demand for particular workload classes. Such models would be particularly helpful for long-term and mid-term resource provisioning. Higher-level optimization can also be achieved using reinforcement learning to tune the decision-making strategy of dynamic resource allocation or workload scheduling. Nonstationary behaviors such as sudden spikes in demand can render previously defined strategies inefficient, but reinforcement learning can absorb such changes by continuously learning from the current environment.

Predictive models are usually supervised, and thus require labeled data for training. The lack of labeled data can be addressed through weak supervision or by relying on other modalities, such as video or audio data. Due to the temporal character of many processes, attention augmented architectures can help improve performance when trained on video data. Such models become particularly relevant in today's world, with massive growth in computer vision and video analysis, enabling new forms of model generation and making it easier to create proxies of real-world processes. Anomaly detection has received a lot of attention from the

research community recently, supported by the growth of sensor data. The difficulty lies in precisely defining the anomaly in the absence of labeled data. In the absence of adequately labeled data with well-defined features and a clear explanation of how they lead to the final decision, model explainability becomes questionable, and part of the model's usefulness may be lost.

Area	Derived equation	Purpose
Utilization	$U_t = \frac{D_t}{C_t}$	Measure capacity usage
Spend improvement	$\frac{Cost_{before} - Cost_{after}}{Cost_{before}} \times 100$	Quantify savings
LSTM	$f_t, i_t, \tilde{c}_t, c_t, o_t, h_t$	Forecast future workload
Forecast loss	$\frac{1}{N}\sum\left(D_t - \widehat{D}_t\right)^2$	Train predictor
Required capacity	$C_{t+1}^{req} = \widehat{D}_{t+1}(1+m)$	Autoscaling target
Instance count	$n_{t+1} = \left\lceil \frac{C_{t+1}^{req}}{k} \right\rceil$	Convert demand to instances
Isolation Forest	$s(x,n) = 2^{-E[h(x)]/c(n)}$	Detect anomalies
Reward	$r_t = -\lambda_1 Cost_t - \lambda_2 L_t - \lambda_3 P_t$	RL decision signal
Bellman	$Q^*(s,a) = \mathbb{E}[r + \gamma \max_{a'} Q^*(s',a')]$	Optimal allocation policy
MTTD	$\frac{1}{N}\sum(t^{detect} - t^{start})$	Detection KPI
MTTR	$\frac{1}{N}\sum(t^{recover} - t^{detect})$	Recovery KPI

8.2. Reinforcement learning for resource allocation

Reinforcement learning applies to decision-making problems where the objective is to optimize a long-term reward function. It consists of an agent that interacts with an environment over a series of time steps. At each time step, the agent observes the current state of the environment, selects an action based on its current policy, and receives a reward signal from the

environment as a feedback of how well it performed. The agent subsequently updates its policy so that it tends to choose actions that lead to greater rewards, emerging as a strategy to maximize the cumulative reward over time.

Dynamics of the environment come from the fact that many environment states are influenced by agents' actions, which follow certain distributions. Thus, a policy can be learned that is optimal for the task being pursued. In the specific case of resource allocation, the environment's state is the current utilization of each resource; the action taken is to add or remove capacity from the resource agent; and the reward reflects the cost of allocating more capacity minus the cost of allocating less capacity, in addition to a penalty if the threshold of the resource is exceeded. A natural trade-off for the agent exists between exploring the environment (i.e., sampling different actions) and exploiting its knowledge (i.e., choosing the action predicted to bring the highest amount of reward).

9. Platform and Tooling Considerations

Cloud-native technologies and DevSecOps practices are essential enablers of AI-driven cloud automation. Kubernetes and its ecosystem of associated tools and technologies make it easier to automate key cloud operations. For example, self-service provisioning, autoscaling, and dynamic placement of workloads can be realized through Kubernetes orchestration. Security automation can benefit from policy-as-code implementations built with Kubernetes operators and admission controllers, while compliance and identity/access management requirements can be integrated into the CI/CD pipeline. Nevertheless, Kubernetes is not a panacea: certain automation tasks may be better served by a serverless architecture and application delivery model. Furthermore, organizations and their cloud environments often span multiple-vendor cloud service offerings—not only for compute resources, but also for higher-level services that cannot easily be implemented in-house. Therefore, orchestration-aware deployment pipelines need to support the creation and ongoing management of multi-cloud workloads and services.

Kubernetes is a powerful container orchestration platform and service mesh offered by all major public cloud vendors. Its rich ecosystem of tools, custom resources and operators addresses a wide variety of automation problems, making it easier for development, operations, security, and compliance teams to fulfill their roles. However, leveraging these technologies effectively requires sufficient expertise, motivation, and capacity. Some awareness of the relevant tooling is necessary, but an in-depth knowledge of the underlying concepts is not. Two additional orchestration-related patterns emerge in the course of deployment automation: cross-

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cloud workload placement and the use of service delivery pipelines for automatic deployment and ongoing management of cloud workloads. Such pipelines are analogous to delivery pipelines for software components, but extend the software development and deployment process across infrastructure-as-code and configuration-as-code.

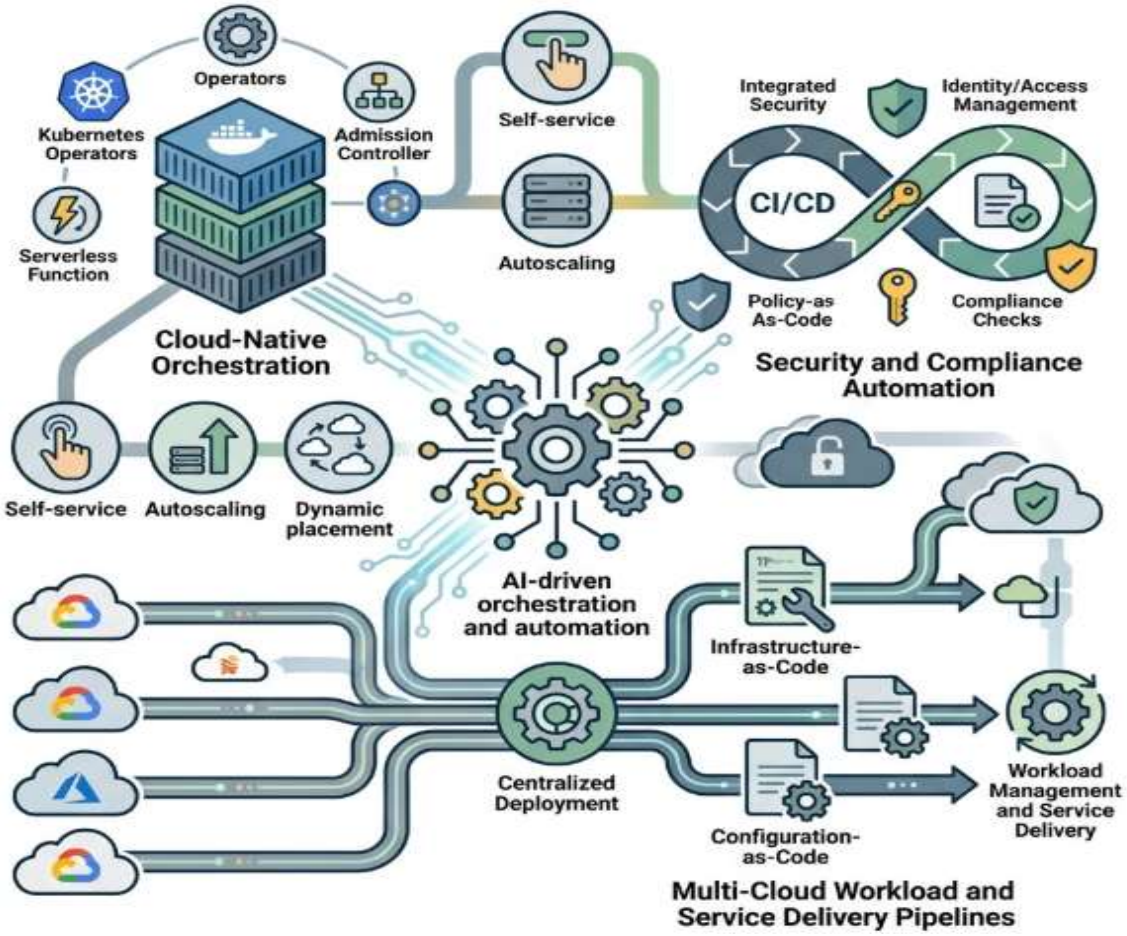

Fig 3: Leveraging Cloud-Native and DevSecOps for Resilient AI-Driven multi-cloud Automation: Beyond Kubernetes

9.1. Kubernetes and multi-cloud orchestration

Kubernetes, an open-source system for automating the deployment, scaling, and operation of application containers, has received significant attention. It serves as a production-grade container cluster manager, primarily for Linux containers, and is supported by a strong ecosystem of complementary solutions. One of its notable features is the ability to manage heterogeneous nodes across various cloud providers. Nevertheless, multi-cloud Kubernetes deployments face issues such as inconsistent interfaces, network communication challenges between providers, and the need to develop cloud-specific drivers for certain services.

Multi-cloud workloads are typically orchestrated by Kubernetes, whose rich network model can also be leveraged for inter-container communication. Multi-cloud service meshes enable the management of communication between services within and outside a Kubernetes cluster, focusing on issues like service discovery, mutual TLS encryption, request monitoring, and traffic routing. Technologies like FluxCD simplify the orchestration of deployment pipelines, especially for multi-cloud workloads.

Deployment pipelines, key to modern CI/CD development approaches, provide automation, consistency, predictability, and auditing for application deployments. Nevertheless, some enterprises remain reluctant to fully adopt deployment pipeline automation, primarily due to fear of errors, lack of expert tooling knowledge, or inadequate verification processes. Deployment automation can be increased by supporting infrastructure setup, enabling A/B deployments, ensuring compliance, and applying policy-as-code approaches. The internal and external security aspects of deployment pipelines are also important; for instance, breach events in the base image of a container can carry over to users of that image.

9.2. Serverless and event-driven architectures

Serverless computing provides an abstraction for deploying a single service function or a single workflow instance without managing the underlying platform and infrastructure. Resources are provisioned only during the execution of the function or service, resulting in cost savings. Scalability is provided for free because the resources scale automatically. Event-driven architectures are based on event notification and processing rather than on well-defined message-sending and receiving activities. Although the integration between components may appear to be less welldefined, a good event pattern can improve decoupling and make the event provide semantically meaningful information. Serverless computing is the preferred abstraction for UI-related components and latency-sensitive APIs. Event-driven architectures are preferred for handling less time-critical but more frequent events.

Serverless integration simplifies the execution of scheduled activities and, in many cases, such activities can be provisioned using a cloud provider. Serverless orchestrators can also be beneficial for managing processes that require complex flows, but caution is required. Since the underlying resources are managed by a provider that is operated on a pay-per-use business model, serverless integration tends to be used for functionality that is required only occasionally and for which scheduling is impractical. The usage of the pattern, therefore, must be analyzed based on cost reductions and the additional latency introduced in the activation of serverless functions. Integration backends, however, offer capabilities that appear to be worth the cost trade-off regardless of the functionality that these patterns provide to an application.

10. Security, Compliance, and Risk Management

Security concerns, compliance requirements, and associated operational risk pose significant challenges to automation success. Automated provisioning workflows must ensure the secure configuration of identity management systems, access controls, data protection mechanisms, and network security infrastructure. The implemented controls should then be continuously monitored for compliance, with deviations automatically remediated where possible or flagged for human review. Moreover, automated processes that trigger change need to balance frequency and risk by incorporating adequate testing and rollback procedures, while incident management should include automatic detection and remediation of known issues.

Identity and access management are critical components of IT security that ideally should follow the principle of least privilege. However, the granularity of control may not always be feasible, and IAM policy correctness is challenging to enforce. Changes to IAM policies may inadvertently open access paths that should be secured, remain undetected for a significant period, or provide excessive privileges to components whose security posture is not regularly examined. A specialized area of automation focuses specifically on IAM security, leveraging classification, clustering, and anomaly detection approaches to allocate the right set of permissions to individuals and services with similar profiles, roles, or access behavior.

Policy as code provides a way to model IAM policy constraints and uses enforcement mechanisms to prevent non-compliant changes. Solutions employing policy-as-code principles embed compliance into the development workflow, scan for policy violations across resources, and integrate with CI/CD frameworks to enforce compliance at deployment time. Automating security policy enforcement for other security-related controls that incur high operational overhead broadens the range of policies that can be applied to facilitate compliance. Such

solutions constantly monitor state for known security threats, map changes to security contexts, understand the impact of changes on policy adherence, and either adjust settings or remediate directly.

Continuous integration and delivery pipelines represent a natural extension point for compliance automation that leverages compliance as code for heightened auditability and enables extended continuous compliance checks, ensuring that the configuration of unmonitored infrastructure is compliant prior to provisioning. More generally, cross-layer compliance automation enables individual components and layers to be developed and validated independently, while still ensuring compliance across all components through checks at each layer.

Equation 4) Spend-improvement equation

The autoscaling implementation led to **about 20% improvement in total spend**. This is naturally written as:

$$\text{Spend Improvement \%} = \frac{Cost_{\text{before}} - Cost_{\text{after}}}{Cost_{\text{before}}} \times 100$$

Step-by-step derivation

6. Initial spend = $Cost_{\text{before}}$
7. New spend = $Cost_{\text{after}}$
8. Savings amount:

$$\text{Savings} = Cost_{\text{before}} - Cost_{\text{after}}$$

4. Relative savings fraction:

$$\frac{Cost_{\text{before}} - Cost_{\text{after}}}{Cost_{\text{before}}}$$

6. Convert to percentage:

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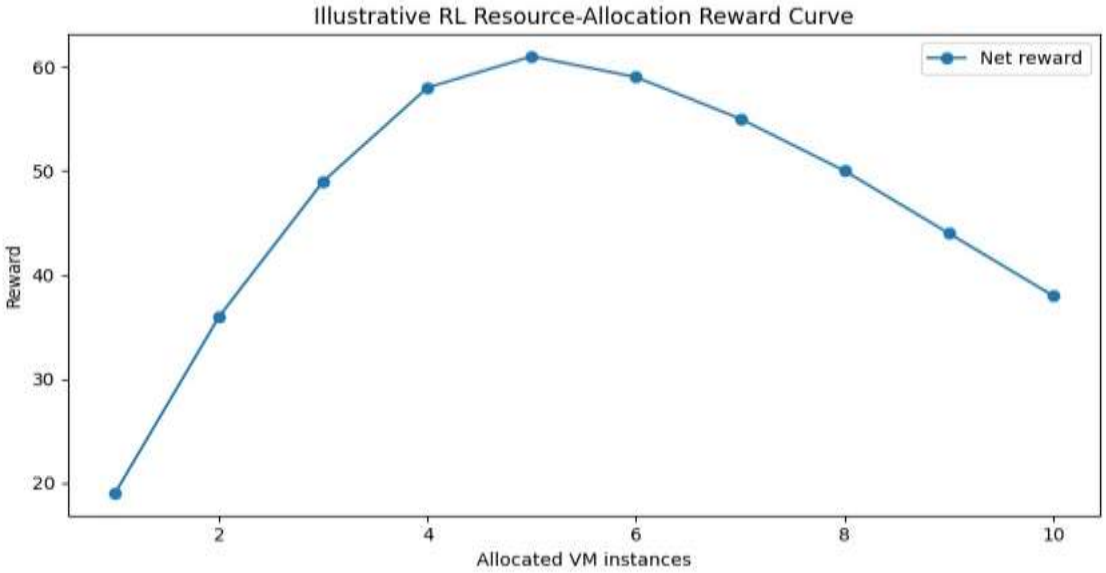
$$\text{Spend Improvement \%} = \frac{Cost_{\text{before}} - Cost_{\text{after}}}{Cost_{\text{before}}} \times 100$$

Example

If spend fell from 100 to 80:

$$\text{Spend Improvement \%} = \frac{100 - 80}{100} \times 100 = 20\%$$



10.1. Policy as code and compliance automation

Policy as code enables automation of policy definition, validation, verification, and application within IT systems. It facilitates the codification of IT policies and associated compliance checks. Compliance automation refers to continuous monitoring of IT systems to ensure compliance with predefined configurations that satisfy policy requirements. Unlike policy definitions concentrated in a single repository, compliance automation checks for misconfigurations not covered by policy statements.

There is a growing tendency to consider compliance automation an integral component of a well-defined governance and compliance framework, instead of a distinct and isolated activity. Nevertheless, aspects of compliance automation can be independently developed and integrated into existing frameworks. A concise definition of compliance automation is provided in the literature:

"Compliance Automation is the continuous verification that a deployed environment conforms to its central governing policies, that changes to that environment are validated against those policies, and that the system operators can provide the evidence that the system conformed to those policies."

Continuous compliance checks and audit trail generation—essential ingredients of effective governance—can be automated and integrated into tooling solutions. The CI/CD pipeline should be considered one of the main technical points of integration for governance/control tooling. Automated compliance checks for the main sub-disciplines within the governance of modern IT systems, including cybersecurity, data protection, government and industry regulations, and supply chain risk compliance, are increasingly available.

10.2. Identity, access management, and encryption

Key capabilities required to ensure the confidentiality, integrity, and availability (CIA) of cloud-hosted applications span identity management, access control, encryption, key management, and secret handling. Identity Management Systems (IdMS) provide user identities for authenticating internal users and services. For external users, cloud Service Providers (SP) leverage IdPs for federated identity management and single sign-on functionality. However, beyond enabling authentication, IdMS should be integrated with CI/CD pipelines to support assigning dynamic entitlements based upon user roles and privileges at deployment time.

Once authenticated, a user's specific entitlements or permissions determine whether access to a requested resource can be granted. Implementing suitable Identity and Access Management (IAM) policies together with the principle of least privilege ensures that user identities can only perform actions or access data that are strictly necessary. Policies-as-Code (PaC) govern entitlements within Infrastructure-as-Code (IaC) deployment manifests so that policy compliance can be continuously validated, and violations immediately detected. Security groups for applications deployed in Cloud IaaS services (e.g., public cloud, virtual private cloud)

should also be treated as code, with any deviations from the deployed codebase monitored via Continuous Compliance Check.

11. Case Studies and Empirical Findings

A capacity planning model forecasts future workload levels based on historical data and external parameters. For instance, data on past daily workloads are combined with forecasting models of future electricity consumption, weather, and population statistics. These inputs inform predictive functions for the summer workload of a medium-sized distribution company. Forecasting models include statistical methods such as ARIMA or Holt-Winters, machine learning approaches such as CATS or random-forgets, and specialized methods based on the underlying physical systems.

Findings from 35 case studies indicate that locally developed models usually perform better than those built by third parties. Underlying forecasting errors should be systematically analyzed and recent error patterns incorporated into the prediction due to their potential impact on resources and costs. The models should be updated and validated frequently, preferably with low effort. Model utilization can be facilitated by combining forecasting functions into one pipeline and using a central repository to ensure accessibility for all relevant stakeholders.

1 Model inputs

Data generated by SAP and Excel are combined in a central database. Internet-based information is retrievable by web services or crawlers. Predictive models are developed per city, which automatically store the outputs in the central database.

.2 Model output

For every service, day, and service group house capacity for T+X time should be determined at designated places in order that work once allocated can be finished without big delays. Therefore for each service DAY_YYYY the model should return a matrix with four columns: LOCATION, SERVICE_TYPE, CAPACITY. (Here SERVICE_TYPE will be EXT or INT and LOCATION is departament, points-of-presence or others.)

3 Model result validation

The performance of the capacity planning function is intuitively validated by detecting obvious breaches on the results and also statistically by using the historical difference between offer and demand.

A self-healing framework detects incidents (security issues, service disruptions, performance degradation, etc.) and triggers the corresponding remediation actions with or without human intervention. Automated incident detection requires good monitoring coverage and capability, while automated remediation action execution requires good automation coverage. Self-healing frameworks help organizations be more robust and efficient without human intervention.

Symbol	Meaning
t	time step
D_t	actual workload demand at time t
$\widehat{D}_{t+1}$	forecasted demand for next step
C_t	provisioned compute capacity at time t
U_t	utilization at time t
n_t	number of active VM/container instances
L_t	service latency
SLA_t	service-level compliance indicator
$Cost_t$	infrastructure cost
x_t	feature vector at time t
h_t, c_t	LSTM hidden state and cell state
s_t	RL state
a_t	RL action
r_t	RL reward
$Q(s,a)$	action-value function

11.1. Case study: automated capacity planning

A case study on automated capacity planning for cloud-based infrastructure, enabling early detection of workload variations and deviations, is presented. Incorporating machine learning, the system determines future workload levels which are used to automatically adjust cloud-hosted service capacity. Models are trained on actual service load data and evaluated on future predictions. The resulting forecasts, when used to reallocate available resources, substantially improve performance and cost. Automation of these processes reduces operational overhead and risk while avoiding practical challenges associated with traditional, human-based capacity management.

Monitoring workload levels and trends in operating services is critical, as failure to react to unusual patterns can have serious consequences. Requests for an under-provisioned service can be delayed or rejected, while over-provisioning incurs unnecessary costs. Early detection of increased or reduced demand allows for timely resource adjustments. In on-premises data centres, these decisions are usually based on past trends and enterprise knowledge. However, cloud environments offer the possibility of automating such operations, eliminating human-induced latency. Data-driven capacity planning further leverages the cloud's pay-for-use model to execute scale-in or scale-out operations only when needed.

Service normals are obtained using a business hour-based clustering approach. Deviation from these patterns is assessed with Anomaly Detection through Isolation Forest, and future workload levels are predicted using Long Short-Term Memory networks.

Using the models, an implementation is tested with Google Cloud Platform's autoscaling. Results show an approximately doubling of resource utilization and 20% improvement in total spend.

11.2. Case study: self-healing infrastructure

Incidents such as equipment and software failures, overloads, and accidental misconfigurations can adversely affect IT service quality. Aiming to enhance infrastructure reliability and restore normal operation as quickly as possible, self-healing systems automatically detect incidents and carry out a preconfigured remediation action. For instance, Kubernetes provides support for the self-healing concept by automatically restarting, rescheduling, or replicating containers. Beyond correcting unavailability, a more ambitious objective is to design a self-healing system capable of resolving incidents without human intervention. In such a setup,

a monitoring system scans for signals associated with specific incidents, identifies the correct incident type, executes the appropriate remediation action, and verifies the result.

A self-healing infrastructure leverages cloud resources and employs proactive monitoring based on explicit business requirements. Specific components continuously watch over managed resources and trigger remediation actions on detection of desired conditions. Monitoring techniques may include static thresholds, dynamic thresholds, and anomaly detection. Remedial actions, whose scope ranges from resource restarts to auto-scaling, are defined based on service-level agreements (SLAs), business impact, and acceptable business risk.

Equation 5) Forecasting model: LSTM equations

The explicitly states workload forecasting is performed using **Long Short-Term Memory (LSTM)** models.

Let the input at time t be x_t, containing workload-related features such as CPU, memory, previous traffic, time-of-day, etc.

An LSTM cell uses four gates.

5.1 Forget gate

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right)$$

5.2 Input gate

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

5.3 Candidate cell content

$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c)$$

5.4 Cell-state update

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

5.5 Output gate

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$

5.6 Hidden-state update

$$h_t = o_t \odot \tanh(c_t)$$

5.7 Forecast output

For one-step-ahead demand prediction:

$$\widehat{D}_{t+1} = W_y h_t + b_y$$

12. Challenges, Limitations, and Ethical Considerations

Bias, reliability, and explainability form a trifecta distinguishing the trustworthiness of AI-powered automation systems underpinning IT cloud operations. These system properties deserve thorough scrutiny to ensure that the solutions are dependable, predictable, and morally responsible. Bias in forecasting models can be mitigated by selecting appropriate training datasets and quantitatively monitoring their correctness. The reliability of a given automation task can be confirmed by assessing its long-term performance and by comparing its outputs against available checks, heuristics, or statistical distributions. The explainability of classification algorithms, from simple decision trees to XGBoost or deep learning methods, can be enforced with adequate model-agnostic techniques, thereby revealing which of the input

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features have influenced the model's decisions.

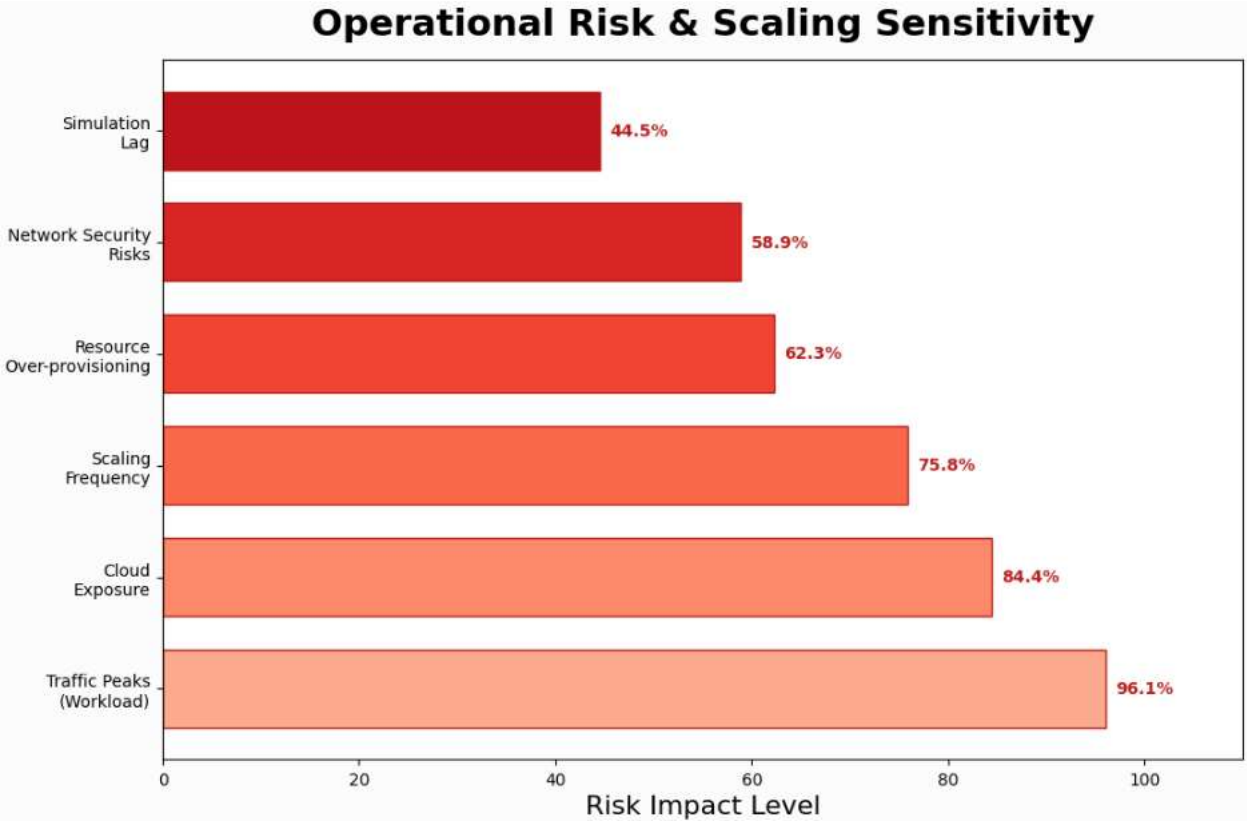

Fig 4: Operational Risk & Scaling Sensitivity

AI-driven automation can incur operational risks. An unusual demand will trigger the dynamic resource provisioning solution, for instance: a sudden peak in incoming traffic could mislead the workload-forecasting algorithm and result in a resource scale-out that, in turn, raises the operational risk through increased cloud exposure. To manage operational risk while maintaining the benefits of resource elasticity and support for sudden surges in demand, the scaling actions can have built-in constraints on the number of resources provisioned and the frequency of scaling events. In any case, the action plan of the dynamic resource-provisioning solution is subject to validation and test-driven development practices, followed by a formal acceptance test before being used for production workloads. For action plans involving network

security, including firewall-policy changes, the verification can also be carried out with simulation. When an automation task is deemed too risky, any new incoming request activating that task is temporarily discarded without executing the associated action plan, or is queued until an adequate set of resources becomes available.

12.1. Bias, reliability, and explainability

Artificial intelligence (AI) enhances a wide range of automation tasks but introduces new concerns. Bias, model degradation, and lack of transparency raise operational and regulatory challenges. For example, a company using AI for resume screening must mitigate discrimination risks. Organizations want insights into AI-driven predictions and decisions, addressing regulatory compliance, trust, and auditability. Ensuring reliability in AI automation processes also means striking a balance between leveraging AI's potential and preventing unintended side effects. Dataset quality, algorithmic and procedural bias, and stakeholder consideration during AI model training and deployment phases contribute to AI system vulnerability.

ANOM is designed to be transparent and easily validated. The bot receives monitoring data from multiple sources, including anomaly-detection systems, and sends them to a risk-analysis database. As anomalies diverge from normal functionality, they may require human attention or invoke self-healing mechanisms. However, users should check the DAAS test results in the final deployment stage and constantly monitor patterns and interpretations along the lifecycle of each AI model, using a business-analyst role to ensure that the model is still learning in line with business expectations.

12.2. Operational risk and rollback strategies

Operational risk emerges from automation decisions, which can affect SLA violations, outage durations, and service security and correctness. While reducing the frequency of operational issues, automation may amplify their consequences if large-scale changes are undertaken without sufficient caution. To counteract increased operational risk, appropriate targets, methods, and data preparation must be chosen, thorough testing conducted, and remediation mechanisms implemented.

Developments in change and deployment management, incident detection, response, and recovery procedures offer ways to curb changes or redeploy environments if issues arise. The ability to design a system that can be quickly reverted or patched is crucial. Overall, whenever an

automation decision is made, consideration should be given to the impact that decision may have on SLA, user experience, cost, and the system's attack surface, and all appropriate mitigation mechanisms should be in place.

13. Results

Empirical findings for selected major KPIs demonstrate that the candidate solutions substantially elevate automation maturity. A comparison of results against baselines strengthens the evidence base and highlights avenues for further improvement.

The implementation of a self-healing framework serves as a concrete validation for the proposed approach. First, implemented solutions detected and resolved configuration drifts across firewalls in a service-based application. Second, a security rule that prevented client application access to database replicas was remediated automatically. Third, the sustained automation of the verification and remediation cycle accelerated detection and remediation times when compared to a manual process.

An automated capacity-planning system capable of adapting the number of deployed application instances to forecasted demand is also presented. Data inputs include workload metrics collected by, information about the configuration and performance of each autoscaling group stored in a dedicated system, global performance and cost considerations, and system decision making. Input data are arranged to feed predictors generating volume, latency, and usage forecasts; collective and individual predictions are then assembled as timestamps of the next scale-out and scale-in operations. Load forecasts are added as features to a one-step-ahead predictor. The decision-support system chooses between predicted action windows by comparing historical performance and cost. Evaluation against baselines showed improvements in cloud cost and resource usage.

14. Conclusion

The study established core definitions and a capability model for AI-driven cloud automation, pointed out critical prerequisites for higher automation levels, and examined relevant operational risks. The research fills gaps in the literature by clarifying the boundaries of the cloud automation concept and providing a foundation for structured practical assessments, especially in terms of maturity models and external validity real-life validation. Additionally, automation actions across AI, DSA, and CCS categories were demarcated, underscoring the

prevalent absence of data quality, work practices, and orchestrator-based governance support in real-world implementations.

Connection to Intelligent Infrastructure Management AI-driven cloud automation is key to intelligent infrastructure management (IIM). IIM establishes a continuous cycle of requirement-analysis-design-provisioning-operations-movement-development-optimization based on artificial intelligence (AI), machine learning (ML), and data-driven insights. In contrast to traditional IT infrastructure management, IIM combines the human-centric aspects of enterprise architecture and business process management with the management of underlying infrastructures. Attention paid to cloud automation moves IIM one step further, focusing on the automation of defined and repeatable operational tasks for environment-agnostic workloads.

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