Guiding Improvement in Data Science: An Analysis of Maturity Models

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Abstract: Maturity models (MMs) can help organizations to evaluate and improve the value of emerging capabilities and technologies by assessing strengths and weaknesses. Since the field of Data Science (DS), with its rising importance, struggles with successful project completion because of diverse technical and managerial challenges, it could benefit from the application of MMs. Accordingly, this paper reports on a structured literature review to identify and analyze MMs in DS and related fields. In particular, 18 MMs were retrieved, and their contribution toward the individual stages of the DS lifecycle and common DS challenges was assessed. Based on the outlined gaps, the development of a meta-maturity model for DS can be pursued in the future.

1 INTRODUCTION

The amount of data generated has been accelerated by the COVID-19 pandemic and is projected to increase even further in the future (Business Wire, 2021). Data Science (DS) aims to leverage improvements in performance for organizations (Chen et al., 2012) by (semi-)automatically generating insights from complex data (Schulz et al., 2020). However, studies show that over 80% of DS projects fail (VentureBeat, 2019) and do not yield any business value (Gartner, 2019). Typical challenges in DS include low process maturity, a lack of team coordination, and the absence of reproducibility (Martinez et al., 2021). Therefore, new approaches for handling the managerial and technical challenges of DS projects are needed (Saltz and Krasteva, 2022).

Maturity models (MM) can be seen as support tools to evaluate and improve an organization's practices in a specific field (Pereira and Serrano, 2020). Furthermore, they assist enterprises in assessing and realizing the value of emerging capabilities and technologies (Hüner et al., 2009). Thus, enterprises are enabled to grade their existing strengths and weaknesses and consequently guide improvement endeavors. DS is a discipline that can benefit from the employment of MMs because of the high project failure rates and the potential increases in return on investments (Gökalp et al., 2021). To assess the contribution of contemporary DS MMs toward this objective, this paper reports on a systematic literature review (SLR) that identifies and analyzes existing MMs in DS in two dimensions. Initially, the MMs are evaluated regarding their consideration of the typical stages in a DS undertaking, which is captured by the first research question (RQ):

RQ 1: Which stages of the Data Science lifecycle are addressed by the maturity models in the literature?

According to Haertel et al. (2022), a DS project can be commonly subdivided into six abstract phases. To fully assess an organization's maturity in this discipline, all activities within the DS lifecycle should be taken into account. Secondly, throughout the individual stages in a DS undertaking, various challenges related to project, team, and data and information management are encountered (Martinez et al., 2021). Therefore, mitigating the obstacles in DS project execution is required to progress toward reducing the number of unsuccessful endeavors. Accordingly, for the second RQ, the coverage of DS challenges by the MMs is investigated:

RQ 2: Which common challenges of Data Science projects are assessed by the maturity models?

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As a result, this work offers valuable contributions for theory and practice. An overview of existing MMs in the academic literature is provided. For practitioners, the discussion of the RQs can facilitate the selection of suitable MMs. Moreover, the analysis unveils potential gaps and weaknesses in the MMs to guide future research endeavors to progress the state of MMs in DS.

The remainder of the article is structured as follows. First, a background discussion on DS and MMs is given. Then, the SLR process is outlined, which follows the PRISMA guidelines (Page et al., 2021). Subsequently, an overview and descriptive analysis of the identified MMs are provided. In the fifth section, the two RQs are discussed. Finally, the study is concluded with a synthesis of the findings and recommendations for future research.

2 THEORETICAL BACKGROUND

The theoretical background discusses the central concepts around DS and MMs to establish the necessary fundamentals for the topic. DS is characterized as the "methodology for the synthesis of useful knowledge directly from data through a process of discovery or of hypothesis formulation and hypothesis testing" (Chang and Grady, 2019). Extracting value from data often involves advanced analytical methods, such as Machine Learning (ML) (Rahlmeier and Hopf, 2024). ML describes algorithms that can learn from data to detect complex patterns without explicit programming (Janiesch et al., 2021; Bishop, 2006). Since DS projects usually involve datasets that can be classified as Big Data (BD), this connection led to the term "Big Data Science" (Chang and Grady, 2019). Furthermore, Data Mining (DM) is closely linked to DS and emerged as a specialization of Data Analytics in the 1990s. Briefly, it is defined as a set of algorithms for "extracting patterns from data" (Chang and Grady, 2019). The tight liaison between these fields is underscored through the uniform application of methodical approaches (e.g., process models).

Based on the work of Haertel et al. (2022), a DS undertaking is typically structured in six phases, namely 1) *Business Understanding*, 2) *Data Collection, Exploration and Preparation*, 3) *Analysis*, 4) *Evaluation*, 5) *Deployment*, and 6) *Utilization*. *Business Understanding* marks the starting point in the DS lifecycle and includes activities such as the definition of business and associated DS objectives, as well as the establishment of a project plan (Haertel et al., 2022). The following stage involves data-related tasks like the identification of data sources, data collection, exploration, and preparation. *Analysis* contains activities such as model selection, development, and assessment. During the *Evaluation* phase, the analytical models are reviewed concerning the business objectives. In case of a decision to progress the project with the *Deployment*, the commissioning of the models is prepared and executed. Finally, *Utilization* includes the use of the models in production and monitoring and maintenance tasks (Haertel et al., 2022). The execution of a DS project is a complex socio-technical (Sharma et al., 2014; Thiess and Müller, 2018) endeavor that is subject to various technical and managerial challenges. The literature highlights aspects such as a low level of process maturity, clarity of objectives, a lack of team communication and collaboration, or the difficulty in developing and deploying models (Martinez et al., 2021). Addressing the typically faced obstacles is needed for improving the DS project success rates (Haertel et al., 2023; Martinez et al., 2021).

On this note, MMs might be helpful support tools for organizations to evaluate and improve their practices in a particular field (Pereira and Serrano, 2020). The assessment of strengths and weaknesses can consequently guide improvement endeavors, including DS. The MM concept arose in the early 1970s, and since then, a variety of MMs have been developed for numerous disciplines (Carvalho et al., 2019). A notable example is the *Capability Maturity Model* (CMM) that was built to evaluate the maturity of software processes (Paulk et al., 1993). In general, an MM features a set of maturity levels for "a class of objects" (Becker et al., 2009) (e.g., dimensions, capabilities). MMs provide different criteria and characteristics that are required to be matched to achieve a certain maturity level (Becker et al., 2009). After the assessment of the maturity level in a given field, measures for improvement can be derived to increase the degree of maturity (IT Governance Institute, 2007). In DS, an exemplary MM is the *Data science capability maturity model* (DSCMM) that was constructed based on the MM development method of Becker et al. (2009) to guide improvement in DS, including technical, managerial, and organizational aspects (Gökalp et al., 2022b). In this work, we aim to obtain a comprehensive view of existing MMs for DS and analyze their impact on the DS lifecycle (RQ 1) and typical DS challenges (RQ 2).

3 METHODOLOGY

The guidelines of PRISMA (Page et al., 2021) were followed to ensure a standardized and peer-accepted process for conducting the SLR. Sufficient source coverage is established through the selection of five renown scientific databases, namely *AIS eLibrary (AISeL)*, *Scopus*, *IEEE Xplore (IEEE)*, *ScienceDirect (SD)*, and *ACM Digital Library (ACM DL)*. To guarantee consistency, a unified search term was applied across all databases to identify MMs in DS. Accordingly, the search query is composed of DS and similar fields as well as terms related to MM:

(”maturity model” OR ”capability model” OR ”maturity level”) AND (”data mining” OR ”data science” OR ”machine learning” OR ”big data”)

In total, the initial database search retrieved 870 articles that were published in 2019 and later. For transparency, the distribution of results per database is given in Table 1. Before the initial content screening, 108 duplicates were removed, leaving 762 publications.

Table 1: Initial search results as of 25th March 2025.

Database	**Search Space**	**Results**
Scopus	Title, abstract, keywords	**384**
SD	Title, abstract, keywords	**76**
IEEE	All metadata	**202**
ACM DL	Title, abstract	**4**
AISeL	All fields	**204**

The three filtering stages of title assessment, abstract screening, and full-text examination, prescribed by Brocke et al. (2009), were applied to identify the relevant contributions for the research endeavor. For this purpose, suitable inclusion and exclusion criteria need to be defined. The criteria for this SLR are presented in Table 2 and discussed in the following. Publications should comprise at least six pages to ensure sufficient depth in the discourse of an MM. Literature reviews on MMs are not considered if they do not result in the construction of a new MM. Only MMs with the typical structure of dimensions and maturity levels (Becker et al., 2009) are considered. Additionally, because of this article’s focus on DS projects in general, MMs that are only applicable to a specific domain are excluded. If an MM has multiple versions (e.g., revisions) across different publications, only the most recent implementation is included. Due to the COVID-19 pandemic’s role in accelerating digital transformation at an unprecedented pace (Shah, 2022) and the significant impact on DS, only articles from 2019 onward are considered. Further inclusion criteria include the language (English or German) and valid article types. To qualify an article for the next filtering stage, all inclusion criteria must be fulfilled. On the contrary, a match with one of the exclusion criteria leads to the dismissal of a reviewed item.

Table 2: Inclusion and exclusion criteria.

Inclusion criteria	**Exclusion criteria**
The publication discusses an MM in DS or a related field.	The publication has less than six pages.
The publication is written in English or German.	The MM does not prescribe dimensions and maturity levels.
The publication was published in 2019 or later.	The publication is solely a literature review on MMs.
The publication is a journal article or conference paper.	The MM is domain-specific and irrelevant to DS projects in general.
	The MM has a revised or updated version.

The 762 remaining records after duplicate removal were then subject to the title screening, which led to the elimination of 649 articles. This significant reduction is attributed to the use of rather generalized search keywords such as ”maturity level”. Consequently, a large portion of the publications had a deviating research context (e.g., articles focusing on agricultural maturity). Afterward, the 97 papers with full-text access were assessed for eligibility in two stages. First, the abstract evaluation removed another 44 articles. Accordingly, 53 contributions were subject to the full examination, leaving 18 studies. Finally, a forward and backward search on these items was performed to identify additional relevant studies and mitigate potential bias from the search string (Webster and Watson, 2002). While six candidate papers were identified using the citation search, none of them passed the filtering process. Therefore, the search and filtering process resulted in a total of 18 publications. Figure 1 visually summarizes this entire process, following the PRISMA guidelines (Page et al., 2021).

4 DESCRIPTIVE ANALYSIS

In this SLR, a primarily qualitative analysis is conducted. Table 3 displays the concept matrix to support this undertaking. It lists all identified MMs of this SLR sorted by year of publication and author names,

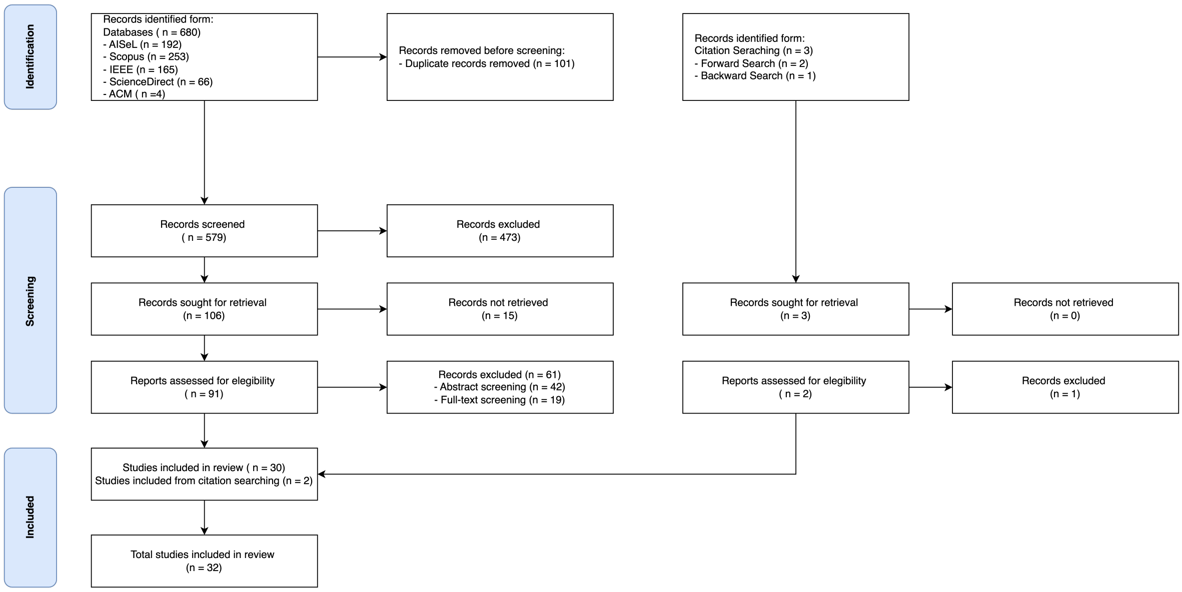

Figure 1: Literature search and filtering process.

assigns an ID to the respective publication, and denotes the focus of the MM. Additionally, it contains the DS lifecycle stages as proposed by Haertel et al. (2022) as units of analysis (RQ 1). Before focusing on this aspect in the next chapter, the retrieved MMs will be introduced.

4.1 Overview of Maturity Models in Data Science

Out of the 18 reviewed MMs, only two are generally designed for DS based on the authors' statements. Cavique et al. (2024) propose a DS MM, which combines business experimentation and causality concepts, featuring four criteria. In this regard, the DSCMM of Gökalp et al. (2022b) is more elaborate, with five process areas and associated processes. The model is grounded on the ISO/IEC standard. The remaining MMs address related fields or subdisciplines of DS. Four MMs focus on (BD) Analytics, including the *capability maturity model for advanced data analytics* (ADA-CMM) that was developed via a Delphi study (Korsten et al., 2024). A maturity framework to guide analytics growth is proposed by Menukhin et al. (2019), constructed through action design research. The BD Analytics MM of Pour et al. (2023) is the result of an SLR to detect BD Analytics practices and their consequent assessment by expert surveys. The process assessment model for BD Analytics of Gökalp et al. (2022a) has similar origins to the DSCMM. The key distinction is situated in the process dimensions being closely aligned with the DS lifecycle stages.

Two articles propose MMs for BD. Helal et al. (2023) present an MM for the effect of BD on processes based on COBIT 5. On the other hand, Corallo et al. (2023) provide an MM for evaluating the maturity level of BD management and Analytics in industrial companies. Five articles discuss MMs for ML or Artificial Intelligence (AI). While Yablonsky (2021) focuses on AI-driven platforms, Fukas (2022) proposes a general AI MM, also relying on the MM development model of Becker et al. (2009). Tackling the issues of defining business cases for AI, Akkiraju et al. (2020) suggest an MM for ML model lifecycle management that is built on the CMM. Schreckenberg and Moroff (2021) developed a maturity-based workflow to assess the capability of an organization to realize ML applications. In a recent article, Fornasiero et al. (2025) present an MM for AI and BD, mainly applicable to the process industry. Another MM related to ML aims to adopt, assess, and advance ML Operations (MLOps) and was developed based on case studies of multiple companies. The remaining MMs have a more niche focus. Following a design science approach, Desouza et al. (2021) propose an MM for cognitive computing systems, which is interpreted as an umbrella term for technologies like AI, BD Analytics, ML, etc. On the contrary, Zitoun et al. (2021) have a condensed focus with their MM for data management. Similarly, Raj M et al. (2023) concentrate on the maturity of industrial data pipelines. Finally, Hijriani and Comuzzi (2024) cover a subdomain of DS, process mining, with their MM.

Table 3: Concept Matrix for DS MMs.

#	Articles	BU	DA	AN	EV	DM	Util	Focus
1	Menukhin et al. (2019)	X	X	X		X		Analytics
2	Akkiraju et al. (2020)	X	X	X	X	X	X	Machine Learning
3	Desouza et al. (2021)	X	X			X	X	Cognitive Computing Systems
4	Schreckenberg and Moroff (2021)	X	X					Machine Learning
5	Yablonsky (2021)		X	X		X		Artificial Intelligence
6	Zitoun et al. (2021)	X	X	X		X		Data Management
7	Fukas (2022)	X	X			X		Artificial Intelligence
8	Gökalp et al. (2022a)	X	X	X	X	X	X	Big Data Analytics
9	Gökalp et al. (2022b)	X	X	X	X	X	X	Data Science
10	Corallo et al. (2023)		X	X				Big Data
11	Helal et al. (2023)	X	X	X	X	X	X	Big Data
12	Raj M et al. (2023)		X			X	X	Data Pipelines
13	Pour et al. (2023)	X	X	X	X	X	X	Big Data Analytics
14	Cavique et al. (2024)	X	X	X				Data Science
15	Hijriani and Comuzzi (2024)	X	X					Process Mining
16	Korsten et al. (2024)	X	X	X	X		X	Data Analytics
17	Fornasiero et al. (2025)	X	X					AI & Big Data
18	John et al. (2025)		X	X		X	X	MLOps

#: Article ID, **BU**: Business Understanding, **DA**: Data Collection, Exploration and Preparation, **AN**: Analysis, **EV**: Evaluation, **DM**: Deployment, **Util**: Utilization

4.2 Dimensions and Maturity Levels

After an overview of the MMs and their context, their contents are analyzed. For this purpose, Table 4 displays the dimensions and maturity levels of each MM. The maturity levels constitute the desired or anticipated state for ”a class of objects” (Becker et al., 2009). Hence, they can be used to evaluate the current state of maturity in an organization for a particular field by determining a maturity level for each dimension in an MM. According to Becker et al. (2009), the lowest level stands for the initial stage of an organization, while the highest level represents a conception of full maturity based on the model. Hence, recommendations for improvement measures can be derived and prioritized to reach higher maturity levels (IT Governance Institute, 2007). The number of maturity levels in the reviewed MMs varies between four and six. The MMs also partly differ in the terminology used to describe these levels. Despite these differences, they all have a common framework: an initial level, which constitutes the starting point, and a highest level, which signifies an optimized state. For example, the MMs proposed by Gökalp et al. (2022b,a) are based on an ISO/IEC standard, which leads to uniform maturity levels in these frameworks. Contrary, the maturity levels of Menukhin et al. (2019) and Akkiraju et al. (2020) have been largely adopted from the CMM (Paulk et al., 1993), essentially consisting of five levels ranging from ”Initial” to ”Optimized”. Raj M et al. (2023); Pour et al. (2023); Cavique et al. (2024), and Fornasiero et al. (2025) use numeric levels to describe the degree of maturity. Notably, the process mining MM of Hijriani and Comuzzi (2024) prescribes unique maturity levels for each of the seven dimensions.

Overall, dimensions are being proposed differently across the publications due to the varying focus

Table 4: Dimensions and maturity levels.

#	Articles	#D	Dimensions	#ML	Maturity Levels
1	Menukhin et al. (2019)	6	Organisation, IT&A Infrastructure, Analytics Processes, Skills, Governance, Data & Analytics Technologies,	5	Initial, Committed, Focused, Managed, Optimised
2	Akkiraju et al. (2020)	9	AI Model Goal Setting, Data Pipeline Management, Feature Preparation Pipeline, Train Pipeline Management, Test Pipeline Management; Model Quality Performance and Model Management; Model Error Analysis, Model Fairness & Trust, Model Transparency	5	Initial, Repeatable, Defined, Managed, Optimizing
3	Desouza et al. (2021)	2	Technical Elements (Big Data, Computational Systems, Analytical Capacity), Organizational Elements (Innovation Climate, Governance and Ethical Frameworks, Strategic Visioning)	5	Ad-Hoc, Experimentation, Planning and Deployment, Scaling and Learning, Enterprise-wide transformation
4	Schreckenberg and Moroff (2021)	5	Process, Data, Technology, Orga. & Staff, Strategy	4	AI-new, AI-enabled, AI-experienced, AI-advanced
5	Yablonsky (2021)	5	AI Awareness, Adjustment of AI, Measurement of AI, AI Reporting & Interpretation, AI Decision-making	5	Human Led; Human Led, Machine Supported; Machine Led, Human Supported; Machine Led, Human Governed; Machine
6	Zitoun et al. (2021)	4	Enterprise & Intent (Business Strategy, Culture & People), Data Management (Data Collection & Availability, Metadata Management & Data Quality, Data Storage & Preservation, Data Distribution & Consumption, Data Analytics/Processing/Transformation, Data Governance, Data Monitoring & Logging), Systems (Architecture & Infrastructure, Data Integration, Security), Data Operations (Processes, Data Deployment & Delivery)	6	No capability, Initial, Developing Awareness & Pre-Adoption, Defined, Managed, Optimized
7	Fukas (2022)	8	Technologies, Data, People & Competences, Organization & Processes, Strategy & Management, Budget, Products & Services, Ethics & Regulations	5	Initial, Assessing, Determined, Managed, Optimized
8	Gökalp et al. (2022a)	6	Business Understanding, Data Understanding, Data Preparation, Model Building, Evaluation, Deployment and Use	6	Incomplete, Performed, Managed, Established, Predictable, Innovating
9	Gökalp et al. (2022b)	5	Organization, Strategy Management, Data Analytics, Data Governance, Technology Management	6	Incomplete, Performed, Managed, Established, Predictable, Innovating
10	Corallo et al. (2023)	5	Organisation, Data Management, Data Analytics, Infrastructure, Governance & Security	4	Unaware, Aware, Action, Mature
11	Helal et al. (2023)	13	Collection, Planning, Management, Integration, Filtering, Enrichment, Analysis, Visualization, Storage, Destruction, Archiving, Quality, Security	5	Ad-hoc, Defined, Early adoption, Optimizing, Strategic
12	Raj M et al. (2023)	5	Security, Scalability, Resiliency, Robustness, Dependability	5	Level 1 - 5
13	Pour et al. (2023)	4	Strategic Capabilities, Managerial Capabilities, People Capabilities, Technological Capabilities	5	Level 1 - 5
14	Cavique et al. (2024)	4	Information system, approach to planning, guidance, function	4	Level 0 - 3
15	Hijriani and Comuzzi (2024)	7	Technology, Pipeline, Data, People, Culture, Governance, Strategic Alignment	4-5	varies by dimension; Technology has 4 levels, the rest 5
16	Korsten et al. (2024)	5	Strategy (ADA Strategy, Strategic Alignment), Data & Governance (Data Architecture, Automation, Data Integration, Data Governance, Data Analytics Tools), People & Culture (Knowledge, Commitment, Team Diversity, Usage), Process Design & Collaboration (Competence & Skills Development, Communication, Portfolio Management, Organizational Collaboration), Performance & Value (Performance Metrics, Innovation Processes)	4	Low, Moderate, High, Top
17	Fornasiero et al. (2025)	5	Strategy, Organisation, People, Technology, Data	5	Level 0-4
18	John et al. (2025)	5	Data, Model, Deployment, Operations & Infrastructure, Organisation	5	Ad Hoc, DataOps, Manual MLOps, Automated MLOps, Kaizen MLOps

#: Article ID based on concept matrix, **#D**: Number of dimensions, **#ML**: Number of maturity levels

of the MMs. Dimensions are characterized as different aspects of organizational capabilities or functions (Gökşen and Gökşen, 2021). These dimensions collectively indicate the general maturity state. The number of dimensions across the MMs varies between four and 13, whereas almost half of the publications employ five dimensions. For instance, the MM for Data Analytics of Korsten et al. (2024) contains the dimensions *Strategy*, *Data & Governance*, *People & Culture*, *Process Design & Collaboration*, and *Performance & Value*. The largest number of main dimensions is featured in the BD MM of Helal et al. (2023) (13). However, other authors assign multiple subcapabilities to a dimension, as can be seen in Zitoun et al. (2021)'s MM for data management. An organizational dimension is prescribed in nine separate articles. However, its scope can differ. Gökalp et al. (2022a) and Corallo et al. (2023) include the degree of communication and collaboration among DS teams and efficient leadership. Menukhin et al. (2019) tightly couple the organizational dimension to the question of whether analytics is used in everyday decision-making in the organization. The related *Strategy* dimension is also quite common among the general DS and analytics-focussed MMs, often assessing the availability of an overall strategy for analytics (Korsten et al., 2024). Business units, such as the management or other stakeholders, must support DS activities to further invest in them (Gökalp et al., 2022b).

Furthermore, *Data Governance* occurs frequently as a dimension, evaluating the degree to which companies address data security, privacy, and quality problems (Gökalp et al., 2022b). According to Corallo et al. (2023) and Korsten et al. (2024), access management and secure management of data fall under this capability but not activities such as data processing or data storage. *Data* and *Data Analytics* are other typical dimensions. For the latter, Corallo et al. (2023) and Menukhin et al. (2019) are both connecting it to the existence of data and analytics processes and how the organization manages them. In the work of Hijriani and Comuzzi (2024), the *Data* dimension provides a rating of the state and availability of the data for analytics but also refers to aspects of data governance. Gökalp et al. (2022b) combines the former activities into their *Data Analytics* dimension. The MM for MLOps of John et al. (2025) unites data governance, data management, data versioning, and the feature store under *Data*. Consequently, it can be stated that the dimensions around data have significant differences in their manifestations across the MMs.

Another common dimension is *Technology*. While Schreckenberg and Moroff (2021) focus here on the use of data warehouses and cross-divisional enterprise resource planning systems, Gökalp et al. (2022b) refer to the degree of consideration of scalable and distributed technologies to efficiently manage the characteristics of BD. Therefore, hardware, software, configuration management, and deployment processes are being taken into consideration. Notably, Pour et al. (2023) combine the sub-dimensions *Analytical Infrastructure*, *Data Management*, and *Analytic tools / Techniques* into the technological dimension. Ultimately, *Organization*, *Strategy*, *Technology*, *Data*, and *Analytics* can be counted as the main dimensions of the MMs in DS. Nevertheless, MMs that address a particular area of DS (e.g., ML, data pipelines) predominantly propose dimensions that are closely related to their respective focus area.

5 RESEARCH AGENDA

After completion of the descriptive analysis of the MMs, including the detailed synopsis of dimensions and maturity levels, this section concentrates on discussing the two RQs.

5.1 Incorporation of Data Science Lifecycle Stages

In addition to listing all included papers of the SLR for transparency purposes, the concept matrix in Table 3 helps to conceptually structure the publications objectively (Klopper and Lubbe, 2007). This approach supports a traceable discussion of the findings and aligns with the principles of the PRISMA guidelines (Page et al., 2021). The concept matrix indicates which stages of the DS lifecycle, outlined in Section 2, are addressed by the MMs. Accordingly, when a corresponding column is marked (**X**), the MM can be used to evaluate the maturity of an organization for some or all activities of the respective DS lifecycle stage. Thus, this analysis allows readers to comprehend which MMs are potentially relevant to the assessment of end-to-end DS maturity.

The concept matrix shows that all of the MMs consider tasks of *Data Collection, Exploration and Preparation*, reinforcing the notion of the pivotal role of data in these undertakings. Apart from four MMs, *Business Understanding* is consistently taken into account with the common organizational and strategic dimensions, covering aspects such as planning, skills, and culture. *Analysis* and *Deployment* are also incorporated by many MMs. On the other hand, *Evaluation* and *Utilization* are addressed the least, with the former finding a mention in only six MMs. Since this stage involves the assessment of the analytical models concerning the business objectives, a reason for this observation could be found in the strongly context-dependent (e.g., project characteristics, analytics type, application) manifestation of this phase.

Five of the reviewed MMs consider aspects of all DS lifecycle stages. For practitioners in search of a holistic MM regarding the DS lifecycle, a look into these models might be useful. One candidate is the ML maturity framework of Akkiraju et al. (2020), which puts superficial emphasis on organizational aspects but includes dimensions like model fairness and transparency. In the case of the BD Analytics MM,

Table 5: Coverage of typical DS challenges by MMs, based on Martinez et al. (2021).

Data Science Challenge	**Maturity Models (#)**
Alignment of objectives	1-4, 6-10, 13, 15, 17-18
Data governance & management	1, 3, 5-11, 13, 15-16, 18
IT infrastructure	1, 3-4, 6-10, 13-14, 18
Analytical model development	1-2, 5-6, 8-11, 13-14, 16, 18
Skills & training	1, 3-4, 6-7, 13, 15-17
Data quality	3, 5-6, 8-9, 11, 15, 17
Data availability	4-6, 8-9, 11, 15, 17
Data security & privacy	6-7, 9-12, 15, 17
Deployment approach	3, 5-6, 8-9, 18
Clear objectives & scope	1-2, 7-8, 11, 16
DS roles & responsibilities	1, 9, 10, 16, 18
Emphasis on Business Understanding	8-9, 11, 14, 16
Knowledge retention	1-2, 4, 9, 12
Setup for reproducibility	1-2, 5, 6, 18
Process maturity	3, 6, 8-9
Result evaluation	2, 8, 11, 16
Team communication & collaboration	8, 10, 16, 18
Control processes	9

the dimensions almost exactly align with the DS lifecycle of Haertel et al. (2022) (Gökalp et al., 2022a). The DSCMM integrates these capabilities as processes across the different dimensions (”process areas”) (Gökalp et al., 2022b). While Helal et al. (2023) touch on all stages, too, the model is mainly aligned with the lifecycle of data (including archiving and destruction) and prioritizes analytics and its evaluation less. In conclusion, it has to be noted that the MMs of Gökalp et al. (2022a) and Gökalp et al. (2022b) achieve the highest coverage of the stages and activities of the DS lifecycle. However, as the *Utilization* is considered together with *Deployment*, the monitoring and maintenance of analytical models appear to be of lower importance. Hence, developing a meta-MM for DS could constitute a worthwhile contribution.

5.2 Assessment of Data Science Challenges

A crucial purpose of MMs is to guide improvement (Pereira and Serrano, 2020). In DS, many projects fail to reach a successful conclusion. Since it is argued that addressing the challenges in DS undertakings is needed to mitigate this circumstance (Haertel et al., 2023; Martinez et al., 2021), in this section, it is analyzed whether common obstacles are considered by the MMs (RQ 2). Consequently, a valuable perspective toward improving DS project execution is covered. Table 5 presents the result of this analysis. It lists the challenges in DS identified by Martinez et al. (2021) in the left column. The right column contains the IDs of all MMs (based on Table 4) that consider the respective issue in their maturity assessment. The table is sorted in descending order based on the number of MMs that address a given obstacle. Seeing the numerous MMs that feature dimensions around strategic, organizational, and data governance, it is not surprising that the challenges *alignment of business objectives and DS goals* and *appropriate data governance and management* are commonly addressed. This also applies to the *IT infrastructure*, which has high significance, especially in BD environments, and the *difficulty of developing analytical models* with suitable technologies. Additionally, the staff *skill and training* aspect and ensuring sufficient *data quality* are valued by many MMs. Among the data-specific obstacles, *data availability* and *data security* are considered often, too.

The remaining challenges identified by Martinez et al. (2021) are evaluated by only one-third or less of the MMs. This includes especially managerial intricacies (e.g., *lacking emphasis on Business Understanding*, *clear project scope*, *suitable approaches for Deployment*). Notably, a *clear structure of roles and responsibilities* and measures to ensure *effective communication and collaboration* in a DS team seem less important to many MMs compared to the availability and advancement of employee competencies. Moreover, tackling the low level of process maturity in lots of DS projects with the reliance on an established *DS workflow* is caught on by merely four MMs and only plays a significant role in the publications of Gökalp et al. (2022a) and Gökalp et al. (2022b). In line with the subpar coverage of the *Evaluation* stage of the DS lifecycle, *evaluation methods* for analytical results are rarely considered in the MMs. Another important issue in DS is insufficient *reproducibility* and *knowledge retention*. These aspects include data, models, experiments, and *lessons learned* (Martinez et al., 2021) and are not of predominant significance in the analyzed MM. One exception is the MLOps MM prescribed by John et al. (2025) since MLOps aims to contribute to reducing the difficulty in ML development through feature stores and experiment and model (metadata) tracking. Finally, it is hard to establish realistic timelines for DS undertakings, motivating the need for *control processes* for DS activities (Martinez et al., 2021). However, this requirement is exclusively reviewed in the article of Gökalp et al. (2022b).

While all of the DS challenges under review were considered at least once and some even played a role in the maturity assessment in a majority of the MMs, none of the models under examination included all considered obstacles. To strengthen the impact of a DS MM toward its intended purpose, that is, helping to improve DS project success rate, high coverage of the typical challenges should be pursued. Therefore, this further intensifies the relevance of a meta-MM for DS, constructed based on the obtained findings of this SLR.

6 CONCLUSION

MMs enable organizations to assess and realize their current value of emerging capabilities and technologies (Hüner et al., 2009). Determining the maturity level of an enterprise across the different dimensions of an MM can foster the identification of recommendations toward improvement measures (Becker et al., 2009). As DS struggles with a high degree of incompleted projects (VentureBeat, 2019), MMs can be considered useful in this domain. In this paper, we retrieved 18 MMs for DS from the literature and analyzed their coverage of the DS lifecycle stages (Haertel et al., 2022) and major DS project challenges. While some MMs address all phases of a DS undertaking, gaps and weaknesses can still be found (RQ 1). Additionally, no MM considers all reviewed DS issues for its maturity assessment (RQ 2). Based on our analysis and the inputs from the existing models, the development and evaluation of a DS meta-MM constitutes a future research stream. For this objective, the knowledge base could be extended through the inclusion of additional literature databases or the expansion of the search query with related keywords (e.g., Industry 4.0, AI).

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