Systematic Mapping of a Process to Support MLOps in Small and Medium-Sized Software Development Companies

Mapeo Sistemático de un Proceso para Soportar MLOps en las Pequeñas y Medianas Empresas de Desarrollo de Software

DOI: https://dx.doi.org/10.17981/ingecuc.22.1.2026.03
Scientific Research Article. Date Received: 26/08/2024, Date Accepted: 11/072025

Esteban Alberto Arteaga Benavides https://orcid.org/0000-0003-1634-066X
Universidad del Cauca. Popayán, (Colombia)
estebanben@unicauca.edu.co

Cesar Jesús Pardo Calvache https://orcid.org/0000-0002-6907-2905
Universidad del Cauca. Popayán, (Colombia)
cpardo@unicauca.edu.co

To cite this paper
E. Arteaga-Benavides & C. Pardo-Calvache "Systematic Mapping of a Process to Support MLOps in Small and Medium-Sized Software Development Companies," INGE CUC, vol. 22, no. 1, 2026. DOI: *https://dx.doi.org/10.17981/ingecuc.22.1.2026.03*

Abstract

Introduction: Currently, software development companies (SDCs) have begun to incorporate Machine Learning into their projects, which has allowed Machine Learning models to move from the experimentation stage to the production stage. This is where Machine Learning Operations (MLOps) comes in, with the goal of bridging the gap between operations, development, and data science teams.
Objective: Conduct research on the current state of knowledge regarding the adoption of MLOps in SDCs through systematic literature mapping, with the aim of studying, identifying, and understanding initiatives, solutions, and issues related to work in this area.
Method: A systematic literature mapping was carried out using a defined protocol, which included the development of research questions and the implementation of a search strategy in six databases. Primary articles were then selected based on pre-established inclusion and exclusion criteria. The research questions were addressed based on the results obtained, allowing the findings to be classified and characterized. Finally, the results were analyzed, and the corresponding conclusions were presented.
Results: The findings of this article reflect the efforts of the scientific community to define the principles, roles, artifacts, technologies, challenges, and crucial factors for the implementation of Machine Learning Operations in SDCs.
Conclusions: The research questions are answered, which reveal the main challenges in implementing Machine Learning.

Key Words

Machine Learning Operations (MLOps); Pipeline, Process Model; Automation; Software Development, Machine Learning (ML).

Resumen

Introducción: Actualmente las empresas de desarrollo de software han empezado a incluir Machine Learning dentro de sus proyectos, lo que ha permitido que los modelos de Machine Learning pasen de la etapa de experimentación a la etapa de producción, aquí surge Machine Learning Operations con el objetivo de disminuir la brecha entre los equipos de operaciones, desarrollo y de ciencia de datos.
Objetivo: Realizar la investigación acerca del estado actual del conocimiento sobre la adopción de MLOps en las EDS por medio de un mapeo sistemático de la literatura, con el objetivo de estudiar, identificar y entender las iniciativas, soluciones y problemáticas de trabajos relacionados en el área.

Metodología: Se realizo un mapeo sistemático de la literatura con un protocolo definido, que contempla la elaboración de preguntas de investigación y la implementación de una estrategia de búsqueda en seis bases de datos. Tras ello, se seleccionan los artículos primarios en función de criterios de inclusión y exclusión establecidos previamente. A partir de los resultados obtenidos, se abordan las preguntas de investigación, lo que permite clasificar y caracterizar los hallazgos. Finalmente, se analizan los resultados y se exponen las conclusiones correspondientes.
Resultados: Los hallazgos de este articulo reflejan los esfuerzos de la comunidad científica para definir los principios, roles, artefactos, tecnologías, desafios y factores cruciales para la implementación de Machile Learning Operations en las empresas de desarrollo de Software.
Conclusiones: Se contestan las preguntas de investigación en las cuales nos arrojan los retos principales a la hora de implementar Machine Learning.

Palabras clave

Machine Learning Operations (MLOps); Pipeline, Modelo de Procesos; Automatización; Desarrollo de Software, Machine Learning (ML).

I. INTRODUCCION

Currently, software development companies (SDCs) have begun to include Machine Learning (ML) and Deep Learning (DL) in their projects. This is due to the great advances that have been made in processing with the inclusion of Graphics Processing Units (GPUs) and Tensor Processing Units (TCUs), which has reduced the training and processing time that they commonly took. In addition, the inclusion of technologies such as Docker and Kubernetes has allowed ML models to move beyond the experimentation stage and into production [1]. All of the above has led to SDCs beginning to migrate to an environment where ML coexists with traditional and/or agile development, which means that the way products and/or services are developed must evolve, since apart from code, ML projects depend on datasets, so there is a need to define new roles, new activities, and new artifacts that traditional and/or agile methodologies do not cover [2], [3].

To talk about machine learning in development is to talk about data science. This statement is based on the fact that developing a machine learning project requires data, which is the cornerstone on which all ML or DL development processes are based. For this reason, different methodologies have been developed to meet the characteristics of data science projects, as mentioned in [4], such as CRISP-DM (CRoss-Industry Standard Process for Data Mining, Methodology for Interactive and Systematic Data Mining Development), DDS (Data Driven Scrum, Data-based Scrum), among others. However, these methodologies lack certain processes to effectively manage and complete data science projects, so many companies resort to an empirical approach. In [5], it is mentioned that 87% of data science projects do not reach production, and 77% of companies have adopted AI initiatives, so this field requires great attention from the scientific and industrial community.

This is where Machine Learning Operations (hereinafter MLOps) comes in, defined as a collection of techniques and tools for deploying ML models into production, integrating the concepts of continuous integration (CI) and continuous deployment (CD) present in DevOps. However, ML projects depend not only on code, but also on data, which is why two new terms are added: continuous monitoring (CM) and continuous training (CT) [6], [7]. In this way, the aim is to reduce the gap between the different teams involved in software development (traditional and/or agile), incorporating new functionalities such as predictive analytics, time series, natural language processing, computer vision, among others.

Likewise, incorporating an ML area into traditional and/or agile software development projects may entail overcoming certain technical challenges, such as: (i) incorporating new processes and tools; (ii) including professionals with the necessary soft and technical skills to support the execution of these processes; and (iii) the high cost of implementation, especially in the cloud. Currently, small, and medium-sized enterprises (hereinafter SMEs) lead industrial and commercial infrastructure in most countries worldwide [8], but these companies face challenges due to cost, size, limited access to financing, lack of training, and low technological development, among other issues [9]. Thus, SMEs have limited capacity to implement MLOps projects due to the associated high costs of implementation, deployment, and maintenance.

On the other hand, it is possible to find that software SMEs can have chaotic processes, which are usually considered empirical, incomplete, and unsuccessful. Due to the nature and composition of software SMEs, a high level of uncertainty is generated when applying an MLOps approach to projects. This makes it necessary to clarify, define, restructure, and include new process elements. These elements include roles, soft skills, technical skills, tools, artifacts, activities, and tasks. These elements were generally carried out in traditional and/or agile software development processes. Now, they require an MLOps-oriented approach. However, according to the characteristics of software SMEs, this approach is also applicable to this type of company. It allows them to produce and maintain high-quality software effectively and at a low cost.

In accordance with the above, an analysis of the information was carried out by means of Systematic Mapping, which revealed that efforts have been made to define proposals and solutions related to the evaluation of MLOps.

The rest of the document is organized as follows: Section II presents the research protocol used to develop systematic mapping. Section III describes the process of conducting the information search. Section IV presents different analyses of the results obtained in response to the research questions. Section V discusses the results, main observations, limitations of the mapping, and significance of the research. Finally, Section VI presents the conclusions and future work.

II. RESEARCH METHOD

Systematic mapping is a methodology that facilitates the collection, classification, and organization of existing information on a research topic, particularly in the field of software engineering. We followed the protocol established by Petersen et al. [10], [11] to design this systematic mapping, as it provides guidelines for performing systematic mapping in this field. Additionally, we considered the recommendations of Kitchenham [12] and Budgen et al. [13] to define the search protocol. The process involved the following stages: (i) defining the research questions, (ii) searching for relevant articles, (iii) selecting primary articles based on inclusion and exclusion criteria, (iv) evaluating the quality of the primary articles, and (v) extracting information. Fig 1 shows the relationship between the proposed activities, followed by a description of each one.

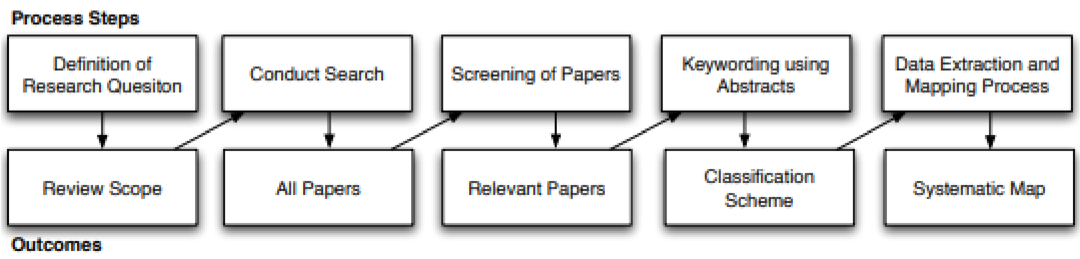

Fig. 1 Stages of the process for systematic mapping suggested by [11].

A. Research Questions

A series of research questions were formulated based on the Goal-Question-Metric (GQM) [14] approach to carry out the systematic mapping. This approach introduces a measurement model organized into three levels of abstraction: (1) the conceptual level, where objectives to establish, understand, and identify the purpose of systematic mapping are defined, (2) the operational level, where questions derived from the conceptual level objectives are developed to focus, characterize, and structure the evaluation of relevant articles on the topic of interest, and (3) the quantitative level, where specific metrics are created for each question to provide quantifiable answers. Within this framework, a set of business objectives is outlined, and a list of measurement objectives is developed to guide the systematic mapping process. The metrics associated with the GQM approach will be addressed in future work. The search objectives (SO) are presented below:

- **SO1:** Classify evidence using demographic, temporal, and academic and business community interest criteria with the aim of evaluating the scientific and research impact of bringing a Machine Learning model into production.
- **SO2:** Analyze the main scientific studies related to the application of MLOps in small and medium-sized SDCs, as evidenced in the current literature using the classification scheme proposed by Wieringa et al. [15], in addition to defining quality criteria for their classification according to their level of relevance.

- **SO3:** Provide support to academics and others interested in researching MLOps application in small and medium-sized enterprises by compiling relevant information, including conceptual definitions, proposals, validations, processes, and research methods. This will enable the degree of progress of initiatives to be identified based on the results obtained.

Based on the search objectives, eight (8) research questions (hereinafter RQ) have been formulated, which are presented in Table 1. This table details the motivation behind each question and its relationship to the established search objectives. These research questions are aimed at categorizing the available information on MLOps in software development, as well as identifying existing gaps in the field of research:

Table 1. Research questions

Id	Research Questions	Motivation	SO
RQ1	What is the time distribution of primary articles?	Present a macro trend in literature between 2017 and 2024.	OB1
RQ2	What is the current state of knowledge regarding the application of MLOps in software development projects?	Determine the current state of knowledge of MLOps in software development projects.	OB1
RQ3	What essential attributes and principles should be considered when implementing MLOps?	Identify the essential attributes and principles of MLOps.	OB2
RQ4	How to correctly apply MLOps in software development companies?	Determining the most effective approach to implementing MLOps in software development companies	OB2
RQ5	How to build and manage an MLOps team?	Determine the right way to build and manage an MLOps team.	OB2
RQ6	What is the quality of the selected items?	Determine the quality of each article selected for the research according to Table 4. Criteria for evaluating the quality of primary articles.	OB2
RQ7	How can you measure the maturity and/or capability of MLOps processes in a software company?	Determine how to classify the maturity level of a software development company that applies MLOps.	OB3
RQ8	What are the benefits and challenges of adopting MLOps?	Identify the benefits and challenges of adopting MLOps in software development companies.	OB3

B. Search Strategy

The systematic mapping was conducted following the guidelines proposed by Piattini et al. [16], [17], Bocco et al. [17], Petersen et al. [11], and Budgen et al. [13]. The search was conducted between 2017 and 2024 using the following search engines: IEEE Xplore, Science Direct, Scopus, Google Scholar, Springer Link, and Web Of Science. As a result, initiatives and articles related to the research topic were identified, highlighting conceptual definitions, terms, challenges, roles, artifacts, practices, activities, and other important approaches related to MLOps in the software development industry. On the other hand, for a first approximation, other articles provided by experts classified as gray literature were taken into account. The search string defined for the mapping was: ("MLOps" OR "machine learning operation" OR "ML4DEV" OR "ML Production") AND ("software Development") AND ("agile" OR "agile release") AND ("Adopt" OR "Integrate" OR 'Integration' OR "Integrating"). The following filters were also applied: (i) articles published in English; (ii) articles exclusively from the fields of computer science, software engineering, and software development; and (iii) articles from journals or scientific event proceedings.

C. Selection of primary articles applying inclusion and exclusion criteria

Initially, the selection of relevant articles was based on a three-level review: (Level 1) review of the title, (Level 2) review of the abstract, introduction, and conclusions, and (Level 3) review of the full text to determine whether the article met at least one of the inclusion criteria (IC) described in Table 2. Subsequently, for the selection of primary articles, those articles that met at least one of the exclusion criteria (EC) described in Table 3 were discarded.

Table 2. Inclusion criteria.

Id	Inclusion criteria (IC)
IC1	Articles published in journals, conferences, or lectures that contain the words MLOps or its variants.
IC2	Articles published in journals, conferences, or lectures that discuss how to bring an ML model into production.
IC3	Articles published in journals, conferences, or lectures that discuss how to maintain an ML model over time.
IC4	Studies that have been published in prestigious journals, congresses, or conferences according to the quartile classification (Q1, Q2, Q3, Q4) with peer review.

Table 3. Exclusion criteria.

Id	Exclusion criteria (EC)
EC1	Duplicate papers.
EC2	Articles that do not address issues related to how software development companies, especially SMEs, are bringing ML models into production and how they are maintained.
EC3	Discussion-type papers or available only in the form of presentations or abstracts.
EC4	Papers that superficially address the research topic.
EC5	Papers that are books or book chapters.
EC6	Papers that are not written in English.

D. Pertinence and relevance evaluation criteria

In order to measure and determine the degree of relevance and relevance of the selected primary papers with respect to MLOps in software development, we took as a reference what was proposed by Kitchenham and Charters [12], which allowed the construction of a questionnaire of fifteen (15) criteria to evaluate the relevance and relevance with a scoring system of three values (-1, 0, +1) as described in Table 4, with the proposed scoring system, each article can obtain a quality rating between -15 and +15. It is important to clarify that a poor score for an article did not imply its exclusion but rather allowed it to be ordered by relevance for future research.

Table 4. Criteria for evaluation of the quality of primary papers

No.	**Criterial**	**Score assigned to the possible answers**		
		+1	**0**	**-1**
C1	The study focuses on research about Machine Learning Operations and its application in medium and small software development companies.	Yes	Partially	No
C2	The study provides a clear description of the research problem addressed.	Yes	Partially	No
C3	The study provides a clear approach to the entire life cycle of an ML project.	Yes	Partially	No
C4	The study follows a structured and informed research process.	Yes	Partially	No
C5	The study provides a clear definition of Machine Learning Operations.	Yes	Partially	No
C6	The study proposes a clear definition of the artifacts needed to carry out Machine Learnig Operations.	Yes	Partially	No
C7	The study clearly describes the technological tools needed to carry out an MLOps project.	Yes	Partially	No
C8	The study proposes a way to monitor ML models that are in production and perform continuous training.	Yes	Partially	No
C9	The study sets out in a clear and detailed manner the results obtained after validating its proposal.	Yes	Partially	No
C10	The study clearly presents research contributions to industry and/or academia.	Yes	Partially	No
C11	The study clearly describes the discussion of the limitations of the research process carried out and the analysis of the results obtained.	Yes	Partially	No
C12	The study clearly describes future work or research alternatives.	Yes	Partially	No
C13	The study proposes how to measure the degree of maturity and/or capability of MLOps processes in a software company.	Yes	Partially	No
C14	The study has been published in a relevant journal, conference or congress.	Very relevant (Quartile Q1)	Relevant (Quartile Q2 or Q3)	Not relevant (Quartile Q4)
C15	The study has been cited by other authors (according to Google Scholar citation index).	The document has been cited by more than three authors.	Between one and three authors	Not cited so far

E. Data Extraction

Table 5 presents the summary sheet defined to support the data extraction strategy. This template allowed for uniformity in the extraction of relevant information from each article and made the classification process easier.

Table 5. Summary card for the extraction of relevant information for the primary papers.

Identification			
Title:			
DOI:		Number of citations:	
Date of publication:	Conference and/or magazine:		
Authors:			
Name	Country	University	Research group
Summary			
Description			
Type of research (Wieringa classification): ☐ Validation research ☐ Evaluation research ☐ Proposed solution ☐ Philosophical article or similar ☐ Opinion paper ☐ Personal experience			
Research methodology:			
Type of solution(s) offered: ☐ Conceptual definition ☐ Causes, effects, impacts and limitations ☐ Evaluation methods or techniques ☐ Technological tools ☐ Industry validation ☐ Documentation methodologies ☐ Others			
Proposal:			
Evaluation of the proposal:			
Issues addressed			
Elements for justification			
Aspects to highlight			

III. SEARCH EXECUTION

The article extraction process is summarized in Fig. 2. In addition, Table 6 shows the results obtained during the selection of relevant studies based on the application of the inclusion and exclusion criteria, as well as the search string adapted for each data source. Table 7 shows the results obtained after applying the criteria to all the selected primary papers, the score is obtained based on the evaluation criteria of relevance and pertinence defined in Table 4, where it was possible to assign a score to each article between -15 and 15. The total score of each article is obtained from the sum of the individual values for each evaluated aspect.

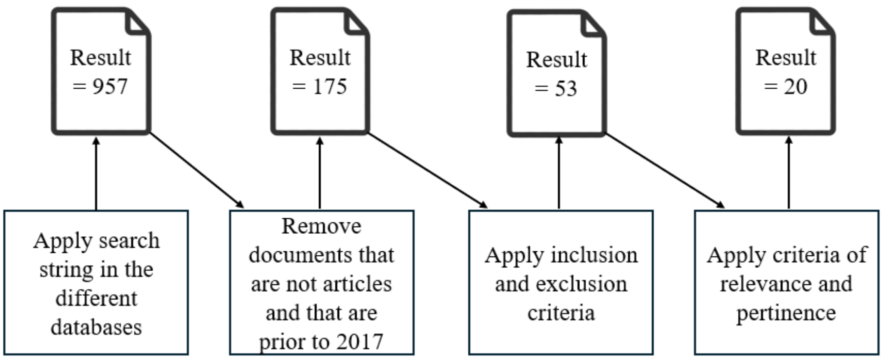

Fig. 2: Systematic mapping filtered data flow.

Table 6. Relevant studies for each database.

No.	Search String	FP	RP	Source
1	("MLOps" OR "machine learning operation" OR "ML4DEV" OR "ML Production") AND ("software Development") AND ("agile" OR "agile release") AND ("Adopt" OR "Integrate" OR "Integration" OR "Integrating")	65	28	Google Scholar
2	("MLOps" OR "machine learning operation" OR "ML4DEV" OR "ML Production") AND ("software Development") AND ("agile" OR "agile release") AND ("Adopt" OR "Integrate" OR "Integration" OR "Integrating")	38	7	Scopus
3	("MLOps" OR "machine learning operations" OR "ML4DEV" OR "ML Production") AND ("software Development") AND ("agile" OR "agile release") AND ("Adopt" OR "Integrate")	15	4	Science Direct
4	("MLOps" OR "machine learning operations" OR "ML4DEV" OR "ML Production") AND ("software Development") AND ("agile" OR "agile release") AND ("Adopt" OR "Integrate" OR "Integration" OR "Integrating")	26	4	Springer Link
5	(("MLOps" OR "machine learning operation" OR "ML4DEV" OR "ML Production") AND ("software Development")	16	5	IEEE Xplore
6	ALL = (("MLOps" OR "machine learning operation" OR "ML4DEV" OR "ML Production") AND ("software"))	15	5	Web Of Science

Acronyms used: FP: Found papers, RP: Relevant papers

Table 7. Primary papers obtained in the search.

Id	Paper	NC	Year	Ref.
A1	Capturing Dependencies Within Machine Learning via a Formal Process Model	9	2022	[18]
A2	Collaboration Challenges in Building ML-Enabled Systems: Communication, Documentation, Engineering, and Process	127	2022	[19]
A3	Accelerating the Machine Learning Model Deployment using MLOps	3	2022	[20]
A4	Jenkins Pipelines: A Novel Approach to Machine Learning Operations (MLOps)	7	2022	[21]
A5	Machine Learning System Development in Information Systems Development Praxis	3	2024	[22]
A6	MLOps: A Taxonomy and a Methodology	61	2022	[23]
A7	The pipeline for the continuous development of artificial intelligence models—Current state of research and practice	42	2023	[24]
A8	Building A Platform for Machine Learning Operations from Open-Source Frameworks	25	2020	[25]
A9	Orfeon: An AIOps framework for the goal-driven operationalization of distributed analytical pipelines	11	2023	[26]
A10	Data Science Methodologies: Current Challenges and Future Approaches	118	2021	[27]
A11	Advancing MLOps from Ad hoc to Kaizen	1	2023	[28]
A12	From a Data Science Driven Process to a Continuous Delivery Process for Machine Learning Systems	23	2020	[29]
A13	MLOps Critical Success Factors - A Systematic Literature Review	1	2024	[30]
A14	MLOps: Practices, Maturity Models, Roles, Tools, and Challenges-A Systematic Literature Review	15	2022	[31]
A15	Machine Learning Operations (MLOps): Overview, Definition, and Architecture	363	2023	[32]
A16	Practices for Managing Machine Learning Products: a Multivocal Literature Review	5	2023	[33]
A17	A joint study of the challenges, opportunities, and roadmap of mlops and aiops: A systematic survey	12	2023	[34]
A18	A Meta-Summary of Challenges in Building Products with ML Components – Collecting Experiences from 4758+ Practitioners	27	2023	[35]
A19	Challenges in Deploying Machine Learning: A Survey of Case Studies	426	2022	[36]
A20	Characterizing Technical Debt and Antipatterns in AI-Based Systems: A Systematic Mapping Study	42	2021	[37]

Acronyms used: NC: Number of citations.

IV. ANALYSIS OF RESULTS

Table 8 shows how each primary article contributes to answering the research questions formulated in Table 1. The following sections detail the results corresponding to each of the research questions defined in this systematic mapping.

Table 8. Classification of primary articles according to research questions.

ID	Paper	P1	P2	P3	P4	P5	P6	P7	P8
A1	Capturing Dependencies Within Machine Learning via a Formal Process Model	X	X	X	X	X	X		X
A2	Collaboration Challenges in Building ML-Enabled Systems: Communication, Documentation, Engineering, and Process	X			X		X		X
A3	Accelerating the Machine Learning Model Deployment using MLOps	X	X	X	X	X	X		X
A4	Jenkins Pipelines: A Novel Approach to Machine Learning Operations (MLOps)	X	X	X	X	X	X		X

A5	Machine Learning System Development in Information Systems Development PraxisDevelopment Praxi	X	X	X	X	X	X		X
A6	MLOps: A Taxonomy and a Methodology	X	X		X	X	X		X
A7	The pipeline for the continuous development of artificial intelligence models—Current state of research and practice	X	X	X	X	X	X	X	X
A8	Building A Platform for Machine Learning Operations from Open Source Frameworks	X	X	X	X	X	X		X
A9	Orfeon: An AIOps framework for the goal-driven operationalization of distributed analytical pipelines	X	X	X	X	X	X		X
A10	Data Science Methodologies: Current Challenges and Future Approaches	X	X		X		X		X
A11	Advancing MLOps from Ad hoc to Kaizen	X	X	X	X	X	X	X	X
A12	From a Data Science Driven Process to a Continuous Delivery Process for Machine Learning Systems	X	X	X	X	X	X	X	X
A13	MLOps Critical Success Factors - A Systematic Literature Review	X	X		X		X	X	X
A14	MLOps: Practices, Maturity Models, Roles, Tools, and Challenges-A Systematic Literature Review.	X	X	X	X	X	X		X
A15	MLOps: Machine Learning Operations (MLOps): Overview, Definition, and Architecture	X	X		X	X	X		X
A16	Practices for Managing Machine Learning Products: a Multivocal Literature Review	X	X	X	X	X	X		X
A17	A joint study of the challenges, opportunities, and roadmap of mlops and aiops: A systematic survey	X	X		X	X	X		X
A18	A Meta-Summary of Challenges in Building Products with ML Components – Collecting Experiences from 4758+ Practitioners	X	X		X		X		X
A19	Challenges in Deploying Machine Learning: A Survey of Case Studies	X	X	X	X		X		X
A20	Characterizing Technical Debt and Antipatterns in AI-Based Systems: A Systematic Mapping Study	X	X	X	X		X		X

A. What is the time distribution of primary articles?

Fig. 3 shows the temporal distribution of primary articles, where we can see that in terms of article production, 10% of publications were made in 2020 (A8, A12), 10% in 2021 (A10, A20), and 35% in 2022 (A1, A2, A3, A4, A6, A14, A19), in 2023 35% (A7, A9, A11, A15, A16, A17, A18), and finally in 2024 10% (A5, A13). Although the term MLOs became popular in 2017. Also, Fig. 3 shows that in the last three years there has been increased interest among the scientific community in integrating MLOps into conventional software development.

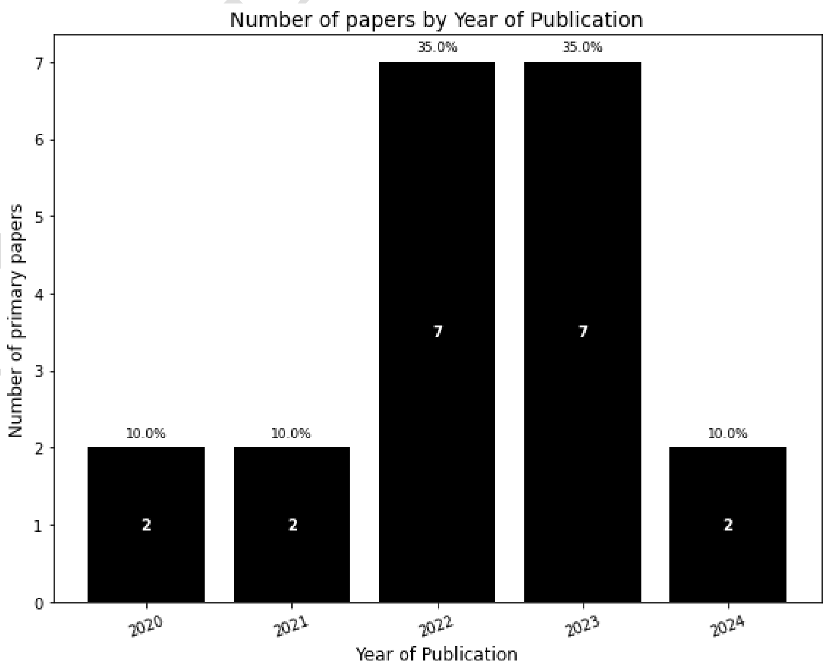

Fig. 3 Number of primary papers per year of publication. Own source.

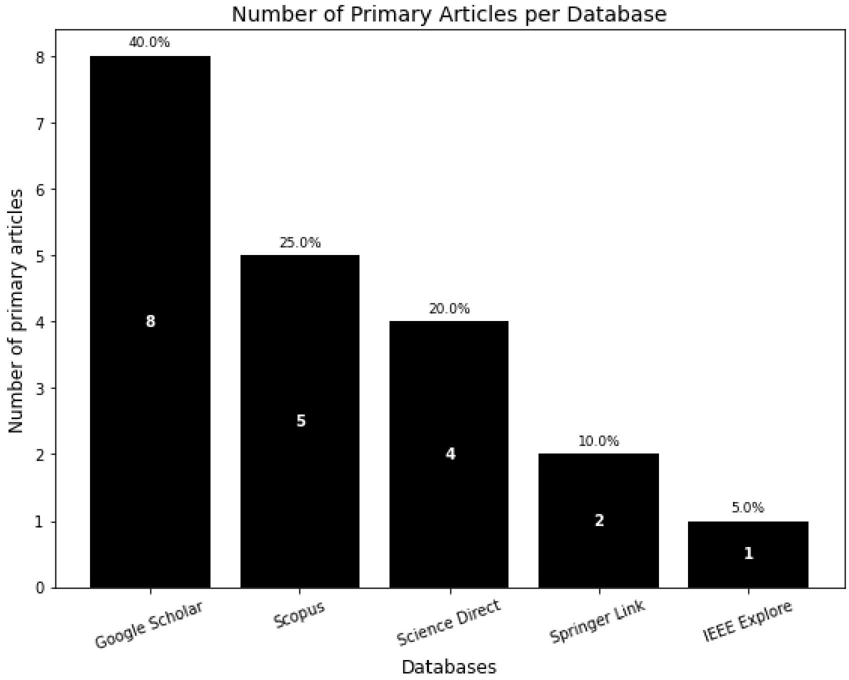

Fig. 4 Number of primary articles per database. Own source.

B. What is the current state of knowledge regarding the application of Machine Learning Operations in software development projects?

MLOps in software development projects reflects a growing field, where practices, tools, and models are being established to effectively integrate machine learning into the software development lifecycle. As organizations seek to harness the potential of machine learning, they face significant challenges that require a deep understanding of MLOps practices such as clearly defining roles within the organization, good coding practices when creating an ML model, interoperability between the tools that make up the different stages of an ML project's lifecycle, and continuous monitoring associated with the ML model once it is in production.

MLOps is defined as a set of practices that seeks to unify the development and operation of ML models. This includes data management, model creation, evaluation, and implementation, as well as the monitoring and maintenance of models in production. The literature in the primary articles indicates that although MLOps has gained attention, it is still in an early stage of adoption in many organizations. This is due to the inherent complexity of ML systems, which require not only technical skills but also effective collaboration between multidisciplinary teams (A1, A2).

A key aspect identified in the review of the primary articles is the need to establish a theoretical framework that contextualizes MLOps practices. This includes identifying specific roles within development teams, as well as creating maturity models that allow organizations to assess their level of MLOps adoption. On the other hand, research has shown that a lack of standardization in MLOps practices can lead to inconsistencies in the quality and reproducibility of models, which in turn affects confidence in the results obtained (A3, A4).

In addition, the primary studies analyzed also highlight the importance of documentation and traceability in the ML model development process. It is important to note that the quality of documentation is essential to ensure that models are understandable and usable by other team members and external stakeholders. However, it has been observed that many organizations underestimate this aspect, which can result in difficulties in maintaining and updating models over time (A5, A6).

In addition, several challenges have been identified in the implementation of MLOps, including: data management, tool integration, and the need for adequate infrastructure. The collection and handling of large volumes of high-quality data are essential to the success of ML models, but many organizations lack the capabilities to manage this data effectively. This results in a reactive rather than proactive approach to data management, which can compromise the quality of the models (A2, A5).

Systematic mapping also suggests that collaboration between software development teams and data scientists is crucial to the success of MLOps. Effective communication and alignment of objectives between these groups can facilitate the integration of ML models into software applications, which in turn can improve the efficiency and effectiveness of projects. However, differences in culture and work approach between these teams often represent a significant obstacle (A1, A3).

In conclusion, the current state of knowledge about MLOps in software development projects indicates that, although significant progress is being made, much remains to be done. The adoption of standardized practices, improved documentation, effective data management, and collaboration between teams are key areas that require attention. As organizations continue to explore the potential of machine learning, the effective implementation of MLOps will be critical to maximizing the value of their technology investments and improving the quality of the products developed (A4, A6).

C. What are the essential attributes or principles for successfully implementing MLOps?

One of the fundamental principles is interdisciplinary collaboration. MLOps is not solely the responsibility of data scientists; it requires the active participation of software engineers, operations experts, and other stakeholders. This collaboration ensures that machine learning models are aligned with business objectives and properly integrated into existing systems. Lack of communication between these groups can result in misunderstandings and the creation of solutions that do not meet business needs (A1, A3).

Process standardization is another essential attribute. In this regard, creating a standardized framework for the development, implementation, and monitoring of ML models helps reduce variability and improves the quality of results. This includes defining common practices for data management, documentation, and model evaluation. Standardization not only facilitates the reproducibility of experiments but also allows for better management of the model lifecycle (A4, A5).

Data management is a critical component in MLOps implementation, which is why the quality of the data used to train ML models directly impacts their performance. Therefore, it is essential to establish robust practices for data collection, cleaning, and storage. This includes implementing data pipelines that ensure data is accessible and in a format suitable for use in ML models. Lack of proper data management can result in ineffective models and poorly informed business decisions (A1, A3).

In addition, continuous monitoring and maintenance of models are vital to the success of MLOps, since once a model is deployed in production, it is essential to monitor its performance and make adjustments as necessary. This involves establishing clear metrics to evaluate the effectiveness of the model and a process for updating it based on new data or changes in the operating environment. Failure to take a proactive approach to monitoring can lead to a deterioration in model performance over time (A1, A4).

Organizational culture also plays a crucial role in MLOps implementation, which is why fostering a culture that values experimentation, continuous learning, and adaptability can facilitate the adoption of MLOps practices. Organizations that promote innovation and are willing to invest in training their staff in ML and data analysis skills are better positioned to succeed in implementing MLOps (A3, A5).

Finally, technological infrastructure is an essential attribute that should not be overlooked. Having adequate infrastructure to support the development and implementation of ML models is critical. This includes the ability to scale computational resources as needed and the integration of tools that facilitate process automation. The lack of a robust infrastructure can limit an organization's ability to effectively implement MLOps (A1, A4).

Table 9 summarizes the essential principles that must be taken into consideration in order to successfully implement Machine Learning Operations.

Table 9. Essential principles for successful MLOps implementation.

ID	Essential Principle	Paper
1	Lack of communication between the team	A1, A2
2	Standardization of processes	A4, A5
3	Data management	A1, A3
4	Continuous monitoring and maintenance	A1, A4
5	Organizational culture	A3, A5
6	Technological infrastructure	A1, A4

D. How to correctly apply MLOps in software development companies?

As with the previous question and delving deeper into the essential principles for successful MLOps implementation, it is first and foremost essential to establish a culture of collaboration between software development teams and data scientists. MLOps integration requires both groups to work together from the early stages of model development. This involves creating multidisciplinary teams that include not only data scientists, but also software engineers, data engineers, DevOps experts, and operations personnel. This collaboration ensures that models are designed with a focus on scalability and integration into existing systems (A1, A3).

A second crucial aspect is processing standardization, where companies must define and document a set of practices and procedures to guide the ML model development lifecycle. This includes data management, model building, validation, and deployment. Standardization not only improves the quality and reproducibility of models, but also facilitates knowledge transfer between teams and the incorporation of new members into the process (A4, A5).

Data management is an essential component of MLOps implementation. Organizations must establish robust data pipelines that guarantee the quality and availability of the data needed to train and evaluate models. This process involves implementing data cleaning, transformation, and storage procedures that facilitate efficient and secure access. The absence of proper data management can lead to ineffective models and business decisions lacking a solid foundation (A1, A3).

In addition, it is essential to implement a system for continuous monitoring and maintenance of models in production, given that once a model has been deployed, it is crucial to monitor its performance and adjust as necessary. This includes defining clear metrics to evaluate the model's effectiveness and creating a process to update it based on new data or changes in the operating environment. Proactive monitoring helps identify problems before they significantly affect model performance (A1, A4).

Process automation is another key principle in MLOps implementation. Companies should seek to automate repetitive and error-prone tasks as much as possible, such as model deployment, data management, and monitoring. This not only improves efficiency but also reduces the risk of human error, decreases waste, and allows teams to focus on higher-value tasks, such as innovation and model improvement (A3, A5).

Finally, it is important to invest in adequate technological infrastructure. In this regard, it is important to note that SDCs must have an infrastructure that supports the development and implementation of ML models, including the ability to scale computational resources as needed and the integration of tools that facilitate process automation. The lack of a robust infrastructure can limit an organization's ability to effectively implement MLOps (A1, A4).

E. How to build and manage an MLOps team?

Building and managing an MLOps team is essential for organizations seeking to deploy machine learning models effectively and sustainably. A well-structured MLOps team not only facilitates model creation and deployment but also ensures their maintenance and scalability in production. Below is some key process elements identified through systematic mapping of primary articles for forming and managing an MLOps team, including necessary roles, artifacts, and best practices.

Roles

An MLOps team typically includes several critical roles, each with specific responsibilities. The most common roles are:

- **Data Scientist:** Responsible for researching and developing machine learning models. Their focus is on creating algorithms and validating models using historical data (A1, A3).

- **Data Engineer:** Responsible for data preparation and management. This role includes collecting, cleaning, and transforming data so that it can be used by data scientists (A2, A4).

- **Machine Learning Engineer:** Focuses on implementing and optimizing models in production. This role is crucial to ensure that models are scalable and efficient (A1, A5).

- **DevOps Engineer:** Ensures that the infrastructure and deployment processes are robust and scalable. This role is fundamental to the continuous integration and continuous deployment (CI/CD) of models (A3, A4).

- **Product Owner:** Acts as the liaison between the MLOps team and business stakeholders. Their role is to prioritize features and ensure that the team is aligned with business objectives (A2).

Artifacts and tools

For an MLOps team to function effectively, it needs to have a series of artifacts and tools. Some of the most important ones include:

- Code Repositories: Tools such as Git are essential for code management and collaboration among team members (A1, A5).
- Data Management Platforms: Tools that facilitate data collection, storage, and processing, such as AWS S3 (A2, A4).
- Development Environments: Jupyter Notebooks and other platforms that allow data scientists to experiment and develop models interactively (A3).
- CI/CD Tools: Jenkins, GitLab CI, and other tools that enable automated model deployment and continuous integration (A1, A5).

F. What is the quality of the selected items?

According to the quality assessment criteria defined in Table 4, each article can be assigned a score between -15 and 15. Table 10 shows the results obtained after applying the criteria to all the selected primary articles. The total score for each article is obtained by adding up the individual values for each aspect assessed.

Table 10. Quality assessment criteria.

Paper	Quality assessment criteria															Total
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	
A1	0	1	1	1	0	0	0	1	0	1	1	1	0	1	1	9
A2	-1	1	0	1	-1	0	0	1	0	1	1	1	0	1	1	6
A3	0	1	1	0	1	0	0	1	0	0	0	1	-1	1	1	6
A4	0	1	1	1	1	0	1	1	1	1	1	1	-1	1	1	11
A5	0	1	0	1	0	0	0	1	0	1	1	1	-1	1	1	7
A6	-1	1	1	1	1	0	1	1	0	1	0	1	0	1	1	8
A7	0	1	1	1	0	0	0	1	0	1	1	0	1	1	1	9
A8	-1	1	1	1	1	1	0	0	1	1	0	1	0	1	1	8
A9	0	1	0	1	1	0	1	0	1	1	1	1	-1	1	1	9

A10	-1	1	0	1	0	0	1	1	1	1	1	1	-1	1	1	8
A11	0	1	0	1	1	0	1	1	0	1	1	1	1	1	1	11
A12	1	1	1	1	-1	0	1	-1	0	1	0	1	1	1	1	8
A13	0	1	0	1	0	0	1	1	0	1	0	1	1	1	1	9
A14	0	1	0	1	1	0	1	1	0	1	1	1	0	1	1	10
A15	-1	1	0	1	1	1	1	1	0	1	0	1	0	1	1	9
A16	-1	1	1	1	0	0	0	1	0	1	1	1	-1	1	1	6
A17	-1	1	1	1	1	0	1	1	0	1	0	1	0	1	1	8
A18	-1	1	0	1	0	0	0	1	0	1	1	0	-1	1	1	5
A19	0	1	1	1	-1	0	1	1	-1	1	-1	1	-1	1	1	4
A20	-1	1	0	1	0	0	-1	0	1	1	1	0	-1	1	1	4

Quality Criteria (C).

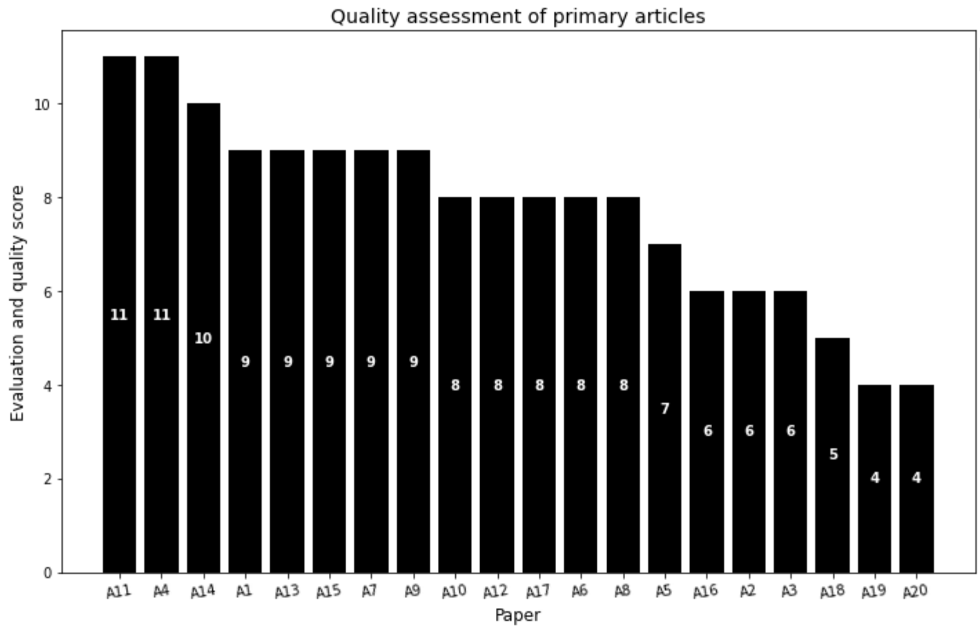

Fig. 5 Quality assessment of primary articles. Own source.

When conducting the evaluation, we can identify, according to Fig. 5, that articles A4, A11, and A14 (15%) are the most relevant, as they meet most of the quality criteria. Therefore, these articles are the basis on which the systematic mapping is founded. Similarly, we can see that articles A1, A13, A15, A7, A9, A10, A12, A17, A6, and A8 (50%) are articles in which, although the score is not high, they allow us to answer several research questions. Finally, articles A5, A16, A2, A3, A18, A19, and A20 (35%) have the lowest scores. However, this does not mean that they have been excluded; they are relevant to several research questions and future challenges.

G. How to measure the maturity and/or capability of MLOps processes in a software company?

To measure the maturity and/or capability of Machine Learning Operations (MLOps) processes in a software company, it is essential to establish an evaluation framework that considers various dimensions of the machine learning lifecycle. This framework should consider aspects such as data management, model quality, process integration, and organizational culture. Below are some approaches and metrics that can be used to assess the maturity of MLOps processes in an organization.

Maturity Models

One of the most effective ways to measure the maturity of MLOps processes is through specific maturity models. These models provide a structured framework that allows organizations to assess their current level and define a path to improvement. For example, the MLOps maturity model may include stages ranging from initialization, where processes are ad hoc and undocumented, to advanced levels where processes are automated, scalable, and based on clear metrics (A12, A19). Each stage may include specific criteria that must be met in order to advance to the next level.

Process and Practice Assessment

Assessing current processes and practices is crucial to understanding the maturity of MLOps. This may include reviewing how data is managed, how models are developed and deployed, and how they are monitored and maintained in production. Tools such as surveys and interviews with development teams can provide valuable insight into perceptions of current processes and areas for improvement (A12, A19). In addition, implementing regular audits can help identify gaps in processes and ensure that best practices are followed.

Performance Metrics

The use of performance metrics is essential for measuring the effectiveness of MLOps processes. Metrics may include model development cycle time, model deployment success rate, and the accuracy and recall of models in production. Collecting and analyzing these metrics allows organizations to identify bottlenecks and areas for improvement in their processes (A12, A19). In addition, setting clear and measurable goals for these metrics can help guide continuous improvement efforts.

Organizational Culture and Training

Organizational culture plays a crucial role in the maturity of MLOps processes. In this regard, fostering a culture of collaboration between development, operations, and business teams is fundamental to the success of MLOps. Continuous training in MLOps tools and practices is also essential to ensure that teams are equipped with the skills necessary to implement and manage effective processes (A12, A19). Assessing the organization's willingness to adopt new technologies and practices can be an important indicator of its maturity in MLOps.

Tools and Technologies

Finally, adopting the right tools and technologies is a key factor in the maturity of MLOps processes, which is why organizations must assess whether they are using tools that facilitate automation, monitoring, and model management. The integration of MLOps platforms that offer CI/CD capabilities, data management, and model monitoring can be an indicator of a high degree of maturity (A12, A19). The organization's ability to adapt and adopt new technologies is also a reflection of its maturity in MLOps.

H. ¿ What are the benefits and challenges of adopting MLOps?

The adoption of Machine Learning Operations (MLOps) in organizations brings with it a number of significant benefits, as well as challenges that must be addressed to ensure successful implementation. These aspects are analyzed below based on the primary articles of the systematic mapping.

Benefits of Adopting MLOps

- **Efficiency in Development and Deployment**

One of the most significant benefits of MLOps is improved model lifecycle efficiency. By automating processes such as continuous integration and continuous deployment (CI/CD), organizations can reduce the time it takes to bring a model from development to production, enabling companies to respond more quickly to market demands and customer needs (A1, A3).

- **Improvement in Model Quality**

MLOps promotes the standardization of development processes, which contributes to the creation of more robust and reliable models. The implementation of validation and continuous monitoring practices allows organizations to identify and correct errors more effectively, resulting in higher quality and more accurate models (A2, A4). In addition, the ability to continuously test and adjust ensures that models remain relevant and effective over time (A5).

- **Interdisciplinary Collaboration**

The implementation of MLOps promotes greater collaboration between teams from different disciplines, such as development, operations, and business. This collaboration is essential for aligning technical objectives with business goals, resulting in more effective solutions tailored to customer needs. It fosters a work environment where knowledge and best practices are shared, which can lead to significant innovations (A6, A7).

Challenges of Adopting MLOps

- **Complexity in Implementation**

One of the main challenges of MLOps is the complexity associated with its implementation. Integrating MLOps into existing processes may require significant changes to infrastructure and organizational culture. Companies must be prepared to invest time and resources in training their staff and adapting their systems (A10, A11).

- **Data Management**

Data quality and management are critical to the success of MLOps. Organizations often face challenges related to collecting, storing, and processing large volumes of data. Ensuring that data is accessible and of high quality is crucial for developing accurate and reliable models (A12, A13).

- **Resistance to Change**

The adoption of MLOps may encounter resistance from employees who are accustomed to working with traditional processes. Changing the mindset and organizational culture to accept new practices and tools can be a significant challenge. It is essential that company management supports and promotes the transition to MLOps (A14, A15).

- **Model Monitoring and Maintenance**

Once models are in production, monitoring and maintenance are crucial to ensuring their continued performance. Organizations should establish processes to detect and address issues such as model deterioration or data bias. This requires ongoing commitment and dedicated resources to ensure that models remain effective over time (A16, A17).

V. DISCUSSION OF RESULTS

The objective of this systematic mapping is to ascertain the current state of the literature on MLOps in SDCs, from which the following observations can be deduced:

- Due to the rise of data science, there is considerable interest within the scientific community in conducting research on the adoption of MLOps in SDCs, particularly as conventional and agile software development begins to converge with ML applications. Therefore, it is necessary to delve deeper into the processes that enable us to quickly bring an ML model into production with optimal features and quality.

- One of the biggest challenges of MLOps is continuous monitoring and training, because ML models are susceptible to small changes such as data variation, which causes them to degrade easily and require retraining to meet requirements. For this reason, this is a field of high interest that the scientific community is addressing, as each retraining requires high computational resources, which generates costs for organizations [19], [21], [22].

- As stated in [19], clearly defining roles within an MLOps process is crucial to successfully implementing ML models in production. Collaboration between different disciplines is crucial, with each team member having a clearly defined role that contributes to the model lifecycle. These roles include data scientists, data engineers and DevOps, each with specific responsibilities that facilitate communication and efficiency. Similarly, [22] mentions that developers' roles are not clearly defined, and that they often support the work of others according to project needs, leading to convergence between the roles of data scientists, ML engineers, and software developers. For this reason, it is necessary to clearly define the roles and responsibilities of everyone involved in the MLOps process.

- To achieve the continuous integration and deployment process of an ML model that is to be put into production, the use of tools similar to those used in DevOps has been proposed, such as Jenkins and Kubernetes, specifically Kubeflow [21][26], which seeks to alleviate the burden of implementing MLOps workflows. Although Kubernetes can meet many of the requirements for implementing ML projects, it is considered a general-purpose framework that does not focus specifically on ML.

- Generally, an MLOps process consists of several stages, which can vary. However, to bring an ML model into production, there are several essential steps to ensure its effectiveness and sustainability. The first step is to define the problem, identifying objectives and gathering business requirements. Next, data is collected and prepared, which includes cleaning, transforming and selecting relevant features. Once the data is ready, the next step is to select and train the model, choosing the appropriate algorithms and adjusting the hyperparameters to optimize performance. Model validation is then carried out using techniques such as cross-validation to ensure the model generalizes well to unseen data. The next stage is implementation, which involves integrating the model into a production environment using tools such as Kubernetes and Kubeflow to facilitate container orchestration and management. Finally, continuous monitoring and maintenance of the model must be established to detect possible performance degradation and make necessary adjustments.

A. Limitations of systematic Mapping.

The limitations of the search engines used prevented us from providing a more comprehensive overview of the state of the art in MLOps in SDCs. Furthermore, restricting the inclusion to articles in English may have excluded relevant publications in other languages. Nevertheless, this systematic mapping has generated valuable results that can serve as a basis for future research.

VI. CONCLUSIONS AND FUTURE WORK

The completion of this systematic mapping made it possible to identify relevant sources of information and research on the application of MLOps in SDCs. Based on the findings, it was possible to demonstrate the interest on the part of the scientific community due to the high impact that documentation has on the success of bringing an ML project to production.

MLOps can be defined as an instance of DevOps in which, through a collection of techniques and tools, an ML model is deployed into production, applying the concepts of continuous integration and deployment present in DevOps, and applying new concepts such as continuous monitoring and training. Additionally, the main roles that must be taken into consideration are identified, such as data scientists, ML engineers, data engineers, product owners, and DevOps engineers.

Continuous monitoring and training are among the most critical activities in MLOps projects because, once released into production, ML models begin to degrade due to the changing nature of the data. Therefore, great care must be taken when monitoring model performance metrics to prevent them from becoming obsolete.

Several challenges have been identified in the implementation of MLOps, such as data management, tool integration, and the need for adequate infrastructure, due to the large amount of processing they use. Similarly, the lack of ability to handle large volumes of quality data can compromise the effectiveness of ML models.

Although many ML developments are carried out by data scientists, most of them lack computer science training and therefore fail to apply best practices in development and programming when creating ML models. Similarly, ambiguity in defining roles and artefacts has resulted in many individuals involved in ML development being overwhelmed with tasks, creating significant social debt.

Future work will focus on identifying the impact of technical debt incurred when creating a productive machine learning (ML) model, given that many data scientists lack training in computer science and software engineering. Similarly, social debt will be investigated, since the roles of many MLOps professionals are not clearly defined, leading software engineers to perform activities outside their usual scope.

VII. CRediT AUTHORSHIP CONTRIBUTION STATEMENT

E. Arteaga-Benavides: Conceptualization, Research, Data curation, Writing—Original draft, Visualization. **C. Pardo-Calvache**: Conceptualization, Methodology, Writing—Review and editing, Supervision, Project management.

VIII. REFERENCES

[1] A. B. Kolltveit and J. Li, “Operationalizing Machine Learning Models - A Systematic Literature Review,” Proceedings - Workshop on Software Engineering for Responsible AI, SE4RAI 2022, pp. 1–8, 2022, doi: 10.1145/3526073.3527584.

[2] P. Ruf, M. Madan, C. Reich, and D. Ould-Abdeslam, “Demystifying MLOps and Presenting a Recipe for the Selection of Open-Source Tools,” Applied Sciences 2021, Vol. 11, Page 8861, vol. 11, no. 19, p. 8861, Sep. 2021, doi: 10.3390/APP11198861.

[3] D. A. Tamburri, “Sustainable MLOps: Trends and Challenges,” Proceedings - 2020 22nd International Symposium on Symbolic and Numeric Algorithms for Scientific Computing, SYNASC 2020, pp. 17–23, Sep. 2020, doi: 10.1109/SYNASC51798.2020.00015.

[4] A. Ordoñez, J. S. Rojas, J. Gomez, and G. Ramirez, “Methodology Based on MLOps (Machine Learning Operations) for Management Support in Data Science Projects,” Revista Colombiana De Tecnologia Avanzada, pp. 87–103, Sep. 2023, Accessed: Nov. 08, 2023. [Online]. Available: https://www.researchgate.net/publication/373654041_Methodology_Based_on_MLOps_Machine_Learning_Operations_for_Management_Support_in_Data_Science_Projects

[5] I. Martinez, E. Viles, and I. G. Olaizola, “Data Science Methodologies: Current Challenges and Future Approaches,” Big Data Research, vol. 24, p. 100183, May 2021, doi: 10.1016/J.BDR.2020.100183.

[6] G. Symeonidis, E. Nerantzis, A. Kazakis, and G. A. Papakostas, “MLOps - Definitions, Tools and Challenges,” 2022 IEEE 12th Annual Computing and Communication Workshop and Conference, CCWC 2022, pp. 453–460, 2022, doi: 10.1109/CCWC54503.2022.9720902.

[7] J. Klaise, A. Van Looveren, C. Cox, G. Vacanti, and A. Coca, “Monitoring and explainability of models in production,” Workshop on Challenges in Deploying and Monitoring Machine Learning Systems (ICML 2020), Jul. 2020, Accessed: Aug. 23, 2024. [Online]. Available: https://arxiv.org/abs/2007.06299v1

[8] “Pequeñas y medianas empresas y creación de empleo decente y productivo,” 2015. Accessed: Nov. 14, 2023. [Online]. Available: http://www.ilo.org/ilc/ILCSessions/previous-sessions/104/reports/reports-to-the-conference/WCMS_358292/lang--es/index.htm

[9] M. Estayno, G. Dapozo, C. Greiner, L. C. Pletsch, and S. Pelozo, “Caracterización de las pymes de software de la región NEA orientada hacia un marco de mejora de la calidad,” XV Congreso Argentino de Ciencias de la Computación, pp. 901–910, 2009.

[10] K. Petersen, S. Vakkalanka, and L. Kuzniarz, “Guidelines for conducting systematic mapping studies in software engineering: An update,” Inf Softw Technol, vol. 64, pp. 1–18, Aug. 2015, doi: 10.1016/J.INFSOF.2015.03.007.

[11] K. Petersen, R. Feldt, S. Mujtaba, and M. Mattsson, “Systematic Mapping Studies in Software Engineering,” 12th International Conference on Evaluation and Assessment in Software Engineering, EASE 2008, pp. 1–10, Jun. 2008, doi: 10.14236/EWIC/EASE2008.8.

[12] B. Kitchenham and S. Charters, “Guidelines for performing Systematic Literature Reviews in Software Engineering,” EBSE Technical Report EBSE-2007-01 School of Computer Science and Mathematics, Keele University, pp. 1–57, Jan. 2007.

[13] D. Budgen, M. Turner, P. Brereton, and B. Kitchenham, “Using Mapping Studies in Software Engineering,” Annual Workshop of the Psychology of Programming Interest Group, 2008.

[14] V. R. Basili and G. Caldiera, “The Goal Question Metric Paradigm,” Encyclopedia of Software Engineering - 2 Volume Set, vol. 2, pp. 528–532, 2000, Accessed: Aug. 24, 2024. [Online]. Available: https://www.cs.umd.edu/~basili/publications/technical/T89.pdf

[15] R. Wieringa, N. Maiden, N. Mead, and C. Rolland, “Requirements engineering paper classification and evaluation criteria: A proposal and a discussion,” Requir Eng, vol. 11, no. 1, pp. 102–107, Mar. 2006, doi: 10.1007/S00766-005-0021-6.

[16] J. D. Patón-Romero and M. Piattini, “Modelos de madurez de Green IT: un mapeo sistemático,” International Journal of Information Systems and Software Engineering for Big Companies (IJISEBC), vol. 4, no. 2, pp. 53–61, 2017, Accessed: Nov. 11, 2023. [Online]. Available: www.ijisebc.com

[17] M. Genero Bocco, J. A. Cruz Lemus, and M. G. Piattini Velthuis, Métodos de investigación en ingeniería. Ra-Ma Editorial, 2014. Accessed: Nov. 11, 2023. [Online]. Available: https://books.google.com.co/books?id=xo2fDwAAQBAJ&printsec=frontcover&source=gbs_ge_summary_r&cad=0#v=onepage&q&f=false

[18] F. Ritz et al., “Capturing Dependencies Within Machine Learning via a Formal Process Model,” Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 13703 LNCS, pp. 249–265, 2022, doi: 10.1007/978-3-031-19759-8_16.

[19] N. Nahar, S. Zhou, G. Lewis, and C. Kastner, “Collaboration Challenges in Building ML-Enabled Systems: Communication, Documentation, Engineering, and Process,” Proceedings - International Conference on Software Engineering, vol. 2022-May, pp. 413–425, Oct. 2021, doi: 10.1145/3510003.3510209.

[20] R. Ginting et al., “Accelerating the Machine Learning Model Deployment using MLOps,” J Phys Conf Ser, vol. 2327, no. 1, p. 012027, Aug. 2022, doi: 10.1088/1742-6596/2327/1/012027.

[21] D. R. Niranjan and Mohana, “Jenkins Pipelines: A Novel Approach to Machine Learning Operations (MLOps),” International Conference on Edge Computing and Applications, ICECAA 2022 - Proceedings, pp. 1292–1297, 2022, doi: 10.1109/ICECAA55415.2022.9936252.

[22] S. Laato, M. Mäntymäki, M. Minkkinen, and D. Dennehy, “Machine Learning System Development in Information Systems Development Praxis,” Communications of the Association for Information Systems, vol. 54, no. 1, pp. 133–154, Feb. 2024, doi: 10.17705/1CAIS.05406.

[23] M. Testi et al., “MLOps: A Taxonomy and a Methodology,” IEEE Access, vol. 10, pp. 63606–63618, Jun. 2022, doi: 10.1109/ACCESS.2022.3181730.

[24] M. Steidl, M. Felderer, and R. Ramler, “The pipeline for the continuous development of artificial intelligence models—Current state of research and practice,” Journal of Systems and Software, vol. 199, p. 111615, May 2023, doi: 10.1016/J.JSS.2023.111615.

[25] Y. Liu, Z. Ling, B. Huo, B. Wang, T. Chen, and E. Mouine, “Building A Platform for Machine Learning Operations from Open Source Frameworks,” IFAC-PapersOnLine, vol. 53, no. 5, pp. 704–709, Jan. 2020, doi: 10.1016/J.IFACOL.2021.04.161.

[26] J. Díaz-de-Arcaya, A. I. Torre-Bastida, R. Miñón, and A. Almeida, “Orfeon: An AIOps framework for the goal-driven operationalization of distributed analytical pipelines,” Future Generation Computer Systems, vol. 140, pp. 18–35, Mar. 2023, doi: 10.1016/J.FUTURE.2022.10.008.

[27] I. Martinez, E. Viles, and I. G. Olaizola, “Data Science Methodologies: Current Challenges and Future Approaches,” Big Data Research, vol. 24, p. 100183, May 2021, doi: 10.1016/J.BDR.2020.100183.

[28] M. M. John, D. Gillblad, H. H. Olsson, and J. Bosch, “Advancing MLOps from Ad hoc to Kaizen,” 2023 49th Euromicro Conference on Software Engineering and Advanced Applications (SEAA), pp. 94–101, Sep. 2023, doi: 10.1109/SEAA60479.2023.00023.

[29] L. E. Lwakatare, I. Crnkovic, E. Rånge, and J. Bosch, “From a Data Science Driven Process to a Continuous Delivery Process for Machine Learning Systems,” Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 12562 LNCS, pp. 185–201, 2020, doi: 10.1007/978-3-030-64148-1_12.

[30] Y. Mehmood, N. Sabahat, and M. A. Ijaz, “MLOps critical success factors - A systematic literature review,” VFAST Transactions on Software Engineering, vol. 12, no. 1, pp. 183–209, Mar. 2024, doi: 10.21015/VTSE.V12I1.1747.

[31] A. Lima, L. Monteiro, and A. P. Furtado, “MLOps: Practices, Maturity Models, Roles, Tools, and Challenges – A Systematic Literature Review,” International Conference on Enterprise Information Systems, ICEIS - Proceedings, vol. 2, pp. 308–320, Apr. 2022, doi: 10.5220/0010997300003179.

[32] D. Kreuzberger, N. Kuhl, and S. Hirschl, “Machine Learning Operations (MLOps): Overview, Definition, and Architecture,” IEEE Access, vol. 11, pp. 31866–31879, 2023, doi: 10.1109/ACCESS.2023.3262138.

[33] I. Alves, L. A. F. Leite, P. Meirelles, F. Kon, and C. S. R. Aguiar, “Practices for Managing Machine Learning Products: A Multivocal Literature Review,” IEEE Trans Eng Manag, vol. 71, pp. 7425–7455, 2024, doi: 10.1109/TEM.2023.3287759.

[34] J. Diaz-De-Arcaya, A. I. Torre-Bastida, G. Zárate, R. Miñón, and A. Almeida, “A Joint Study of the Challenges, Opportunities, and Roadmap of MLOps and AIOps: A Systematic Survey,” ACM Comput Surv, vol. 56, no. 4, p. 84, Oct. 2023, doi: 10.1145/3625289/ASSET/DA01A099-7C83-41B7-AC56-943B511E94BC/ASSETS/GRAPHIC/CSUR-2022-0938-F07.JPG.

[35] N. Nahar, H. Zhang, G. Lewis, S. Zhou, and C. Kastner, “A Meta-Summary of Challenges in Building Products with ML Components - Collecting Experiences from 4758+ Practitioners,” Proceedings - 2023 IEEE/ACM 2nd International Conference on AI Engineering - Software Engineering for AI, CAIN 2023, pp. 171–183, Mar. 2023, doi: 10.1109/CAIN58948.2023.00034.

[36] A. Paleyes, R.-G. Urma, and N. D. Lawrence, “Challenges in Deploying Machine Learning: a Survey of Case Studies,” ACM Comput Surv, vol. 55, no. 6, Nov. 2020, doi: 10.1145/3533378.

[37] J. Bogner, R. Verdecchia, and I. Gerostathopoulos, “Characterizing Technical Debt and Antipatterns in AI-Based Systems: A Systematic Mapping Study,” Proceedings - 2021 IEEE/ACM International Conference on Technical Debt, TechDebt 2021, pp. 64–73, Mar. 2021, doi: 10.1109/TechDebt52882.2021.00016.