# Appendix A

The inclusion and exclusion criteria.

Table 3: Inclusion Criteria

|  |  |
| --- | --- |
| Criteria | Inclusion Criteria |
| IC 1 | Research articles and Conference Papers |
| IC 2 | Studies that address Machine Learning Operations (MLOps) in general |
| IC 3 | Studies that identify challenges associated with MLOps |
| IC 4 | Studies that included AIOps challenges |

Table 4: Exclusion Criteria

|  |  |
| --- | --- |
| Criteria | Exclusion Criteria |
| EC 1 | The study that was not published in English |
| EC 2 | Studies that talk about the building and application of ML models |
| EC 3 | Studies that do not allow access to its content |
| EC 4 | Papers that did not have relevance to the research question |

# Appendix B

The protocol for the systematic literature review.

Systematic Literature Review

Search chains: MLOps OR "machine learning in production" OR "machine learning operations"

SCOPUS: 229 document results

Science Direct: 323 results

Only research articles & conference papers: 185

Only research articles & conference papers: 185

Abstract review: 11

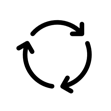
Abstract review: 15

Full-text analysis led to final primary articles: 9

Figure 1: Search strategy: mapping the scientific literature

Documents with open access: 75

Documents with open access: 80



Inclusion & Exclusion Criteria

Limit to 2015-2023

Limit to 2015-2023

Figure 2: Systematic literature review protocol.

# Appendix C

Table 5: Participant Profile

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Participant | Participant Job title | ML Experience (Years) | Country | Domain |
| 1 | MLOps Lead Engineer | 9 | Netherlands | Publishing |
| 2 | ML and DS Manager | 6 | India | Tech |
| 3 | VP of Data Science | 9 | India | EdTech |
| 4 | AI and ML Manager | 4 | Norway | Software provider |
| 5 | ML team Manager | 7 | Denmark | Software provider |
| 6 | Data Scientist | 4 | Netherlands | Software provider |
| 7 | ML Engineer | 4,5 | Netherlands | Consulting |
| 8 | Data Scientist | 9 | Netherlands | Bank |
| 9 | Machine learning consultant | 5 | Netherlands | Consulting |
| 10 | Product Owner for ML | 3 | Netherlands | Insurance |
| 11 | MLOps Engineer | 2 | Netherlands | Insurance |
| 12 | AI architect | 4 | Netherlands | Startup |

# Appendix D

* Scarce of Data engineers
* Scarce of ML engineers
* Scare of skilled professionals
* Retaining staff
* Lack of knowledge
* Long onboarding time
* Knowledge Gap
* Skillset mismatch
* Tough to keep people involved.
* Showcasing the benefits
* Keeping teams interested
* Different priorities
* Multiple approvals needed.
* Multiple checks to move to production
* Long chain of approvals
* People's mindset
* Conservative culture
* Lacking the long-term vision
* Collaboration challenges between teams
* Communication challenges
* Separation of business and IT
* Miscommunication between teams
* Variation in data
* Resource utilization on Infrastructure
* Integration issues
* Risks of Data misusage
* No proper documentation
* Gap in best practices and development of technology
* Lacks way of working
* high complexity for testing
* Available tools are Suboptimal
* Choosing right tool is difficult
* Learning about new tools
* Generalising the pipelines
* Handling large amount of data
* Model Scalability
* Versioning of models
* Complexity versus reusability
* Low Costs versus Slow process
* Over-engineering
* Hard to convince business
* Perceived business value
* Low budget allocation
* High cost of run
* sunk cost fallacy
* Tools are expensive
* No budget for research

Human resources and Skills

User Engagement and Resistance

Slow Processes

Collaboration and communication

Infrastructure and Data management

Standards and Framework

Technical Tools

Deployment process

Implementation trade-offs

Business Value

Cost and Budget

Figure 3: The Coding Schema (grey boxes represent first level codes, the orange boxes represent the second level codes and the yellow ovals on the right represent the third level codes).

Figure 3: The Coding Schema (grey boxes represent first level codes, the orange boxes represent the second level codes and the yellow ovals on the right represent the third level codes).

# Appendix E

## Additional Findings

During the interview, there were some additional findings that do not directly answer the research question but can be useful for researchers and managers looking for MLOps practices.

**Prerequisites to MLOps implementation:** Most of the participants spoke about when MLOps is needed for an organisation and what should be the prerequisites to consider.Firstly, there should be a strong business case to build ML models, and the organisation should have enough clean and valid data. As Participant 3 described, *“I'm a strong believer in keeping things simple and not complicated because of the buzzword of big data and ML and AI. Literally, everyone wants to use AI, but in reality, just an Excel with some VBA and macros are enough sometimes.”*

Secondly, the need for MLOps comes only when there is already a manual deployment happening. If there is only one person working on a Proof of concept with ML, there is no need for MLOps yet. *“At what level of maturity you are in that needs to be factored in for each project, if you are in the very early stage, implementing ML OPS doesn't really make any sense,”* says Participant 2. Lastly, the frequency at which the model needs to be deployed into production should be considered. If the model needs to be updated often and the frequency can be as low as a day or at least a week, then MLOps is needed. “*If it is anywhere once or twice in a year, then you really don't need to maintain all these things” -* Participant 4

**Benefits after implementing MLOps:** Organisations may face challenges while implementing MLOps, but after implementing, they also reap its benefits. Some of the participants shared the benefits that they could measure. Firstly, the cost aspect is shared by multiple participants. Before implementing MLOps, every team had to build things from scratch, which added to more costs; after implementing MLOps, *“80% of the work is already done, teams should just make insurance specific changes”-Participant 7.*

*“Price has been reduced a lot, we had lots of LSTM models in the production for the CRF tagging, and for a single LSTM model, our project cost was around €4221.00 for Sage Maker. After MLOps, we are now hosting that model on our own system. And we are spending €750 per year.”- Participant 1*

Secondly, They see increased cycle time to production and a reduction in latency. For one of the participants, the latency was around 35 seconds, and after implementing MLOps, it reduced it to 700 milliseconds. It made it easier to trigger a pipeline to train the model, put the model in artefact feeds, and with a click, put it in production or to do deploying it for testing or acceptance.