

AIOps and MLOps: Redefining Software Engineering Lifecycles and Professional Skills for the Modern Era

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ABSTRACT

AIOps or Artificial Intelligence for IT Operation and MLOps or Machine Learning Operations are two novel trends that are shifting the dynamics of software engineering by bringing automation and optimization into each facet of SW programming cycle. This paper aims to discuss how these new practices are transforming the software engineering lifecycle, influencing delivery cycles and changes in skills demand among professionals. Through a systematic literature review, the paper identifies the tools and practices that are critical for organizations which are operating in the AIOps and MLOps milieu based on industry case studies.

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Introduction

AIOps (Artificial Intelligence for IT Operations) and MLOps (Machine Learning Operations) are emerging best practices to use artificial intelligence and machine learning for improving IT operations and Machine Learning processes. As a result of AIOps on big data, the use of machine learning, and automation, detection of incidents and their root cause, and prediction of future problems in IT operations enhances resulting to improved IT operations. By contrast, MLOps is concerned with the seamless CI/CD of ML models and their subsequent deployment and management in production [1].

Artificial Intelligence for IT Operations (AIOps) has emerged as IT operations has grown more complex, with traditional tools being unable to handle the sheer volume and diversity of data from modern systems. AIOps enhances IT operations by automating routine tasks, offering real-time insights, and enabling proactive issue resolution, thereby improving the system reliability and reducing operational costs. The key steps in AIOps include data collection from various sources, data processing through machine learning algorithms, event correlation to identify relationships, anomaly detection to recognize deviations, and predictive maintenance to anticipate and address potential issues before they impact the system (Figure 1).

Machine Learning Operations (MLOps) has evolved as machine learning has become crucial to business operations, necessitating robust frameworks for model deployment and management. MLOps bridges the gap between data science and IT operations by facilitating seamless model deployment, continuous integration, and real-time monitoring, thereby enhancing ML system reliability and efficiency. Its main steps involve model development, versioning, CI/CD for automating testing and deployment, monitoring performance, and retraining models with new data to ensure sustained accuracy (Figure 2).

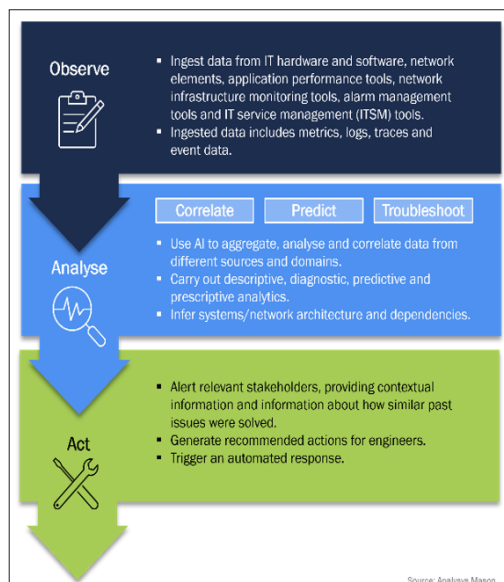


Figure 1: The steps involved in AIOps

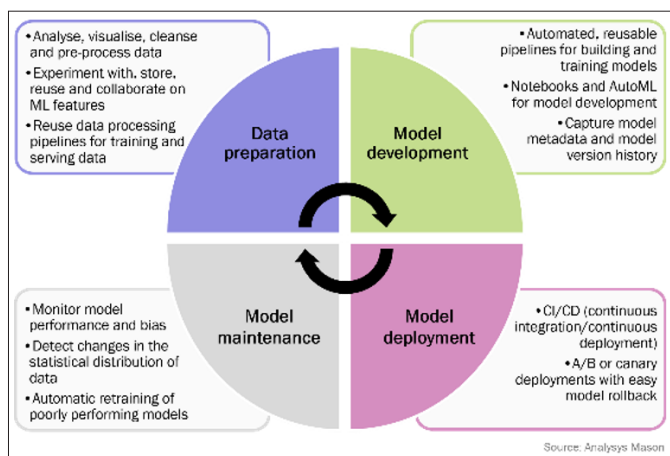


Figure 2: The activities involved in MLOps

Agile and DevOps are current methodologies that define the state of the software engineering lifecycle, which is based on iterative development, integration, and collaboration between development and operations teams. However, some issues remain to be addressed, including enhanced system complexity, faster deployment, and reliability.

	DevOps	Agile
Focus	Collaboration between dev and ops teams	Frequent customer feedback
Iterations	Rapid feedback loops	Iterative cycles
Scope	Large-scale projects	Smaller, incremental changes
Tools	Automation tools (e.g. Jenkins)	Task management software (e.g. Jira)
Frameworks	Kanban, DevOps lifecycle	Scrum, XP

HubSpot

Figure 3: Agile vs DevOps

DevOps is a set of practices designed to unify software development (Dev) and IT operations (Ops) to enhance collaboration and streamline processes. Originating from the Agile methodology, DevOps addresses inefficiencies in traditional siloed teams by focusing on continuous integration, continuous delivery, and automation. Its significance lies in improving the speed and reliability of software release through better collaboration, automated workflows, and continuous feedback. The key steps in DevOps include the continuous integration of code changes, continuous delivery of updates to production, infrastructure as code (IaC) for managing resources, and robust monitoring and logging for application performance and system health (Figure 3).

Agile Methodology is a framework that emphasizes iterative development, collaboration, and flexibility, aiming to deliver functional software incrementally and gather frequent feedback. Emerging from the discontent with ineffective, hierarchical, and slow waterfall approaches, Agile encourages flexibility and timely fluid reaction to the changes in needs so that the teams can provide useful software faster. Some of the elements of logistics include determining objectives for the project, prototyping, and feedback loops, developing small cycles of work, testing on an ongoing basis, and regular release of new versions incorporating end user feedback. Concerns in the Agile and DevOps space include higher system complexity owing to tool management, reduced ability to maintain software quality as cycle times shrink, and reliability as

systems evolve quickly. The continuously increasing complexity and scope of these challenges are managed by AIOps and MLOps by improving automation, data analysis, and integration for the betterment of software delivery and IT processes.

The concepts of AIOps and MLOps should be explored because these practices present solutions to these challenges in the form of greater automation, data analysis, and integration. Reflecting on how AIOps and MLOps transform software delivery cycles and how they can assist in understanding the means of optimizing delivery timelines, improving system reliability, and changing the specifications of IT professionals for more effective and efficient software delivery and existence to happen.

Evolution of Software Engineering Lifecycles Traditional Software Development Lifecycles (SDLCs) Waterfall Model

The Waterfall Model is one of the first SDLC models and is best identified by its phase-by-phase approach to software development. The Requirements Analysis phase is followed by the Design phase, which is subsequently succeeded by the Implementation phase. This is then followed by the Testing phase, the Deployment phase, and finally, the Maintenance phase. Despite having a well-defined and structured process, this model tends to rigidly adhere to strict deadlines, which can lead to the identification of errors at a later stage. As a result, this model may not be well-suited for projects that require flexibility and the ability to make swift modifications [2].

Agile Methodology

Due to the drawbacks in Waterfall Model, Agile methodology came into existence. Agile development is incremental and involves breaking development into smaller cycles and receiving feedback from the users after each cycle of development. This strategy increases flexibility, time to deliver functional software, and response to customer requirements. Two prominent Agile practices are Scrum, which divides projects into sprints, and Kanban, which involves the visualization of work and its flow [3].

DevOps Practices

DevOps is an extension of Agile, it focuses on bringing people together from the development and operations sides of the company. This is a practice that focuses on the integration of development and delivery on an ongoing basis and the automation of the procedures involved in the delivery of software. Thus, DevOps seeks to challenge organizational structures that compartmentalize roles and duties to improve the velocity, reliability, and quality of the software delivery process. DevOps enablers, such as Jenkins, Docker, and Kubernetes, help implement DevOps practices and facilitate fast and frequent deployments [4].

Emergence of AIOps and MLOps Definition and Differentiation

AIOps and MLOps are improved software engineering lifecycles that incorporate artificial intelligence and machine learning for IT operations and ML processes. AIOps (Artificial Intelligence for IT Operations) refers to the application of machine learning and big data to IT operations tasks like event correlation, detection of anomalies, and predictive maintenance. MLOps or Machine Learning Operations can be described as a set of practices that enable machine learning models to be deployed, integrated, delivered, and monitored post-deployment and during production [5].

Historical Context and Development

AIOps and MLOps have emerged to address current large and complicated IT structures as well as the integration of ML into essentially all businesses. Legacy monitoring and management solutions cannot handle the current scale, scope and speed of data created by complex applications. These challenges are mitigated through AIOps since it offers real-time information and automated measures to counter them thus making them less demanding on the IT teams. Likewise, MLOps implies that ML models can be deployed and governed at a scale, which ties data science to implementation. These practices have occurred because of developments in AI & Big data & cloud computing; there is a change in how SW & IT operation is managed [6].

Impact on Software Engineering Lifecycles

Integration of AIOps in SDLC

Automation in Incident Detection and Response

AIOps interrelate meaningfully to augment traditional software development lifecycles (SDLC) using artificial intelligence and machine learning to handle incident detection and management. The existing approaches primarily consist of log analysis and manual monitoring of system activity, which is more time consuming and error prone. For instance, it might take days or even hours to sift through considerable logs to pick out abnormalities if performed manually.

AIOps tools perform this task by perpetually analyzing large volumes of operational data and identifying symptoms of potential problems at the earliest possible stage. This automation is not only effective in reducing the detection time of incidents but also in improving system availability. IT professionals can then turn their attention to more proactive, high value-added activities as opposed to troubleshooting. Some tangible improvements in this area due to AIOps that are MTTD and MTTR are lowered, making operations more efficient and minimizing unproductiveness. For instance, ING Bank found that zero-touch automation through AIOps resulted in cutting operational costs and improving system availability, providing a real-world example of the benefits of automating incident management.

Predictive Analytics for Proactive Problem Management

Another characteristic of AIOps is the capacity for predictive analytics, which means that the potential problem can be identified, and preventive actions can be taken to avoid negative consequences. Most problem management models are reactive in nature and come into the picture when problems are evident. This can result in customer dissatisfaction and delays in service provision.

Analytical AIOps involves the use of predictive algorithms to identify patterns in data, to forecast system failures or performance issues in the future. Based on these predictions, the IT department can prevent such a situation from happening or lessening its consequences. For instance, Netflix uses AIOps for predictive maintenance to avoid disruptions to services on streaming platform. The technical process of the 'predictive maintenance model' comprises extracting and preparing historical performance data, deploying machine learning models to identify patterns that indicate likely failures, and comparing the system performance against such models. The result is a more reliable system with minimal downtime, improved service quality, and reduced mean time to recovery (MTTR).

Case Studies/Examples

The AIOps implementation was admired in use at ING Bank, wherein AIOps tools, the incident detection and response had been automated, this reduced operational cost and increased system uptime. Another good example is the enhancement of IBM in its IT operation using AIOps, which has been able to cut 50% on incident resolution time, at the same time, increase overall system performance [7].

Role of MLOps in Machine Learning Lifecycle Model Development, Deployment and Monitoring

MLOps transforms the machine learning lifecycle by establishing comprehensive frameworks for model development, deployment, and monitoring. Model Development starts with data preparation, which involves collecting, cleaning, and preprocessing data to ensure its quality and relevance. It is important that the input data be used to build the model, and that the performance of the model depends on the data used. Components implemented in the MLOps workflow help in the versioning of datasets and managing the data provenance of the datasets necessary to make experiments repeatable and reproducible [8].

Model training included choosing the correct algorithm, setting hyperparameters, and performing experiments. This can be supported by MLOps frameworks that encapsulate tools for tracking experiments, managing model versions and collaboration between data scientists. Experiment tracking applications record incoming parameter values, existing metrics, and results to compare and choose the most effective models easily.

In MLOps, deployment is made easier by using a pipeline that allows the movement of models to production environments. This encompasses issues such as managing dependencies, configurations and scaling conditions pertaining to the application. Continuous delivery pipelines in turn test the models to the production stage to check for performance and reliability before they are deployed. Infrastructure and Configuration Management using Infrastructure as Code (IaC) is particularly used in the provisioning of facilities necessary for model deployment to be scaled and made consistent.

Supervision is an essential process for evaluating and ensuring that a model continues to perform at optimal levels in its successive iterations. Most MLOps frameworks in the market offer mechanisms to monitor models deployed in production with metrics such as accuracy, latency, and resource consumption. Ongoing tracking and monitoring can alert an organization of any such deviation so that remedial action in the form of retraining and calibration can take place. This makes it possible to maintain models relevant to dynamics in data and to be proactive with respect to organizational needs [8].

Continuous Integration and Delivery for ML Models

MLOps explain the best practices needed to apply CI/CD on the models in machine learning. MLOps can also ensure that the CI/CD pipelines of the models are fully automated and that the models are tested, validated, and deployed, thereby minimizing the risks and time required in the process. This can also further aid in continuous model monitoring and, with the necessary changes, in retraining real-time data to ensure the accuracy and efficacy of the model.

Case Studies/Examples

For instance, the leading example of MLOps implementation is Airbnb. Automated CI/CD pipelines of recommendation

algorithms in MLOps flow like running water, allowing updates and improvements at a fast rate. Similarly, Google has adopted practices in MLOps for more seamless model deployment and monitoring within AI models, enhancing scalability and high-quality service [9].

Incorporating AIOps and MLOps into the software engineering lifecycle allows for increased efficiency, reliability, and agility, resulting in enhanced service delivery and user satisfaction.

Changes in Delivery Cycles and Timelines Accelerated Development and Deployment Reduction in Manual Intervention

AIOps and MLOps have revolutionized the handling of software development and IT operations by cutting down manual tasks. Automation now manages routine activities such as spotting incidents, finding causes, and deploying models. As such, this shift centralizes the tasks of such teams on more challenging and valuable work. Thus, the development and deployment cycles accelerate, which implies that newer updates and other features can be released much faster.

Enhanced Testing and Quality Assurance

Regarding AIOps and MLOps, even testing and quality assurance have become more efficient. Regular and extensive testing is done on both code and models through automated testing frameworks and continuous monitoring before going live. This early detection of issues results in an improvement in the quality and the reliability of the software that is to be released. For instance, MLOps at Microsoft enables testing and monitoring of AI models, ensuring the models are always in optimal form under various circumstances [10].

Impact on Project Management Adjustments in Timelines and Deliverables

As development and deployment increase, it becomes crucial for project managers to redesign their time horizons and goals. Faster growth requires not only fewer but also more frequent and short intervals between events' releases. Processes like scrum have become even more important since these enable teams to quickly respond to changes and integrate the feedback that is received consecutively.

Risk Management and Mitigation

AIOps and MLOps also come in handy in developing ways of managing risks. AIOps employs risk analysis where the system predicts risks and issues that are likely to occur on the system, hence avoiding them. In MLOps, the models are maintained and checked consistently and so the worry of experiencing poor performance by the models is almost eliminated. Such an approach assists to ensure that projects are on schedule and minimize interference [11].

Metrics and KPIs for Measuring Impact Time to Market

One of the primary KPIs for measuring the effectiveness of AIOps and MLOps is the time to market. Both practices drastically reduce the meantime needed for the development and deployment of new features and updates. This not only increases competitiveness but also improves the level of satisfaction of customers.

Frequency of Deployments

The other critical metric is how often deployments are being done. The AIOps and MLOps integrate and deliver more often

and accurately because of the mechanization of these procedures. For instance, Amazon can release updates several times a day because of its progressive DevOps and MLOps.

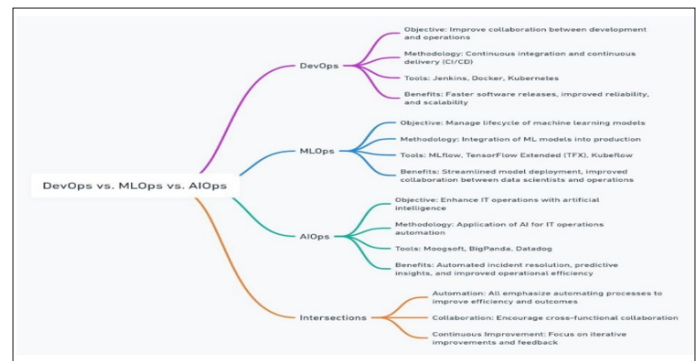


Figure 4: DevOps vs MLOps vs AIOps [12]

Figure 4 compares DevOps, MLOps, and AIOps, outlining their unique objectives, methodologies, tools, and benefits. DevOps aims to improve collaboration between development and operations through continuous integration and delivery, utilizing tools like Jenkins and Docker. MLOps focuses on managing the lifecycle of machine learning models, integrating them into production with tools such as TensorFlow Extended and Kubeflow. AIOps enhances IT operations using artificial intelligence, leveraging tools like BigPanda for predictive insights and automated incident resolution. The diagram also highlights intersections, emphasizing automation, collaboration, and continuous improvement across all three practices.

Incident Resolution Time

The time taken to resolve the incident is essential for maintaining operational effectiveness. The use of AIOps minimizes this time because the automatic occurrence of the incident simplifies the determination of the problem and its resolution. For example, Splunk AIOps has helped organizations to address incidents faster by 70% and enhance the availability and usability of systems for end users [13].

This is due to value creation through the advancement of speed and efficiency, as in the case of AIOps and MLOps, maturing of project portfolio management, and delivery of tangible and quantifiable improvements in key performance indicators.

Changing Skill Requirements for Professionals New Roles and Responsibilities Data Scientists vs. Machine Learning Engineers

Owing to the qualitative separation between AIOps and MLOps, the job responsibilities of data scientists and machine learning engineer differ. Data scientists are mainly concerned with the creation of models of machine learning and extraction of insights from data, whereas machine learning engineers are concerned with all the activities of putting these models to work or practically applying them. It often helps to ensure that both roles become a specialization and teamwork with a distinctive skills set being utilized correspondingly [14].

AI/ML Ops Engineers

With the rise of AIOps and MLOps, a new role has emerged: The key roles involved as the AI/ML workloads are being deployed and managed are the AI/ML Ops Engineers. These people also serve as the bridge between data scientists and IT. They make sure that AI and ML models give a seamless interface and are easily

incorporated into regular tasks. Their work involves automating how these models are deployed, monitoring their performance to ensure they remain effective, and setting up processes for continuous integration and delivery. Essentially, they ensure that everything works together seamlessly, helping both technology and the team succeed.

Required Skill Sets

Technical Skills: AI/ML Algorithms, Cloud Computing, Automation Tools

Modern AIOps and MLOps specialists must possess a strong foundation for technical competencies. Expertise in AI and ML algorithms is essential for developing and optimizing models. Proficiency in cloud computing platforms, such as AWS, Azure, and Google Cloud, is crucial for deploying and scaling these models. Familiarity with automation tools, such as Jenkins, Docker, Kubernetes, and specific MLOps frameworks (e.g., MLflow, TensorFlow Extended), is also critical for managing continuous integration and delivery pipelines [15].

Soft Skills: Collaboration, Problem-Solving, Continuous Learning

In addition to technical skills, soft skills are becoming increasingly important. Collaboration across cross-functional teams is essential for integrating AI and ML solutions into business processes. Strong problem-solving abilities help to address complex challenges in deployment and operations. Continuous learning is vital given the rapid advancements in AI/ML technologies and tools.

Training and Certification Programs

Available Resources and Courses

A plethora of training and certification programs are available to help professionals develop the necessary skills for AIOps and MLOps. Online platforms such as Coursera, Udacity, and edX offer specialized courses in machine learning, AI, cloud computing, and DevOps. Certifications from cloud providers, such as AWS Certified Machine Learning and Google Cloud Professional Data Engineer, are valuable credentials that demonstrate expertise [16].

Large services companies such as IBM, Capgemini, Infosys, and Cognizant are actively enabling their workforce to adopt AIOps and MLOps through targeted training and upskilling programs. These firms equip their teams with skills in AI/ML algorithms, cloud computing, and automation tools, ensuring that they can effectively deploy and manage AI-driven solutions. Additionally, they are evolving their service offerings to focus on managed services for infrastructure and applications. By integrating AIOps for enhanced IT operations and MLOps for streamlined model deployment, these companies are differentiating their services. They emphasize automation, real-time analytics, and predictive maintenance to offer more proactive and efficient solutions, thereby improving operational performance and customer satisfaction. This strategic shift positions them as leaders in delivering advanced, data-driven managed services [17].

Organizational Support for Skill Development

Organizations play a crucial role in supporting skill development. Many organizations invest in training programs and provide access to educational resources. Some organizations partner with academic institutions to offer tailored training programs for their employees. Encouraging continuous learning and providing opportunities for skill enhancement helps organizations stay competitive and ensures that their workforce is well equipped to effectively leverage AIOps and MLOps.

By adapting to these changing skill requirements, professionals can thrive in the dynamic landscape of software engineering and IT operations, contributing to the successful implementation and optimization of AIOps and MLOps practices.

Tools and Processes for Success in AIOps and MLOps

Key Tools for AIOps

Effective implementation of AIOps relies on several key tools. Monitoring and logging tools, such as Prometheus, Grafana, and Elasticsearch, provide real-time insights into the system performance and detect anomalies. Incident management platforms such as ServiceNow and PagerDuty, streamline the resolution process by automating incident detection, notification, and response. Additionally, AI-powered analytics tools such as Splunk and Moogsoft leverage machine learning to analyze vast amounts of operational data, offering predictive insights and proactive issue-resolution capabilities. These tools collectively enhance IT operations, ensuring that systems are more reliable and resilient [18].

Essential MLOps Tools

For MLOps, essential tools focus on the end-to-end machine learning lifecycle. Data versioning and experimental tracking tools like DVC (Data Version Control) and MLflow ensure reproducibility and accountability in model development. Model-serving and monitoring platforms such as TensorFlow Serving and Seldon enable seamless deployment and real-time performance tracking. Continuous integration and deployment (CI/CD) pipelines, implemented with tools such as Jenkins, GitLab CI, and Kubernetes, facilitate the automated testing, validation, and deployment of machine learning models. These tools ensure that the models are efficiently developed, deployed, and maintained [19].

Best Practices for Implementing AIOps and MLOps

The successful implementation of AIOps and MLOps requires adherence to several best practices. Collaboration between development and operations teams is crucial; fostering a culture of shared responsibility and continuous communication enhances coordination and problem-solving. Continuous feedback loops also make it easier for teams to deal with emerging problems and enhance existing processes because of monitoring automation. Data quality and governance are perhaps basic, as no organization can risk having incorrect data used in AI and ML models. Adhering to data governance best practices and regulations ensure data authenticity and protection, which in turn enables more effective AIOps and MLOps [20].

With these tools and guidelines, it is possible to integrate AIOps and MLOps into organizational processes to increase performance, stability, and adaptability.

Case Studies and Industry Examples Success Stories from Leading Companies

Companies such as Netflix, Google, and ING Bank have already adopted AIOps and MLOps and observed definite enhancements in their operations. Netflix's integration of AIOps has significantly transformed its software engineering lifecycle, particularly in terms of enhancing service reliability. The company uses AIOps to proactively manage its vast streaming infrastructure, which serves millions of users globally. By employing machine learning algorithms, Netflix's AIOps platform continuously analyzes operational data from its streaming servers and network components. This real-time analysis allows for the early detection of potential issues such as server failures or network bottlenecks before they impact users.

For instance, AIOps tools predict and prevent outages by identifying patterns in historical data and system metrics, thereby enabling preemptive actions that mitigate service disruptions. This proactive approach reduces downtime and improves overall user experience. As a result, Netflix has not only enhanced its operational efficiency but also minimized the operational costs associated with manual monitoring and incident response, highlighting a marked improvement in both service reliability and cost management [21].

Measurable Benefits and Outcomes

The advantages and results that can be quantified by these implementations are significant. For example, Netflix provides evidence of a dramatic decrease in service outages and, therefore, increased customer loyalty. Thus, Google's MLOps has reduced the time to deploy new models from weeks to hours, enhancing the tech giant's model innovation cycle. Operationally, this has led to a 50% decrease in the time taken to resolve incidents, which is a major boost to system efficiency. These outcomes show that AIOps and MLOps have great potential for achieving meaningful improvements in key performance metrics [22].

Challenges and Lessons Learned

These companies had sets of challenges and learned lessons from their achievements. Potential challenges include inadequate appreciation of COTS products' interoperability with existing applications and the data management regimes that are required. To mitigate these risks, it is imperative that there be due consideration in the planning and testing phases of operations while staff members always undergo training. The tactics used depend on the organizational environment, but many involve using pilot projects to establish the benefits and develop organizational competence before moving to broader implementation. Furthermore, it is crucial to promote collaboration between development and operations to eliminate resistance and successfully implement AIOps and MLOps practices [23].

Conclusion

AIOps and MLOps are transforming software engineering lifecycles by providing solutions for smarter approaches to automation, more accurate forecasting, and better integration. This reflects the nature and requirements of contemporary IT management and ML processes, resulting in enhanced performance, stability, and flexibility. In leading organizations, the combination of AIOps and MLOps has shown positive improvements in accelerating the development of new products, decreasing costs, and improving system performance. Thus, the changing nature of the demand for skills and compliance with best practices as organizations continue to implement these practices will be essential for further optimization of results and continued success in the digital environment.

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