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AI-Driven Cloud Automation for IT Service Management Platforms

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ABSTRACT: AI-driven cloud automation for IT Service Management platforms in 2023 leverages Artificial Intelligence (AI) to improve operations and meet service-level agreements via integration of AI components within data source pipelines. Automation reduces operational workload, but only gradual adoption for complex tasks; AI adds cognitive ability to processes and accelerates implementation. Key areas for acceleration—incident management, change, and configuration management—serve as foundation for deeper integration. AI-assisted cloud automation enhances efficiency across all operations via improved routing, triaging, and remediation management of incidents; defect detection in changes and configurations; and policy-driven deployment of cloud resources. Benefits include sharper focus on core tasks, lower mean-time-to-repair, and improved user experience; costs must be weighed against reduced total cost of ownership and potential return-on-investment.

The increasing adoption of cloud infrastructure has accelerated development of Automation-as-a-Service for Infrastructure as Code (IaC) deployment. The resulting IT Service Management (ITSM) workload has restricted delivery of innovative Infrastructure- and Platform-as-a-Service (IaaS and PaaS) offerings and adversely affected support for Software-as-a-Service (SaaS) applications. Automation of easy or repetitive tasks alleviates operational pressure, but these initiatives often deliver limited benefit due to narrow scope or bypassing of established processes. The growing diversity of alerts produced by IT operations platforms can now be managed through wider adoption of Artificial Intelligence (AI) techniques. Clinical application of proven AI methods enables more efficient routing within and between teams; faster, consistent first-line triage actions; and faster identification of suitable auto-remediation actions.

KEYWORDS: AI-Driven Cloud Automation, IT Service Management (ITSM), Automation-as-a-Service (AaaS), Infrastructure as Code (IaC), Intelligent Incident Management, AI-Based Change and Configuration Management, Policy-Driven Cloud Resource Provisioning, Predictive Defect Detection, Auto-Remediation Systems, Alert Correlation and Triage Optimization, Infrastructure-as-a-Service (IaaS) Operations, Platform-as-a-Service (PaaS) Enablement, Software-as-a-Service (SaaS) Support Automation, Mean-Time-to-Repair Reduction, AI-Enhanced Cloud Operations.

I. INTRODUCTION

Organizations are increasingly using cloud-based technologies. To support these developments, IT Service Management (ITSM) processes must increasingly operate across different cloud environments ("multi-cloud"). However, the new complexity that emerges from joining resources and services natively offered with resources and services offered as a service by third-party suppliers leads to new challenges for ITSM processes. The automation of these processes is frequently hampered by the lack of integrated automation operating models, corralling strategy and process, design, build, and test/devops phases, and continuous operations.

To what extent can and should AI not only support but automate ITSM processes in organizations? The answer not only has profound implications for the operating models governing these processes but also requires investigating cloud-native AI development and operational concepts. The development of cloud automation for ITSM platforms is an intensely practical area for consideration. Organizations are already experimenting with AI models. However, deploying AI capable of going beyond decision support to actual decision-making has only recently become possible for enterprise use.

1.1. Overview of the Study and Its Objectives

AI-driven cloud automation for platforms dedicated to the execution and provision of IT services has a significant impact on operational spending, capital expenditure, service levels, mean time to repair, user experience, and satisfaction. However, these solutions remain at an early stage in their lifecycle, both in terms of development and deployment.

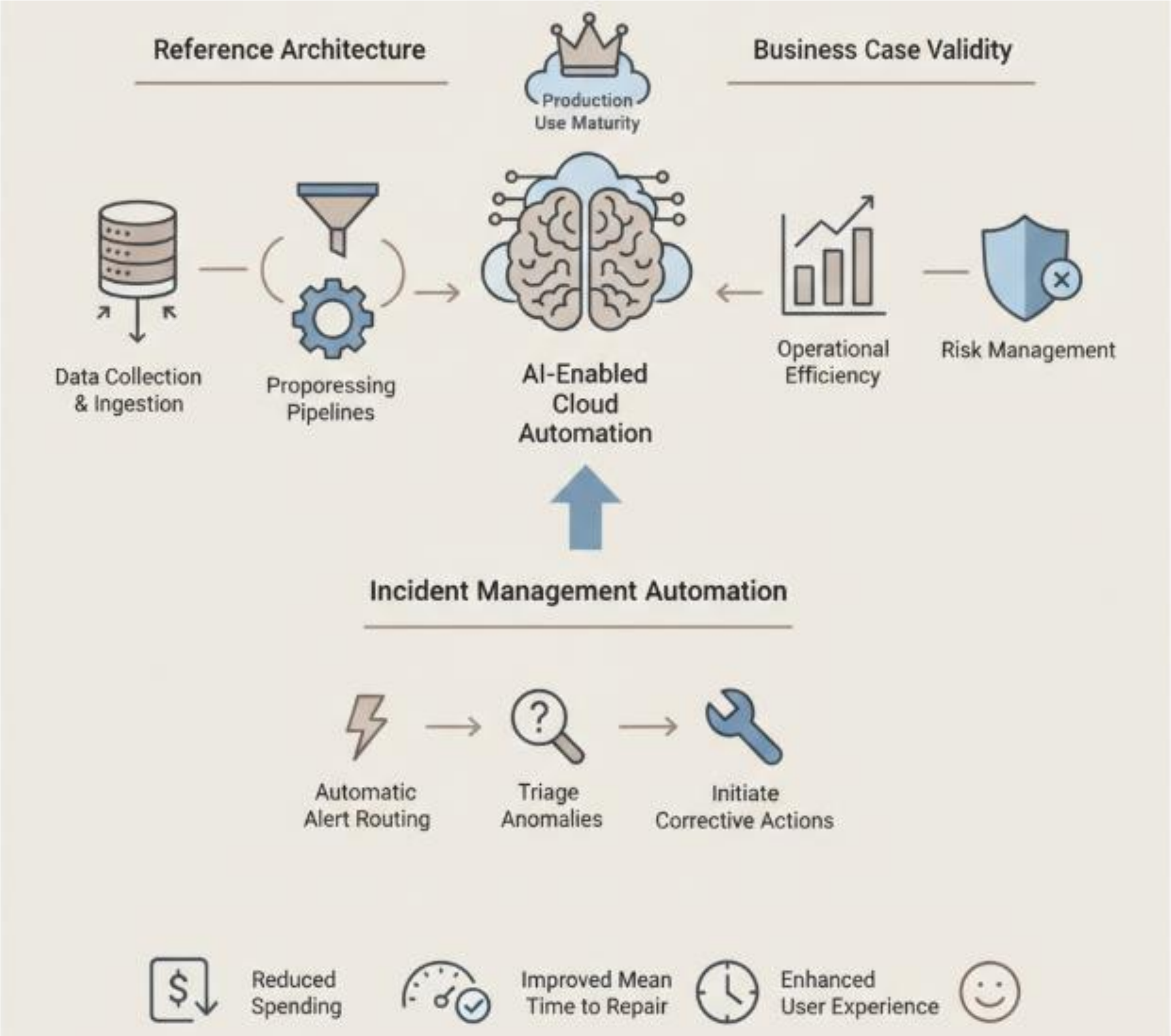
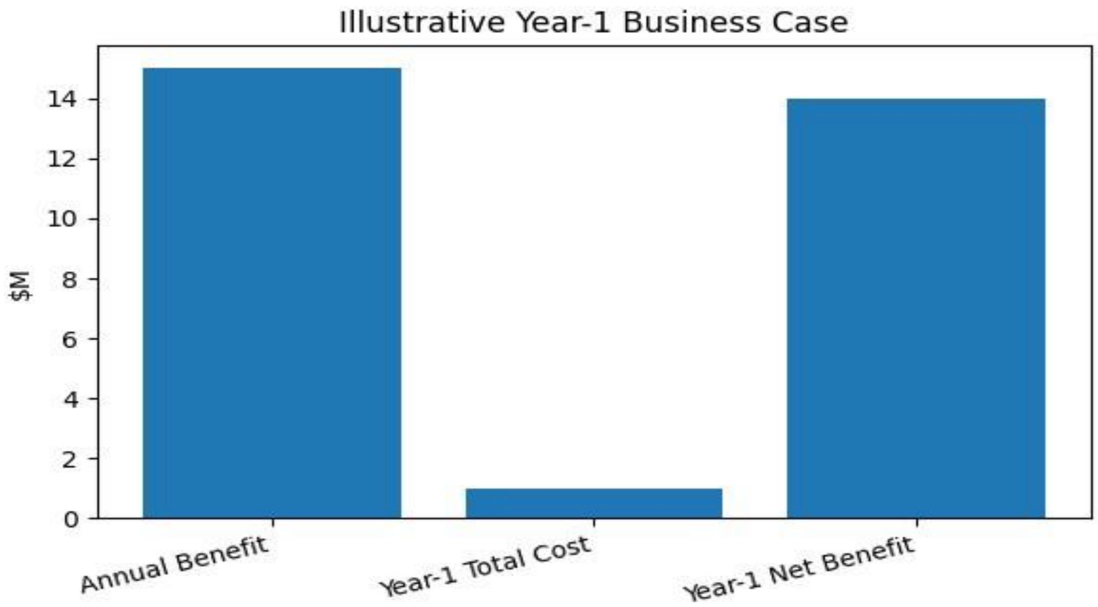


Fig 1: Assessing Production Maturity in AI-Driven ITSM: A Reference Architecture for Automated Incident Management and Cloud Operational Efficiency

The study investigates whether AI-enabled cloud automation for ITSM platforms has matured sufficiently for production use in IT environments. The evaluation framework is in two parts: A reference architecture identifies the required data collection, ingestion, and preprocessing pipelines; measures of operational efficiency and risk provide an opinion on business case validity. Of particular relevance to AI-driven cloud automation of ITSM platforms is the automation of incident management. These workflows encompass the automatic routing of alerts, triage of anomalous conditions, and initiation of corrective actions.



Equation 1) MTTR (Mean Time To Repair/Restore): full derivation
Step-by-step

1. Assume you had N incidents over a period.
2. Let incident i have:

○ start time $t_{\text{open}}^{(i)}$

○ end time $t_{\text{resolved}}^{(i)}$

3. The repair time (duration) for incident i is:

$$\Delta t_i = t_{\text{resolved}}^{(i)} - t_{\text{open}}^{(i)}$$

4. MTTR is the arithmetic mean duration:

$$\text{MTTR} = \frac{1}{N}\sum_{i=1}^{N} \Delta\, t_i$$

“Percent reduction in MTTR” equation (used in the paper narrative)
If baseline MTTR is MTTR_0 and after automation it becomes MTTR_1:

$$\text{MTTR reduction }\% = \frac{\text{MTTR}_0 - \text{MTTR}_1}{\text{MTTR}_0} \times 100$$

Rearranging to compute the *new* MTTR after a stated reduction $r\%$:

$$\text{MTTR}_1 = \text{MTTR}_0 \left(1 - \frac{r}{100}\right)$$

The example mentions a **75%** **reduction** (mean-time-to-restore). So:

$$\text{MTTR}_1 = 0.25\ \text{MTTR}_0$$

II. FOUNDATIONS OF IT SERVICE MANAGEMENT AND CLOUD AUTOMATION

Information Technology Service Management (ITSM) focuses on a set of processes and activities that support service delivery to customers. Although there are various descriptions, a comprehensive definition highlights ITSM's strategic and tactical perspectives. In the short term, ITSM ensures smooth and reliable service delivery, while in the long run, it keeps service delivery aligned with business objectives. The widely adopted Service Support and Service Delivery frameworks define a core set of processes, including incident, problem, change, configuration, release, service-level, and availability management. Several existing standards also support ITSM implementations, notably ISO/IEC 20000.

The successful implementation of ITSM processes is a combined effort of various supporting organizational roles. A dedicated service desk serves as the single point of contact for end users, while IT coordinators and process owners govern service support and service delivery. These roles, along with information from external sources, help the service desk create a pool of knowledge that can be leveraged for a variety of purposes. Efficient ITSM labor management can facilitate the completion of routine activities based on historical records. The automation of repetitive and knowledge-intensive tasks can optimize performance and meet defined service levels, thereby improving user satisfaction. Such improvements can, in turn, translate into a lower total cost of ownership over time, making ITSM process automation increasingly desirable for IT service management organizations.

Cloud automation encompasses Orchestration and Provisioning. Orchestration is the process of automatically triggering and coordinating the execution of multiple related tasks, often in multiple cloud environments. Provisioning is the process of provisioning cloud services, such as servers, databases, and network devices, on-demand and in a timely manner, based on Requests raised by Applications, business units, or Users.

2.1. ITSM frameworks and standards

IT Service Management (ITSM) comprises the planning, delivery, support, and governance of IT services within a business context. Advanced ITSM deployment requires an operation model structured around Service Value Systems (SVS), and multiple processes forming a service delivery lifecycle. Formulae improve operations using standards such as ITIL, ISO20000, COBIT, and SABIeither independently or in conjunction. They encapsulate the knowledge necessary to consistently achieve a desired result.

Cloud service delivery and support involve specific processes that need to be automated or simplified, based on an alternative security paradigm. Operations Security compensates for Cloud customers' mismanagement of shared resources. Internal and external cloud automation use the MITRE ATT&CK Framework for Cloud. High maturity with cloud-derived incident data allows predictive automation technologies to improve Service Level Agreements (SLA) by addressing the alert noise problem. Data categorization enhances help desk routing efficiency and, especially in urgent incidents, reduces mean time to repair (MTTR) and SLA breaches. Cloud-native Change Management identifies and enables secure policy-driven configurations in Few-Click deployment use case defect_plans, while maintaining updated plans in Configuration Management Systems (CMS).

2.2. Cloud computing models and orchestration

International Organization for Standardization (ISO) defines Cloud computing as a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction. Cloud computing is a composition of multiple Cloud models: Software as a Service (SaaS), Platform as a Service (PaaS) and Infrastructure as a Service (IaaS). SaaS provides normal users as well as enterprises peer to applications, that usually no technical department of the enterprise supports. Examples of SaaS are Google Docs and Zoho Office Suite. PaaS offers an online site-building environment for the Web application developers. IaaS supplies virtualized computing capacity as cost-effective, scalable and reliable service. Most of the entrepreneurs use this service. They can consider WindowsAzure, Cloud.com, Vmware. Cloud computing can be secure and privacy concern if the enterprise uses encryption and web services with throttling.

Cloud orchestration means automatic setup, coordination, management of complex computer systems, middleware and services. It varies from systems management in that it controls the entire orchestration. Orchestration specification is layered framework that captures the high-level structure of an application and its possible provisioning operations. An orchestration system takes high-level service-specific requests (written in orchestration) provides services to the end-users by translating them into senior-level virtualization-specific requests and managing the services across all the data centers.

Metric	Value
Annual automation savings ($M)	5.0
Lost-business impact reduction ($M)	10.0
Development investment ($M)	0.75
Annual support cost ($M)	0.25
MTTR reduction (%)	75.0

III. ARCHITECTURE OF AI-DRIVEN CLOUD AUTOMATION

An AI-driven cloud automation solution relies on a stable architecture and integrated model-inference components executing specific AI tasks. Data sources such as service management tools generate massive volumes of data connected to a multitude of entities (alerts, incidents, changes, etc.). These entities are ingested via pipelines designed for the data types they represent, then pre-processed before reaching the model-inference components. Within the architecture, specialized models and decision engines are defined along with the respective data ingesting pipelines, model types employed, and links to the cloud-orchestration platform.

To realize ITSM automation across an organization’s cloud workloads, incidents are to be created, triaged, routed, resolved, or integrated into change management policies. An overview of the full scope of AI cloud-service automation from this perspective is provided in Figure 4. The recommended configuration aligns with particular orchestration models that determine how hierarchical tasks are assigned and monitored. The orchestration approach may vary according to specific enterprise needs. Public-cloud services may also introduce default recommendations for setting up such a hierarchical structure.

Equation 2) SLA / Availability equations (how MTTR ties to SLA)
Availability (classic ITSM/SRE form)
Let:

- Total time in the measurement window be T (e.g., 30 days)
- Total downtime be D (sum of outage minutes)

Then:

$$\text{Availability} = \frac{T - D}{T}$$

In percent:

$$\text{Availability}(\%) = \left(\frac{T - D}{T}\right) \times 100$$

Downtime as a function of incident durations
If you approximate downtime as the sum of incident repair times that actually impact service:

$$D \approx \sum_{i=1}^{N} \Delta t_i$$

Substitute into availability:

$$\text{Availability} \approx \frac{T - \sum_{i=1}^{N} \Delta t_i}{T}$$

3.1. Data ingestion and pre-processing

An AI-driven data ingestion pipeline collects and processes incident management data for incident response workflows. Data Sources encompass the IT service management (ITSM) platform, IT monitoring tools, and IT asset management repositories. The ITSM platform generates operational data, while monitoring tools provide rich telemetry about resource state and behavior during IT service delivery. The IT asset repository generates context information about resource dependencies. Data ingestion pipelines process this information, making it suitable for AI-driven IT automation.

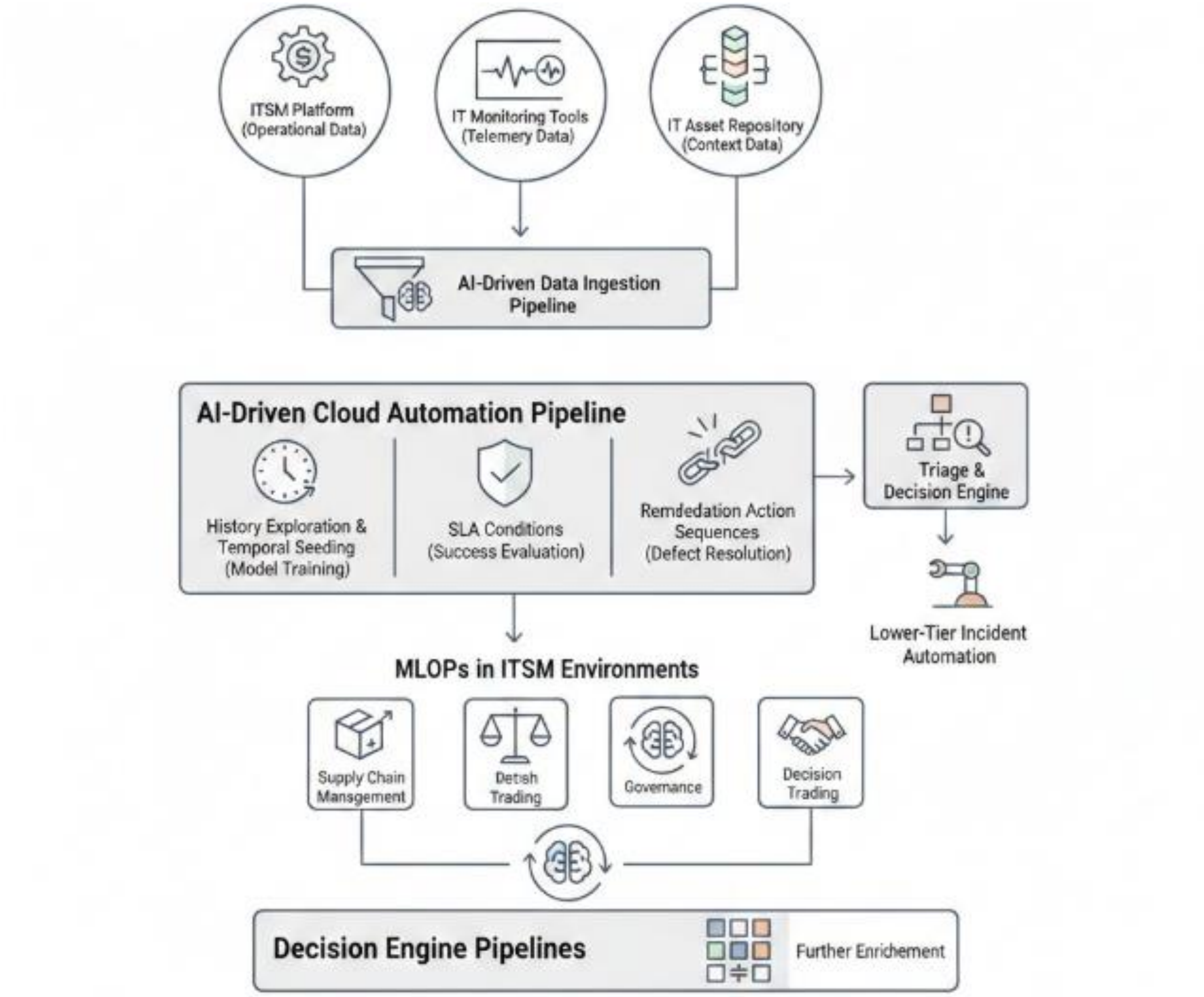

ITSM Platform (Operational Data)
IT Monitoring Tools (Telemery Data)
IT Asset Repository (Context Data)
AI-Driven Data Ingestion Pipeline
AI-Driven Cloud Automation Pipeline
History Exploration & Temporal Seeding (Model Training)
SLA Conditions (Success Evaluation)
Remdedation Action Sequences (Defect Resolution)
Triage & Decision Engine
Lower-Tier Incident Automation
MLOPs in ITSM Environments
Supply Chain Mansgement
Detsh Trading
Governance
Decision Trading
Decision Engine Pipelines
Further Enrichement

Fig 2: Synergistic AI-Driven Incident Response: An Integrated Framework for Autonomous Triage, MLOps Governance, and Multi-Source Data Ingestion in Cloud Service Environments

The AI-driven cloud automation pipeline traverses processes relevant to incident management. Data related to cloud service incidents undergoes history exploration and temporal seeding for model training, with labeling requirements defined. Service-level agreement conditions govern success evaluation. For escalated incidents classified as defects, remediation action sequences are modeled.

An AI-driven Decision Engine routes monitoring alerts relating to cloud services. Decision rules enforce triage workflows and primary diagnostics. As automation covers lower-tier incidents, Requirements for MLOps in ITSM environments encapsulate supply chain management, governance, and decision trading, controlling the AI lifecycle and operational quality. Decision Engine pipelines manage resource pattern classification, with classification rules designated for further enrichment.

3.2. AI components and decision engines

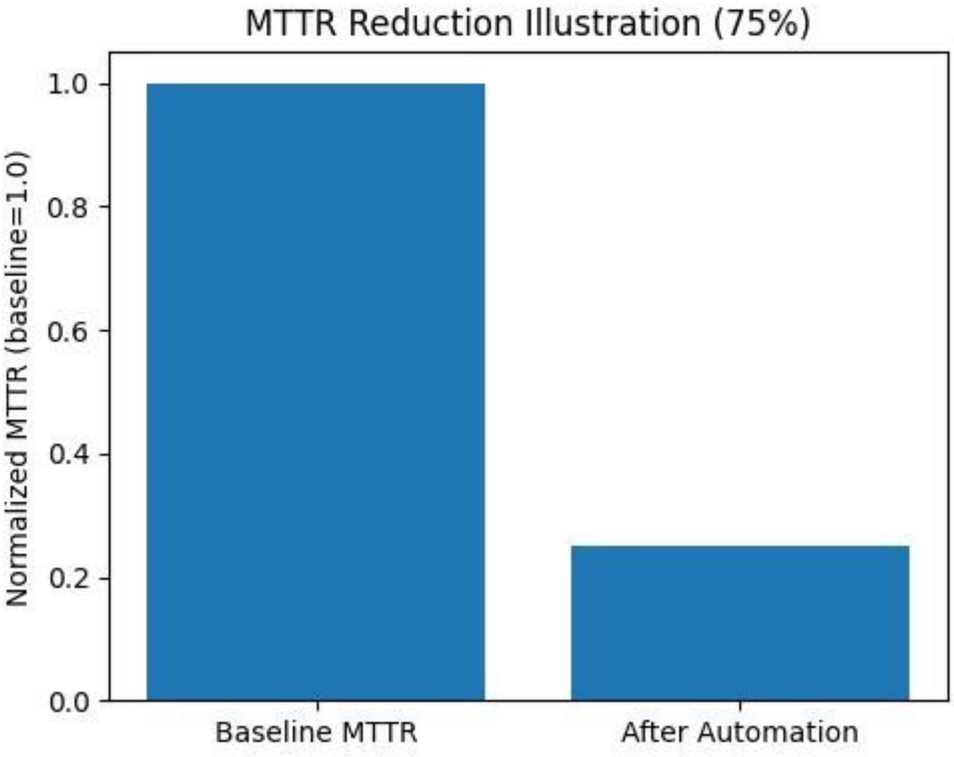
The heart of cloud automation consists of components responsible for processing data emitted by different sources and making intelligent decisions. These components are essential for any automated process in any IT service management (ITSM) tool platform. Automated processes deal with multiple types of decisions that can be classified based on the nature and type of data involved and the desired outcome of the automated process. The first group includes supervising decision engines that route either hardware or software alerts and other incident requests to the best-suited domain owner. The second group comprises triage engines that aim to automate the root cause analysis and resolution of alerts and tickets, usually in parallel. The third group comprises change request engines that orchestrate automated change requests whenever a set of conditions is met.

Various sources of data govern the hierarchical structure in the areas being supervised, the technical affinities between sources of alerts, and the preservation of continuous service delivery according to the established service level agreements. The nature of such data is multimodal, requiring a heterogeneous mix of model families to be handled properly. A part-based architecture makes it possible to deploy models for each of the decision tasks according to their nature while ensuring that all models are trained and operational in a coherent ITSM environment. The deployment process adheres to MLOps principles from model governance through lifecycle management and performance monitoring, offering transparency, impartiality, and audibility.

IV. USE CASES AND APPLICATIONS

Four use cases illustrate AI-driven automation for ITSM platforms in cloud environments. AI techniques automate workflows for incident management, helping operational teams route alerts to subject matter experts, conduct first-level triage, and perform automated remediation actions for predictable incidents. For change and configuration management, AI models enable detection of defects or regressions in test environments and guide deployment as well as configuration of new or updated services through policy-driven automation.

Automating decision-making for infrastructure operations reduces the volume and impact of incidents. Machine learning models analyze historical service desk data to identify root causes and generate natural-language explanations. Natural-language processing techniques enhance the efficiency of service desk teams by classifying and labelling tickets at first touch and suggesting resolutions for recurring queries. AI-driven tools monitor system performance and business services in real time. When anomalies occur, alert routing automates the process of notifying the right team and personnel, logical first-level triage of alerts is streamlined, and predictable failures trigger automatic mitigation actions.



Equation 3) ROI: complete derivation + computed
Step-by-step definition
Let:

- B = total benefit (monetized) over a period (often annual)
- C = total cost over the same period

Then net benefit:

$$\text{Net Benefit} = B - C$$

ROI as a percentage:

$$\text{ROI(\%)} = \frac{B - C}{C} \times 100$$

Mapping to the example numbers
The states (example):

- Savings = **$5M/year**
- Lost-business impact reduction = **$10M** (attributed to a 75% MTTR reduction)
- Development investment = **$0.75M**
- Support cost = **$0.25M/year**

So for **Year 1**:

$B = 5 + 10 = 15$ (million) $C = 0.75 + 0.25 = 1.0$ (million) ROI $= \frac{15-1}{1} \times 100 = 1400\%$

Payback period (how fast you recover the initial investment):
If annual net operating benefit (excluding the one-time dev cost) is:

$$B_{\text{annual}} - C_{\text{support}} = 15 - 0.25 = 14.75$$

Then:

$$\text{Payback years} = \frac{0.75}{14.75} \approx 0.051 \text{ years} \approx 18.6 \text{ days}$$

4.1. Incident management automation

A comprehensive list of incident management automation use cases includes automating workflows for alert routing, triage, and remediation actions. Alert routing involves analyzing incidents to determine their nature and urgency. Categorization is determined using a trained supervised machine learning model that predicts the most likely category and sub-category based on a feature vector derived from the nature and text fields of the alert as well as prior categorization patterns. The predicted category is then compared to the alert severity policy for the affected service and, in cases of a high-severity service alert, is reviewed by a senior manager or team leader from the affected service team who decides whether the alert should be escalated and paged or can be left to be managed during office hours.

For triage automation, the feature vector is similar to that used for alert categorization, excluding the category information, and is classified into three target classes: “known issue,” “likely false positive,” and “unknown.” A triage decision can trigger two other actions: updating the ticket with a root cause if the alert corresponds to a known issue and closing the ticket if it is classified as a likely false positive by the triage model. Remediation actions are identified as simple playbooks corresponding to the triaged alert category. Playbooks can be enforced following confirmation that the alert is not a known issue and also if they relate to an alert for a critical service during off-hours.

Derived Metric	Value
Annual benefit ($M)	15.0
Year-1 total cost ($M)	1.0
Year-1 net benefit ($M)	14.0
Year-1 ROI (%)	1400.0
Steady-state ROI (%)	5900.0

4.2. Change and configuration management

Change and configuration management automation includes incident detection, change implementation, and change and configuration policy enforcement. Changes usually result from a perceived need to mitigate future incidents. Policies can include blacklists, location-based restrictions, access control lists, and abusive behavior detection and punishment. Detecting and reporting incidents can be part of a supervised machine-learning model, using any relevant incident data. Change-management platforms often require incident tickets to implement changes, and model-driven automation often relies on configuration management to avoid unwarranted changes.

AI-based automated change and configuration management listens to the network and system-alerting space and applies any known or custom policies. An example is detecting a vulnerable application version and escorting the change management process; if policy detection fails, human supervision and governance can mitigate risk. Defect detection follows the same logic but uses only blacklists and reported problems. Adding remote execution enhances the automation toolkit. Configuration management brakes—effectively, whitelists—can include rules for flagging unresponsive or potentially harmful addresses, patterns, and protocols. Adding a detection layer for abusive behavior augments the scope of this management category.

Equation 4) “Reduction in defects / violations / wasted testing” equations
If baseline count is X_0, reduction is $r\%$, new count is:

$$X_1 = X_0\left(1 - \frac{r}{100}\right)$$

Example:

- If baseline violations $= 1000$, reduction $= 27\%$:

$$X_1 = 1000(1 - 0.27) = 730$$

V. EVALUATION OF BENEFITS AND RISKS

When evaluating the adoption of AI-driven cloud automation for ITSM platforms, it can be observed that operational costs continue to rise while budgets remain constrained. For those who operate cloud environments that support development and production workloads, mean time to repair (MTTR) and service levels can become critical factors for cloud team success. Total costs of ownership (TCO) are also important, although specific deployments may fall within acceptable TCO bands even when overall cloud TCO exceeds expectations. As with any complex deployment, the evaluation of AI-driven cloud automation for IT service management platforms must be carried out in an objective manner.

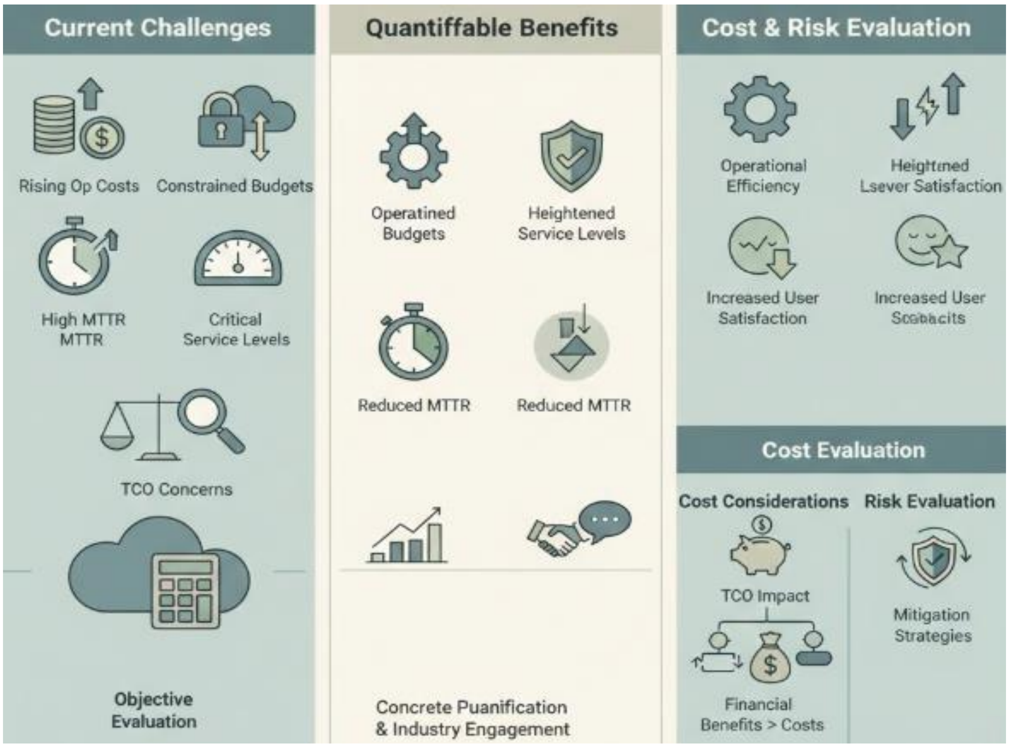


Fig 3: Evaluating AI-Driven Cloud Automation in ITSM: A Multi-Dimensional Framework for Operational Efficiency, TCO Optimization, and Risk Mitigation

Benefits of AI-driven cloud automation for ITSM platforms include improved levels of operational efficiency, heightened service levels, reduced MTTR, and increased user satisfaction. These positive attributes can generally be quantified in concrete terms, although specific figures should be established through engagement with industry practitioners. Cost considerations surround the business case and include the impact on TCO, ROI, and any other pertinent aspects of expenditure that can be associated with AI-driven cloud automation for ITSM platforms—financial benefits should normally outweigh cost consequences. Risk evaluation encompasses the challenges and hazards associated with implementation, with suggested mitigation strategies aiding in addressing them.

5.1. Operational efficiency and service levels

Decision engines within automation workflows can encapsulate knowledge related to incident management, service assurance, or change management, enabling self-healing without human intervention. Full automation reduces labour cost, enabling the reallocation of FTEs to more proactive and less time-consuming teams. Cost reductions are complemented by improvements in service levels—both in terms of availability assurance and in terms of user experience.

In addition to the resolutions made to incidents through automation, the alerts generated are automatically routed to the L3 team only when the L2 team is already overloaded. The ticket triage is further assisted by an NLP-based application that maps the human-written ticket description to the categories available in the ITSM tool. When the detected category is that of an ongoing incident, it is flagged and highlighted by the system to allow the L3 team to focus on the most urgent issues. All the user requests detected as automation candidates are either fulfilled automatically or routed to the L2 team only when this is the most optimal option. Automated actions fulfil user requests without further action and delays.

5.2. Cost implications and ROI

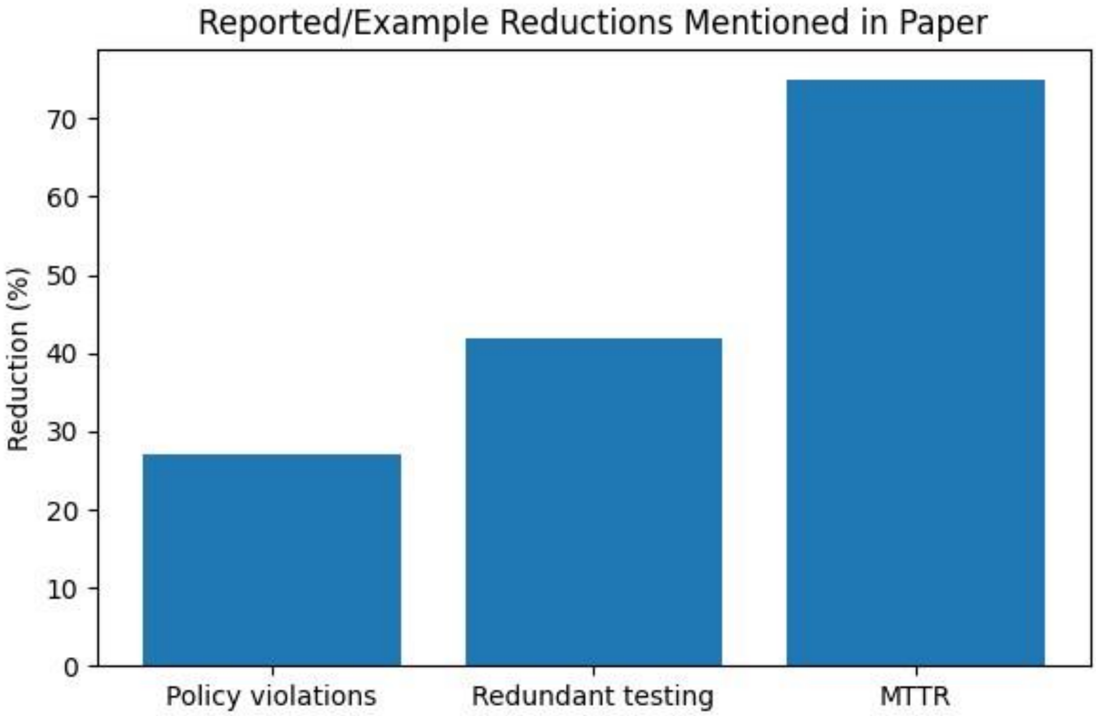
Return on investment (ROI) incorporates both the cost of implementing automation and the benefits derived from automation, expressed as a percentage of the implementation cost. If there are significant negative consequences resulting from failure to automate but are not reflected in existing metrics, then it may be necessary to assign a monetary value to them to justify the investment in automation. The total cost of ownership (TCO) of an IT system quantifies the costs incurred during the systems lifecycle including software, hardware, networking, support, training, failure prevention, and performance enhancement. Some costs and benefits associated with MLOps and ITSM automation are illustrated in the TCO framework, although valuation can be difficult.

For a self-service automation framework such as implemented by a global technology company, the estimated savings were $5 million per year (including a 75 % reduction in mean-time-to restore was estimated to lower lost-business impact by $10 million) compared with a development investment of $0.75 million and support cost of $0.25 million per year. A leading IT service provider estimated that automating incident resolution of garden-variety alerts with a self-healing engine was 10 to 15 times more cost-effective than a manual approach. An AI-based approach to change management reduced the incidence of successful test case failure (policy violations) in pre-production environments by 27 and the use of redundant testing resources by 42 Supporting the business justification of the total allocation of testing resources across non-production environments, these cost-of-living considerations are abstract but necessary.

VI. METHODOLOGIES FOR DEPLOYMENT AND EVALUATION

Deploying and evaluating AI-driven cloud automation solutions for ITSM platforms requires adaptation of MLOps practices to the specific characteristics and constraints of the ITSM environment. Defining an effective governance framework, which incorporates key stakeholders from engineering, architecture, operations, compliance, security, and risk, is crucial. Data used to train AI/ML models should be managed according to relevant policies for privacy and security. Testing strategies must cover performance, reliability, security, and compliance aspects, with a special focus on model drift, data shift, and model accuracy, including possible consequences of failure on business service delivery.

Governing the deployment of AI solutions requires different areas of involvement: Engineering and Architecture govern the MLOps and cloud automation platforms on which the AI solutions run. They align on prerequisite steps needed for AI/ML solutions to be deployed onto these MLOps platforms: pipelines for data ingestion, data formatting, and data consumption; monitoring and retraining strategies; and the associated workflows that must be run whenever these stages in the AI/ML solution lifecycle are reached. Operations govern the operational aspects of the deployed AI/ML solution, including routine checks on performance, reliability, and compliance.



Equation 5) TCO: complete decomposition equation

A standard decomposition that matches the paper's wording is:

$$\mathrm{TCO} = C_{\mathrm{software}} + C_{\mathrm{hardware}} + C_{\mathrm{network}} + C_{\mathrm{support}} + C_{\mathrm{training}} + C_{\mathrm{prevention}} + C_{\mathrm{performance}} + \cdots$$

When automation is introduced, you compare:

$$\Delta\mathrm{TCO} = \mathrm{TCO}_{\mathrm{after}} - \mathrm{TCO}_{\mathrm{before}}$$

Automation is financially justified if:

$$\Delta\mathrm{TCO} < 0$$

6.1. MLOps in ITSM environments

Benefits of AI-driven cloud automation for ITSM platforms extend beyond the individual organization. Cost savings accrue from greater efficiency in operational activities and from better service levels. For example, reduced mean time to repair (MTTR) contributes to service-level agreement (SLA) compliance. Improved user satisfaction lowers support request volume, especially for incidents that are costly to resolve. Collectively, these effects reduce the total cost of ownership (TCO) of IT infrastructure and services.

Major cost savings arise as automation handles a greater volume of operational work. A combination of intelligent chatbots handling simple tasks, automated detection of defects in service delivery, and automated testing and deployment of changed or new services reduces the number of alerts seen by human agents, makes it cheaper to resolve remaining alerts, and lowers the cost of change and other service actions. Overhead costs are fixed and provide limited scope for cost reduction, so the most economical benefits come from increasing the volume of work handled by automation at low cost. It is also important to align the capabilities of automated processes with the need for reliable service delivery at the lowest possible cost.

6.2. Testing strategies and metrics

Testing AI applications deployed to ITSM environments must assess operational performance, quality, reliability, security, compliance, and risk mitigation. These dimensions differ from existing guidance related to cloud-native applications, necessitating external methods to catalogue features, functions, and performance metrics. AI cloud services, decisions, and models must be tested for performance, reliability, security, and compliance during development and deployment. MLOps expertise is essential for managing cloud services, their operational data, decision-making processes, and batch or online machine learning.

Security testing ensures risks and vulnerabilities affecting the service's architecture, platform, and supporting infrastructure are managed. Testing the risk management strategy for the ML model deployment is critical, as the deployment environment and external data are both constantly changing. Security monitoring must be capable of detecting and responding to suspicious activity in MLOps processes, systems, and pipelines.

VII. CONCLUSION

The 2023 SDLC of AI-driven Cloud Automation for IT Service Management Platforms paper proposes methodologies for deploying and evaluating AI-enhanced automation of ITSM tools in IT service delivery. A high-level architecture specifies roles, processes, and data sources supporting the development of AI components, decision engines, and output types. Data sources need to be identified together with the associated ingestion pipelines with the necessary pre-processing. MLOps practices tailored to an ITSM environment are established with SDLC consideration for governance, lifecycle, and monitoring. Testing practices ensure that use cases integrate well under both functional and non-functional aspects.

By focusing specifically on the development, testing, and deployment of AI components that enhance cloud automation within an ITSM context, the paper addresses open research questions not fully covered in existing academic literature. The considerations presented in the paper engender greater confidence in leveraging AI-enabled automation within existing ITSM tools, ultimately more efficiently achieving the objectives of Cloud Operations Services.

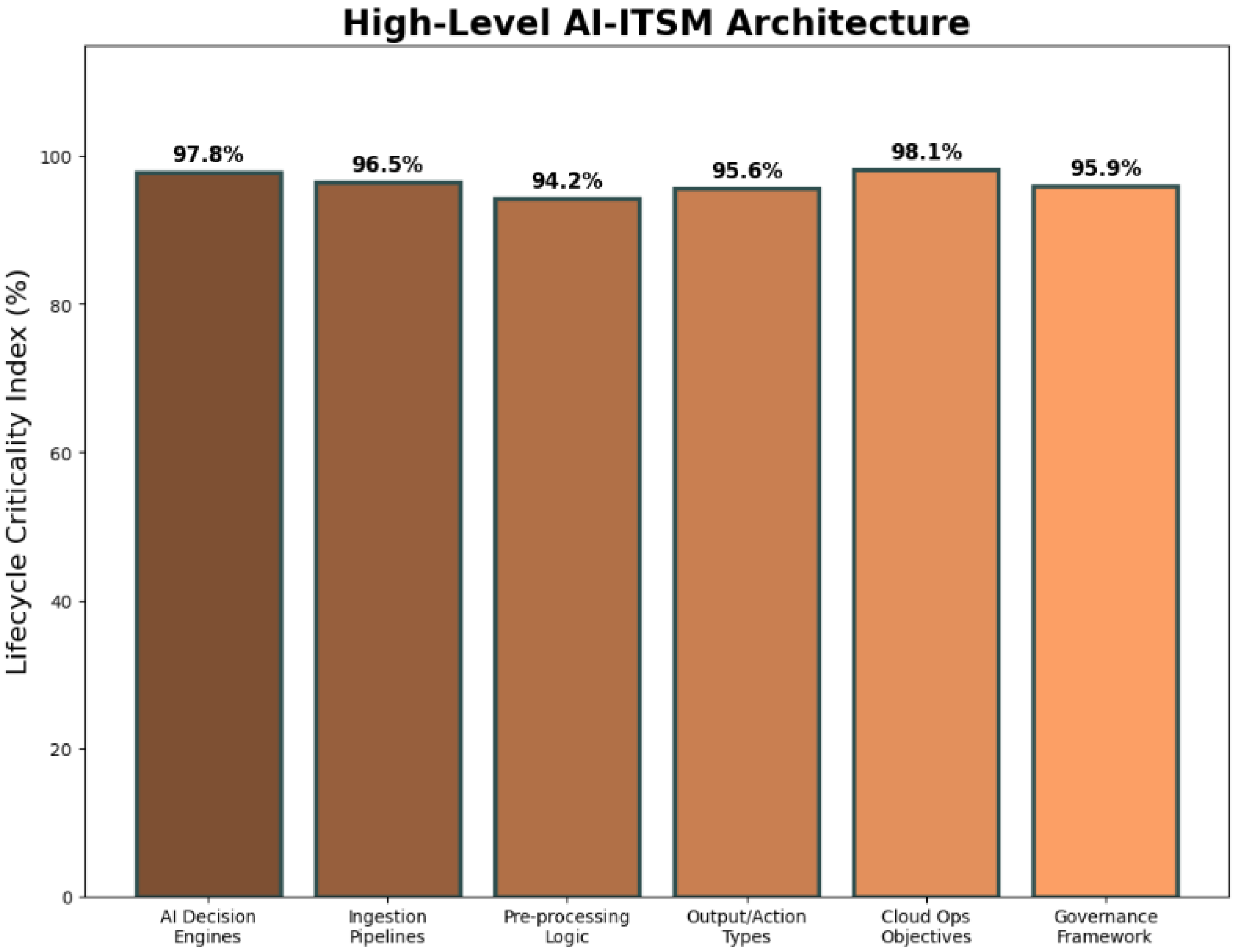


Fig 4: High-Level AI-ITSM Architecture

7.1. Summary and Future Directions

Key findings indicate that hybrid models combine supervised and unsupervised learning with a knowledge graph backbone. Such architectures enable automation of IT service management (ITSM) platforms in key areas, such as incident management, change management, and configuration management. In comparison with traditional IT service model development, these approaches yield reduced time to deployment and operating costs and increased service quality.

Current developments in artificial intelligence (AI) bolster cloud infrastructure automation and provide viable low-code and no-code solutions for IT operations (ITOps) through AI-enabled IT automation. More specifically, cleverly designed sets of algorithms automate repetitive tasks, increase the efficiency of operations teams, and reduce the time needed for incident root-cause analysis. Current advancements improve and augment organizations' existing IT service management (ITSM) platforms through automations based on MLOps principles. MLOps practices custom-tailored to ITSM environments address governance, model development, deployment, lifecycle management, monitoring, and health preservation. Proposed testing strategies ensure that performance, reliability, security, and compliance standards align with the organization's objectives while reducing maintenance overhead. Hybrid learning strategies improve the automation of alert routing, incident-management triage and remediation, change management, and configuration management capabilities.

Industry demand for low-code automation and innovation enables deployments across a broad spectrum of environments and use cases. Continued convergence of AI hyper models and MLOps increases the pace of such initiatives and further reduces delivery times. Future innovations focus on enhancing support for AIops and intelligent adaptive assurance, optimization, and design. A code-free AI model-building environment allows broader participation of experts who lack data-science skills or machine-learning development experience.

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