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AI-Powered Cloud Observability for Proactive Infrastructure Management

Shashikala Valiki

Independent Researcher, India

ABSTRACT: Sustaining cloud-computing infrastructure and services in the face of increasing complexity require comprehensive monitoring and analysis of operating conditions and performance. Observability delivers actionable insights from telemetry data by enabling analysis throughout the entire data life cycle, from data collection and feature engineering through detection, diagnosis, and response. Cloud observability typically focuses on understanding the current state of the infrastructure, but integrating artificial intelligence adds predictive and prescriptive capabilities that inform future resource usage requirements and enable proactive adjustments—behavior that SRE teams are likely to welcome despite initial investment costs.

Proactive observability incorporates a range of proactive features, including predicting unusual usage patterns requiring scaling, identifying maintenance opportunities and their risk impact, forecasting demand from new customers or planned marketing campaigns, assessing risk when implementing changes, guiding resource provisioning for new services, and automating runbook execution when known issues occur. These capabilities can be used to augment the quality of service or control costs, with machine learning models learning from past experiences in human-in-the-loop scenarios.

KEYWORDS: Cloud, Observability, Artificial Intelligence, Machine Learning, Infrastructure Management, SRE, Data Pipeline.

I. INTRODUCTION

Cloud computing promises lower cost and faster speed. However, effective governance of cloud services is costly and complex, requiring investing in engineering talent and deploying structured processes and monitoring observability. Therefore, companies may be tempted to move to the cloud without sufficient internal expertise. Such "cloud first, think later" migrations may lead to poor design that can create risk during normal operations. Observability is being advocated to address this risk pattern. A larger level of observability is usually viewed as an improvement, although its definition is often vague or inconsistent. However, despite this view, dashed hopes are associated with observability, suggesting that merely increasing observability to overcome past design flaws is not a cure-all. In fact, only rarely does a human being examine the observability data in a pre-defined manner. Such a reactive form of observability, as practiced today, may be necessary but cannot be sufficient. The true power of cloud observability lies in enabling AI to turn the petabytes of observability-related data and alerts into proactive guidance on what actions should be taken.

Proactive observability enables AI to provide anticipatory guidance for cloud infrastructure. As the holy grail of observability, it has been explored from the point of view of providing anticipatory guidance for capacity scaling, autoscaling, performance, availability, and cloud security. The problem space has been synthesized in order to clarify the quality of guidance that can be expected and to clarify for what tasks the development of AI-enabled observability should focus. The quality of the anticipatory guidance is constrained by explainability, either inherent or by development of a proxy MIRROR agent, that provides information in a form that human beings can easily digest.

Cloud computing is often promoted as a pathway to lower costs and faster innovation, yet the governance required to operate cloud environments effectively is neither simple nor inexpensive. Organizations must invest in skilled engineering talent, disciplined architectural standards, and mature monitoring and operational processes. Without this foundation, “cloud first, think later” migrations can result in fragile system designs that introduce operational risk rather than eliminate it. Observability has emerged as a response to this challenge, promising deeper insight into system behavior through metrics, logs, traces, and events. While greater observability is commonly equated with improvement, its meaning is frequently inconsistent, and simply collecting more data does not resolve flawed architecture or poor operational discipline. In practice, observability today is largely reactive—humans examine dashboards and alerts only after incidents occur, and rarely in a structured, pre-defined way. Although necessary, this reactive model is insufficient for managing the scale and complexity of modern cloud environments. The real transformative potential of cloud observability lies in leveraging AI to analyze vast volumes of telemetry data, detect patterns beyond human perception, and deliver proactive, context-aware guidance on corrective or preventive actions. Rather than serving merely as a diagnostic tool, observability must evolve into an intelligent decision-support system that strengthens resilience, reduces risk, and enables truly adaptive cloud operations.

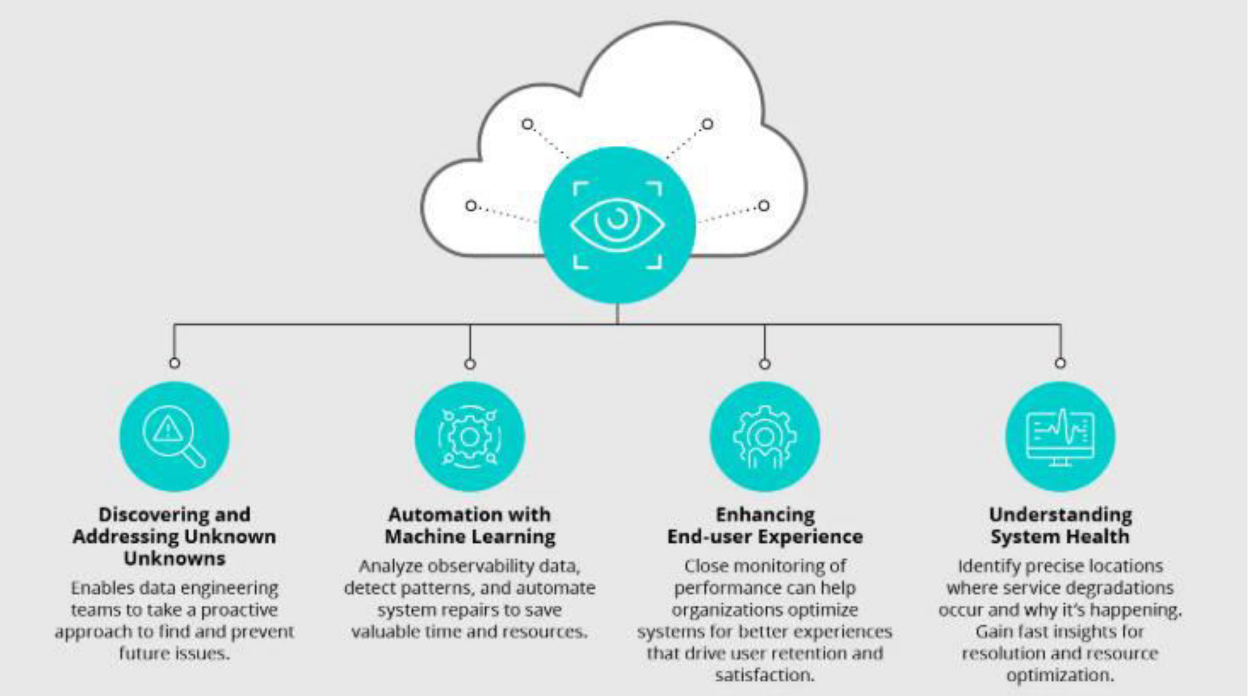

Discovering and Addressing Unknown Unknowns
Enables data engineering teams to take a proactive approach to find and prevent future issues.
Automation with Machine Learning
Analyze observability data, detect patterns, and automate system repairs to save valuable time and resources.
Enhancing End-user Experience
Close monitoring of performance can help organizations optimize systems for better experiences that drive user retention and satisfaction.
Understanding System Health
Identify precise locations where service degradations occur and why it's happening. Gain fast insights for resolution and resource optimization.

Fig 1: Cloud Observability

1.1. Background and Significance

The increasing complexity and data volumes of cloud infrastructures create significant challenges in managing the sites of complex systems. Providers, customers, and site reliability engineering (SRE) teams are suffering from cloud's hidden and growing costs, risks, and reliability issues. Existing approaches to observability, detection, and resolution are largely reactive, consuming too much human effort and focus. AI-assisted observability through improvement of detection, classification, explanation, and resolution would lower these costs and improve reliability. The observability dilemma considers how these capabilities can be achieved within cloud environments. AI's potential roles in observability are analyzed and mapped to the needs of SRE and Aleph's six questions. Prior work provides a starting framework for an AI-powered observability architecture.

Infrastructure monitors, log managers, analyzers, and service mesh solutions provide the visibility and observability required to maintain the reliability of these systems. However, these technologies lack proactive guidance and procedure automation, and the data collected is either of low quality or incorrectly expressed. Consequently, site reliability engineering (SRE) teams spend too much time detecting and explaining problems. As a result, AI solutions to reduce labor and increase reliability—historically treated as second-order considerations in infrastructure—have become truly compelling. Machine learning, anomaly detection, causal inference, and the MIRRORing of human-in-the-loop operational decisions all help make cloud observability more accessible. A taxonomy of the associated capabilities categorized as a form of preventive or predictive maintenance would assist in communicating its value. Moreover, a roadmap depicting future directions and mature implementations would allow practitioners to anticipate the deployable scope within their enterprises.

Equation 1: Put demand into the same feature space

To compare demand vs. feature-augmented supply, map demand into a "required" vector:

$$\mathbf{r}_t = \begin{bmatrix} r_t^{(1)} \\ r_t^{(2)} \\ \vdots \\ r_t^{(k)} \end{bmatrix}$$

A simple, common mapping is proportional requirement (domain-specific):

$$r_t^{(1)} = d_t, r_t^{(2)} = a_2 d_t,\ \dots, r_t^{(k)} = a_k d_t$$

II. FUNDAMENTALS OF CLOUD OBSERVABILITY

Cloud observability describes a category of monitoring solutions capable of answering complex questions about distributed cloud-hosted services using telemetry data. Conventional monitoring tools are designed to alert on operational failures based on a set of predefined thresholds and to enable investigation thereafter. These capabilities, often termed reactive observability, support Site Reliability Engineering (SRE) objectives such as reducing incident frequency and mean time to recovery (MTTR). By contrast, AI-enabled cloud observability pursues proactive insight into service behaviour by interpreting data with techniques ranging from machine learning to causal models. These solutions play a key dialectic role in the business-IT relationship, revealing the impact of operational decisions on business outcomes from an IT perspective and enabling resource-efficient deployments from a business perspective.

Success metrics for observability and associated evaluation criteria form the foundation for experimental inquiries into cloud-hosted service behaviour. Reactive behaviour is captured through the judicious selection of deployment topology (SaaS, IaaS, PaaS) and observability coverage with respect to the spectrum of defined failure modes. A cloud-hosted service is a natural candidate when optimising for failure mode repetition. Data collection combines public telemetry sources with user-generated event data from incident reporting platforms such as Sentry and GitHub. The data sources, sampling techniques, ethical implications, and sequence of analysis steps are thoroughly documented to support reproducibility. Key performance indicators are drawn from the Euclidean distance relation between demand and feature-augmented feature supply.

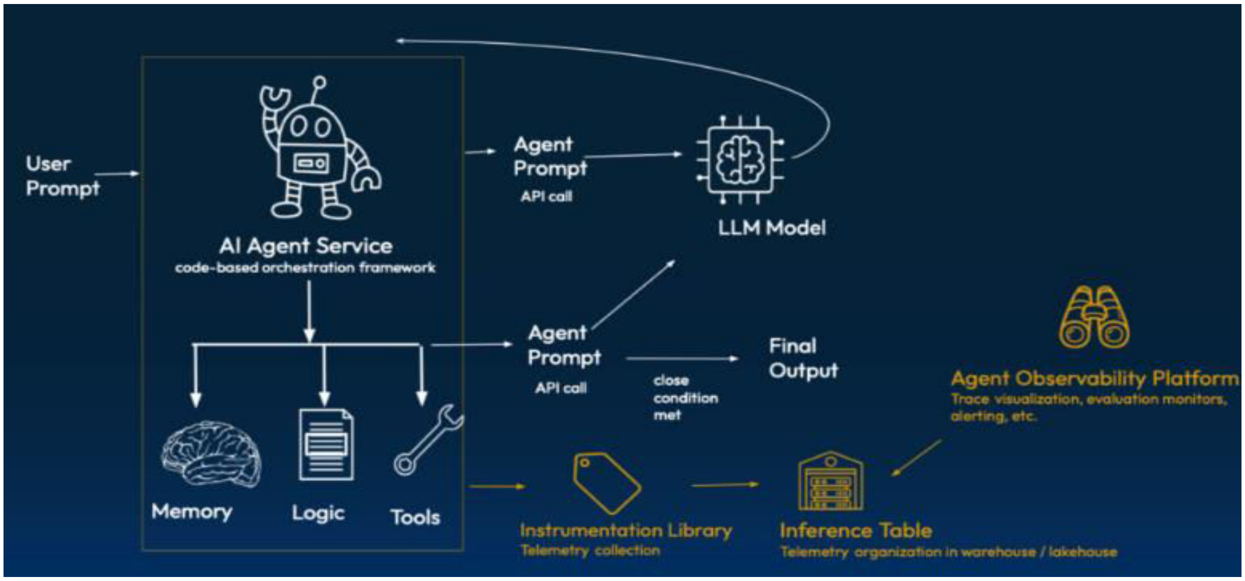


Fig 2: Fundamentals of Cloud Observability

2.1. Research design

The research design addresses the data sources and sampling strategy and describes ethical considerations, the contribution to knowledge and practice, and the means of validation.

Observability research draws primarily on primary sources of monitoring and telemetry data from a cloud infrastructure compute cluster. Because this data might be considered sensitive, it was subjected to a cloud hosting provider's controlled-access agreement. The analysis reconstructs critical factors for approximately four months across the COVID-19 pandemic's early phase in the Northern Hemisphere. The combination of telemetry featurization and informatics about predictive capacity planning offers an original contribution to knowledge, and the work as a whole serves Site Reliability Engineering practice. Labelling as redacted those aspects that might typically breach the confidentiality agreement fortifies reflection testing and reproducibility.

Equation 2: KPI equation in the paper: Euclidean distance (fully derived)
For two vectors $\mathbf{r}_t$and $\mathbf{x}_t$in $\mathbb{R}^k$,

$$\mathrm{dist}(\mathbf{r}_t, \mathbf{x}_t) = \sqrt{\sum_{i=1}^{k} \left(r_t^{(i)} - x_t^{(i)}\right)^2}$$

1. Difference vector:

$$\Delta_t = \mathbf{r}_t - \mathbf{x}_t$$

2. Squared length (dot product with itself):

$$\| \Delta_t \|_2^2 = \Delta_t^\top \Delta_t$$

3. Write it as a sum of squared components:

$$\Delta_t^\top \Delta_t = \sum_{i=1}^{k} \left(r_t^{(i)} - x_t^{(i)}\right)^2$$

4. Take square root to get Euclidean norm:

$$\boxed{K_t = \| \mathbf{r}_t - \mathbf{x}_t \|_2 = \sqrt{\sum_{i=1}^{k} \left(r_t^{(i)} - x_t^{(i)}\right)^2}}$$

This $K_t$is a **single KPI time series** you can trend, alert on, and feed into anomaly detection.
If units differ wildly (CPU vs memory), normalize or weight:

$$K_t = \sqrt{\sum_{i=1}^{k} w_i \left(\frac{r_t^{(i)} - x_t^{(i)}}{\sigma_i}\right)^2}$$

III. ARTIFICIAL INTELLIGENCE IN OBSERVABILITY

Integrating AI capabilities into observability enhances the knowledge gained from collected telemetry, improving cloud quality, reliability, and costs. Machine learning underpins these benefits, supporting anomaly detection, causal inference, and the MIRRORing of human-in-the-loop decision-making patterns. Key enabling factors include the development of high-quality data pipelines, sufficient data volume, data instrumentalization through dedicated telemetry sources, and a commitment to standard schema-based telemetry collection.

Machine learning and anomaly detection assume primary roles in tracking signals, association patterns, and causal relationships. Advances in these fields enable better visibility into complex cloud systems. Artificial intelligence acts as a catalyst for organizations, enabling support for cloud-native architectures and delivering proactive insights. When carefully-designed and properly-assembled data pipelines supply diverse cloud telemetry to the AI engine, usually composed of specialized machine-learning models, the observability platform gains a comprehensive self-learning capability. Such a system can close the loop by using detected anomalies for autoscaling, cloud capacity planning, runbook automation, risk assessment, and other decision-making processes normally performed by SREs.

Fig 3: AI in Network Observability

3.1. Data collection and instrumentation

The practical implementation of AI-enabled observability requires effective data collection across multiple types, with infrastructure and application-level instrumentation key to comprehensive coverage. Data sources can be classified according to the cloud services model—from infrastructure as a service (IaaS) up to serverless containers—and supplemented by custom application signals. For any service type, the major available telemetry data sources are metrics, traces, logs, and events.

The relevant telemetry types should be collected and correlated for all cloud-managed services. Metrics convey aggregated time-series data from multiple types of signal sources at different granularities and have become indispensable for runtime monitoring of cloud resources. Content distribution networks, queues, autoscalers, and other managed or serverless services generate events at runtime that can be useful for context or activity attribution. Log data provide host-level details about cloud-managed services. Observability solutions operate at higher layers in the stack and solve different technical and business problems but fundamentally rely on traces and logs to monitor cloud-managed backends. Well-instrumented libraries generate span metadata, and correct signal production is usually covered by normal operating procedures.

Equation 3: From KPI → anomaly detection (as described conceptually)

Given KPI values $K_1, \dots, K_T$:

1. Mean:

$$\mu = \frac{1}{T}\sum_{t=1}^{T} K_t$$

2. Sample standard deviation:

$$s = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(K_t - \mu)^2}$$

3. Z-score at time t:

$$\boxed{z_t = \frac{K_t - \mu}{s}}$$

4. Alert rule (example):

$$\text{Anomaly if } |z_t| \geq \tau(\tau \text{ often } 3)$$

IV. ARCHITECTURAL PATTERNS FOR AI-DRIVEN OBSERVABILITY

Two architectural patterns supporting AI-driven observability are identified: centralized and federated models. The centralized model comprises a unified, modular architecture for high-level decision-making and a set of granular modules for automated actions at the service level. The federated model is usually deployed with a simpler federation of decentralized teams supporting observability across independent cloud deployments. Each pattern satisfies different deployment needs.

The centralized model comprises centralized data pipelines, often coupled with a feature store, that feed a centralized observability solution responsible primarily for high-level, long-term decision-making. At the service level, specialized building blocks take care of real-time data analysis and automated actions. These components can analyze service-specific data and initiate automated responses that require execution in proximity to the service (such as scaling operations). By decoupling these actions from high-level decision-making, the architecture provides sufficient flexibility and scalability.
Architecture and Organizational Structure

Deployment of dedicated observability teams can significantly accelerate speed of development while simplifying the project's management at the expense of an increased integration effort. The centralized pattern can be complemented with a properly designed organizational structure capable of federating observability across a set of independent cloud deployments.

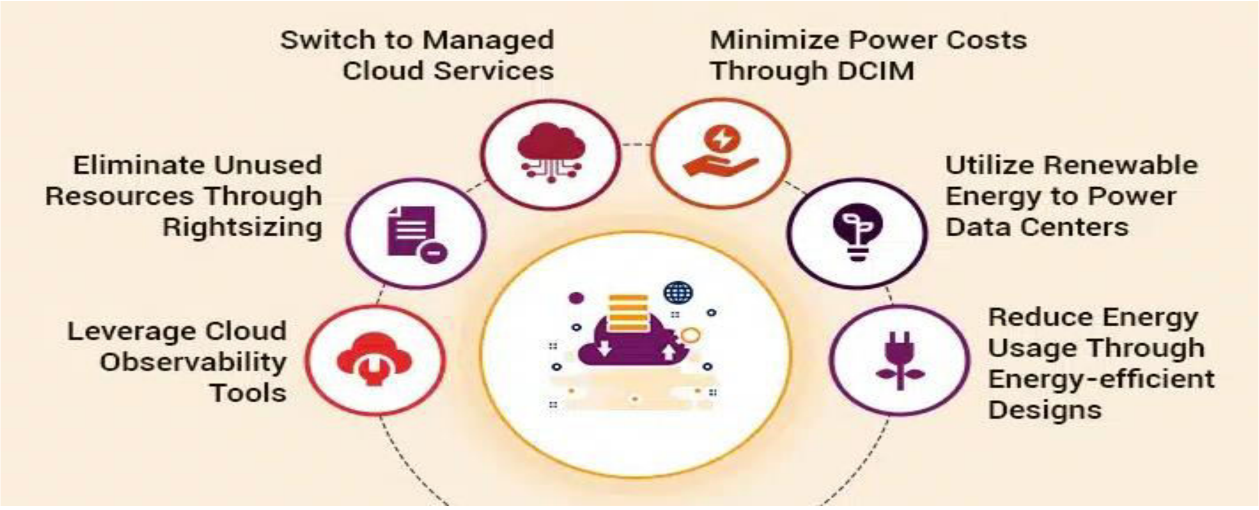

Switch to Managed Cloud Services
Minimize Power Costs Through DCIM
Eliminate Unused Resources Through Rightsizing
Utilize Renewable Energy to Power Data Centers
Leverage Cloud Observability Tools
Reduce Energy Usage Through Energy-efficient Designs

Fig 4: Cloud Computing Architecture for AI, Sustainability

4.1. Data pipelines and feature stores

Recent years have seen increasing interest in the application of artificial intelligence to observability. In some cases, these efforts claim the inclusion of AI translates into a shift from reactive to proactive observability. To clarify this notion—and to provide practical guidance to those looking to instantiate AI-enhanced observability in their infrastructures or products—it is helpful to consider a series of architectural patterns supporting different variants of such an approach.

At the highest level, observing clouds powered by AI can take either a centralized or federated approach to data, modeling, and control planes. With the former, a specialized team owns, maintains, and operates the corresponding infrastructure. Any entities wishing to leverage it must integration it with all their respective systems and manual workflows. The latter approach offers higher agility, empowering and encouraging business units to independently build and deploy their models and cause-effect analyses.

Regardless of the above distinction, AI-powered observability is usefully viewed as a modular stack. Observability-as-a-service products in this space typically provide a low-code environment that enables business units to independently tap into the functionailties of dedicated feature-ML and MLOps engineering offerings specifically designed to support them. As these observability products impose a cost on each functioning business unit, pressure typically arises at some point to supplant the service with supporting in-house infrastructures, often feeding into the same central business unit as that for AI-enhanced cloud security.

Data pipelines—whether streaming or batch-based—constitute a key architectural building block. Those implementing the former may select among open-source, commercial, or SaaS services. For the latter case, in particular, the use of dedicated feature stores is increasingly being established as a best practice allowing important metadata to be easily maintained for the features supporting training, validation, and scoring of predictive models.

Equation 4: EWMA (Exponential smoothing) derivation

Let $\hat{d}_t$be the forecast of demand at time t.

1. Define recursion:

$$\boxed{\hat{d}_t = \alpha d_{t-1} + (1-\alpha)\hat{d}_{t-1}} \text{for } 0 < \alpha < 1$$

2. Expand it to show it is a weighted sum of history:

$$\hat{d}_t = \alpha d_{t-1} + (1-\alpha)\big(\alpha d_{t-2} + (1-\alpha)\hat{d}_{t-2}\big)$$
$$= \alpha d_{t-1} + \alpha(1-\alpha)d_{t-2} + (1-\alpha)^2\hat{d}_{t-2}$$

Continuing expansion:

$$\hat{d}_t = \alpha \sum_{j=1}^{m} (1-\alpha)^{j-1} d_{t-j} + (1-\alpha)^m \hat{d}_{t-m}$$

V. PROACTIVE MANAGEMENT WITH AI

AI empowers observability to transition from its traditional reactive-mode roots toward proactive management. Anomaly prediction adds a forward-looking capability, enabling resource autoscaling in anticipation of demand changes, supporting capacity forecasting, automating fault isolation with runbook execution, and ultimately closing the operational feedback loop. Anomaly prediction moreover feeds directly into predictive capacity-planning methods, which bolster robustness and resiliency by establishing solid signal foundations for accurately matching supply with demand. AI also strengthens capacity-planning processes by predicting resource demand for future time periods, facilitating service-level-management evaluations, optimizing resource allocation, scoring infrastructure risk exposure, estimating resource discontinuities, and supporting scenario or what-if analysis.

Methodological foundations for predicting resource demand over future time periods draw heavily from time series analysis and forecasting literature. Techniques available for addressing predictive capacity planning span statistical methods, machine learning, and hybrid approaches. The aim of demand forecasting is to develop effective and efficient models for predicting future resource demand at various levels of granularity. Five basic dimensions define the nature of the forecasting problem: resource type, time period, geographic region, forecast frequency, and forecast horizon. Two additional dimensions of the forecasting problem relate to observed demand patterns: demand seasonality and demand certainty. Clearly defined assignment of the various dimensions of the forecasting problem serves to create a tailored forecasting framework with maximum predictive efficacy and efficiency.

Equation 5: Forecast → risk scoring equation (capacity failure risk)
Let $c_t$be capacity and $D_t$be the (random) future demand.

$$\text{Failure at } t \iff D_t > c_t$$

5.2 Use a probabilistic forecast
Assume forecast distribution:

$$D_t \sim \mathcal{N}(\hat{d}_t, \sigma^2)$$

(where σcomes from forecast residuals)
Then:

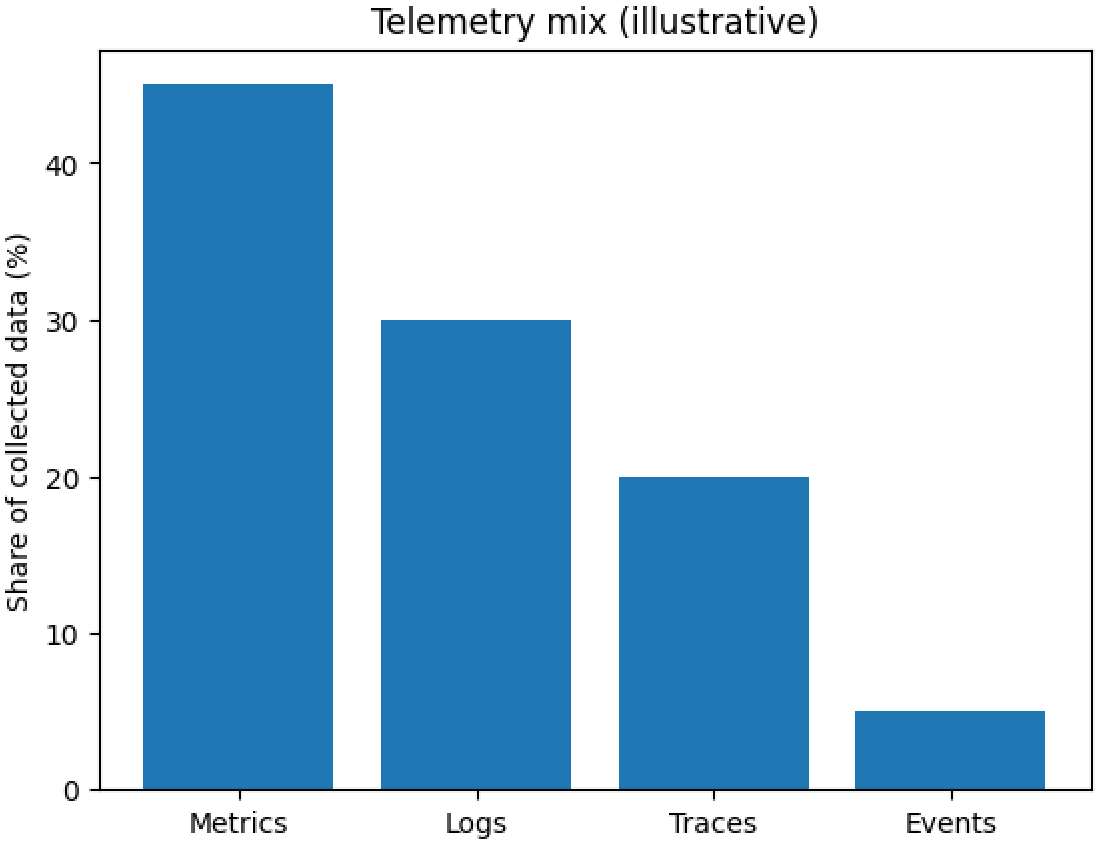
$$\text{Risk}_t = \mathbb{P}(D_t > c_t) = 1 - \Phi\left(\frac{c_t - \hat{d}_t}{\sigma}\right)$$

$$\boxed{\text{Risk}_t = 1 - \Phi\left(\frac{c_t - \hat{d}_t}{\sigma}\right)}$$

5.1. Predictive capacity planning
Cloud-native applications feature resource provisioning and scheduling mechanisms that aim to achieve self-adaptive capacity allocation by scaling the infrastructure and platform in response to demand fluctuations. These built-in mechanisms complement cloud autoscaling capabilities triggered by changes in resource utilization levels.CAPACITY PLANNING SUPPORT IS ONE MAJOR ASPECT OF PROACTIVE INFRASTRUCTURE MANAGEMENT.The goal of capacity planning is to have adequate resource capacity at all times to cope with incoming workloads OR demands while preventing wasted resources and associated costs. Capacity planning problems include forecasting future resource demands, making decisions when and in what characteristics to add or remove resources (at scale), and scoring risk associated with no capacity failure.

Demand forecasting feeds into these decisions. Extrapolating demand patterns over time series (time series forecasting) is a commonly-used approach INSPIRED BY MACHINE LEARNING TIME SERIES FORECASTING. However, other demand models exist, including category demand·predictive resource allocation modeling, which formulates an optimization approach to allocate resources of different types to multiple service clusters for a specific time interval; RESOURCE SCORING AND RESOURCE LEASING PROBLEMS; SCENARIO ANALYSIS-BASED RESOURCE RISK.

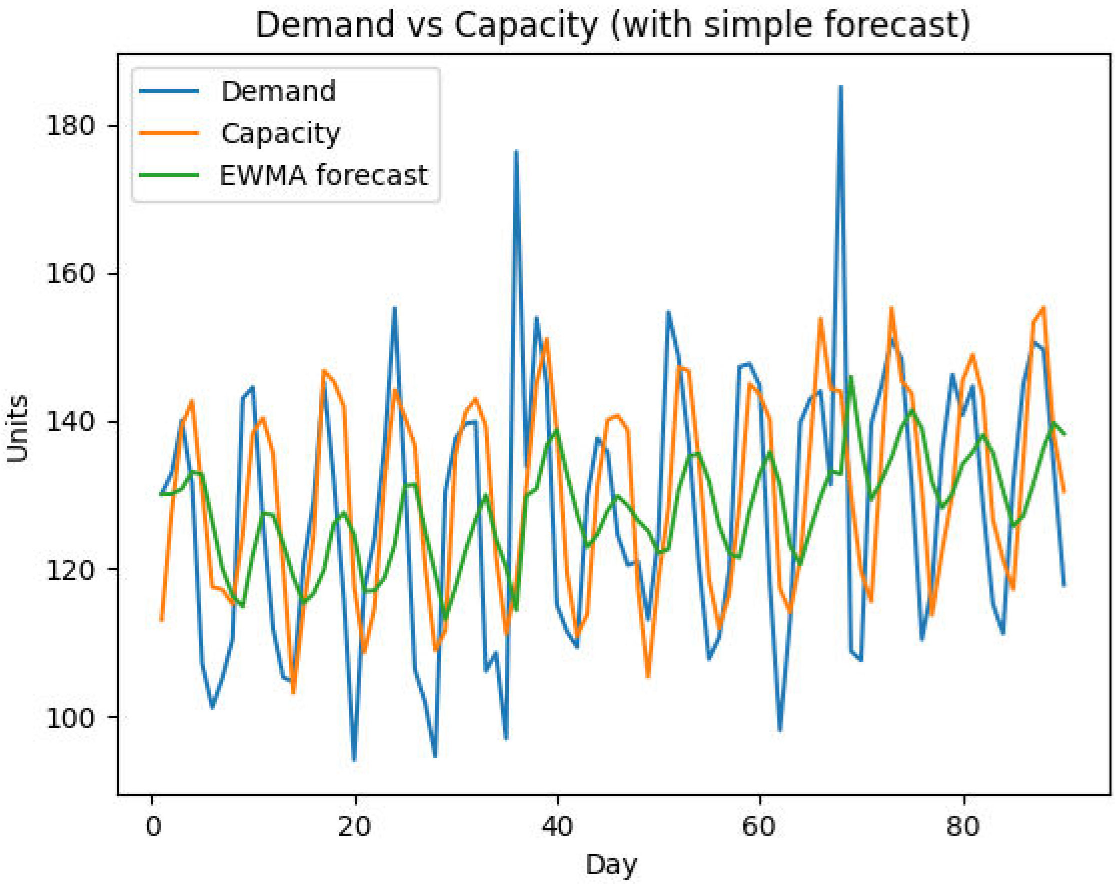
Demand forecasting plays a critical role in operational and strategic decision-making, particularly in environments where resources must be allocated efficiently under uncertainty. One widely adopted approach is time series forecasting, which extrapolates historical demand patterns into the future using statistical and machine learning techniques. Inspired by machine learning time series forecasting methods—such as recurrent neural networks, gradient boosting models, and transformer-based architectures—these models capture seasonality, trends, and complex nonlinear relationships to improve predictive accuracy. However, forecasting demand alone is often insufficient for optimal decision-making. Alternative demand modeling frameworks extend beyond prediction to prescriptive analytics. For example, category demand predictive resource allocation modeling formulates an optimization problem that distributes heterogeneous resources across multiple service clusters within a given time interval to maximize performance objectives such as service level, cost efficiency, or utilization. Related formulations include resource scoring and resource leasing problems, where resources are evaluated based on expected marginal contribution and dynamically leased or reassigned to address fluctuating demand. Additionally, scenario analysis-based resource risk models incorporate uncertainty by simulating multiple demand and disruption scenarios, enabling decision-makers to assess trade-offs and build resilient allocation strategies. Together, these approaches integrate forecasting, optimization, and risk analysis to support robust and data-driven resource planning.



VI. CONCLUSION

Cloud services simplify infrastructure management for businesses of all sizes, yet complexity still poses a barrier to service reliability and cost-efficiency. The development and deployment of software increasingly leverage cloud computing and storage resources, motivating enhanced observability to help Engineering and Site Reliability (SRE) teams maintain consistent quality and control operational costs at scale. Advanced observability solutions go beyond asynchronous detection of detection of unhealthy and non-cost-efficient configurations and proactively guide adjustment actions for these aspects.

The insights necessary for such proactive observability are typically costly to generate and do not come free of trade-offs. Artificial Intelligence (AI) and Machine Learning (ML) enable realizations of proactive observability that systematically leverage human-in-the-loop decisions made to solve complex cross-cloud behavioural issues, while simultaneously mitigating the risks and effort scales of past reactive observability approaches. Formalizing the research direction in this area involves defining observability and its objectives; assessing the suitability of AI for the purpose of proactive observability, articulating the necessary training data requirements, and specifying a set of techniques that support such proactive behaviour.



6.1. Future Directions

Avenues for future work encompass: further exploration of data quality, including anomaly detection and data validation; integration of cloud security observability with existing data for risk scoring; support for cross-cloud observability by integrating data from different cloud providers with data from the on-premise environment; and research on standardized data storage schemas for cloud observability data to enable the use of the same AI models in different organizations.

The challenge of ensuring high-quality data can also be addressed using AI. Different types of data problems can be classified into five categories: data anomalousness; system anomalousness; description-fit; historical-fit; and description-cross-section. Each of these problems can be further assisted by supervised learning or unsupervised-learning-based methods. Some of these methods assist in detecting data problems through automation, while others assist in checking model fitness. These data problems can impact not only the quality of the services using such data but also the quality of the services using such data quality checks. An anomaly-detection-and-correction architecture as an end-to-end data quality pipeline can enhance data quality. The detection and correction mechanisms can be integrated to form a fully automated architecture, allowing a human-in-the-loop version to be used in specific monitored segments.

day	demand	capacity	Euclid
4	131.57	142.61	19.81
5	107.19	130.6	45.06
6	101.26	117.57	31.48
7	105.26	117.21	18.27

day	demand	capacity	Euclid
8	110.52	115.24	8.6
9	142.94	124.59	42.75
10	144.45	138.27	7.28

Table : Example telemetry + derived KPIs (synthetic)

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