AIOps: A Multivocal Literature Review

Laxmi Rijal [1], Ricardo Colomo-Palacios [1[0000-0002-1555-9726]], Mary Sánchez-Gordón [1[0000-0002-5102-1122]]

Østfold University College, Halden 1783, Norway
{laxmi.rijal, ricardo.colomo-palacios, mary.sanchez-gordon }@hiof.no

Abstract. In the age of Internet of Things (IoT) and Big Data, Artificial Intelligence for IT Operations (AIOps) plays an important role to enhance IT operations. Such operation tasks include automation, performance monitoring, and event correlations among others. Although AIOps has proved to be important, it has not received much academic attention. Thus, by means of Multivocal Literature Review, this study is aiming to define AIOps, the benefits gained from it, the challenges an organization might face, and finally, what lies in the foreseen future of the AIOps. The findings revealed that adopting AIOps helps in monitoring IT work, efficient time saving, improved human-AI collaboration, proactive IT work, and faster mean time to recovery (MTTR). However, there are also reported challenges like doubt about the efficiency of artificial intelligence and machine learning, low-quality data, identifying use cases, constrained by traditional engineering approaches. In conclusion, this study aims to contribute to the body of knowledge to the adaptation of AIOps in IT industry and may benefit IT organizations. Finally, further research can be done to better understand how AIOps provides human augmentation to enhance human productivity in terms of senses, cognition, and human action.

Keywords: Artificial Intelligence, Cloud Computing, AIOps, IT & Operations, Multivocal Literature Review

1 Introduction

Information Technology (IT) has transformed almost every industry and created an impact from business to everyday life. As technology is becoming a crucial part of society, IT installations are becoming larger and more complex, especially for large-scale data centers [1]. The increasing number of systems and applications is creating new challenges and the communication among these applications makes the interconnectivity so narrow that applications become inseparable and complicated living ecosystem [2]. At the same time, IT operators are challenged to complete the complex task manually without additional automation and assistance [3]. Moreover, support services are challenged due to improper incident management, problem management, and service level management [4]. In order to minimize these challenges, IT service management (ITSM) plays an important role as it delivers the quality of the IT services in the best possible way by implementing, managing, and delivering the quality product to meet the business needs [5]. ITSM ensures the proper mix of people, processes, and technology which helps to reduce the risk of losing business opportunities and client trust [5, 6].

In the last years there is a move towards a continuous improvement of ITSM [7] in which, following standards like ITIL or CMMi Service, there is a continuous approach in getting maturity, including personnel aspects as one of the cornerstones of the approach [8]. Other approaches include the implementation of service management offices [9], co-creation approaches [10] or gamification [11], citing some of the current developments. A broad review of the new approaches could be found in the work of Marrone and Hammerle [12]. Traditionally, ITSM facilitates cost savings, reduced occurrences of incidents, and increased customer satisfaction [6]. However, the shift to multi-cloud environments, DevOps, microservices architectures, and rapid data growth are increasing IT complexity [13] that IT operators are increasingly unable to deal with [14]. Thus, it has become clear that the IT business itself needs a digital transformation to cope with the increasing operational uncertainty and its costs [3, 14]. This digital transformation must be constructed upon, among other factors, artificial intelligence.

Given the growing interest and investment in this process, Gartner introduced the concept of Algorithmic IT Operations back in 2016. Later on, it was changed to Artificial Intelligence for IT operations (AIOps) based on public opinion [15]. AIOps explores the use of Artificial Intelligence (AI) to control and optimize IT services [3]. It uses Big data, machine learning, and other advanced computational tools to develop IT operations directly and indirectly [16]. Moreover, it provides strategic insights and suggestions to minimize errors, boost mean time to recovery (MTTR), and effectively distribute computing resources [14, 17–19] in the look for lowering also personnel costs [20], an aspect crucial for modern IT [21].

Besides, AIOps has started getting more industry attention in literature as well as in research [14, 22]. So far, this specific branch of the IT industry is seeing massive growth, as new products, open-source projects, and service provider companies are emerging. In fact, Gartner predicts that 40% of the large business will combine machine learning and big data to replace legacy services by 2022, however, only 5% were using it by 2018 [15]. Tools in the AIOps panorama include AppDynamics, BigPanda, SL1, Instana, Dynatrace, Moogsoft, PagerDuty, SysTrack, Optanix, DataDog or Splunk, naming just some of the most important tools available in the market early 2021 [23].

Despite of the importance of AIOps, to the best of our knowledge, there is a lack of work devoted to review and provide insights on the use of AI for IT Operations. Therefore, this study aims to identify the definition of AIOps, its benefits and opportunities as well as its challenges by conducting a multivocal literature review (MLR). The search string is applied to two databases (Google Scholar and Google Search). In fact, no prior literature review on AIOps, with the same objective as the one proposed in this study is available. However, there is a systematic mapping study conducted by Notaro et al., [3] to identify the past research in AIOps. These authors considered data-driven approaches based on ML and data mining for searching for and identifying relevant studies. They performed the searches in 3 database libraries (IEEE Xplore, ACM Digital Library, and arXiv). The result of the study is a taxonomy in which the majority of papers is associated with failure-related tasks (62%), i.e. anomaly detection and root cause analysis. Our work will complement the work performed by these authors adding also insights from grey literature as well as more recent works on the topic.

The paper is organized as follows. The next section presents the background about AI and AIOps. Section 3 presents the research methodology including research questions and the data collection procedure. Section 4 presents results of the research questions and the limitation of the study. Finally, the conclusions and future work are presented in Section 5.

2 Background

2.1 Artificial Intelligence

Nilsson et al. [24] define Artificial Intelligence (AI) as *"that activity devoted to making machines intelligent…[where] intelligence is that quality that enables an entity to function correctly and with foresight in its environment*".

AI is not relatively a new term [25]. The concept of modern-day AI was created in 1955, by Mr. John McCarthy along with Marvin Minsky, Nathan Rochester, and Claude Shannon in a conference at Dartmouth by submitting a proposal named 'A proposal for the Artificial Intelligence Summer Research Project in Dartmouth' [26]. Although AI was introduced back then, currently the discipline has gained momentum both in popularity and real repercussion. Over time, AI is making some impact in society and it is often associated with the term "Machine Learning" (ML) or "deep learning" [25, 27].

AI is the blend of various advanced technologies having the capabilities of replicating and/or improving different human tasks and cognitive capabilities such as image and speech recognition, planning, and learning [28]. More precisely, AI is a technological domain with core components such as Machine Learning (ML), Deep Learning, Natural Language Processing (NLP) platforms, predictive Application Programming Interfaces (APIs), and image and speech recognition tools [29]. More importantly, the reason electronic devices and machines are assumed to be crossing the boundaries is due to the blend of technologies, knowledge, and materials. In fact, most groundbreaking elements lie in the AI-equipped machines to change their actions and alter their objective based on the previous experience as well as in response to changing environment [30, 31].

While AI has become an integral part of common applications, a study by McKinsey Global Institute predicts that the use of AI in industries will result in a USD 13 trillion global value-added contribution by 2030 [32]. In addition, The International Data Corporation (IDC) predicts that global spending on AI and ML will be double, rising from $50.1 billion in 2020 to over $110 billion by 2024 [33]. Thus, this trend also should be addressed seriously which might also have a direct or indirect impact on AIOps.

2.2 Artificial Intelligence for IT operations (AIOps)

As mentioned earlier, AIOps is the combination of Artificial Intelligence for IT operations. In particular, Gartner states that "*AIOps platforms utilize big data, modern ma-*

chine learning and other advanced analytics technologies to directly and indirectly enhance IT operations (monitoring, automation and service desk) functions with proactive, personal and dynamic insight. AIOps platforms enable the concurrent use of multiple data sources, data collection methods, analytical (real-time and deep) technologies, and presentation technologies." [34].

AIOps evolved from the need to monitor and analyze the activities performed in an IT environment (both hardware and software), such as processor use, application response times, API usage statistics, and memory loads [18]. AIOps offers the information needed to filter out the info required for faster and safer decisions with intelligent data correlation and dynamic pattern analysis, techniques that are not possible by means of classic methods [22].

In recent years, AIOps has evolved and now it offers a wide variety of tools for different applications from resource and complexity management to task scheduling, anomaly detection, and recovery [22, 35, 36]. Besides, OpsRamp [37] conducted a survey named “The OpsRamp State of AIOps Report” of 200 IT managers throughout the United States to understand their experience with AIOps. The result of the study showed that 85% of responses were for automating the tedious tasks, followed by, 80% suppression/de-duplication/correlation of alerts, and 77% reduction in open incident tickets. In fact, a study by Digital Enterprise Journal shows that, since 2018, there has been an 83% increase in the number of companies implementing or looking to deploy AIOps capabilities in their IT operations [38].

3 Research Methodology

To address the goal of this study, a Multivocal Literature Review (MLR) was conducted based on the guideline provided by [39]. A MLR is a form of systematic literature review that allows us to include primary, secondary as well as grey literature (e.g., blog posts, videos, and white papers) [39]. Such an approach is gaining interest in academic literature [39] and it diminishes the gap by combining the knowledge of the state of arts and practice. As a result of its usefulness, there are many recent studies in computing at large including aspects on microservices [40], function as a service [41] or software as a service [42], mentioning just some of the most recent publications.

In what follows, a brief description of the research procedure is presented including a description of the three research questions for this study and an explanation of the search strategy adopting, mentioning and discussing aspects on data sources, search string used, search process and search execution.

3.1 Research Questions

The goal of this MLR is to get a state of the art and practice related to AIOps by defining AIOps, the benefits gained from it, and the challenges organizations adopting AIOps might face. Based on the above goal, three research questions (RQs) are formulated:

RQ_1: How does the literature define AIOps?

RQ_2: What are the reported benefits of AIOps?

RQ$_3$: What are the reported challenges of AIOps?

3.2 Search Strategy

The scope of this step is to characterize the search and evaluation strategy for identifying the primary studies. This allows a thorough search of the available literature needed to answer the proposed research questions. **Fig. 1** depicts an overview of the process.

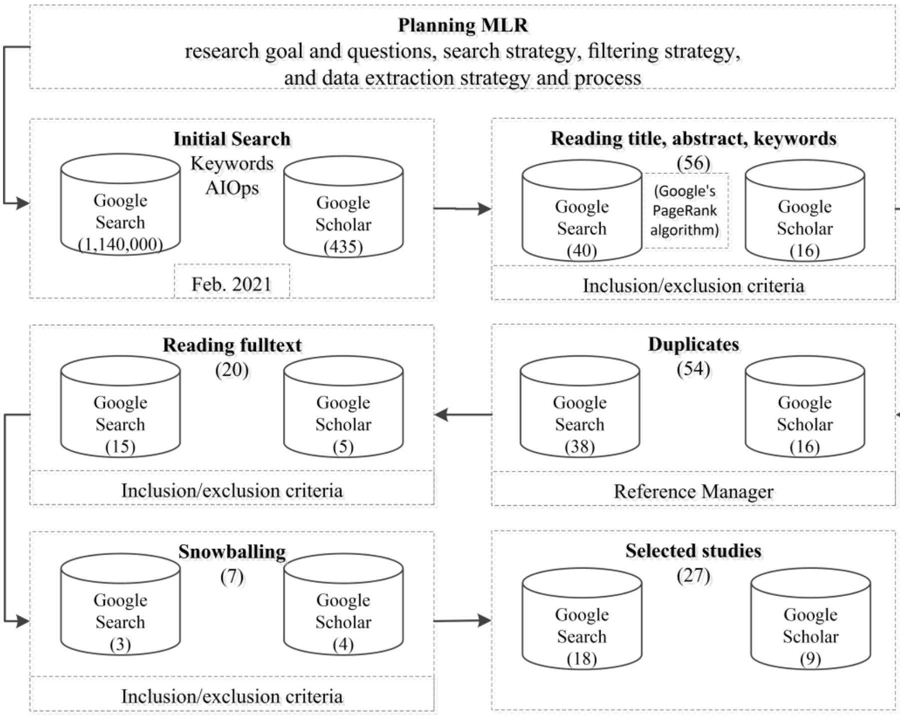

Fig. 1. Overview of the search process.

Data source. To conduct a literature review, data on AIOps were collected by using two search engines: Google Scholar (http://scholar.google.com/) and Google Search (http://www.google.com/). For this study, both engines were estimated to be adequate since they cover all major publishing venues (i.e., IEEE, ScienceDirect, Springer, ACM or Wiley). Google Scholar was used to collecting the scientific literature while grey literature was collected using Google Search.

Search term. The search string is constructed in order to retrieve the most relevant literature on AIOps. As AIOps is relatively a new term, "AIOps" was identified as the search string to have the broader scope of the results and to answer the aforementioned research questions.

Search process. The search process allows us to select primary studies from the scientific literature (Google Scholar). The process is comprised of four phases that follow a test-retest approach to reduce bias in the selection process. The same process was also conducted to identify grey literature on Google Search. The four phases are as follows:

Phase 1. Initial search. The search string was applied to the search engines in order to identify the literature related to topic under review. Searches are limited to title, abstract, and keywords. In terms of timeline, our study was conducted in February 2021, and thus we included the papers published until that time.

Phase 2. Remove duplicates. Studies identified during phase one of the selection process will be checked in order to remove the duplicates. If duplication is identified, papers providing detailed information such as an abstract or the full text of the paper, complete references of the publication will be selected.

Phase 3. First selection process. Studies selected in phase two will be evaluated with inclusion and exclusion criteria. In this phase, the title and abstract of each paper will be reviewed. If the papers are out of inclusion criteria papers will be completely discarded however if the papers fall under inclusion criteria, papers will be selected for the next phase.

Phase 4. Second selection process. Studies selected during phase three will be reviewed thoroughly. This stage will be done to ensure that publication contains the relevant information for the study under review. This approach helps in omitting irrelevant literature.

Search criteria. The search criteria aim at identifying those studies that provided direct empirical evidence about our research questions. In order to narrow down the initial search results, a general set of inclusion and exclusion criteria were established (see **Table 1**).

Search execution. The search procedure was carried out using the method described above. However, it is worth mentioning that search space was restricted using the relevance ranking approach (e.g., Google's PageRank algorithm) while using Google Search. In this case, the above search string was applied to the Google Search and returned 1,140,000 results. However, after observation, it is found that only the first few pages were relevant for the study. Therefore, in this work authors adopted an approach to proceed further only if needed as proposed in [43]. In other words, $(n+1)^{th}$ page was checked only if the result on n^{th} page was found relevant. In Google Scholar, the same search string was applied and returned 435 results. In this case, all papers retrieved from Google Scholar were reviewed by researchers.

Table 1. Summary of inclusion/exclusion criteria.

Inclusion criteria	Exclusion criteria
Studies discuss the concept of AIOps. Studies that highlighted benefits of AIOps. Studies that highlighted challenges of AIOps. Studies written in English language.	Studies are not relevant to AIOps. Studies are inaccessible. Studies contained a summary only. Studies that are duplicated/repeated.

Fig. 1 shows a summary of the search results. First, the search strings were applied in Google Scholar and Google Search. The initial results include 1,140435 results (Google Scholar returned 435 results and Google Search returned 1,140,000). In the first phase, 1140387 results were excluded after reviewing the title, keywords, and abstract. And this resulted in 56 articles, in Phase 2, all the duplicate papers were removed, which left 54 papers. Then, those papers were checked with inclusion/exclusion criteria again and the total papers were 31. Afterward, full texts were analyzed, and 20 studies were selected. Finally, a snowballing approach was carried out and 7 papers were selected. **Table 2** shows the papers selected from full reading (20) and snowballing (7) approaches.

Table 2. Paper selected from full reading and snowballing.

	Google Search		Google Scholar		Total
Full Reading	15	[18, 34, 44–56]	5	[1, 3, 14, 22, 57]	20
Snowballing	3	[37, 58, 59]	4	[60–63]	7

All 27 papers were sorted in a reference manager tool, namely Zotero. To ensure the inclusion of all relevant papers, forward and backward snowballing approach was used as recommended by MLR guidelines, on the set of sources already in the pool. Forward snowballing is identifying articles that have cited the articles found in the search and backward snowballing is identifying articles from the reference lists.

All the selected sources were used to answer the three research questions listed in Section 3.1. **Table 3** presents the search results according to the research questions and the search engines. First column presents RQs, second and third, presents the number of papers collected from Google Scholar and Google Search to answer the specific research question. Based on the select studies, it is observed that 8 out of 27 (30%) sources are related to challenges while 16 (60%) are related to benefits. Therefore, the selected sources reported more challenges than benefits in the AIOps scope.

Table 3. Sources and their relevance to research questions.

RQs	**Google Scholar**		**Google Search**	
RQ_1 (Definition)	2	[22, 57]	4	[18, 44, 45, 58]
RQ_2 (Benefits)	6	[1, 3, 14, 60, 61, 63]	10	[18, 34, 46–50, 56, 58, 59]
RQ_3 (Challenges)	2	[22, 62]	6	[37, 51–55]

4 Results

In the following sections, the results of the MLR with regards to the RQs, limitation and trends of the study are presented. The results of the search process are analyzed taking into account the selected sources retrieved from both the grey and formally published literature and the RQs formulated.

4.1 Trends

As mentioned above, a total of 27 sources are included in this MLR (see the bibliographic details in appendix A). To visually see the growth of the field (AIOPs), we report next a summary on the trends in the final pool of sources, based on two aspects: number of sources by source type and number of sources per year (growth of attention in this area) by literature type (formally published versus grey literature).

Fig. 2 shows the number of sources by source type in each of the two categories: formally-published versus grey literature. In the formally-published literature category, there were 6 conference paper followed by 2 journal papers and 1 book chapter. In the grey literature category, there were 10 blog post and 8 web pages. It is not surprising that the grey literature in this area has surpassed the formally published literature due to the contextual fact that the AIOps term and discussions have their origins in industry.

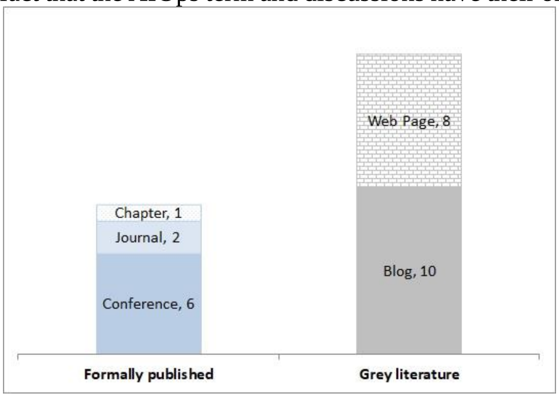

Fig. 2. Number of sources by year.

Fig. 3 shows the cumulative number of sources per year. As one can see, sources in both literature categories have been on a steady increasing trend from 2017 to 2020. However, there is a group of web pages (4 out of 27 sources) in which their year of publication is not available (N/A) while there is one web page in 2021. The formally published literature in this area seems to start around year 2019, denoting the increasing attention of scholars on this important topic.

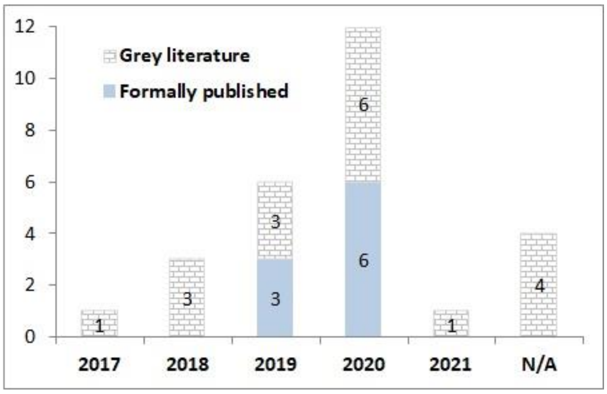

Fig. 3. Cumulative number of sources by year (No Available, N/A).

Before analyzing the paper, we got an overview of the topics covered in the sources according to their titles. Word clouds are a suitable tool for this purpose. **Fig. 4** shows a word cloud of all sources (we used the online tool https://www.wordclouds.com/).

Fig. 4. Overview of topics shown by the word cloud of all source titles.

Finally, Fig. 5 shows an overview of the results as observed in the selected studies. Businesses are turning to AI, ML or Big data for IT operations (AIOps). As one can see, there are a set of benefits (see section 4.3) and challenges (see section 4.4) related to AIOps. In fact, previous research identified AIOps contributions in failure management and resource provisioning [3]. The first one is related to how to deal with undesired behavior in the delivery of IT services while second one is about allocation of energetic, computational, storage and time resources for the optimal delivery of IT services.

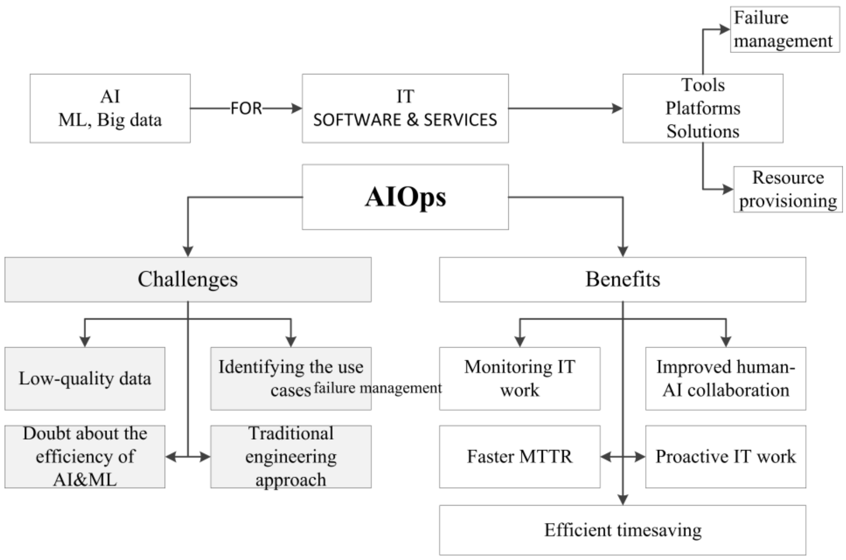

Fig. 5. Overview of the results as observed in the selected studies.

4.2 Definition of AIOps (RQ$_1$)

Although there is still not a generally accepted definition of AIOps, in order to answer this question, 6 papers were selected of which two are scientific literature and the remaining 4 are grey literature. The scientific literature [22] highlights that AIOps seeks to empower software and service engineers to use AI and ML techniques to develop software and services that are easy to handle in an accessible and productive way. On the other hand, the grey literature defined AIOps as a new approach for automating and enhancing IT operations through ML and analytics in order to identify and respond to IT operational issues in real-time [18, 45, 58]. According to [57], a leading company in Cambridge Massachusetts named Forrester has defined AIOps as follows:

"AIOps primarily focuses on applying machine learning algorithms to create self-learning— and potentially self-healing—applications and infrastructure. A key to analytics, especially predictive analytics, is knowing what insights you're after."

Similarly, techopedia dictionary defines [44]:

"AIOps is a methodology that is on the frontier of enterprise IT operations. AIOps automates various aspects of IT and utilizes the power of artificial intelligence to create self-learning programs that help revolutionize IT services."

4.3 Benefits of AIOps (RQ$_2$)

AIOps is relatively young and far from a mature technology, even so, it already has reported some potential benefits. To answer this question, 16 papers were selected, 6 are scientific literature while the remaining 10 are grey literature. The right side of **Fig.**

5 shows the identified benefits grouped in 5 categories: i) Monitoring IT work, ii) Efficient time saving, iii) Improved human-AI collaboration, iv) Proactive IT work, and v) Faster MTTR.

Monitoring IT work. AIOps solutions monitor and analyze the activities performed in an IT environment (both hardware and software), e.g. processor use, application response times, API usage statistics, and memory loads [18, 61]. These analytics and ML capabilities allow AIOps to perform powerful root cause analysis that speeds up troubleshooting and solution to difficult and unusual problems [47, 59] e.g., if the workload traffic exceeded a normal threshold by a certain percentage, the AIOps platform could add resources to the workload or migrate it to another system or environment much like a human admin does [56].

Efficient timesaving. When AIOps platforms are set up properly the time and effort of IT professionals can be spent on more productive tasks in their jobs [1, 34, 47]. Meaning, less time to spend with routine request and system monitoring every day [14, 46]. Therefore, IT teams can work on innovative tasks to add value to the business [50, 61].

Improved human-AI collaboration. Collaboration and workflow activities between IT teams and other business units can be enhanced by AIOps [14, 49]. Given that AIOps learns from the input data, they can automate the process requiring less human effort. In this sense, customized reports and dashboards can help teams to understand their tasks and requirements faster and better, and to communicate with others without having to understand the complexity of the various areas in detail [18, 60]. Moreover, the IT operations team can focus on tasks with greater strategic value to the business [60]. As an example, if AI teams get specific alerts to meet the service level threshold instead of being loaded with an alert from the various environment, IT teams can respond to them more quickly and possibly stops the slowdown and outages of the services with less effort [18].

Proactive IT work. AIOps reduces the operational burden of IT systems and facilities with constructive actionable dynamic insight by utilizing big data, machine learning, and other advanced analytics technologies to boost IT operations [47, 58]. This means that AIOps platforms can provide predictive warnings that allow potential issues to be solved by IT teams before they lead to slow-downs or outages. In fact, a survey from 6000 global IT leaders about AIOps revealed that 74% of the IT professionals want to use proactive monitoring and analytics tools [48]. However, 42% of them are still using monitoring and analytics tools reactively to detect and fix technological challenges and issues.

Faster MTTR. MTTR is the average time taken to resolve an outage and restore service to end-users. AIOps assists the IT operators in finding the root causes and assist in finding the solutions quicker and more effectively than humanly possible [3]. Infrastructure failure must be addressed at ever-increasing speeds. According to [18], it saves millions of dollars by avoiding direct (fines, opportunity costs) and indirect (customer dissatisfaction and lost reference) costs in IT operation. In fact, one study highlights that MTTR can be reduced from 60 minutes to 30 seconds with the help of AIOps [63].

4.4 Challenges of AIOps (RQ_3)

Despite that AIOps shows real promise as a path to success, it upholds some challenges from both technical and non-technical perspectives [22]. To understand the challenges a total of 8 papers were identified, 2 papers are scientific literature while the remaining 6 papers are grey literature. The left side of **Fig. 5** shows the identified challenges grouped into 4 categories: i) Doubt about the efficiency of AI&ML, ii) Low-quality data, iii) Identifying the use cases, and iv) Traditional engineering approaches.

Doubt about the efficiency of AI&ML. AIOps solutions' basic approach is to learn from experience to predict the future and to recognize trends from huge volumes of data [22]. However, IT professionals who are already working in the field for a while are questioning the efficiency of analytics and ML, even after realizing the need for digital transformation [53, 62]. One possible explanation is their previous experience on piloted projects or attempted analytics projects in-house or with other suppliers which resulted in failed or mixed responses [22]. Therefore, it seems that businesses require more time to develop trust in the validity and reliability of recommendations from AIOps [37].

Low-quality data. The performance of the AIOps highly depends on the quality of the data [53]. While major cloud providers capture terabytes and even petabytes of telemetry data every day/month today, there is still a shortage of representative and high-quality data for developing AIOps solutions [22]. It is simply becoming too complex for manual reporting and analysis. In this scenario, current issues are noisy data, irregular or inadequate reporting frequencies, and even inconsistent naming convention [51, 53]. Besides, essential pieces of information are "unstructured" types of data presenting poor data quality[53]. Therefore, a constant improvement of data quality and quantity is essential, taking into account that AIOps solutions are based on data [22].

Identifying the use cases. Use cases in the AIOps is the process of analyzing and identifying the challenges and opportunities across the IT operation environment [51]. In addition, building the models to solve these problems and monitoring the performance of the developed model [55]. Companies believe using AI and ML related features will increase the efficiency of current development within the organization [52]. However, without identifying the underlying issue AIOps implementation might not be effective [51]. As AIOps solutions require analytical thought and adequate comprehension of the whole problem space such as market benefit and constraints, development models and, considerations of system and process integration [22]. Therefore, the organization should start examining underlying systems, applications, and processes from the top level and decide the integration of AIOps to have the greatest leverage [51].

Traditional engineering approach. Successful AIOps implementation requires significant engineering efforts [22]. As it is relatively young and far from mature technology only limited AIOps-engineer are available [22]. Therefore, instead of focusing on building new AIOps initiative, reshaping the existing approach and processes in the organizations is important for the new realities of digital business [54, 55]. These works indicate that traditional approaches do not work in dynamic, elastic environments. However, ideal practice/principles/design patterns are yet to be established in the industry [53].

4.5 Limitations and Potential Threat to Validity

In order to make sure that this review is repeatable, the systematic approach is described in Section 3.2. However, despite that search engines, search terms and inclusion/exclusion criteria are carefully defined and reported, there are some limitations in the selection process that can lead to incomplete set of primary studies.

As a single term has been used in the search string (AIOps), the main threat to the validity of our study is that the literature regarding AIOps is still scarce. A significant part of the available information about AIOps comes from informal publication channels as blogs. In order to mitigate risk of finding all relevant studies, we included publications that apparently are not peer reviewed but that we consider being of high enough quality or that have already been cited by peer reviewed publications.

For controlling threats due to search engines, we have included an academic database “Google scholar” and a general web search database “Google search”. Moreover, a snowballing process of the selected studies was done to ensure that other relevant studies had been included. While this introduces a subjective quality assessment step that has the risk of being biased, it gives us the opportunity to provide a definition of AIOps according to how the term is currently being used by scholars and practitioners.

In addition, applying inclusion/exclusion criteria can suffer from researchers’ bias. To reduce researcher biases, two authors were actively involved in the search process while the remaining author supervised all the process. We also limited ourselves to publications written in English so that relevant studies in other languages are missed out. Therefore, although, we recognized that additional relevant published studies may have been overlooked, we believe that our MLR provides an adequate overview of the field. Finally, it worth to note that our findings are within the IT field particularly AIOps. Beyond this field, we had no intention to generalize our results, but we believe that the value of our MLR should not be undermined.

5 Conclusions and Future Work

This study aims to identify the definition of AIOps, the benefits gained from it, and the challenges an organization might face. It is expected that this study will help to achieve a deeper and wider understanding of this field from a practitioner's point of view based on literature.

In this study, a MLR was conducted based on Google Scholar and Google Search. As a result, 27 sources were identified after applying the inclusion and exclusion criteria (see **Table 2**). Among them, only 9 were academic literature, and the remaining 18 consists of grey literature. The findings reveal that AIOps is defined as an approach for automating and enhancing IT operations through ML and analytics to identify and respond to IT operational issues in real-time. AIOps evolves from the need to track and manage the highly demanding big data and advanced analytics strategies with adequate means. In other words, AIOps can be thought of as continuous integration and deployment (CI/CD) for core IT functions.

Moreover, a set of benefits and challenges related to AIOps were identified. As AIOps is not yet fully developed, it upholds challenges such as IT organizations questioning the efficiency of AI and ML, poor quality of data affecting the results, lack of engineering effort to think strategically about reshaping the approach, processes, and organizations to account for the new realities of digital business. On the other side, adopting a AIOps solution will not only have improved human-AI collaboration, but also, AIOps monitors the IT work, analyze the root cause, and speeds up troubleshooting by saving the time of IT teams. In addition, AIOps could foster proactive IT work, improve the MTTR and provide a solution to difficult and unusual problems in IT operation.

Given the increasing attention that AIOps has gained from practitioners, further research is needed to better understand how AIOps provides human augmentation to enhance human productivity in terms of senses, cognition, and human action. Taking this into account, authors aim at continuing this work by investigating specific aspects on the connection of AIOps with DevOps and DevSecOps environments, including needed competences and pipelines towards the integration of security aspects in the automation picture. A second proposed line of research is the one devoted to investigating aspects on IT Governance and IT compliance and their cascading over AIOps tools and processes. Finally, authors would like to work on the integration of ITSM methods and frameworks (e.g. ITIL) in AIOps-enabled IT service operations.

Appendix A. List of sources included in the MLR

	Reference	Year	Authors	Title	Type
1	[1]	2020	Gulenko, A., Acker, A., Kao, O., Liu, F.	AI-Governance and Levels of Automation for AIOps-supported System Administration	Conference

2	[3]	2020	Notaro, P., Cardoso, J., Gerndt, M.	A Systematic Mapping Study in AIOps	Conference
3	[14]	2019	Levin, A., Garion, S., Kolodner, E.K., Lorenz, D.H., Barabash, K., Kugler, M., McShane, N.	AIOps for a Cloud Object Storage Service	Conference
4	[18]	2020	IBM Cloud Education	AIOps	Web Page
5	[22]	2019	Dang, Y., Lin, Q., Huang, P.	AIOps: real-world challenges and research innovations	Conference
6	[34]	2017	Lerner, A	AIOps Platforms	Blog
7	[37]	2019	OpsRamp	The OpsRamp State of AIOps Report	Web Page
8	[44]	Not available	Techopedia	What is AIOps? - Definition from Techopedia	Web Page
9	[45]	2020	Sagemo, I.	What is AIOps?	Web Page
10	[46]	2018	Oats, M.	What is AIOps? The Benefits Explained	Web Page
11	[47]	2020	Oehrlich, E.	What is AIOps? Benefits and adoption considerations	Web Page
12	[48]	2018	Jacob, S.	The Rise of AIOps: How Data, Machine Learning, and AI Will Transform Performance Monitoring | AppDynamics	Blog
13	[49]	2019	Mercina, P.	The Benefits of AIOps	Blog
14	[50]	Not available	Moogsoft	What is AIOps | A Guide to Everything You Need to Know About AIOps	Web Page
15	[51]	2019	Rogers, P.	Four problems to avoid in order to have a successful AIOps integration	Blog
16	[52]	2019	OPTANIX	AIOps Solutions Concerns Considered by IT Leaders	Blog
17	[53]	2018	Paskin, S.	Concerns and Challenges of IT Leaders Considering AIOps Platforms – BMC Blogs	Blog
18	[54]	2020	CloudFabrix	Top 5 Practical Challenges & Considerations with AIOps | Our Latest Blog Posts | CloudFabrix Buzz	Blog

19	[55]	2020	Analytics Insight	AIOps: Understanding the Benefits and Challenges in IT landscape	Blog
20	[56]	Not available	Bigelow, S. J.	What is AIOps (artificial intelligence for IT operations)? - Definition from WhatIs.com	Web Page
21	[57]	2019	Masood, A., Hashmi, A.	AIOps: Predictive analytics & machine learning in operations	Chapter
22	[58]	Not available	AISERA	AIOps Platforms: A Guide to What You Should Know About AIOps	Blog
23	[59]	2021	Sacolick, I.	What is the AI in AIops?	Blog
24	[60]	2020	Banica, L., Polychronidou, P., Stefan, C., Hagiu, A.	Empowering IT Operations through Artificial Intelligence–A New Business Perspective	Journal
25	[61]	2020	Gheorghiță, A.C., Petre, I.	Securely Driving IoT by Integrating AIOps and Blockchain	Journal
26	[62]	2020	Kostadinov, G., Atanasova, T., Petrov, P.	Reducing the Number of Incidents in Con-verged IT Infrastructure Using Correlation Approach	Conference
27	[63]	2020	Shen, S., Zhang, J., Huang, D., Xiao, J.	Evolving from Traditional Systems to AIOps: Design, Implementation and Measurements	Conference

References

1. Gulenko, A., Acker, A., Kao, O., Liu, F.: AI-Governance and Levels of Automation for AIOps-supported System Administration. In: 2020 29th International Conference on Computer Communications and Networks (ICCCN). pp. 1–6. IEEE (2020).
2. Astakhova, L., Medvedev, I.: The Software Application for Increasing the Awareness of Industrial Enterprise Workers on Information Security of Significant Objects of Critical Information Infrastructure. In: 2020 Global Smart Industry Conference (GloSIC). pp. 121–126. IEEE (2020).
3. Notaro, P., Cardoso, J., Gerndt, M.: A Systematic Mapping Study in AIOps. ArXiv Prepr. ArXiv201209108. (2020).

4. Jäntti, M., Cater-Steel, A.: Proactive management of IT operations to improve IT services. JISTEM-J. Inf. Syst. Technol. Manag. 14, 191–218 (2017).
5. Galup, S.D., Dattero, R., Quan, J.J., Conger, S.: An overview of IT service management. Commun. ACM. 52, 124–127 (2009).
6. Iden, J., Eikebrokk, T.R.: Implementing IT Service Management: A systematic literature review. Int. J. Inf. Manag. 33, 512–523 (2013).
7. Heikkinen, S., Jäntti, M.: Studying Continual Service Improvement and Monitoring the Quality of ITSM. In: Piattini, M., Rupino da Cunha, P., García Rodríguez de Guzmán, I., and Pérez-Castillo, R. (eds.) Quality of Information and Communications Technology. pp. 193–206. Springer International Publishing, Cham (2019). https://doi.org/10.1007/978-3-030-29238-6_14.
8. Dávila, A., Janampa, R., Angeleri, P., Melendez, K.: ITSM model for very small organisation: an empirical validation. IET Softw. 14, 138–144 (2019). https://doi.org/10.1049/iet-sen.2019.0034.
9. Lucio-Nieto, T., Gonzalez-Bañales, D.L.: Implementation of a Service Management Office Into a World Food Company in Latin America. Int. J. Inf. Technol. Syst. Approach IJITSA. 14, 116–135 (2021).
10. Winkler, T.J., Wulf, J.: Effectiveness of IT Service Management Capability: Value Co-Creation and Value Facilitation Mechanisms. J. Manag. Inf. Syst. 36, 639–675 (2019). https://doi.org/10.1080/07421222.2019.1599513.
11. Orta, E., Ruiz, M., Calderón, A., Hurtado, N.: Gamification for Improving IT Service Incident Management. In: Mas, A., Mesquida, A., O'Connor, R.V., Rout, T., and Dorling, A. (eds.) Software Process Improvement and Capability Determination. pp. 371–383. Springer International Publishing, Cham (2017). https://doi.org/10.1007/978-3-319-67383-7_27.
12. Marrone, M., Hammerle, M.: Relevant Research Areas in IT Service Management: An Examination of Academic and Practitioner Literatures. Commun. Assoc. Inf. Syst. 41, (2017). https://doi.org/10.17705/1CAIS.04123.
13. Larrucea, X., Santamaria, I., Colomo-Palacios, R., Ebert, C.: Microservices. IEEE Softw. 35, 96–100 (2018). https://doi.org/10.1109/MS.2018.2141030.
14. Levin, A., Garion, S., Kolodner, E.K., Lorenz, D.H., Barabash, K., Kugler, M., McShane, N.: AIOps for a Cloud Object Storage Service.

In: 2019 IEEE International Congress on Big Data (BigDataCongress). pp. 165–169. IEEE (2019).
15. Prasad, P., Rich, C.: Market Guide for AIOps Platforms. Retrieved March. 12, 2020 (2018).
16. Wang, H., Zhang, H.: AIOPS Prediction for Hard Drive Failures Based on Stacking Ensemble Model. In: 2020 10th Annual Computing and Communication Workshop and Conference (CCWC). pp. 0417–0423. IEEE (2020).
17. Goldberg, D., Shan, Y.: The importance of features for statistical anomaly detection. In: 7th {USENIX} Workshop on Hot Topics in Cloud Computing (HotCloud 15) (2015).
19. IBM Cloud Education, I.: AIOps, https://www.ibm.com/cloud/learn/aiops, last accessed 2021/02/05 (2020).
20. Liu, X., Tong, Y., Xu, A., Akkiraju, R.: Using Language Models to Pre-train Features for Optimizing Information Technology Operations Management Tasks (2020).
20. Dařena, F., Gotter, F.: Technological Development and Its Effect on IT Operations Cost and Environmental Impact. Int. J. Sustain. Eng. 0, 1–12 (2021). https://doi.org/10.1080/19397038.2020.1862342.
21. Casado-Lumbreras, C., Colomo-Palacios, R., Gomez-Berbis, J.M., Garcia-Crespo, A.: Mentoring programmes: a study of the Spanish software industry. Int. J. Learn. Intellect. Cap. 6, 293–302 (2009).
22. Dang, Y., Lin, Q., Huang, P.: AIOps: real-world challenges and research innovations. In: 2019 IEEE/ACM 41st International Conference on Software Engineering: Companion Proceedings (ICSE-Companion). pp. 4–5. IEEE (2019).
23. Sen, A.: DevOps, DevSecOps, AIOPS- Paradigms to IT Operations. In: Singh, P.K., Noor, A., Kolekar, M.H., Tanwar, S., Bhatnagar, R.K., and Khanna, S. (eds.) Evolving Technologies for Computing, Communication and Smart World. pp. 211–221. Springer, Singapore (2021). https://doi.org/10.1007/978-981-15-7804-5_16.
24. Nilsson, N.J.: The quest for artificial intelligence. Cambridge University Press (2009).
25. Long, D., Magerko, B.: What is AI literacy? Competencies and design considerations. In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. pp. 1–16 (2020).
26. Rajaraman, V.: JohnMcCarthy—Father of artificial intelligence. Resonance. 19, 198–207 (2014).

27. Touretzky, D., Gardner-McCune, C., Martin, F., Seehorn, D.: Envisioning AI for k-12: What should every child know about AI? In: Proceedings of the AAAI Conference on Artificial Intelligence. pp. 9795–9799 (2019).
28. Martínez-Plumed, F., Tolan, S., Pesole, A., Hernández-Orallo, J., Fernández-Macías, E., Gómez, E.: Does AI qualify for the job? A bidirectional model mapping labour and AI intensities. In: Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society. pp. 94–100 (2020).
29. Martinelli, A., Mina, A., Moggi, M.: The enabling technologies of industry 4.0: Examining the seeds of the fourth industrial revolution. Ind. Corp. Change Forthcom. (2020).
30. Fanti, L., Guarascio, D., Moggi, M.: The development of AI and its impact on business models, organization and work. Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced … (2020).
31. Brynjolfsson, E., Mitchell, T., Rock, D.: What can machines learn, and what does it mean for occupations and the economy? In: AEA Papers and Proceedings. pp. 43–47 (2018).
32. Bughin, J., Seong, J., Manyika, J., Chui, M., Joshi, R.: Notes from the AI frontier: Modeling the impact of AI on the world economy. McKinsey Glob. Inst. (2018).
34. IDC Corporate USA, I.: International Data Corporation Spending Guide, https://www.idc.com/getdoc.jsp?containerId=prUS46794720, last accessed 2021/01/23 (2020).
34. Lerner, A.: AIOps Platforms. Gart. Blog August. (2017).
35. Bogatinovski, J., Nedelkoski, S., Acker, A., Schmidt, F., Wittkopp, T., Becker, S., Cardoso, J., Kao, O.: Artificial Intelligence for IT Operations (AIOPS) Workshop White Paper. ArXiv Prepr. ArXiv210106054. (2021).
36. Li, Y., Jiang, Z.M., Li, H., Hassan, A.E., He, C., Huang, R., Zeng, Z., Wang, M., Chen, P.: Predicting Node Failures in an Ultra-large-scale Cloud Computing Platform: an AIOps Solution. ACM Trans. Softw. Eng. Methodol. TOSEM. 29, 1–24 (2020).
38. OpsRamp: The-OpsRamp-State-of-AIOps-Report.pdf, https://www.opsramp.com/wp-content/uploads/2019/04/The-OpsRamp-State-of-AIOps-Report.pdf, last accessed 2021/02/06 (2019).

39. Simic, B.: Strategies of Top Performing Organizations in Deploying AIOps", https://www.dej.cognanta.com/2020/05/04/the-aiops-maturity-research-study-key-findings/, last accessed 2021/02/09 (2020).
39. Garousi, V., Felderer, M., Mäntylä, M.V.: Guidelines for including grey literature and conducting multivocal literature reviews in software engineering. Inf. Softw. Technol. 106, 101–121 (2019).
40. Pereira-Vale, A., Fernandez, E.B., Monge, R., Astudillo, H., Márquez, G.: Security in microservice-based systems: A Multivocal literature review. Comput. Secur. 103, 102200 (2021). https://doi.org/10.1016/j.cose.2021.102200.
41. Scheuner, J., Leitner, P.: Function-as-a-Service performance evaluation: A multivocal literature review. J. Syst. Softw. 170, 110708 (2020). https://doi.org/10.1016/j.jss.2020.110708.
42. Saltan, A., Smolander, K.: Bridging the state-of-the-art and the state-of-the-practice of SaaS pricing: A multivocal literature review. Inf. Softw. Technol. 133, 106510 (2021). https://doi.org/10.1016/j.infsof.2021.106510.
43. Garousi, V., Mäntylä, M.V.: A systematic literature review of literature reviews in software testing. Inf. Softw. Technol. 80, 195–216 (2016).
47. What is AIOps? - Definition from Techopedia, http://www.techopedia.com/definition/33321/aiops, last accessed 2021/02/06 (2019).
48. Sagemo, I.: What is AIOps?, https://www.aims.ai/resources/what-is-aiops, last accessed 2021/02/07 (2020).
49. Oats, M.: What is AIOps? The Benefits Explained, https://www.intellimagic.com/resources/aiops-benefits-explained/, last accessed 2021/02/05 (2018).
50. Oehrlich, E.: What is AIOps? Benefits and adoption considerations, https://enterprisersproject.com/article/2020/3/what-is-aiops, last accessed 2021/02/05 (2020).
51. Jacob, S.: The Rise of AIOps: How Data, Machine Learning, and AI Will Transform Performance Monitoring | AppDynamics, https://www.appdynamics.com/blog/news/aiops-platforms-transform-performance-monitoring/, last accessed 2021/02/06 (2018).
52. Mercina, P.: The Benefits of AIOps, https://www.parkplacetechnologies.com/blog/the-benefits-of-aiops/, last accessed 2021/02/05 (2019).

53. moogsoft, M.: What is AIOps | A Guide to Everything You Need to Know About AIOps, https://www.moogsoft.com/resources/ai-ops/guide/everything-aiops/, last accessed 2021/02/09 (2021).
54. Intelligent, C.A.: Four problems to avoid in order to have a successful AIOps integration, https://www.intelligentcio.com/africa/2019/03/12/four-problems-to-avoid-in-order-to-have-a-successful-aiops-integration/, last accessed 2021/02/10 (2019).
55. OPTANIX: AIOps Solutions Concerns Considered by IT Leaders, https://www.optanix.com/aiops-solutions-challenges-and-concerns/, last accessed 2021/02/10 (2019).
56. Paskin, S.: Concerns and Challenges of IT Leaders Considering AIOps Platforms – BMC Blogs, https://www.bmc.com/blogs/concerns-and-challenges-of-it-leaders-considering-aiops-platforms/, last accessed 2021/02/10 (2018).
57. CloudFabrix: Top 5 Practical Challenges & Considerations with AIOps | Our Latest Blog Posts | CloudFabrix Buzz, https://cloudfabrix.com/blog/aiops/top-5-practical-challenges-considerations-with-aiops/, last accessed 2021/02/10 (2020).
58. Analytics Insight: AIOps: Understanding the Benefits and Challenges in IT landscape, https://www.analyticsinsight.net/aiops-understanding-benefits-challenges-landscape/, last accessed 2021/02/10 (2020).
59. J. Bigelow, S.: What is AIOps (artificial intelligence for IT operations)? - Definition from WhatIs.com, https://searchitoperations.techtarget.com/definition/AIOps, last accessed 2021/02/21(2019).
57. Masood, A., Hashmi, A.: AIOps: Predictive analytics & machine learning in operations. In: Cognitive Computing Recipes. pp. 359–382. Springer (2019).
61. AIOps Platforms: A Guide to What You Should Know About AIOps, https://aisera.com/blog/aiops-platforms-a-guide-to-aiops/, last accessed 2021/02/06 (2020).
62. Sacolick, I.: What is the AI in AIops?, https://www.infoworld.com/article/3603953/what-is-the-ai-in-aiops.html, last accessed 2021/02/13 (2021).
63. Banica, L., Polychronidou, P., Stefan, C., Hagiu, A.: Empowering IT Operations through Artificial Intelligence–A New Business Perspective. KnE Soc. Sci. 412-425 (2020).

61. Gheorghiță, A.C., Petre, I.: Securely Driving IoT by Integrating AIOps and Blockchain. Romanian Cyber Secur. J. 2, (2020).
62. Kostadinov, G., Atanasova, T., Petrov, P.: Reducing the Number of Incidents in Converged IT Infrastructure Using Correlation Approach. In: 2020 International Conference Automatics and Informatics (ICAI). pp. 1–4. IEEE (2020).
63. Shen, S., Zhang, J., Huang, D., Xiao, J.: Evolving from Traditional Systems to AIOps: Design, Implementation and Measurements. In: 2020 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA). pp. 276–280. IEEE (2020).