

AGENTIC AI FOR ENTERPRISE CLOUD OPERATIONS: AUTOMATION, GOVERNANCE, AND SECURITY RISKS

Rohit Gorle

Senior Software Engineer. Email:rohit.gorlee@gmail.com

Abstract. Cloud computing has ushered in a radical shift in enterprise IT delivery to facilitate the use of IT resources. Moreover, cloud environments afford operational activities, which take care of provisioning, scaling, and management of IT resources, provided that user-defined policies are in place. The emergence of Artificial Intelligence technologies allows these management activities to be fully automated, which means that these activities, which are responsible for resource management and operation and mainly triggered by event notifications sent by the infrastructure provider, can now be executed without direct human supervision, enabling a higher degree of autonomy. Activities managed in this fashion can be considered agentic as in addition to performing tasks they can take decisions and act in a self-directed manner, as long as they meet a system-chosen goal.

The conditions in which these IT environments can be managed with a higher degree of autonomy must consider the implementation of a governance framework that establishes the authorization model for the agentic activities. Several roles are defined within the governance framework including functions that specify the policies on which the offence is constructed, integration with security services, and audit. The agentic capabilities introduced in the cloud environments also bring to the surface security concerns that demand extra control. Considering the threat landscape, agentic cloud environments are particularly vulnerable to Jacking, DIverting and MeTro (JIM) attacks, where the perpetrator takes control of these activities, diverts their execution, or transfers control to a rogue cloud providing by exploiting Identity & Access Management (IAM) keys or other management information associated with the cloud provider.

Keywords: Agentic Cloud Computing, Autonomous Resource Management, Cloud Governance, Policy-Based Automation, Identity And Access Management, Security Governance, Cloud Automation, Autonomous Operations, Audit Controls, JIM Attacks.

1. Introduction

Rapidly evolving information-technology capabilities and the rise of internet-based service models now enable resources to be provisioned, tracked, and managed with unprecedented speed and reliability. However, the complex interdependencies between heterogeneous enterprise-cloud resources, services, and regulatory requirements create difficulties in verifying their state. Effective agency—understanding changed service or resource-status conditions and taking appropriate action—remains. In the effort to scale up agentic capabilities to enterprise levels, the proposal is to influence agency through providing a set of focused properties instead of focusing on bequests of intelligence and awareness.

Enterprise cloud operations today depend on complex systems-for-action that dynamically combine services from external providers with custom resources and capacity provided by the enterprise. Automation has long been considered essential to manage the ongoing volume of operations, configuration, and performance-management tasks created by these services. Such automation traditionally relies on pre-authored scripts or workflows that are executed when pre-defined conditions are matched. Nevertheless, the needs of enterprise-cloud environments have pushed conventional automation beyond its original design—cost reduction—and have resulted in a new form of automation that is also devoted to risk management and efficiency. The automation-enabled capability of having a resource consume another service other than from its primary provider—such as for backup, billing, or to fulfil demand-peaks—depends on being able to detect, understand, and act on a resource or service state that is outside its normal operating envelope. Enterprise-cloud environments’ detection, understanding, and action properties are on the path to arrange a self-healing capability, a goal that organisations such as the Autonomic Computing group rightly set down long ago, but in a different form. This new capability blends the properties of intelligent systems—natural-language processing,

pattern recognition, machine learning—with those of self-healing. The terminology for the new logic-based capability, agentic AI, captures both streams.

2. The Emergence of Agentic AI in Cloud Operations

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Understanding the emergence of agentic AI in enterprise cloud operations requires historical awareness, acknowledgment of recent developments in enabling technologies, and clarity on the distinction between agentic AI in orchestration and traditional automation. While enterprise cloud environments are becoming increasingly autonomous, recent trends in decision latency, control loops, and autonomy levels highlight the potential emergence of agentic AI in cloud operations.

The timeline of enterprises moving workloads into the cloud suggests that important state-of-the-art developments are occurring along two spines: cloud service providers are implementing increasingly autonomous control of their global cloud resources (the upper spine), while on-premises deployments are integrating increasingly complex management of the entire cloud resources under the ceaseless pressure of management costs (the lower spine). The Control section of Cloud Computing Control depicts the increasing levels of autonomy within cloud service providers with network, storage, server, application, and service automation, which has evolved from basic Automation through Orchestration, Activation, and Adaption to the advanced stage of Self-aware networks that might resemble self-organizing Autonomic networks. These management capabilities are being extended to AI and Data Lakes/AI/ML and the growing interest in Agent-based modelling and interaction are converging towards the concept of Agency.

2.1 Automation Value and Efficiency

[1] measures the value of automation as the cumulative effort hours saved over an agreed period, because the consistency of the measurement matters more than its length. Let N_{auto} of N_{tot} events be handled without a human decision. The automation rate is

$$\alpha = \frac{N_{\text{auto}}}{N_{\text{tot}}} \quad (\text{Eq. 1})$$

where $\alpha \in [0,1]$ is the share of events closed by automation. With t_m minutes of manual effort per event and t_a minutes of residual human oversight per automated event, the cumulative effort hours saved over M months is

$$V(M) = M N \alpha \frac{t_m - t_a}{60} \quad (\text{Eq. 2})$$

where N is the monthly event count. Eq. 2 is the value metric of [1] expressed in hours; it grows linearly in M and in α .

2.2 Latency Models

Agentic control closes the loop from detection to action. The end-to-end decision latency is the sum of the four stages of the loop,

$$L = L_{\text{det}} + L_{\text{dec}} + h T_h + L_{\text{act}} \quad (\text{Eq. 3})$$

where L_{det} , L_{dec} and L_{act} are the detection, decision and action latencies, h is the fraction of decisions that require human approval and T_h is the mean human-approval time. Risk-tiered approval lowers h in Model D, while still keeping human intervention available for high-impact actions as required by [1]. If an attempt succeeds with probability s , geometric retries give the mean time to resolve

$$\text{MTTR} = \frac{L}{s} \quad (\text{Eq. 4})$$

Events also wait for service capacity. Modelling the pipeline as an M/M/1 queue [3] with arrival rate λ and capacity μ (events/h), utilization $\rho = \lambda/\mu$, the mean waiting time and mean response time are

$$W_q = \frac{\rho}{\mu - \lambda}, \quad T(\lambda) = L + \frac{\lambda}{\mu(\mu - \lambda)} \quad (\text{Eq. 5})$$

The 95th-percentile waiting time follows from the exponential tail $P(W_q > t) = \rho e^{-(\mu - \lambda)t}$:

$$W_q^{95} = \frac{1}{\mu - \lambda} \ln \left(\frac{\rho}{0.05} \right), \quad \rho > 0.05 \quad (\text{Eq. 6})$$

and equals zero otherwise. Both expressions diverge as $\lambda \rightarrow \mu$, which is why the manual pipeline saturates first.

2.3 Detection Quality Metrics

Policy-violation and anomaly detection is scored on the labelled audit set with the confusion-matrix counts TP, FP, FN and TN [4]:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (\text{Eq. 7})$$

$$P = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (\text{Eq. 8})$$

$$R = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (\text{Eq. 9})$$

$$F_1 = \frac{2PR}{P + R} \quad (\text{Eq. 10})$$

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}}, \quad \varepsilon = \frac{\text{FP} + \text{FN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (\text{Eq. 11})$$

Precision penalizes spurious remediations, recall penalizes missed violations, and F_1 is their harmonic mean. Because [1] requires iterative agentic pipelines with controlled change management, the F_1 -score of the agent is modelled as an exponential learning curve over weekly iterations k :

$$F(k) = F_\infty - (F_\infty - F_0) e^{-k/\tau} \quad (\text{Eq. 12})$$

with initial score $F_0 = 0.70$ (shadow mode), time constant $\tau = 3$ weeks and asymptote $F_\infty = 0.894$, which is solved so that $F(12)$ equals the F_1 of Model D in Table 4.

2.4 Resource Utilization and Cost

For hourly demand d_t and provisioned capacity c_t (vCPU), utilization counts only the demand that is actually served:

$$U = \frac{\sum_t \min(d_t, c_t)}{\sum_t c_t} \quad (\text{Eq. 13})$$

Capacity follows a control law with headroom η , step size Δ and a demand estimate $\hat{d}_t$ that reflects each model's lag or forecast quality,

$$c_t = \Delta \left\lceil \frac{(1+\eta)\hat{d}_t}{\Delta} \right\rceil \quad (\text{Eq. 14})$$

$$v = \frac{1}{T} \sum_{t=1}^T \mathbb{1}[c_t < d_t] \quad (\text{Eq. 15})$$

where v is the fraction of under-provisioned hours. Model A provisions statically for the peak ($\eta = 0.30$); Model B reacts with a two-hour lag ($\eta = 0.35$, $\Delta = 10$); Model C reacts with a one-hour lag ($\eta = 0.20$, $\Delta = 5$); Model D uses a one-step-ahead forecast with a deterministic 5% error ($\eta = 0.12$, $\Delta = 2$). The monthly total cost of operations aggregates infrastructure, labour, AI/governance tooling, SLA penalties and expected security loss:

$$C = p_c \bar{c} H_m + r H_{\text{lab}} + C_{\text{AI}} + \pi n_{\text{sla}} + \lambda_a P_{\text{JIM}} I \quad (\text{Eq. 16})$$

where $\bar{c}$ is the mean provisioned vCPU, $H_m = 720$ h, $H_{\text{lab}} = N[\alpha t_a + (1 - \alpha)t_m]/60$ is the human effort, C_{AI} is the agent-inference and governance-tooling cost, π is the SLA penalty per under-provisioned hour with $n_{\text{sla}} = 30 vT$ hours per month, and the last term is the expected breach loss defined in Eq. 19. Operating-model selection is posed as constrained cost minimization:

$$\min_{m \in \{A, B, C, D\}} C(m) \quad \text{s.t.} \quad L(m) \leq L_{\text{max}}, \quad P_{\text{JIM}}(m) \leq P_{\text{max}}, \quad \text{GCS}(m) \geq G_{\text{min}} \quad (\text{Eq. 17})$$

with $L_{\text{max}} = 300$ s, $P_{\text{max}} = 0.05$ and $G_{\text{min}} = 0.9$.

2.5 Security and Governance Metrics

[1] identifies JIM attacks, in which an adversary takes control of automated activities by exploiting IAM keys or other management information, and notes that the attack surface grows with the complexity of the agentic system. With a base compromise probability p_0 , an attack-surface factor $\kappa \geq 1$ and n independent control layers of effectiveness e_i (least-privilege IAM, policy guardrails, anomaly detection, audit with human suspend), the success probability of a JIM attempt is

$$P_{\text{JIM}} = \min(1, p_0 \kappa \prod_{i=1}^n (1 - e_i)) \quad (\text{Eq. 18})$$

and the expected monthly security loss, for λ_a attempts per month and breach impact I , is

$$R_{\text{sec}} = \lambda_a P_{\text{JIM}} I \quad (\text{Eq. 19})$$

Governance maturity is summarized by a weighted compliance score over audit coverage (share of decisions with a forensic trail), policy-as-code coverage, intervention readiness (share of high-risk actions with an approve/suspend gate) and data-provenance validation:

$$GCS = \sum_{k=1}^4 w_k s_k, \quad \sum_k w_k = 1 \quad (\text{Eq. 20})$$

with weights $w = (0.30, 0.30, 0.20, 0.20)$.

2.6 Composite Performance and Improvement

Each metric is normalized to the best model: higher-is-better metrics use $\tilde{m} = m/m^*$ and lower-is-better metrics use $\tilde{m} = m^*/m$. The performance index and the cost-efficiency are

$$PI = \sum_j w_j \tilde{m}_j \quad (\text{Eq. 21})$$

$$\eta_{\text{eff}} = \frac{PI}{C/10^3} \quad (\text{Eq. 22})$$

The weights are 0.30 (latency), 0.25 (F_1), 0.15 (utilization), 0.20 (security, P_{JIM}) and 0.10 (automation rate); η_{eff} is performance per USD 1,000 of monthly cost. Improvements of Model D over a reference model are reported as

$$\Delta_{\%}^{\downarrow} = \frac{m_{\text{ref}} - m_D}{m_{\text{ref}}} \times 100, \quad \Delta_{\%}^{\uparrow} = \frac{m_D - m_{\text{ref}}}{m_{\text{ref}}} \times 100 \quad (\text{Eq. 23})$$

for lower-is-better and higher-is-better metrics respectively.

3. Automation in Enterprise Cloud Environments

Automation reduces human workload through mechanization of simple or repetitive actions. In computing, the term usually refers to the use of tools or scripts to automatically create, manage, or update systems and applications, manage IT infrastructures, or respond to events. Enterprise cloud environments require not just process automation of individual tasks, but also orchestration across multiple, often complementary workflows. An automation framework specifies how process automation and orchestration should be defined, executed and monitored. It defines workflows for cloud operations and management tasks, tools used to execute these tasks, and integration patterns for combining these tools into high-level orchestration workflows. Using such frameworks increases the level of automation across the cloud by providing a common approach to combine and extend tools. Many cloud service operations and management tasks are common across most enterprise cloud environments. The implementation of these tasks will therefore occur in isolation. Automation frameworks provide reusable process automation for these tasks together with cohesive orchestration that links these automations and executes them in response to events. By applying a cloud automation framework across a cloud environment, all cloud service operations and management tasks can be automated. The value of the automation can be measured against normal operational workload. Automation represents a reduction in this workload so the value is simply the cumulative effort hours saved over an agreed measurement period. The duration of the period is less important than the consistency of the measurement over time.

3.1 Operating Models Under Comparison

The governance study in [1] distinguishes traditional, script-driven automation from agentic operations that detect, decide and act in a self-directed manner under a governance framework. To quantify that distinction, four operating models are evaluated on a common Azure-based cloud-operations workload. The models follow the maturity progression described in [1] (manual operation, process automation, orchestration, agentic control) and are summarized in Table 1.

Table 1: Architecture summary of the four operating models (Azure realization).

Model	Autonomy level	Azure-based realization	Governance / security controls
A	Manual operations; human detects, decides and acts	Azure Monitor alerts routed to ITSM tickets; engineers act through Azure Portal / CLI	RBAC role assignments; manual change review
B	Scripted automation; predefined trigger-action rules	Azure Automation runbooks and Azure CLI/PowerShell scripts; threshold-based autoscale	RBAC; secrets in Azure Key Vault

C	Orchestrated automation; event-driven multi-step workflows	Event Grid and Azure Logic Apps / Data Factory pipelines orchestrating runbooks; Log Analytics telemetry	RBAC; Key Vault; Defender for Cloud (CSPM) alerts
D	Governed agentic AI; closed-loop detect–decide–act with risk-tiered approval	Azure OpenAI-based agents calling Logic Apps and Azure Resource Manager; Event Hubs → Stream Analytics → ADLS Gen2 → Synapse/Databricks telemetry pipeline	Entra ID managed identities with PIM; Azure Policy guardrails; Microsoft Sentinel anomaly detection; immutable audit log; human suspend switch

3.2 Workload and Parameter Assumptions

The workload is an operations-telemetry data platform on Azure that produces configuration, performance and security events. 5,760 operational events per month arrive at a nominal rate of $\lambda = 8$ events/h. A labelled audit set of 10,000 configuration/policy events, of which 1,200 are true violations, is used for detection quality. Table 2 gives the workload and Table 3 the per-model parameters. The parameters encode the qualitative claims of [1] (faster closed-loop control, fewer human decision points, stronger auditability, a larger attack surface that must be governed); they are stated assumptions, so every result below is a model-based projection rather than a field measurement and should be recalibrated with production telemetry before use in decisions.

Table 2: Dataset and workload summary.

Item	Value	Azure source / note
Evaluation horizon	30 days (720 h); 12-month projection for savings	Azure Monitor / Log Analytics
Operational events per month (N)	5,760	Event Hubs ingestion
Nominal arrival rate (λ)	8 events/h	Stream Analytics aggregate
Manual effort per event (t_m)	12 min	ITSM ticket history
Audit / policy evaluation set	10,000 events (1,200 violations, 12%)	Azure Policy / Defender for Cloud
Demand profile d_t	24 h, mean 50 vCPU, peak 104 vCPU at 14:00	AKS / VM scale-set metrics
Compute price (p_c)	USD 0.048/vCPU-h	Assumed list-price level
Labour rate (r)	USD 45/h	Assumed fully loaded rate
Breach impact (I), attempts (λ_a)	USD 120,000; 0.5/month	Assumed risk register values
Credential-compromise base rate (p_0)	0.2	Assumed; scaled by κ in Eq. 18

Table 3: Model parameters used in Eqs. 1–22 (assumed; see text).

Parameter	Symbol	A	B	C	D
Automation rate	α	0.00	0.45	0.70	0.92
Residual human effort (min)	t_a	12	3	2	1
Detection latency (s)	L_{det}	600	120	60	15
Decision latency (s)	L_{dec}	1800	300	120	20
Human-approval fraction ($T_h = 600$ s)	h	1.00	0.80	0.50	0.15
Action latency (s)	L_{act}	240	60	45	30
First-attempt success rate	s	0.92	0.90	0.94	0.96
Service capacity (events/h)	μ	12	24	40	120
Violation recall (true-positive rate)	R	0.78	0.84	0.89	0.95
False-positive rate	FPR	0.060	0.090	0.060	0.025

Attack-surface factor	κ	1.0	1.2	1.5	2.0
Number of control layers	n	1	2	3	4

4. Governance Frameworks for Agentic AI

Numerous models exist to provide oversight of automating Cloud Operations across all or specific functional areas. Cybersecurity frameworks also are available for enterprises adopting novel disruptive technologies. These models assist enterprises in translating regulatory compliance requirements into appropriate policies, processes, and controls supported by technology, including and relating to Agentic AI.

Governance frameworks are crucial as cloud environments mature into complete ecosystems that are versatile enough to support the testing and adoption of novel technologies. Integrating agentic AI into operation requires a controlled change management process that incorporates the testing of new models and their workflows within iterative agentic automation pipelines that facilitate recovery from errors, allowing for the detection and isolation of potential damages caused during the tested period. Therefore, any labour adjustment gained by agentic AI testing must also be adjustable when Agentic AI-based services become fully operational.

The defining characteristics of separately driven agentic AI models also enable compliance risk management at a faster pace than could be achieved through traditional labour approval processes extended through traditional asymmetrical analysis. The sensitivity to change and the presence of agentic AI also require monitoring and detection capabilities for policy violations in real time, as such automated processes for Built-In CyberSecurity support continuous information security auditing and real-time detection of non-compliance through but not limited to Business Intelligence operational Dashboards capable of issuing alerts upon failing thresholds or internal validation processes included in the Enterprise Resource Planning for Incident Management and Security Information Log Management.

4.1 Roles, Responsibilities, and Accountability

Subordinate roles, responsibilities, and accountability for algorithmic decisions should be clearly defined and documented in accordance with established procedures. Mechanisms must be established to ensure a close alignment in the development of AI models with the enterprise's internal expertise and external best practices. Responsibilities for validating independent testing of the models prior to rollout must be designated and include the following aspects: testing data and controls for aspects including ethical and liability conformity, analysis of model drift post-implementation, compliance with service-level agreements in production, and actions for managing potential degradation of the model. Consideration must be given to timely human intervention to suspend operation. Finally, compliance with data privacy and data-sharing regulations and guidelines for the enterprise must be observed.

Particular attention must be given to the provenance of data used to feed the AI model, ensuring that the data is fit for purpose and free of any manipulative elements, overt or covert. Clear escalation rules for deviation from expected patterns of consumption must be defined. These rules should include general controls to cover all model-driven provisioning and dynamic scaling activities, as well as specific control measures for high-value processes, extra-hazard locations or situations, and critical domains (for example, cyber security). Similarly, strong audit-trail capabilities must permit forensics on decisions, explanation of results, and the identification of the individual responsible for the AI-driven decision.

5. Security Risks in Agentic AI Systems

Security is a critical dimension for governance frameworks conducting enterprise cloud operations with agentic AI. Confidentiality, integrity, and availability of assets, information, functions, and processes in the enterprise must be safeguarded from security breaches. Security controls and mechanisms are paramount for enterprise risk management. Security identifies a broad range of intentional and unintentional threats and includes a wide variety of recovery measures. Operative cloud processes and the interface between clouds constitute a vulnerable area where Agentic AI can be exploited. The cloud provider and its customers can be attacked, as the cloud serves as a repository for a large number of data (hidden information) and data accessible on the Internet and at the interface between clouds.

The agentic nature of AI-based resources leads to new specific risks in autonomous decision-making and execution abilities. Agentic systems are capable of designing their own improvements, thus entering a new threat space in Rare Event Risk Management. With capability may come desire, according to the argument that true general intelligence would contain the motivation to pursue un-understandable ideas with unpredictable outcomes for the human world. The attack surface is relatively small in simple Agentic AI systems but grows with their complexity and variety. For an enterprise-chosen Agentic AI-based resource, the nine dominant categories of tactics and techniques from the MITRE ATT&CK framework for information technology are instructive; multiple attack vectors can come together to compromise a resource, mesh-based security analysis becomes complex.

5.1 Decision Latency and Queuing

Fig. 1 decomposes the end-to-end latency of Eq. 3. Model D completes the detect–decide–act loop in 2.6 min against 54.0 min for manual operation, 16.0 min for scripts and 8.8 min for orchestrated workflows. The largest absolute saving comes from the decision stage, where agentic reasoning replaces human triage.

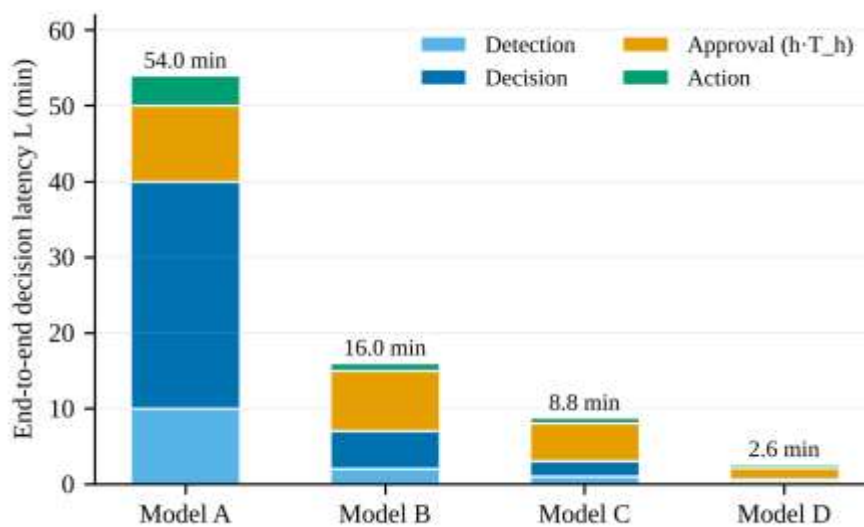


Fig. 1: Decomposition of end-to-end decision latency (Eq. 3) into detection, decision, approval and action stages for Models A–D.

Fig. 2 adds queuing delay (Eq. 5) as the arrival rate rises. At the nominal $\lambda = 8$ events/h the mean wait is 600 s for Model A but 2.1 s for Model D; Model A has no stable operating point beyond its capacity of 12 events/h.

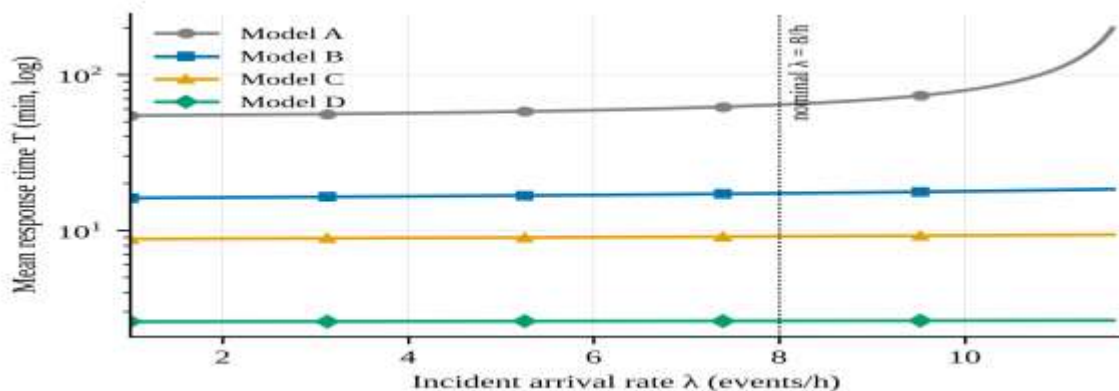


Fig. 2: Mean response time versus incident arrival rate (Eq. 5, log scale). The dotted line marks the nominal load of 8 events/h.

5.2 Detection Quality

Fig. 3 reports accuracy, precision, recall and F_1 (Eq. 7–Eq. 11) on the audit set. Model D reaches $F_1 = 0.891$ with precision 0.838 and recall 0.950. Static threshold rules (Model B) generate the most false positives (792 versus 220 for Model D), which lowers its precision to 0.560.

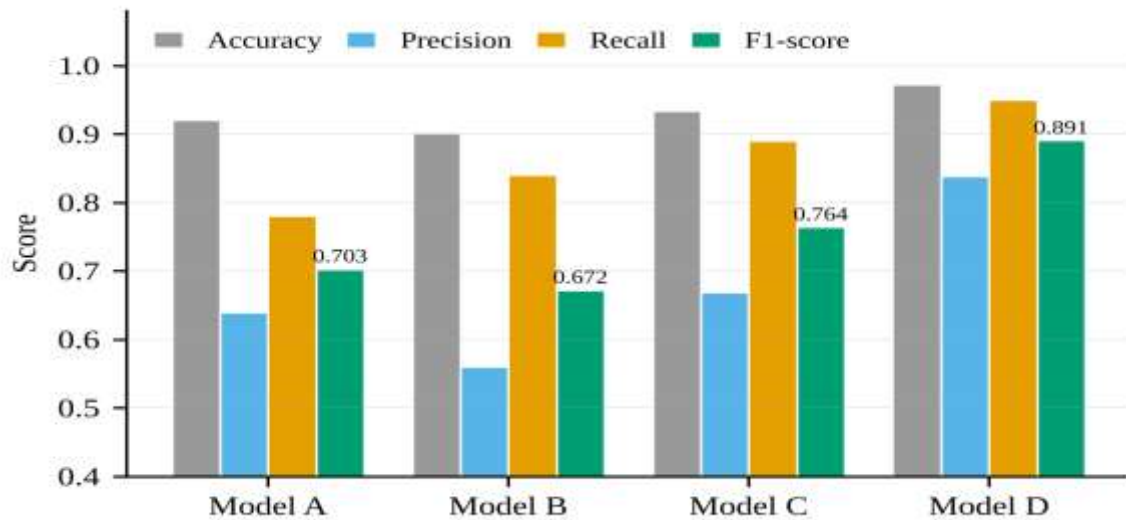


Fig. 3: Accuracy, precision, recall and F1-score of the four operating models on the policy-violation audit set (Eqs. 7–10).

Fig. 4 shows the learning curve of Eq. 12 over 12 weekly iterations of the agentic pipeline. Model D overtakes the best static baseline (Model C, $F_1 = 0.764$) after the second iteration. The dash-dotted curve is an ablation in which drift monitoring stops after week 8 and the score degrades by 0.012 per week, ending at 0.833 versus 0.891 with monitoring; this is the post-implementation drift analysis that [1] assigns to the governance roles.

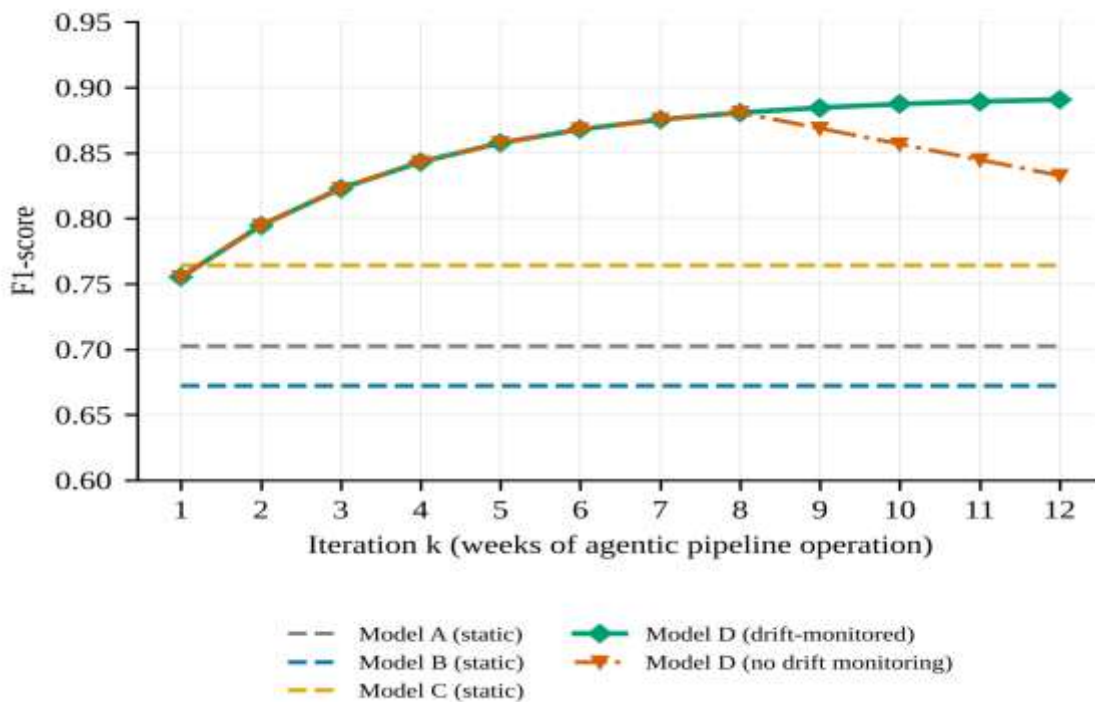


Fig. 4: F1-score trend over 12 weekly iterations of the agentic automation pipeline (Eq. 12), compared with static baselines and a no-drift-monitoring ablation.

5.3 Resource Utilization

Fig. 5 plots provisioned capacity against the 24-hour demand profile and the resulting mean utilization (Eq. 13). Static peak provisioning yields 39.9% utilization; lagged reactive scaling reaches 70.1% (Model B) and 79.6% (Model C) but leaves 3 and 1 under-provisioned hour(s) per day, respectively. Forecast-driven agentic scaling reaches 87.7% with no under-provisioned hours.

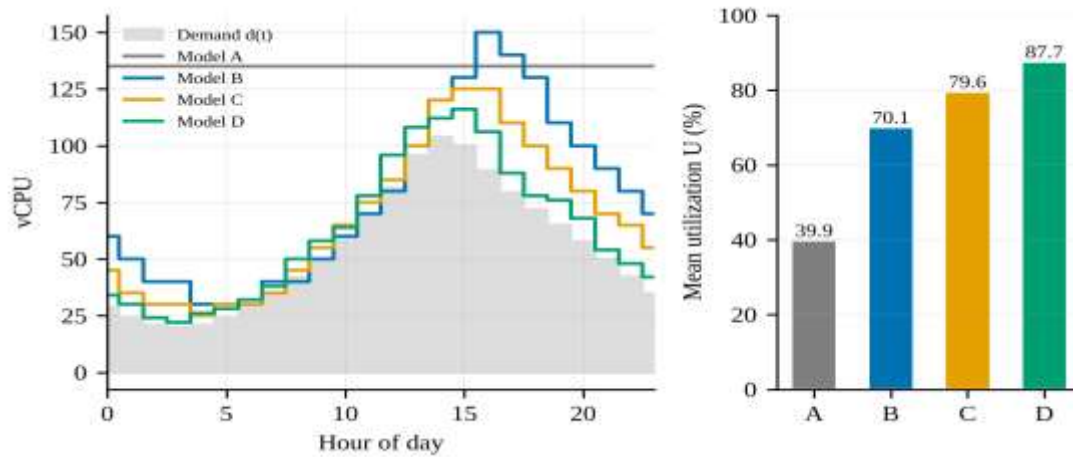


Fig. 5: Provisioned capacity versus demand over 24 h (left) and mean utilization (right) (Eqs. 13–15).

5.4 Cost versus Performance

Fig. 6 places each model by monthly cost (Eq. 16) and performance index (Eq. 21). Model D is both the cheapest (USD 13.5k per month) and the best performing ($PI = 1.00$); the cost-efficiency of Eq. 22 is 0.074 versus 0.015 for Model C.

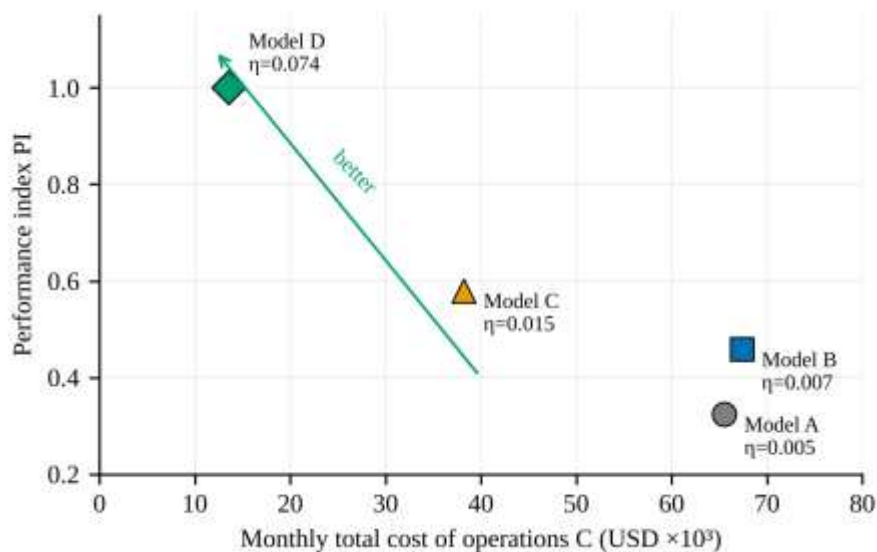


Fig. 6: Cost versus performance of the four operating models (Eqs. 16, 21 and 22). The arrow marks the direction of improvement.

5.5 Security Risk under Layered Controls

Fig. 7 applies Eq. 18 to the agentic architecture. Without governance, the larger attack surface ($\kappa = 2.0$) gives a JIM success probability of 0.400, higher than manual operation (0.150). Adding least-privilege IAM, policy guardrails, anomaly detection and audit with a suspend switch reduces it stepwise to 0.033, below the constraint $P_{\max} = 0.05$.

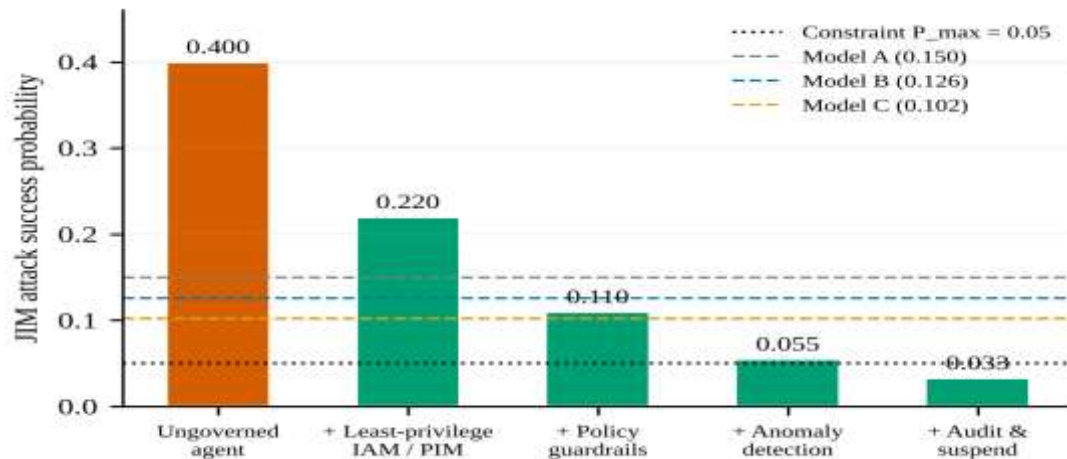


Fig. 7: JIM attack success probability of the agentic architecture as governance layers are added (Eq. 18). Dashed lines show Models A–C.

5.6 Effort Savings

Fig. 8 shows the cumulative effort hours saved (Eq. 2). Model D saves 972 h per month, i.e. 11,658 h over 12 months, compared with 8,064 h for Model C and 4,666 h for Model B.

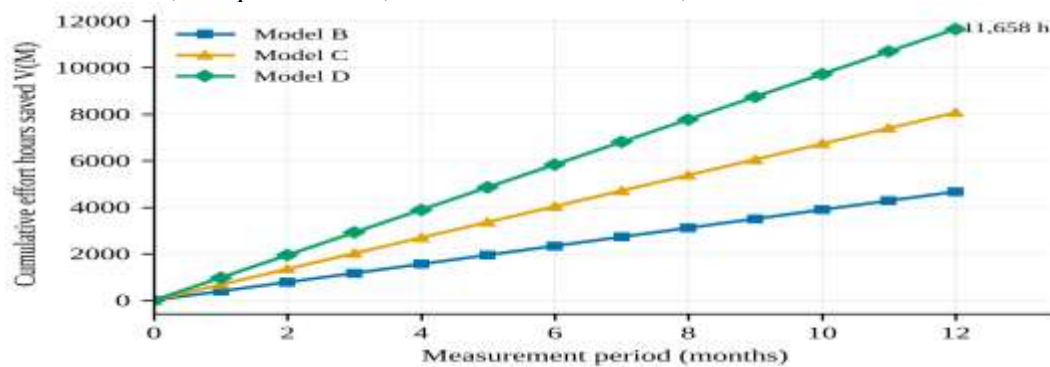


Fig. 8: Cumulative effort hours saved over a 12-month measurement period (Eq. 2).

5.7 Normalized Multi-Metric Comparison

Fig. 9 shows the five normalized components of the performance index (Eq. 21). Model D scores 1.00 on every component by construction of the best-model normalization; the visible gaps of the baselines are largest for latency (Model A: 0.05) and security (Model A: 0.22) and smallest for F_1 (Model C: 0.86).

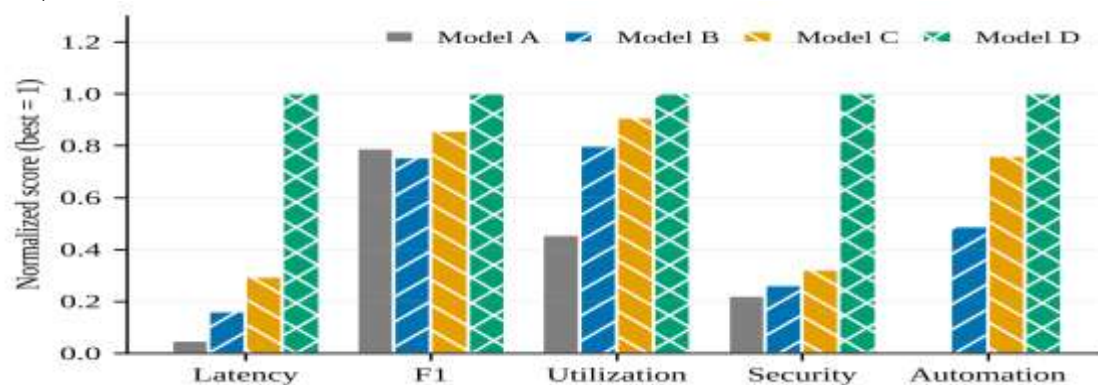


Fig. 9: Normalized metric scores (best model = 1) used to compute the performance index (Eq. 21).

6. Conclusion

The recent emergence of application programming interfaces (APIs) that employ generative models in agentic architectures provides a practical basis for realizing fully autonomous AI for enterprise cloud operations. The prospect of AI that autonomously enacts requests without human intervention ushers in a range of opportunities and threats. On one hand, agentic systems will simplify and accelerate the deployment of automation. On the other hand, the autonomous nature of these systems introduces new considerations that differ from traditional automation scripts and cloud deployment tools.

The conventional approach to enterprise process automation relies on policies and operational procedures that describe the behaviors expected of human actors. AI agentic systems and autonomous scripts are expected to follow rules systematically. Responsibility and accountability within and for agentic AI execution must be understood clearly and unambiguously. Agentic systems also introduce security weaknesses, threats, and attacks distinct from other classes of AI system. While all AI systems are vulnerable to data bias, poisoning, and misrepresentation, agentic systems exhibit vulnerabilities similar to those of traditional automation systems but distinct from web services.

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