International Journal of Computer (IJC)

ISSN 2307-4523 (Print & Online)

https://ijcjournal.org/index.php/InternationalJournalOfComputer/index

AI-Driven Predictive Maintenance in Retail IT Systems Using DevOps: A Review

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Abstract

Retail IT infrastructure needs to be extremely reliable and highly available to provide seamless operations, best customer experience, and effective resource utilization. Predictive maintenance driven by Artificial Intelligence (AI) and natively integrated with DevOps practices has become a game-changing solution in this regard. This paper provides an extensive review of 40 recent research articles on AI-DevOps convergence for predictive maintenance in retail IT infrastructures. A systematic literature review methodology was adopted, involving structured search, selection, and thematic analysis of peer-reviewed studies from 2019 to 2026. Some of the prime subjects discussed include common DevOps practices in retail IT, using AI for predictive analytics assistance, and merging machine learning models with failure prediction. Techniques for anomaly detection and pattern recognition in favour of early detection of possible problems are given special attention. Also, merging AI insights with DevOps pipelines is discussed in terms of automated feedback loops, CI/CD optimization, and real-time monitoring of system health. The review also addresses open issues like data quality, model drift, and integration complexity, and explores growing trends in self-healing systems and AIOps. This research aims to offer researchers and practitioners an extensive review of state-of-the-art techniques and their probable contribution to increased operational resilience and cost-effectiveness in retail IT systems through smart, automated maintenance practices.

Keywords: Predictive Maintenance; Retail IT Systems; AI; DevOps; Machine Learning; AIOps; Machine Learning Models; Monitoring.

Received: 1/4/2026
Accepted: 3/4/2026
Published: 3/14/2026

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1. Introduction

In today's fast-changing retail environment, the backbone of business activities is digital infrastructure. From point-of-sale infrastructure and inventory management systems to customer relationship systems and e-commerce websites, IT systems are an integral part of the retail environment [1,2]. A dysfunction in these systems can cause operational delays, customer dissatisfaction, as well as huge losses in revenues. Therefore, maintaining the performance and dependability of retail IT infrastructure has become a strategic imperative [3]. This is where predictive maintenance, fuelled by the power of DevOps and AI, comes into play as a disruptor Reference [4]. Predictive maintenance is the practice of using advanced analytics and machine learning to forecast when components of an IT system will fail so that something can be done in advance. Unlike reactive or schedule-driven maintenance paradigms, predictive maintenance reduces downtime, maximizes the use of resources, and optimizes maintenance expenses [5]. When coupled with the flexible and automated nature of DevOps, predictive maintenance becomes more robust, with continuous monitoring, real-time diagnostics, and swift deployment of updates or patches. This combination enables IT systems not only to run but improve continuously in terms of performance and reliability [6,7]. AI is the pivot of this paradigm. As it digests vast amounts of information created by an army of sources from system logs to performance statistics to user activity machine learning algorithms can identify patterns and anomalies that indicate impending failures long before they have an impact on operations [8]. DevOps fills the gap with the practices and tools for integrating these into the operations and dev pipelines. Automation, CI/CD, and IaC are only a few of the DevOps practices through which it is made easy to implement predictive strategies [9]. Being most impactful in business efficiency and customer experience within the retail industry, the advantages of the strategy are enormous. Predictive maintenance using AI and DevOps makes firms strong enough to maintain the most critical IT systems at their best levels at every moment [10]. It improves service availability, supports digital transformation, and enables innovation through freeing IT resources from time-consuming manual debugging.

This article introduces the convergence of AI and DevOps for retail IT infrastructure predictive maintenance, highlighting methodologies, tools, advantages, and disadvantages used. It seeks to offer a complete end-to-end framework that retail business operations can pursue for future-proofing IT systems and remaining competitive in a rapidly digitalizing market. The key contributions of this paper include a comprehensive review of recent advancements in AI-DevOps integration for predictive maintenance, a synthesis of best practices and implementation challenges, and the proposal of a conceptual framework tailored for retail IT infrastructures. Unlike prior literature, this study uniquely emphasizes the operationalization of AI-driven predictive maintenance within DevOps pipelines, offering actionable insights for both researchers and practitioners.This paper contains six sections. Section 2 covers literature review like DevOps practices in retail IT, employing AI for predictive maintenance, predictive failure models using machine learning, anomaly and pattern detection, DevOps with AI integration, system architecture and deployment strategies. Section 3 covers challenges and implementation limitations. Section 4 comprises real-world case studies of the provided framework. Section 5 provides an articulation of major findings and implications. Finally, Section 6 is the conclusion of the paper with an overview along with directions for future studies.

2. Literature Review

2.1. DevOps Practices in Retail IT

In 2019, Mohammad [11] explored how automation through the use of the guidelines of a DevOps and Agile approach, helps software release management practice in the IT industry. The gap of an iterative and ad-hoc model does not meet today's requirements, however through the use of the DevOps environment and by using a Continuous Delivery, the frequency of release has increased while also impacting stability. The study highlights that automation has provided improved use of operations, encouraged future technologies, and satisfied the changing requirements of the business. The study does have literature evidencing a significant correlation between automation and better releases, which included that clearly established operational and scalable processes are evident in larger IT systems.

Banala [12] examined the fundamental processes of DevOps in 2024, with an emphasis on CI/CD. The article discusses continuous integration (CI) as correct method for identifying bugs earlier through the utilization of automated builds and tests. Continuous delivery (CD) supports deployment/automation in a expedient manner and safer way. The article highlights various tools to assist with CI and CD, such as Jenkins, GitLab CI, Docker and Kubernetes; it reports best practice, real-world scenarios, and ways of debugging CI/CD challenges to improve software delivery outcomes.

Wiedemann and his colleagues [13] made a transition from traditional project control in software development to control in DevOps teams at the core of the digital transformation in 2023. DevOps coincides development and operations to adjust to changes in the marketplace by supporting collaboration across functional and production boundaries. From an inductive approach to theory development, the research identified four sources of tension (goal conflict, discomfort with methods, decision rights, and the rhythm of time) and how they are resolved. The resulting model provides practical recommendations for controlling DevOps teams and adds theoretical value in terms of control in this new context.

Vaish and his colleagues [14] developed a performance model of software delivery and system availability of a DevOps and IoT-based software delivery process that included continuous monitoring and feedback in 2024. The performance model, intended to measure software delivery and systems availability, takes IT organization data from multiple markets. The findings show that by embedding DevOps practices alongside IoT monitoring, it maximizes performance and availability including all other gains made associated with DevOps while increasing overhead and recognizing the limited importance of IoT monitoring considering security and immaturity of delivered IoT systems. The work is valuable in stressing the importance of operational capabilities, as well as, presenting actionable suggestions to organizations wanting to be high performing through maximizing their software delivery processes and increased system reliability and availability through adopting DevOps practices and IoT mechanisms.

Table 1: DevOps and AI Integration in Retail IT

Author(s)	Year	Contribution Focus	Key Contributions
Mohammad [11]	2019	DevOps and Agile Practices	Streamlined release management; enhanced operational efficiency.
Banala [12]	2024	CI/CD Tools for Deployment	Discussed Jenkins, GitLab CI, Docker, Kubernetes for faster and reliable deployment.
Wiedemann and his colleagues [13]	2023	DevOps Organizational Control Theory	Identified tensions and trade-offs in DevOps team control; offered resolution models.
Vaish and his colleagues [14]	2024	DevOps Integration with IoT	Improved service availability through IoT-enhanced monitoring.

2.2. Role of AI in Predictive Maintenance

Banerjee and his colleagues [15] discussed in 2024 the potential of AI to cut costs and increase operational continuity. They promote a data-driven approach to decision making and suggest strategy-first positioning AI as a direction for resource investment. The conclusions state the main obstacle remains a lack of sufficient data. As AI builds momentum, it will likely realize considerable advancement into maintenance strategy.

Gadde [16] presented in 2021 an AI based predictive maintenance framework for relational database systems focused on making performance improvements by decreasing down time, utilizing machine learning algorithms with historical performance data to predict system failure events as well as system operational schedules. The framework incorporates anomaly detection, trend detection and predictive models to monitor early indicators of an event or malfunction.

In 2019, Lee and his colleagues [17] provided an analysis of predictive maintenance (PdM) using AI based algorithms to decrease unplanned downtime through increased equipment utilization. Traditional maintenance strategies to manage maintenance, such as scheduled maintenance or reactive maintenance, can result in increased financial losses or inevitably agricultural efficiency losses. The introduction of Industry 4.0 provides a new pathway to move towards smart solutions such as PdM to manage component lifespans while increasing sustainability. The paper applies a data driven modelling method to monitor cutting tool wear and the bearing system of the spindle motor, enhancing both fault detection and maintenance planning.

In 2020, Matzka [18] created an explainable machine learning model trained on the dataset, complete with an interactive explanatory interface. The model is assessed on accuracy and interpretability and the comparisons help characterize the quality of the explanations, allowing for valuable insight into model transparency and usability in the context of predictive maintenance for retail IT systems.

Table 2: AI/ML-Based Predictive Maintenance and Forecasting

Author(s)	Year	Contribution Focus	Key Contributions
Banerjee and his colleagues [15]	2024	AI for Predictive Maintenance	Enhanced continuity and cost-efficiency; highlighted data dependency issues.
Gadde [16]	2021	Database Failure Prediction	Used ML models to predict failures in relational database systems.
Lee and his colleagues [17]	2019	PdM in Industry 4.0	AI-based failure detection for motors and tools; reduced downtime.
Matzka [18]	2020	Explainable AI in PdM	Applied XAI to ensure interpretability in predictive models.

2.3. Machine Learning Models for Failure Prediction

In 2015, Pellegrini and his colleagues [19] introduced the framework of Failure Prediction Models (F2PM), a machine-learned approach for estimating Remaining Time to Failure (RTTF), while software anomalies exist in the environment. F2PM is unique in that it employs only system-level feature measurements to construct application-agnostic prediction models. F2PM also allows for feature selection to focus feature measurement on what is determined to have the greatest impact on the prediction. This provides the opportunity for optimization and different modelling approaches. Users are free to assess their models by predicting accuracy or estimate times to build a model.

Andaur and his colleagues [20] in 2021 addressed grocery retail Season's most persistent problem surrounding Out-of-Stock (OOS) occurrences from a manufacturer's standpoint. The research also served as a case study at a Latin American packaged foods company and introduced two systems for the detection of OOS occurrences based on machine learning. The first system is a single Random Forest classifier operating on balanced data. The second system is an ensemble of six classifiers. Both systems used transactional data provided by the retail environment in relationship to physical audits (manual counts of inventory) developed from existing work processes. A novel contribution of the case study was the system's use of new predictive variables. The systems were successfully implemented in practice, and evaluations indicated that a detection accuracy was obtained in excess of 95%.

In 2024, Deepan and his colleagues [21] proposed an AI-based predictive maintenance framework for Industrial IoT (IIoT) systems within the context of Industry 4.0. The system anticipates equipment failures before they happen by adopting machine learning algorithms and real-time data analytics. The predictability of equipment failure means organizations can intervene in a cost-effective and timely manner. This system can add value through lengthening equipment lifespan, improving maintenance scheduling, and improving resources. The paper outlines the system architecture, implementation challenges, real-world case studies, and previews how the integration of AI and IoT fundamentally changes the nature of maintenance practices from lethargic to proactive, efficient, and predictable.

Ayvaz and Alpay [22] in 2021 used machine learning methods to study potential failure indicators allowing operator to intervene before unplanned downtime occurred. Evaluating real world manufacturing data, the system was able to detect specific failure indicators. Amongst the classification algorithms random forest and XGBoost ensemble models produced the best outcomes relative to the individual classifiers. The optimal models were incorporated as a output to enhance operational reliability and efficiency for the factory's production system.

2.4. Anomaly Detection and Pattern Recognition

Nguyen and his colleagues [23] proposed two data-driven methodologies to support decision-making in supply chain management in 2021. The first is an LSTM network for forecasting multivariate time series; the second is an LSTM Autoencoder combined with a one-class SVM for anomaly detection of sales data. They identify that forecasting them was better with more sources of external data and with more internal data due to hyperparameter tuning.

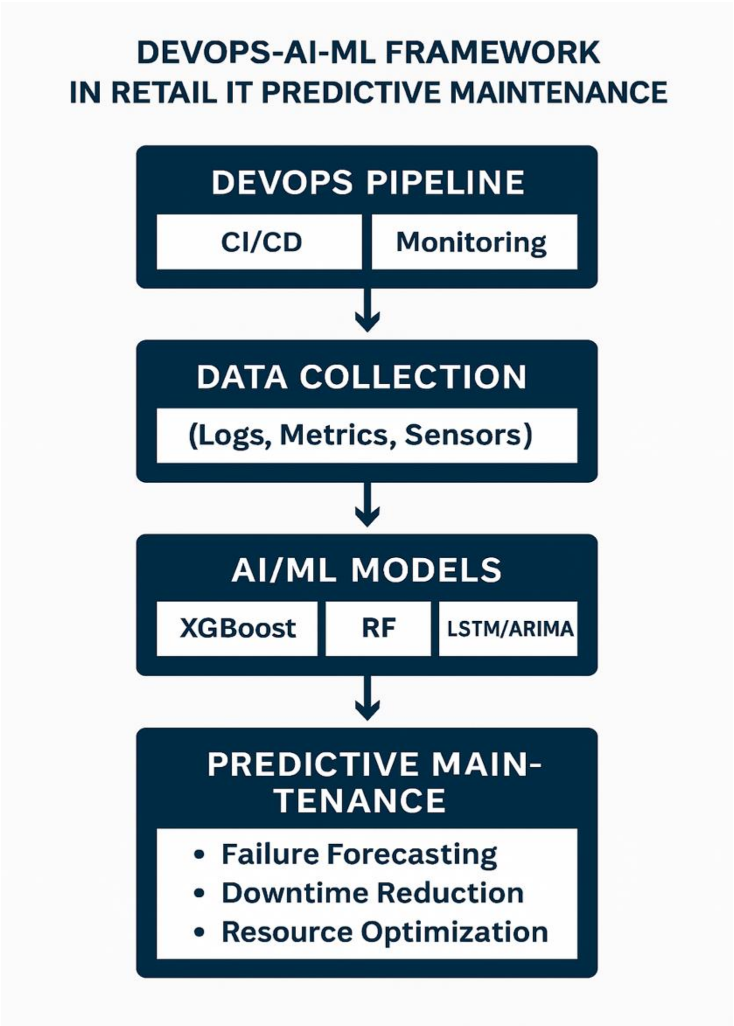

Figure 1: DEVOPS-AI-ML Framework for Intelligent Software Development Lifecycle

In 2023, Kapoor and his colleagues [24] proposed the Co-AD framework that introduces a concept-based anomaly detection method by using a Vision Transformer (ViT) to detect misplaced retail items, not based on planogram data. Co-AD employs an auto-encoder architecture, with outlier detection in latent space, Co-AD was able to achieve the best performance when evaluated on the RP2K dataset, better than the best ViT baseline. To prove its effectiveness, we developed a robotic mobile manipulation pipeline to enable autonomous autonomy to fix the discrepancies, thus, limiting human effort involved in tracking retail inventory or redistributing misplaced items. Fig. 1 shows the integrated DevOps, AI, and ML framework supporting automation, prediction, and intelligent software delivery.

In 2019, Bozbura and his colleagues [25] studied the anomaly detection techniques for the detection of real-time anomalies in the key performance indicator (KPI) values of e-commerce systems. Six univariate methods were studied, concluding that Long Short-Term Memory (LSTM) networks provided the best F1 scores and recall scores. Eventually, they were able to integrate campaign data into a multivariate LSTM model for better performance and integration, as they specifically were aware of the false positives data confused by e-commerce systems during special promotions.

A systematic review by Gangula[26] examined monitoring tools, metrics, and best practices for optimizing retail application performance. The study identified critical gaps in end-to-end observability that directly impact the effectiveness of predictive maintenance strategies. Key findings emphasized the need for unified monitoring frameworks that integrate real-time metrics collection, anomaly detection, and automated alerting mechanisms to support proactive failure prevention in retail IT systems.

2.5. Integrating DevOps with AI

Gangula[27] developed a comprehensive framework for secure DevOps practices in retail cloud environments, emphasizing strategies for compliance and operational resilience in large-scale deployments. The framework addresses critical security challenges in CI/CD pipelines, including real-time threat detection, vulnerability scanning, and automated remediation workflows. This work demonstrates how security-first DevOps practices enable retail organizations to maintain regulatory compliance while implementing AI-driven predictive maintenance at scale.

In 2021, Vadde and Munagandla [28] suggested that an AI-based security framework improves the security posture of the DevOps pipeline in cloud-based environments by integrating and incorporating real-time threat detection into the CI/CD process. Extracting from the machine learning models they trained on historical data, the framework can identify, and alert organizations to, potential threats. This allows organizations to recognize and mitigate threats to their systems early in the development process and before code is deployed. The value of the AI component of the framework is the ability to continuously learn from new threats, which will provide the organization with ongoing, dynamic protection. The paper presents the framework architecture, implementation, and evaluation and presents evidence of its success in securing cloud-based DevOps apps from potential attacks.

In 2021, Ali and Puri [29] examined the potential impact of the implementation of artificial intelligence (AI) techniques as part of DevOps practices to improve productivity, automation, and decision-making as part of a Digital Transformation Journey. Their study includes a comprehensive literature review and their own real-life case study demonstrating the impact of AI in a purely DevOps environment. Through their examination of its supposed efficiencies, barriers to implementation, and ethical implications, they provide a pragmatic demonstration of how AI can optimize workflows in a DevOps environment. This will ultimately assist organizations in adopting intelligent automation to enhance the resilient and adaptive nature of their software development and operational activities.

Including Artificial Intelligence into CI/CD pipelines to improve continuous testing capabilities within modern day software development was suggested by Vadde and Munagandla [30] in 2021 with the research using AI principles and techniques like predictive analytics and anomaly detection to analyse historic test data, code changes, and other relevant metrics to help foresee possible defects. This can help with defect detection, and improved test prioritization.

Figueiredo and his colleagues [31] examined the joint integration of Artificial Intelligence (AI) and DevOps in Agile Product Development as a transformative approach in 2022. The authors employed Systematic Literature Review (SLR) of 24 scientific articles, thereby reviewing how AI and DevOps could work together. Furthermore, it addresses the high demand for innovation provided by Industry 4.0, and examines AI's uptake and integration barriers in practice, including emerging topics such as AIOps, and Intelligent DevOps. The findings form key benefits and barriers relevant to the adoption and application of AI and to take a holistic approach to enable significant AI-DevOps collaboration within the agile paradigm.

3. Challenges and Limitations

The application of DevOps and AI for predictive maintenance raises a number of technical, operational, and regulatory challenges. Automation, efficiencies, and pre-emptive support are the advantages these technologies have to deliver; however, the realities of deploying and applying this technology are constrained by regulation, change inertia, integration and orchestration, and data quality. Overall, these challenges need to be addressed in order to achieve the full value potential of predictive maintenance in an evolving retail environment.

Perhaps the most important technical limitation is data quality and availability. AI needs tons of clean, labelled, and relevant historic data to be able to make predictions. And retail system data tends to be fragmented or siloed - specifically legacy system data. And then to bring all the AI models together one has to work at an infrastructure and human scale that most retail organizations are simply incapable of. Other issues affecting long-term upkeep are model drift and continuous retraining.At an organizational level, resistance to change and absence of cross-functional coordination may be impediments to implementation. DevOps demands a change in culture, i.e., everyone owning things together and feedback loops, and AI is all about embracing the decisions of machines. In brick-and-mortar retail space, these changes in culture are hard to deal with. Moreover, early downtime that leads to project delays during collaborative system implementation and integration can have a detrimental effect on business continuity, and that can lead stakeholders to resist change.

Gangula[32] conducted a comprehensive review of ITIL frameworks for managing large-scale retail cloud operations, identifying significant challenges in aligning traditional ITIL processes with modern DevOps and AIOps workflows. The study highlighted governance complexities, integration bottlenecks, and the need for adaptive frameworks that can accommodate both established service management practices and agile, AI-driven automation. These findings underscore the importance of organizational readiness and process maturity when implementing predictive maintenance strategies in complex retail IT environments.As that takes place, retail IT infrastructures are now also burdened with data privacy legislation such as GDPR and CCPA. Predictive maintenance systems founded on a high degree of data gathering and real-time monitoring. Predictive maintenance systems need to be supplied with safe, transparent data processing, and feedback loops executed clearly describe the machine-based decision-making to the staff that will be making efficient use of big amounts of data. With regards to AI, standard ethical issues like model behaviour and algorithmic bias result in that employees shouldn't remain in the dark over matters like explainability and so forth. Solutions need layered and involve data governance, employee training and development, scalable architecture, and transparency in AI as well to fix operations issues like these.

4. Case Studies

Combining DevOps and AI to achieve predictive maintenance for retail IT infrastructure has yielded genuine improvements in operational efficacy, reliability, and ultimately better customer experience, as was possible in some actual case studies. For instance, Walmart had remarkable success through the use of an AI-managed system, aided through DevOps pipelines, to provide continuous monitoring of IT infrastructure, in particular the critical point-of-sale (POS) systems. Key performance indicators (KPIs) were 99.95% uptime, a 40% reduced Mean Time to Detect (MTTD), 35% reduced Mean Time to Repair (MTTR), and a 30% per annum reduced volume of incidents. All these outcomes translated to significantly increased overall service availability, and infrastructure resilience. Similarly, Amazon took advantage of machine learning models in its fulfilment centres to predict failure of robots and conveyor belts in the warehouse. The unit achieved 25% less equipment downtime, 20% savings in maintenance costs, 15% increased throughput rate, and 92% accurate fault prediction. All of these KPIs represent evidence of operations and resource optimization. In another example, Target made use of a hybrid AI-DevOps solution to monitor the health of applications across both its mobile and e-commerce properties. AI-based anomaly detection provided real-time incident response, and able to maintain service uptime 24/7. The key indicators we monitored included maintaining API responses under 200 milliseconds, reducing crash rates by 50%, increasing customer satisfaction by 12% and reducing time to resolve errors by 45%. The fact that we measured these results demonstrates how strategic and effective use of AI in DevOps both helps prevent system crashes and also provides Booleans and business value in retail.

5. Discussion

This work set out to explore the intersection of AI and DevOps in the context of predictive maintenance in retail IT systems through the two research questions: (1) How well do AI models predict failures in retail IT systems? and (2) How does the integration of DevOps practice help achieve availability of predictive maintenance services? Results indicate that AI improves failure prediction by determining anomalies and patterns with a good enough model that is trained with high-quality historical data. However, the models rely heavily on data consistency and relevance which is among the greatest challenges in disparate retail systems. DevOps practice—specifically CI/CD, automated monitoring, and feedback loops—facilitate rapid change to model updates and deployment answering our second research question by supporting operational continuity and scalability. Importantly, the literature reviewed often assumes the situation in which the data will be ideal, while neglecting the unique challenges involved in the real-world contexts, such as data silos, legacy system integrations, and intra-national resistance to automation. These assumptions may be problematic for bias, which could lead to positive recommendations. Generally, the focus of articles is on technological efficiencies, and almost ignores the managerial and ethical factors to consider, such as AI decision-making transparency and employee displacement adjustments.

As emphasized by Gangula[32], the alignment of established frameworks like ITIL with emerging DevOps and AIOps practices requires careful consideration of governance models, change management processes, and cross-functional collaboration. Organizations must balance the structured approach of traditional service management with the agility and automation enabled by AI-driven predictive maintenance. Therefore, our recommendations for organizations are to take a holistic viewpoint: in addition to technological deployment, organizations should also make investments in data governance, cross-functional team training, and explainable AI frameworks. This is to help mitigate risk, and, improve ethical compliance and stakeholder trust. Next steps for research should focus on long-term (potentially longitudinal) research of live retail environments, to better understand the long-lasting impact of AI-DevOps practices over time, while being cognisant of changing compliance requirements and business structures. To conclude, while deserving of future exploration in predictive maintenance, the utility of AI and DevOps in retail IT infrastructures is dependent on appropriate planning, ethical considerations, and change management led by management.

6. Conclusion

This paper has provided a comprehensive review of 40 new research papers focused on the intersection between AI and DevOps for predictive maintenance within a retail IT context. We explored predominant DevOps practices in retail IT, the role of AI-enabled predictive analytics and machine learning models for predicting failure. We emphasized novelty around anomaly detection and use of pattern recognition techniques to visualize the early best opportunity to identify the failure. Additionally, we examined the incorporation of AI insights into a DevOps pipeline with automated feedback loops, CI/CD enhancements and real-time system health. The challenges presented were data quality, model drift and integrating into existing practices while also presenting trends in self-healing systems and AIOps. Our goal was to provide researchers and practitioners with a combined viewpoint of the existing practices and highlight shared implications to improve operational resilience and reduce operational costs in retail IT systems to better implement intelligent, automated maintenance strategies.

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