

# Elevating Data Science Maturity: Toward a Process Model that Harnesses MLOps

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**Abstract:** Data Science (DS) uses advanced analytical methods, such as Machine Learning, to extract value from data to improve organizational performance. However, numerous DS projects fail due to the complexity and difficulty of handling various managerial and technical challenges. Because of shortcomings in existing DS methodologies, new standardized approaches for DS project management are needed that respect both the business and data perspectives. In this paper, the concept for a DS process model to address common problems in DS, including a low level of process maturity and a lack of reproducibility, is outlined. This artifact is developed using the Design Science Research methodology and relies on MLOps principles to support the development and operationalization of the analytical artifacts in DS projects.

## 1 INTRODUCTION

With the prospect of improving firm performance in various aspects by extracting valuable knowledge from data (Müller et al., 2018; Wamba et al., 2017; Chen et al., 2012), Data Science (DS) has attracted significant interest. DS constitutes an interdisciplinary field, involving a complex socio-technical process (Sharma et al., 2014; Thiess and Müller, 2018), different technologies (Haertel et al., 2023b), and diverse competencies (Holtkemper and Beecks, 2024). Unfortunately, most DS projects fail (VentureBeat, 2019; Hotz, 2024), indicating a low maturity in DS for many organizations. According to Gökalp et al. (2021), achieving success in DS initiatives requires managing organizational and technical aspects and their various challenges, including poor team coordination, reproducibility, and low process maturity (Martinez et al., 2021).

Hence, effective project management (PM) is considered fundamental for positive project outcomes, especially in DS (Martinez et al., 2021; Saltz and Shamshurin, 2016). The particularities of DS necessitate dedicated DS methodologies for its unique

tasks and skillsets. While multiple DS process models (e.g., CRISP-DM) from academic and industry backgrounds are available (Haertel et al., 2022), the literature suggests several shortcomings, imposing the need for new standardized approaches (Saltz and Krasteva, 2022). Beyond their underutilization in real DS projects, aspects such as the definition of roles and responsibilities, dependency on certain service providers, and reproducibility stand out as worth improving in contemporary DS process models (Martinez et al., 2021; Schulz et al., 2020).

Furthermore, PM encompasses more than planning, budgeting, solving conflicts, and managing requirements (Iriarte and Bayona, 2020; Gökay et al., 2023) and also extends to supporting technical facets of the undertaking (Haertel et al., 2023b). In DS, this relates to advanced analytics like Machine Learning (ML), which are often leveraged to gain value from data (Rahlmeier and Hopf, 2024). Yet, the development, deployment, and maintenance of ML is a difficult venture, suffering from poor traceability, (data) quality assurance (Sculley et al., 2015), and a lack of automation (Kreuzberger et al., 2023). Nonetheless, guidance for analytics is often neglected in current DS process models (Martinez et al., 2021). For these aspects, ML Operations (MLOps) is a promising paradigm that extends the DevOps principles (Symeonidis et al., 2022) to DS to support the creation of mature, efficient, and robust ML systems by

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leveraging principles such as data, model, and code versioning, workflow orchestration, Continuous Integration (CI), Deployment (CD), and Training (CT) (Kreuzberger et al., 2023).

Generally, an effective methodology for DS management should cover the areas of project, team, data, and information management (Martinez et al., 2021). Therefore, we argue that the incorporation of MLOps into a standardized DS lifecycle workflow that prescribes common tasks, deliverables, and defines team roles and responsibilities can mitigate common managerial and technical challenges and thus contribute to increasing maturity in DS. Yet, despite its potential, to the best of our knowledge, no process model for DS currently integrates MLOps principles to guide analytical model building, operationalization, and maintenance. Therefore, the following research question (RQ) is formulated:

*RQ: How can a Data Science process model be designed that incorporates MLOps principles to improve end-to-end Data Science maturity?*

Such an artifact can provide valuable contributions for scholars and practitioners. For the former, the development of a holistic DS process model featuring the integration of MLOps principles addresses a significant gap in the academic body of knowledge. Furthermore, DS practitioners can apply this artifact to manage DS initiatives since it aims to address both organizational and technical process aspects.

The rest of the manuscript is structured as follows. After introducing the methodology and the theoretical foundation for this research, typical DS challenges and avenues to address them are discussed. This establishes the basis for the concept of the MLOps-based DS process model, which is presented in detail in the fifth section. The paper closes with an outlook on the next steps for progressing this research endeavor in the future, emphasizing artifact formalization and evaluation.

## 2 METHODOLOGY

To ensure rigor, the Design Science Research (DSR) methodology is adopted (Hevner et al., 2004). In particular, we rely on the DSR approach of Peffers et al. (2007), encompassing a nominal process of six stages for the design, development, and evaluation of an artifact. Taking a problem-centered entry point, the first stage involves problem identification.

**Problem Identification and Motivation.** The high failure rate in conducting DS initiatives (Hotz, 2024)

is attributed to numerous managerial and technical difficulties, including a low level of process maturity, poor team coordination, a lack of knowledge retention, reproducibility, quality assurance checks, and low data quality (Martinez et al., 2021). While multiple DS process models can be found in the literature (Haertel et al., 2022), these methodologies display several flaws (Martinez et al., 2021) in providing sufficient support for addressing common DS challenges. Hence, the call for new approaches for DS PM (Saltz and Krasteva, 2022) indicates a low maturity in DS.

**Objectives of a Solution.** Accordingly, an artifact in this regard should primarily contribute to standardizing and consistently implementing DS processes, as the success of DS projects depends, inter alia, on the comprehensive management of their managerial and technical aspects (Gökalp et al., 2021). Consequently, the frequently encountered issues, which are detailed in the next section, need to be addressed (Haertel et al., 2023a; Martinez et al., 2021) by the solution to support DS project execution.

**Design and Development.** Therefore, this research aims to develop a DS process model that tackles the aforementioned obstacles and contributes to improving end-to-end DS maturity. This artifact is designed by integrating a standardized DS project workflow, including common tasks, team roles and responsibilities, and deliverables with MLOps principles from the literature. In DSR terms, the artifact is characterized as a method, since it offers "actionable instructions that are conceptual" (Peffers et al., 2012). A draft of this artifact is described in the fifth section.

**Demonstration.** To showcase the applicability of the artifact for addressing the problem, it will be demonstrated through various DS case studies in the future.

**Evaluation.** To verify the suitability of the artifact to fulfill the formulated objectives, the evaluation of the proposed method is conducted according to the Build-Evaluate pattern of Sonnenberg and vom Brocke (2012), consisting of ex ante and ex post evaluation activities. In particular, evaluation criteria such as feasibility, clarity, understandability, completeness, and effectiveness need to be considered to assess the artifact's asserted contribution (knowledge claims) (Larsen et al., 2025). Thus, we will mainly rely on case studies and expert feedback from practitioners with different roles in the context of DS.

**Communication.** The intermediate and completed results of this research endeavor are and will be disseminated to different scientific outlets.

### 3 THEORETICAL BACKGROUND

First, key terminology needs to be clarified. DS denotes the interdisciplinary field that aims to synthesize “useful knowledge directly from data through a process of discovery or of hypothesis formulation and hypothesis testing” (Chang and Grady, 2019). The concept of maturity, generally understood as a measure of the quality of an organization’s operations in a certain domain, can also be applied to DS. In this context, DS maturity indicates how well an organization standardizes and consistently implements DS processes (Gökalp et al., 2021). To support DS initiatives in this regard, DS process models aim to provide a chronological and logical sequence of stages, tasks, and best practices. For example, based on the work of Haertel et al. (2022), a DS project can be roughly structured into six stages, as shown in Figure 1.

As the entry point, *Business Understanding* involves a situation assessment, defining project objectives, forming a project team, and creating a project plan. Next, the *Data Collection, Exploration and Preparation* phase includes data acquisition, exploratory analysis, and consequent data preparation. This leads to the *Analysis* stage, where analytical models are developed and assessed based on the DS objectives. Here, the process of extracting knowledge from large datasets typically requires advanced analytics techniques like ML (Rahlmeier and Hopf, 2024). ML encompasses algorithms that learn from training data to uncover hidden insights and complex patterns without explicit programming (Janiesch et al., 2021; Bishop, 2006). This capability enables reliable, data-driven decisions across various applications. *Evaluation* reviews whether the models meet the initial business goals. For a positive checkpoint decision, *Deployment* entails final planning, testing, and implementing the analytical artifacts into the production environment, depending on the type of DS product. *Utilization* includes monitoring and maintenance tasks (Haertel et al., 2022).

Recently, MLOps emerged as a paradigm that includes best practices, concepts, and cultural aspects for the end-to-end implementation and scalability of ML products (Kreuzberger et al., 2023). MLOps is based on key DevOps principles (Symeonidis et al., 2022) that are extended to the analytics domain. For example, CI/CD is in place for build, test, delivery, and deployment steps for data and ML pipelines, enabling automation together with a workflow orchestration engine. Components such as a source code repository, feature store, metadata store, and model registry implement versioning of data, models, and code in addition to ensuring reproducibility

and traceability of processes (e.g., for ML experiments) (Kreuzberger et al., 2023). While CI/CD handle the deployment of the ML pipelines, in production, Continuous Monitoring (CM) periodically evaluates ML components (data, model, and infrastructure) to detect quality issues (Makinen et al., 2021) like concept drift, which denotes changes between input data and the target variables that occur over time (Gama et al., 2014), potentially necessitating periodic retraining (Continuous Training (CT)) on new data (Kreuzberger et al., 2023). MLOps can be implemented at varying maturity and automation levels, with Google defining three degrees of MLOps (Kazmierczak et al., 2024).

### 4 DATA SCIENCE CHALLENGES AND THEIR MITIGATION STRATEGIES

DS projects often fail to reach a successful conclusion (Hotz, 2024), which is, inter alia, attributed to challenges related to PM, team management, and data and information management (Martinez et al., 2021). Therefore, to improve the maturity in DS, frequently encountered obstacles need to be addressed by a DS PM approach (Martinez et al., 2021; Haertel et al., 2023a). In the following, some key issues in DS and propositions to mitigate them are discussed. The first subsection focuses on aspects related to the project and team. Afterward, data- and information-centric obstacles are addressed.

#### 4.1 Process Maturity and Team Coordination

While several DS process models can be found in gray and academic literature, various shortcomings are evident, undermining the availability of integral DS methodologies (Kutzias et al., 2023; Martinez et al., 2021; Schulz et al., 2020). According to an extensive survey of DS process models, many methodologies underrepresent management tasks, and concrete deliverables for the individual DS tasks are lacking (Haertel et al., 2022). Consequently, in practice, lots of DS projects are managed ad-hoc and forego the use of DS methodologies to support the execution (Kutzias et al., 2023). Accordingly, a fundamental prerequisite of a DS process model to address the low level of process maturity is a well-defined DS lifecycle workflow to determine which and how tasks need to be performed throughout the initiative (Martinez et al., 2021).

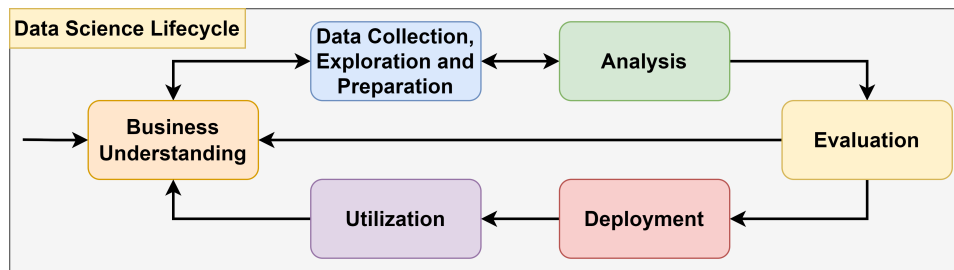


Figure 1: Data Science Lifecycle, adapted from Haertel et al. (2022).

Due to the variety and complexity of DS tasks, diverse competencies are required in a DS team (Holtkemper and Beecks, 2024), and effective coordination is crucial (Martinez et al., 2021). As defining team roles and responsibilities is considered integral in PM (Mishra et al., 2022), DS process models should also cover this aspect. However, most methodologies (e.g., CRISP-DM), do not adequately address roles and responsibilities throughout the DS lifecycle (Haertel et al., 2022; Saltz and Krasteva, 2022). Traditionally, the Data Scientist has been the key figure in DS, requiring a diverse skillset (e.g., Data Analysis, Data Engineering, software development, PM, domain knowledge) (Demchenko et al., 2016), which is rarely consolidated in one individual (Schumann et al., 2016). Accordingly, a DS methodology needs to account for team coordination between different, interdisciplinary actors (Martinez et al., 2021). As the literature features a plethora of job profiles related to DS and their specific demand can differ depending on project scope and scale, or industry, it is sensible to define broader DS role categories that cover the general responsibilities necessary across the DS lifecycle. Therefore, typical DS team role groups are *Domain Expertise*, *Strategy & Project Management*, *Data Management & Analysis* for aspects around data access, exploration, and preparation, *Data Infrastructure & Operations* responsible for the technological basis for data analyses and all modeling activities, and *Analytical Modeling*, which is leading the development and evaluation of ML models (Haertel et al., 2025). To facilitate team coordination with a process model, the individual DS workflow tasks need to be assigned to the respective responsible actors.

## 4.2 Reproducibility and Analytical Models

In many DS process models, a guiding framework for analytics (i.e., ML) is only superficially covered, and vendor dependencies aggravate adoptability (e.g., Microsoft's Team DS Process) (Martinez et al., 2021). Building ML models, which involves data input, fea-

ture extraction, model construction, and assessment (Janiesch et al., 2021), can be complicated, with numerous pitfalls (Kreuzberger et al., 2023). Development is just one aspect, and the deployment and maintenance of the models are equally important, specifically in the context of changing data and business environments (Gerhart et al., 2023). In DS projects, these activities are often accompanied by issues with reproducibility, knowledge retention, a lack of quality assurance checks, and low data quality for ML (Martinez et al., 2021), which hinder leveraging the full potential of ML. These challenges stress the need for including ML guidance, particularly with emphasis on traceability and preservation of knowledge and versions about data, models, and code in DS methodologies (Martinez et al., 2021).

This requirement aligns with the objectives of MLOps, which address the typical challenges in DS around ML. CI and CD automation foster deployment, quality assurance, and flexibility. Traceability and reproducibility of experiments, artifacts, and pipelines are achieved through components such as the feature store, model registry, and metadata store. Thus, MLOps contributes to enhanced transparency in ML processes, improving collaboration (Kreuzberger et al., 2023). For operationalization, the literature suggests that strong capabilities in DevOps are crucial to ensure and maintain the quality of ML systems and the consequent realization of business value (Shollo et al., 2022), which MLOps accounts for with CM and CT (Kreuzberger et al., 2023).

Thus far, no DS process model integrates MLOps practices and components. Despite its potential to standardize ML development, deployment, and monitoring, MLOps cannot address all challenges encountered in DS projects. Existing MLOps frameworks mostly neglect the aspects of *Business Understanding* and *Evaluation* (Haertel et al., 2023c). A missing link between organizational objectives and the technical perspective can lead to the DS results not being used by the business (Martinez et al., 2021), especially when investigating the wrong or no analytical question (Leek and Peng, 2015; Thiess and Müller, 2018). Therefore, MLOps practices should be embed-

ded in a DS methodology to combine the data-centric view with the management perspective to effectively support DS project execution (Haertel et al., 2023c; Martinez et al., 2021).

## 5 A CONCEPT FOR AN MLOps-BASED DATA SCIENCE PROCESS MODEL

This section presents the high-level concept of the MLOps-based DS process model, illustrated in Figure 2. For this draft, the notation is oriented toward the Business Process Model and Notation (BPMN) standard and will be formalized and detailed with appropriate submodels as a next step. The model aims to address the discussed managerial and technical issues in DS from the literature by incorporating the proposed solutions to mitigate them. In particular, for its construction, the MLOps principles and components (Kreuzberger et al., 2023) are integrated into the DS workflow of Haertel et al. (2022) due to its origins in the best practices of 28 existing DS process models. Furthermore, the method indicates the responsible team roles of major DS tasks, identified based on a survey of DS roles and competencies (Haertel et al., 2025). Consequently, this artifact combines a structure for managing organizational and technical process aspects, which is crucial for the maturity and success of data-driven initiatives (Gökalp et al., 2021). The process model is technology-agnostic, allowing the realization of the individual components through different tool vendors and (MLOps) automation levels.

First, a notable challenge is bridging the gap between the business aspects and technical realization. DS projects come in different variations (e.g., data characteristics, type of ML product, timeliness of analytics, type of analytical problem), imposing different implications for the undertaking. Essentially, the encountered challenges in DS project execution are influenced by the project characteristics (Saltz et al., 2017). Therefore, a DS categorization model, developed based on the analysis of a significant number of DS case studies, aims to assign the DS project proposal at hand to a cluster of similar undertakings to allow for drawing inferences for guiding the project execution based on the assigned category. This constitutes valuable input for the *Business Understanding* phase and can include aspects such as tools, required data analysis and preparation activities, suitable analytical models, and conclusions for deployment and monitoring.

Depending on the requirements of the use case and the conclusions drawn from the categorization model output, the actual DS lifecycle (Haertel et al., 2022) starts with the *Business Understanding* activity to plan and prepare the project. Afterward, in case of continuation, relevant data from the identified data sources are acquired and explored to enable developing the data pipeline to streamline data preparation steps. Created features and processed datasets are provided to a feature store to accelerate model building and predictions (Kreuzberger et al., 2023) and promote reusability. In the experimentation conducted in the development environment, various (ML) models are trained and tested based on the feature data to fulfill the DS objectives. Due to the explorative nature of DS (Das et al., 2015), a separation of environments is essential. To ensure reproducibility and traceability, tracking and logging of ML metadata (e.g., training time, (hyper)parameters, performance metrics, and model lineage) and models are implemented for all training runs and stored in the model registry and metadata store (Kreuzberger et al., 2023). All code artifacts for data and modeling are further held in a source code repository for improved collaboration.

After a positive conclusion regarding the satisfaction of business goals in the *Evaluation*, the *Deployment* phase commences, primarily executed by the *Data Infrastructure & Operations* team. Instead of merely commissioning an analytical model, an entire orchestrated ML pipeline is deployed to the production environment. Therefore, the CI/CD component is leveraged to quickly execute the build, test, delivery, and deployment tasks, enhancing productivity and enabling fast adaptability of the system (Kreuzberger et al., 2023).

Fed with curated feature data from the feature store, the deployed ML pipeline is executed, resulting in production-ready model(s) that are, similar to the training metadata, recorded in the model registry. Via CD, the generated model is made available to the application domain through the serving component, enabling it to support business value creation. Furthermore, a monitoring component supervises model and system performance and health through a broad set of metrics (e.g., model accuracy, resource utilization). Anomalies are investigated and handled by the operations and analytics team. For instance, the retraining of the model is enabled via the CT component, which can trigger the ML pipeline automatically or be subject to human evaluation beforehand. If the maintenance activities fail to mitigate errors or revert model and system performance to an acceptable threshold, a reinitiation of the DS project can be decided when the

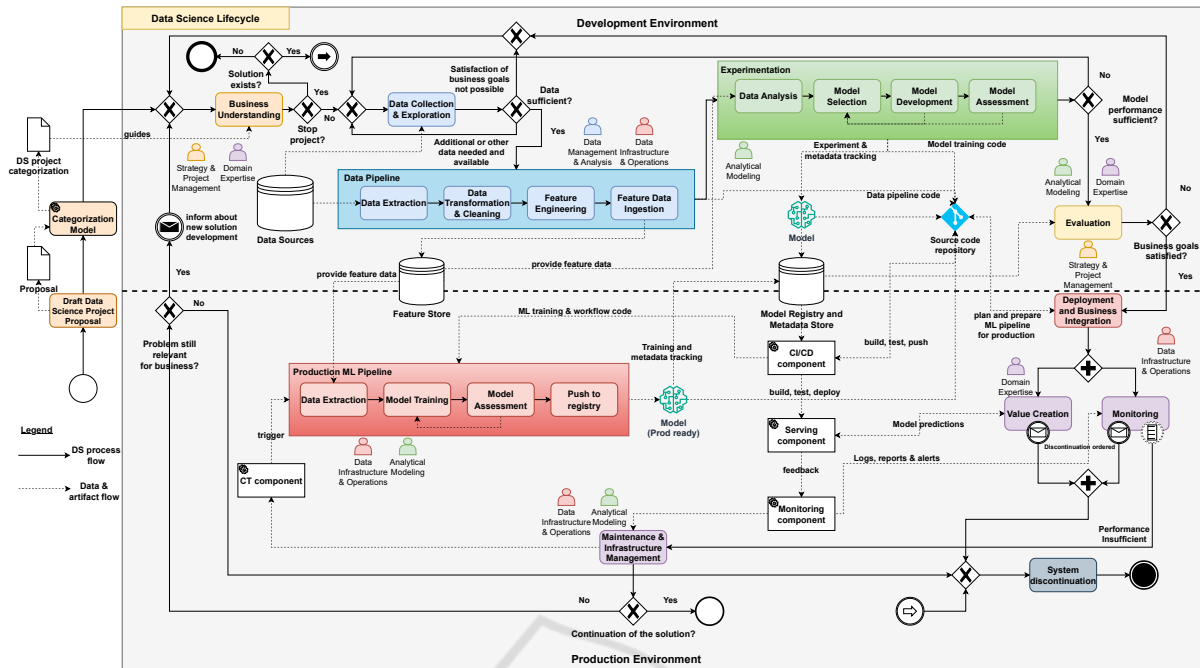


Figure 2: DS process model (concept) based on Haertel et al. (2022) and Kreuzberger et al. (2023).

objective of the solution is still considered relevant for the organization. Otherwise, the system is discontinued.

In summary, the proposed artifact aims to address common DS challenges as follows. The feature store, model registry, metadata store, and the source code repository enable versioning, knowledge retention, transparency, and reproducibility. CI/CD and the orchestration of data and ML pipelines foster automation and efficiency. Through the separation of environments and the components for monitoring and CT, system quality and robustness are ensured. These MLOps practices are incorporated into an end-to-end DS workflow with defined team roles to establish process maturity and aid coordination. Nevertheless, while the artifact prescribes the relevant abstract technical components, it does not provide concrete guidance for setting up the generally necessary IT infrastructure for DS projects.

For the future formalization of the process model, the involvement of the actors can be clarified more clearly (e.g., via swimlanes). Furthermore, the data and artifact flow between the components is subject to a detailed specification. The verification of the artifact's utility to fulfill the intended objectives requires a comprehensive evaluation. Therefore, we rely on the Build-Evaluate pattern of Sonnenberg and vom Brocke (2012). Briefly, the applicability of the model is demonstrated by its instantiation in multiple DS case studies. This will be supplemented by detailed

expert feedback. Here, beyond the artifact's effectiveness, its understandability and clarity are major concerns to ensure that practitioners are able to use this approach for managing DS projects. Accordingly, experts with different roles and skillsets in the context of DS should be considered.

## 6 CONCLUSION AND FUTURE WORK

The need for new approaches (e.g., process models) for DS (Saltz and Krasteva, 2022) is motivated by the high failure rates of DS initiatives (Hotz, 2024) due to various managerial and technical challenges. Many DS projects do not follow an established methodology, and gaps in current DS process models are highlighted in the literature (Kutziyas et al., 2023; Martinez et al., 2021; Schulz et al., 2020). Consequently, this paper reports on an ongoing research endeavor that aims to develop an MLOps-based process model for DS through the adoption of the DSR methodology of Peffers et al. (2007). A high-level concept of this artifact is presented, including a discussion on how it aims to address managerial and data-centric challenges in DS. The focus of future work will be placed on continuing the development of the artifact and its components, including formalization with established modeling notation. Furthermore, the evaluation will play a major role in assessing its feasibility for the

different flavors of DS projects. Moreover, the potential of incorporating Generative AI capabilities into DS process models for increasing automation and efficiency in DS project tasks can be explored.

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