MASTER DATA MANAGEMENT AS PART OF DATA GOVERNANCE: A MATURITY MODEL TO IMPROVE EFFICIENCY AND TRUST IN MASTER DATA AND THUS BUSINESS PERFORMANCE

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Abstract

An optimized master data management correlates with improved data quality, enhanced process integration and increased business agility, leading to overall better business performance. This study proposes a maturity model for structured master data management improvement that has emerged from analysing previous maturity model research, data governance, master data management and the practical experience of the researcher. The model comprises six maturity levels for eight design levels with 23 assessment factors, which are framed by six organizational factors. It extends previous maturity models by expanding organizational dimensions and considering the measurement of success across all design levels. The results serve the purpose of creating an artifact for measuring the success of master data management that is informed by data governance experience.

Keywords: Master Data, Master Data Management, Data Governance, Maturity Assessment

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1. INTRODUCTION

In today's highly networked and data-driven business environment, organisational agility is becoming increasingly important. The effective management of data assets is crucial for organisations of all sizes. Master data management as a branch within enterprise information management is at the forefront of this. The concept focuses on specific company data, the master data, and forms the cornerstone for ensuring data quality, consistency and reliability across different systems and processes (Schmuck, 2024).

An organisation's level of master data management maturity is a key indicator of its ability to manage and use this data efficiently. A high level of maturity in master data management means that a company has mature processes and systems in place that ensure consistent and high-quality data management. This in turn enables the company to make informed decisions, optimise operational processes and react quickly to market changes. A low level of maturity, on the other hand, can lead to inconsistent data, inefficient processes and sub-optimal decisions, which can significantly impair the company's competitiveness.

This study proposes a maturity model as a result of analysing previous research on maturity models, data governance, master data management and the practical experience of the researcher.

The present research results are relevant to the scientific literature, as previous models are extended by new findings from research in data governance and performance measurement. This model supports the development of new strategies in master data management to improve data quality and process integration as well as to reduce the complexity of master data management initiatives, which is essential for the long-term competitiveness and innovative strength of companies.

Furthermore, this research is of great practical importance as it provides organizations with clear guidance and targeted recommendations for action to optimize their master data management processes. By applying this model, companies can systematically assess the current status of their master data management practices, integrate the results into their data governance and thus identify development needs. This enables them to take targeted measures to improve data quality, the efficiency and integration of their business and decision-making processes and the efficient use of resources in order to achieve sustainable competitive advantages and increase agility in an increasingly data-driven business environment.

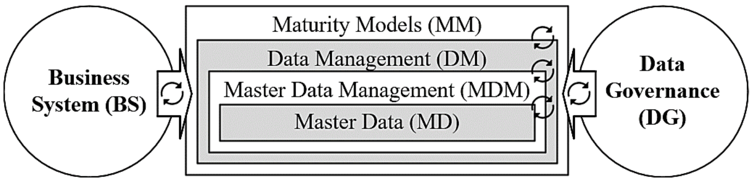
The paper is structured as follows: After the introduction to the research topic (Section 1), the theoretical basis (Section 2) is presented. This is followed by the presentation of the research design and the qualitative analysis of previous research (Section 3) and the description of the maturity model (Section 4). The study concludes with a discussion (Section 5) and conclusion (Section 6).

2. RELATED WORK: A LITERATURE REVIEW

2.1. Theoretical background

The first step is to set out the theoretical foundations. To do this, the researcher uses a framework, shown in Figure 1. The framework also provides the basis for designing successful master data management in operational organisations.

Figure 1. Theoretical framework



Source: Author's elaboration.

From a systems theory perspective, *business systems* (synonym: companies, organisations) are open, goal-oriented and socio-technical systems (Benker & Jürck, 2016). The characteristics "open" and "goal-oriented" determine the behaviour, and the characteristic "socio-technical" refers to the structure of a business system. An expression of the *openness* of business systems is the exchange of outputs (products, services) and corresponding steering messages (e.g., an order confirmation). Business systems proceed in a *goal-oriented* manner, i.e., they pursue factual and formal goals. To fulfil operational tasks, business systems use resources that together form a *socio-technical system*. Resources are personnel (specified as organisational structure) and application systems as well as machinery and equipment, specified in technical (development) models. Business systems form the organisational framework, the design environment for the master data management, in a cybernetic manner.

Data governance is a holistic approach to corporate data that addresses the question of how, why and by whom data is managed in business systems. At its core, data governance refers to the rules and authorisations that determine how data is managed and handled and who is allowed to access the data (Abraham et al., 2019). Data governance is not just a purely technical undertaking; there are very strong links to business processes and organisational culture. The set of rules for data management in each organisation depends on the specific needs and objectives of a business system. Data governance is, therefore, not available "off the shelf", but must be customised to the specific circumstances of a business system.

Master data forms the backbone of every company and includes basic information about customers, products, suppliers and other business partners (Otto & Hüner, 2009), although the content of this information varies depending on the company's sector. This data serves as the basis for all business processes and decisions and must, therefore, be of the highest quality and consistency (Beckmann, 2019). Effective management of master data, known as master data management, is crucial to ensure that master data is reliable, up-to-date and accurate. This enables organisations to maintain a unified view of their data and use it efficiently across different systems and applications.

Master data management as a specialised data management and sub-area of operational information management is a holistic strategy, business processes and set of technologies aimed at ensuring the quality, consistency and availability of master data across all business areas (Otto &

Hüner 2009). At the centre of master data management is the creation and maintenance of a single, reliable source of truth for key business data, including customer information, product attributes and supplier data (Otto & Hüner 2009). Master data management involves a number of processes, including data capture, validation, cleansing, harmonisation and distribution, as well as the implementation of policies and governance structures to ensure the integrity and quality of the data. Maturity models are used to determine the company's own performance in master data management.

A *maturity model* is a structured framework that supports business systems in assessing and improving their level of maturity and effectiveness in a specific area (Jacobs, 2019). In this respect, maturity models are helpful tools for determining the status of business systems own performances (Becker et al., 2009). To determine the maturity level, specific requirements for the object under consideration are identified and then assigned to different maturity levels. Depending on which requirements are fulfilled, a defined maturity level, a grade, is awarded and the object under consideration is thus categorised. A maturity level is only considered to have been achieved if both the criteria described there and in the previous level have been demonstrably achieved. Furthermore, a lower level implies less ability or less maturity (Grande, 2011). From the categorisation into a maturity level, the business system should derive actions that it must implement in order to improve its maturity level. In the context of master data management, a maturity model enables companies to analyse their current status in terms of master data management practices and define benchmarks for further development.

2.2. Analysis of existing maturity models and their application

Various maturity models can be found in the literature. The maturity models differ in the number of maturity levels along the respective object of consideration to be assessed. They are described below, grouped according to the families master data management, data management, data governance and specific focus (like data protection).

2.2.1. Maturity models in the field of master data management

There are several master data maturity models (Table 1).

Table 1. Comparison of maturity models in the field of master data management

Reference(s)	***Focus areas***	***Maturity levels***	***Assessment questions***
Oracle (2011)	1) User data profiling; 2) Data strategy definition; 3) Definition of data consolidation plan; 4) Data maintenance; 5) Data utilization	1) Marginal; 2) Stable; 3) Best practice; 4) Transformational	./.
Loshin (2010)	1) Architecture; 2) Governance; 3) Management; 4) Identification; 5) Integration; 6) Business process management	1) Initial; 2) Reactive; 3) Managed; 4) Proactive; 5) Strategic performance	./.
Kumar (2010)	./.	1) Ignorant; 2) Initial; 3) Isolated; 4) Organized; 5) Unified; 6) Optimized	./.
Gartner (2015)	./.	1) Initial; 2) Developing; 3) Defined; 4) Managed; 5) Optimizing	./.
Dyché and Levy (2007)	./.	1) No master data management; 2) List provisioning; 3) Peer-based access; 4) Centralized hub processing; 5) Business rule & policy support; 6) Enterprise data convergence	./.
Spruit and Pietzka (2015)	1) Data model; 2) Data quality; 3) Usage and ownership; 4) Data protection; 5) Maintenance	1) Initial; 2) Repeatable; 3) Defined process; 4) Managed and measurable; 5) Optimized	Yes (69)
Zúñiga et al. (2018)	1) Policies; 2) Data governance; 3) Data model; 4) Data integration; 5) Data quality; 6) Monitoring	1) Initial; 2) Managed; 3) Defined; 4) Quantitatively managed; 5) Optimized	

Source: Author's elaboration.

Oracle's (2011) maturity model contains five dimensions and four maturity levels. It is also very general, treating master data like any other form of data, i.e., it does not take into account the specific characteristics of master data. Loshin (2010) describes a maturity model, which became known as "DataFlux", with six main areas, to each of which five maturity levels are assigned. Loshin's (2010) maturity model includes master data management processes in all dimensions and maturity levels, which are, therefore, difficult to delineate and thus difficult to compare. Some maturity models only describe maturity levels with their specific characteristics and requirements. For example, Kumar (2010) defines six maturity levels in his maturity model, Gartner (2015) describes a maturity model with five maturity levels and Dyché and Levy (2007) describe a maturity model with six maturity levels. There are no specific main topics or focus areas in any of these three maturity models, which makes it difficult to compare them with other maturity models and to apply them in business systems because the defined requirements must first be further operationalised. Spruit and Pietzka (2015) present a maturity model with five main topics, 13 focus areas and five maturity levels. They formulated 69 assessment questions to determine the maturity level. It is by far the most detailed maturity model in master data management and the most widely used maturity model for master data management assessments in business systems (see Appendix: all references with the note "Comments"). When comparing the maturity model mentioned above, it can be seen that they do not address all design levels that are relevant in today's world of advancing digital transformation. Increasing cybercrime activities are forcing data protection and data security to be included in greater detail, i.e., also from a technical perspective. In this respect, the maturity model by Spruit and Pietzka (2015) is too narrowly focused (only on technical data protection). Measuring success is also important, as master data management activities are investments that need to be justified to top management on an ongoing basis. Therefore, control mechanisms that not only promote the external image of master data management but also motivation, are relevant. For this reason, the information base was expanded to a maturity model of data management, data governance and a special maturity model for data protection.

2.2.2. Maturity models in the field of data management in general

Three maturity models in the field of data management are included for the maturity model to be constructed in this study (Table 2).

With the "*TDWI Data Management Maturity Model Assessment Guide*", Larson (2023) presented a maturity model of the TDWI. Five maturity levels are assessed using five dimensions and 27 focal points. 72 assessment questions were formulated to determine the maturity level. In 2014, the CMMI Institute presented its maturity model (Mecca, 2014), which assesses five maturity levels along six dimensions with 26 focal points. In 2017, DAMA International provided the "*DAMA-DMBOK: Data Management Body of Knowledge*" as a collection of processes, best practices and references for each key knowledge area of data management (DAMA International, 2017). Six maturity levels are assessed through eleven dimensions, components (business objectives, principles, key concepts, activities, tools and techniques, implementation guidance) and metrics, detailed in 31 capabilities and 106 sub-capabilities. This framework is very comprehensive and needs to be customised to an organisation.

Table 2. Comparison of maturity models in the field of data management in general

Reference(s)	*Focus areas*	*Maturity levels*	*Assessment questions*
Larson (2023)	1) Organization; 2) Resources; 3) Architecture; 4) Data life cycle; 5) Governance	1) Nascent; 2) Developing; 3) Established; 4) Managed; 5) Optimized	./.
Mecca (2014)	1) Data management strategy; 2) Data governance; 3) Data quality; 4) Data operations; 5) Platform & architecture; 6) Supporting processes	1) Performed; 2) Managed; 3) Defined; 4) Measured; 5) Optimized	./.
DAMA International (2013)	1) Data architecture; 2) Data modelling & design; 3) Data storage & operations; 4) Data security; 5) Data integration & interoperability; 6) Documents & content; 7) Reference & master data; 8) Data warehousing & business intelligence; 9) Meta data; 10) Data quality	1) Absence; 2) *Ad hoc*; 3) Repeatable; 4) Defined; 5) Managed; 6) Optimized	./.

Source: Author's elaboration.

2.2.3. Maturity models in the field of data governance

Three maturity models in the field of data governance are included for the maturity model to be constructed in this study (Table 3).

Table 3. Comparison of maturity models in the field of data governance

Reference(s)	*Focus areas*	*Maturity levels*	*Assessment questions*
IBM (2007)	1) Organizational structures & awareness; 2) Stewardship; 3) Policy; 4) Value creation; 5) Data risk management & compliance; 6) Information security & privacy; 7) Data architecture; 8) Data quality management; 9) Classification & metadata; 10) Information lifecycle management; 11) Audit information; 12) Logging & reporting	1) Initial; 2) Managing; 3) Managing; 4) Quantitatively; 5) Managed; 6) Optimizing	./.
Merkus (2015)	1) Governance; 2) Risk management; 3) Compliance;4 4) Processes; 5) People; 6) Technology; 7) Data assets; 8) Business alignment; 9) Organization; 10) Data management	1) No process; 2) Beginning process; 3) Established process; 4) Managed process; 5) Optimizing process	./.
Firican (n.d.)	1) Maturity components (project, foundational); 2) Dimensions (people, policies; capabilities); 3) Measurement types (quantitative, qualitative)	./. (Scorecard)	./.

Source: Author's elaboration.

IBM published its maturity model for master data management and data governance in 2007 (IBM, 2007). The model comprises five maturity levels along twelve main areas. In 2015, Merkus presented his maturity model for data governance (Merkus, 2015). Five maturity levels are assessed by ten dimensions. 27 assessment questions were formulated to determine the maturity level. Stanford University presented its maturity model in 2011 (Firican, n.d.). The maturity model consists of two maturity components, three dimensions and two measurement types. A simple scorecard (no maturity levels) is used for measurement.

2.2.4. Maturity models in the field of data protection

Two maturity models in the field of data protection are included for the maturity model to be constructed in this study (Table 4).

Table 4. Comparison of maturity models in the field of data protection

Reference(s)	*Focus areas*	*Maturity levels*	*Assessment questions*
Bitkom (2022)	Various subject areas, structured into three main topics: documents; processes; physical objects	Depending on proof of implementation of a defined set of (technical and organizational) aspects within a subject area	./.
Grant Thornton (2019)	1) Governance and accountability; 2) Subject rights, breach & complaints management; 3) Training; 4) Collection; 5) Processing; 6) Third party compliance; 7) Information security; 8) Retention and disposal; 9) Transparency; 10) Data protection impact assessment and risk management	1) *Ad hoc*; 2) Repeatable; 3) Defined; 4) Managed; 5) Optimised	./.

Source: Author's elaboration.

In 2022, Bitkom e.V., the industry association of the German information and telecommunications sector, presented a data protection maturity model for mapping technical and organisational measures in order of processing (Bitkom, 2022). The maturity model is structured into a series of subject areas that have three characteristics (documents; processes; physical objects). The structure of the subject areas is designed in a way that a further level in the maturity level of the respective subject area is achieved when proof of the implementation of a defined set of aspects is provided. The individual aspects can be of a technical (T) and/or organisational (O) nature.

In 2019, Grant Thornton, one of the leading medium-sized auditing firms in Germany, presented their data protection maturity model (Grant Thornton, 2019). It contains ten dimensions of data protection against five levels of maturity.

2.2.5. Maturity models in the field of data security

Two maturity models in the field of data security are included for the maturity model to be constructed in this study (Table 5).

Table 5. Comparison of maturity models in the field of data security

Reference	*Focus areas*	*Maturity levels*	*Assessment questions*
DSMM (n.d.)	1) Identify and classify (with four objectives); 2) Protect (with four objectives); 3) Detect (with two objectives); 4) Respond (with two objectives); 5) Recover and improve (with three objectives) and improve on 1) Technology; 2) People; 3) Processes	Three maturity levels	./.

Source: Author's elaboration.

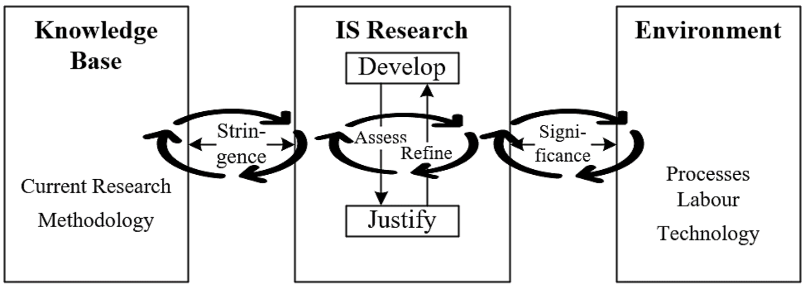
A Comprehensive Cyber Capabilities Working Group (C3WG) of twelve people — thereof ten chief information security officers, one vice president of security and one chief execution officer — developed a data security maturity model, currently available in version 2.0 (DSMM, n.d.). It is organized into five key functions of a data security program (identify and classify; protect; detect; respond; recover and improve). Each of these functions covers multiple underlying objectives, which focus on a particular aspect of security that supports the higher-level function. Each objective is addressed at up to three levels of maturity. Each level includes practices/activities that are needed in order to meet the given level of maturity and include examples of methods and tools that can be used to implement and fulfil those practices.

3. RESEARCH DESIGN

3.1. Methodology

The research in this study is based on the methodology of design science research (DSR). This is a research paradigm for developing scientifically sound design knowledge and validating it in practice (Hevner et al., 2004; Peffers et al., 2012). The DSR is based on a problem, which is usually application-orientated. Based on this problem, an artefact, i.e., a solution to the problem, is created, which is then analysed in terms of its performance in order to understand what this solution does (Figure 2).

Figure 2. Research design



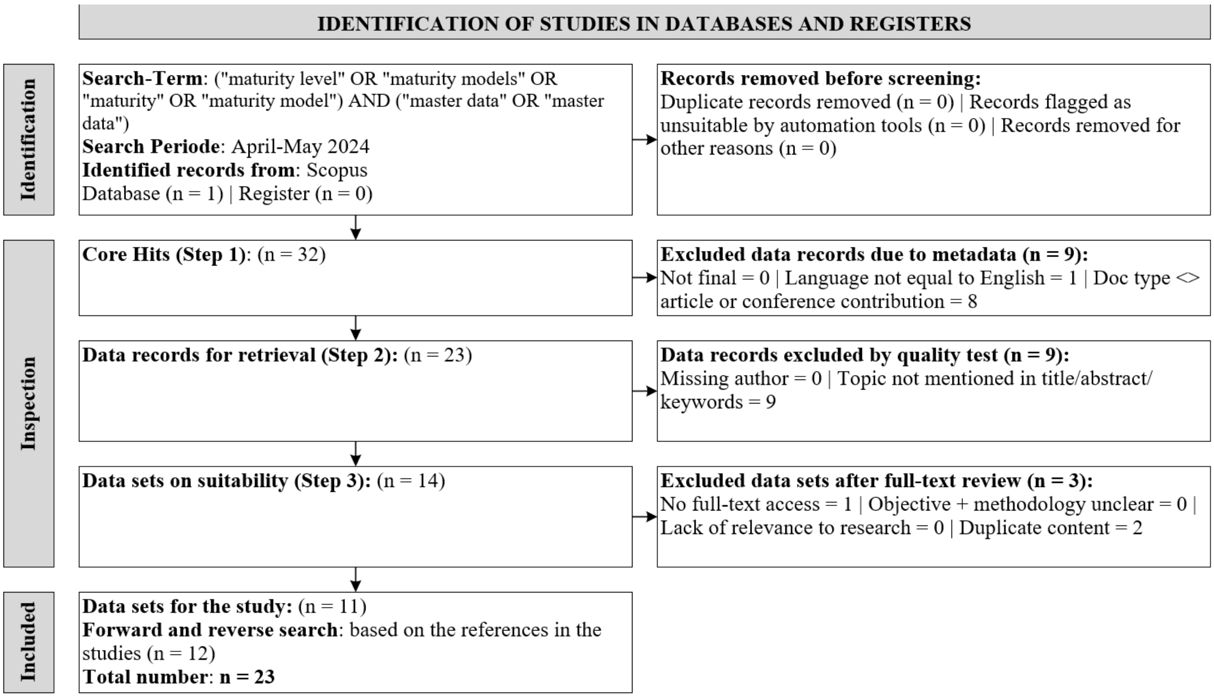
Source: Author's elaboration with consideration of Hevner et al. (2004).

Hevner et al. (2004) divides the DSR into three cycles to illustrate the iterative nature of the DSR process. The "significance cycle" establishes the application context, determines the requirements for the artefact to be developed and defines the criteria that characterise the artefact as successful. The knowledge base is created as part of the "stringency cycle", in which existing knowledge and theory (if helpful), as well as related and existing artefacts, are collected. In the "design cycle", the artefact is designed, implemented and evaluated, taking the above-mentioned success criteria into account. All three aspects form the DSR knowledge space, which is systematically developed using scientific methods. Potential methods include literature analyses, interviews, experiments, taxonomies, simulations, case studies, ethnography or grounded theory (Siemon, 2022). For this study, systematic literature analysis (subsection 3.2) and semi-structured expert interviews (subsection 3.3) are used from the aforementioned potential portfolio of scientific methodologies. Due to the nature of the research subject and the given restrictions (including the time and resources available), the researcher utilised an "*ex-ante* strategy" (Venable et al., 2016). The systematic literature analysis serves as a foundation, as a building activity for the DSR, and the expert interviews as an evaluation methodology, which has proven to be suitable for the type of research (Peffers et al., 2012).

3.2. Literature analysis

Literature analyses are a systematic process in which existing scientific and practical literature on a specific topic is examined and evaluated (Fink, 2019). This process involves identifying, summarising and critically appraising relevant studies and publications to gain an in-depth understanding of the research topic (Kitchenham, 2004). In this study, established concepts of literature analysis were applied and the PRISMA concept (Page et al., 2021) was used to visualise the results (Figure 3).

Figure 3. Process and results of the systematic literature search



Source: Author's elaboration with consideration of Page et al. (2021).

The researcher used the Scopus digital library for previously published papers. The search period was June 2024 and the search terms ("maturity level" *or* "maturity models" *or* "maturity" *or* "maturity model") *and* ("master data" *or* "master data management") were used and applied to titles, abstracts and keywords. Abbreviations were not used because they can also be used in a different context (e.g., MDM for "meta data management" or "mobile device management"). The following research questions were formulated to successfully guide the selection and review of the literature:

RQ1: Which factors (functions) determine the maturity level of master data management?

RQ2: Are there already maturity models for master data management and if so, what do they have in common or how do they differ?

RQ3: What is the practical application of existing maturity models, i.e., are use cases documented, and if so, what are their characteristics (e.g., application environment)?

RQ4: Are there any gaps in the previous maturity models, if so, how can these be overcome?

In the first application of the search term, 32 publications were surveyed. Exclusion criteria were then applied to this result. Only final publications of the type "article" or "conference contribution" from 2013 to 2023 in the language "English" were included. This led to an interim result of 23 publications, which were then subjected to a content review. Publications were excluded a) if metadata (author, title or keywords) were missing, b) if the research topic was not specified in the title, abstract and keywords, c) if there were restrictions on free access (not freely available), d) if the objective and methodology were unclear, e) if they were not relevant to the selected topic and f) if the content was duplicated. After applying these quality criteria, 11 publications remained. Using the references given in these documents, a forward and backward search was carried out in order to include further publications in the research. This resulted in 12 additional publications, so 23 publications were ultimately included in the qualitative analysis. The complete list of publications and their contribution to the guiding questions can be found in the Appendix (Table A.1).

3.3. Expert evaluation

To evaluate the maturity model for master data management, the researcher used semi-structured interviews (Saunders et al., 2019). A guideline was developed for the interviews, consisting of the phases a) opening, b) eliciting personal circumstances of the people involved, c) developing a common understanding of master data management, d) presenting the master data management maturity model, e) in-depth discussion and f) closing. The researcher selected a group of participants: people of different genders and ages, each with different professional experience, different professional values/backgrounds and different positions in companies from different industries (Table 6) in order to represent as broad a spectrum as possible (Saunders et al., 2019).

Table 6. Interview participants for the evaluation of the maturity model

No.	Gender	Position	Industry	Age	Job experience	Degree	Duration
1	Male	Business intelligence architect	Safety engineering	52	> 25 years	Business informatics (M. Sc.)	30 min
2	Female	Sales engineer	Safety engineering	43	> 15 years	Engineering science (Engineer's degree)	30 min
3	Female	Strategic purchasing	Safety engineering	34	> 10 years	Economics (Business Economist's degree)	30 min
4	Male	Chief security officer	Safety engineering	41	> 20 years	Business informatics (M. Sc.)	30 min
5	Male	Digitisation expert	Steel industry	33	< 5 years	Informatics (IT specialist)	30 min
6	Female	Controller	Steel industry	35	> 10 years	Economics (B. Sc.)	30 min
7	Female	Controller	Steel industry	30	> 5 years	Economics (B. Sc.)	30 min
8	Male	Senior IT consultant	Consulting	36	> 15 years	Business informatics (M. Sc.)	30 min
9	Female	Senior IT consultant	Consulting	38	> 15 years	Business informatics (M. Sc.)	30 min
10	Male	Principal IT consultant	Consulting	55	> 30 years	Engineering science (Dr. of Engineering)	30 min

Source: Author's elaboration.

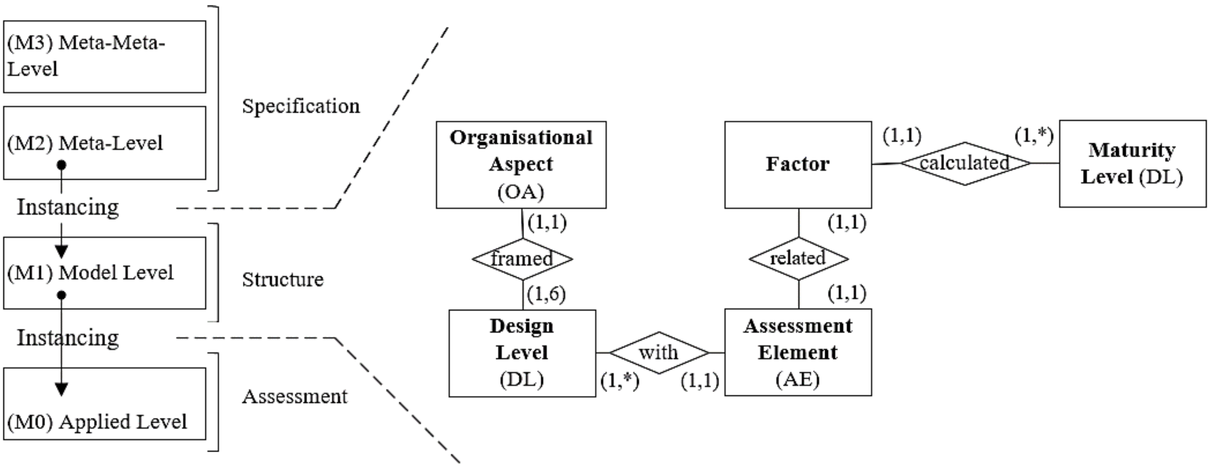
All interviews were conducted in the period of May 2024, partly as a video conference, partly in person, then transcribed and agreed with the participants. Finally, the relevant information for the evaluation of the model was extracted from the results (thematic coding according to Braun and Clarke, 2006).

4. RESULTS

4.1. Schematic overview

Figure 4 visualizes the meta-levels and extensions in the schematic meta-modelling approach (on the left) and the meta-model of the proposed maturity model for master data management (on the right).

Figure 4. Schematic overview



Source: Author's elaboration (supported by Bley et al., 2020).

The meta-meta level M3 is described by the meta-meta model that has been introduced and is standardized for all maturity models. The meta-level M2 contains the meta-model of the respective maturity model; the contents of the meta-level are, therefore, different for the various maturity models. The subject of the schema/model level M1 is a schema described in accordance with the maturity model, which satisfies the associated meta-model M2 in terms of consistency and completeness. The instance level M0 comprises the concrete characteristics of a schema. The adjacent levels are connected by an extension relationship, e.g., level M1 is the extension of level M2, and a set of concrete instances M0 is the extension of the associated schema M1.

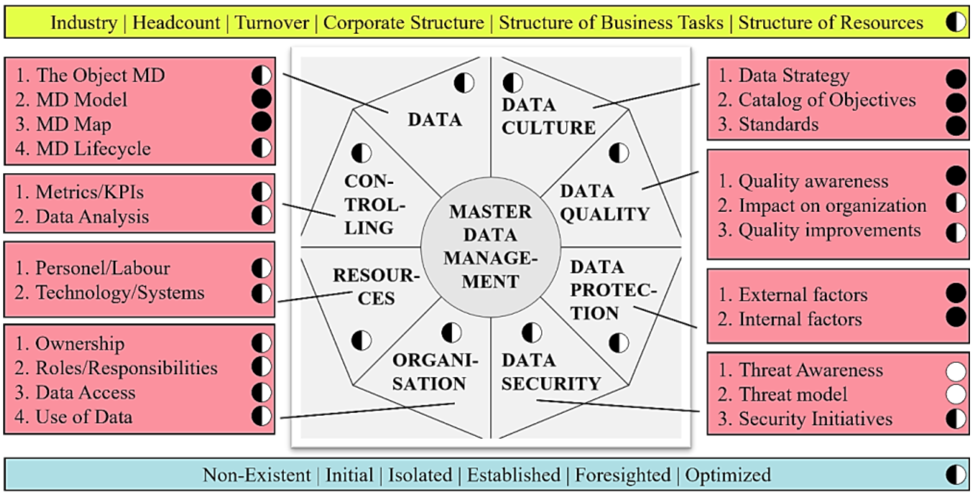
The design levels of the proposed maturity model consist of one or more assessment elements. Each of the assessment elements is assigned a factor. The maturity level, the score, is then calculated from these factors. Six organisational aspects frame the environment.

4.2. Model structure

The maturity model for master data management proposed by the researcher (Figure 5) consists of four groups of elements: organisational aspects (*OA*), design levels (*DL*), assessment elements (*AE*) and maturity levels (*ML*). In detail, the maturity model comprises eight *DL* (grey) with a total of 23 *AE* (red) and six *ML* (blue), framed by six *OA* (yellow).

All elements were specially marked to indicate the basis on which the elements were incorporated into the model. Elements resulting from the systematic literature review (SLR) are marked with a black circle. Elements that emerged from the SLR and were confirmed in the interview are marked with a black semicircle. Elements that only emerged from the interviews are marked with a white circle.

Figure 5. Maturity model for master data model: Overview



Note: organisational aspects, OA (yellow); design levels, DL (grey); assessment elements, AE (red); maturity levels, ML (blue);
● *SLR result;* ○ *interview result;* ◐ *SLR result and confirmed by experts.*
Source: Author's elaboration.

The maturity model takes previous research findings into account, expands or sharpens already known maturity models and fits seamlessly into the research landscape.

4.3. Organisational aspects of influence

The organisational aspects of influence (*OA*) are characterised by the characteristics present in the business system that can have an effect on master data management. The following factors were selected for the designed maturity model:

OA1 — Industry: An economic sector (or industry) is a group of business systems that produce similar products or provide similar services as part of their economic activity (Statistisches Bundesamt, n.d.). The industry was included as a factor in the study because it indicates whether a business system is part of a country's critical infrastructure (business systems with important significance for the state community, the failure or impairment of which would result in lasting supply bottlenecks, significant disruption to public safety or other dramatic consequences) or belongs to a particularly heavily regulated industry (e.g., banks or insurance companies). Both have a significant influence on the treatment of master data and thus the degree of maturity in master data management.

OA2 — Headcount: The headcount of a company is a key figure that provides an indication of the organisational strength of a business system (Cambridge University Press, n.d.). It can be used to determine whether the business systems can basically operate the master data management "under its own steam".

OA3 — Turnover: Turnover is the total value of goods sold or services provided within a certain period (usually a financial year) and provides an indication of the financial strength of the business system (Simon et al., 2018).

OA4 — Corporate structure: The corporate structure is the organisational structure of a business system, the complex framework that shows the existing hierarchies and competencies of the individual functional areas (Kampker et al., 2011). It provides information on whether the organisation being assessed is part of a group of a business system or an international business system and gives an indication of the corporate culture, corporate policy and corporate constitution.

OA5 — Structure of task: In organisational theory, task structure is used to describe the various types of tasks (business processes) of the business system, i.e., the extent to which objectives, solutions and instructions for action are present or known and defined in detail in a task. It is the result of task analysis (systematic decomposition of complex tasks into distributable subtasks, i.e., subtasks that can be transferred to actors according to various decomposition criteria) (Schewe, 2018a) and task synthesis (summarisation of the subtasks obtained through task analysis into task complexes for imagined actors) (Schewe, 2018b). The task structure of a business system provides information on the process diversity and the scope of the data and the exchange of data between the systems.

OA6 — Structure of resources: The organisational theory distinguishes the structure of resources in persons/labour and application systems, machines and systems to which certain tasks have been assigned according to their degree of automation (Zimmermann, 1999). Together they form a socio-technical system. The structure of resources as a designable structure of a business system provides indications of the complexity of the organisational structure, the complexity of the application systems, machines and equipment used and the distribution of responsibility between the two types (an expression of the degree of digitalisation).

4.4. Design levels and evaluation criteria

The design levels (*DL*) and assessment factors (*AF*) were developed based on the literature found, the expert interviews and the researcher's experience.

Table 7. Design levels and their support in previous maturity models

Family		MDM							DM			DG			DP		DS
Model		Oracle (2011)	Loshin (210)	Kumar (2010)	Gartner (2015)	Dyché und Levy (2007)	Spruit und Pietzka (2015)	Zúñiga et al. (2018)	Larson (2023)	Mecca (2014)	DAMA International (2013)	IBM (2007)	Merkus (2015)	Firican (n.d.)	Bitkom (2022)	Grant Thornton (2019)	DSMM (n.d.)
Design levels	Data	×	×	×	×	×	×	×	×	×	×	×	×	×	×		
	Data culture	×	×	×	×	×	×	×	×	×		×	×	×			
	Data quality	×	×	×	×	×	×	×	×	×	×	×	×	×			
	Data protection								×			×			×		
	Data security						×		×		×	×				×	×
	Organisation	×	×	×	×	×	×	×	×	×		×	×	×		×	×
	Resources								×	×			×				
	Controlling						×	×	×			×	×	×			

Note: MDM is master data management; DM is data management; DG is data governance; DP is data protection/privacy; DS is data security.
Source: Author's elaboration.

As a result of the analysis of existing maturity models, the researcher derived eight *DL* with a total of 23 *AF*, which are supported in the analysed maturity models (Table 7) and are relevant for this model. The details are presented below.

1. *Master data* (*DL1*): This level is about the basic understanding of master data as an intangible asset in business systems and includes the following *AF*:

- *Object master data* (*AF1*): An expression of this are definitions of master data that are standardised in semantics and that are companywide valid.
- *Master data models* (*AF2*): Master data models are overviews of all attributes of business-critical entities including examples, descriptions, etc.
- *Master data map* (*AF3*): Master data maps are overviews of all processes and systems that use or access master data, including data descriptions, and their relationship between data and intersections.
- *Master data lifecycle* (*EC4*): The master data lifecycle refers to the entire period of time that master data exists in a system. This lifecycle encompasses all phases that master data go through from initial capture.

2. *Data culture in master data management* (*DL2*): This level is about the collective behaviours and beliefs of individuals who favour, practice and promote the use of master data to improve decision-making. The level includes the following *AF*:

- *Master data strategy* (*AF5*): The master data strategy defines the (mostly) long-term, planned behaviour of a company to achieve its objectives in relation to its business-critical entities.
- *Catalogue of objectives* (*AF6*): In addition to the (overall) description of objectives, the catalogue of objectives records all master data management objectives, divided into must, should and can objectives.
- *Standards* (*AF7*): Standards (guidelines, principles, methods) are procedures that an organisation introduces to manage and ensure the quality, availability, usability, integrity and security of its business-critical data assets.

3. *Data quality in master data management (DL3):* This level is about designing behaviours and measures to overcome inaccuracies, inconsistencies and incompleteness in master data to avoid erroneous processes, incorrect analyses and flawed decisions. The level includes the following *AF*:

- *Quality awareness* (*AF8*): Quality awareness means that business systems personnel know, understand and consider the reasons for quality problems in their business-critical entities and the consequences that faulty master data can have.
- *Impact on the organisation* (*AF9*): Impact on the organisation concerns discrepancies that (can) lead internally to losses in effectiveness and efficiency, and externally to losses in financial assets, revenue and reputation.
- *Quality improvements* (*AF10*): Improvements in data quality include all (technical and organisational) measures that increase the overall quality of master data.

4. *Data protection in master data management* (*DL4*): This level is about the design of the structure and behaviour in dealing with master data with a personal reference. The level includes the following *AF*:

- *External factors for data protection* (*AF11*): External factors of data protection arise in the environment of the organisation and affect the organisation from the outside. This concerns, among other things, the legal framework. As all stakeholders in the business system must be aware of these factors, they are the subject of the maturity model.
- *Internal factors for data protection* (*AF12*): Internal factors of data protection have their origin within a business system and, therefore, influence the business system from within. These include strategies, culture and dissemination related to data protection.

5. *Data security in master data management* (*DL5*): This level is about the design of master data protection against threats, manipulation, unauthorised access or knowledge. The level includes the following *AF*:

- *Threat awareness* (*AF13*): Threat awareness means that personnel in a business system know the reasons for threats to data (including master data), understand and consider the consequences that threats (risks) that occur may have.
- *Threat modelling* (*AF14*): Threat modelling is the overall process of analysing risks, threats and vulnerabilities to an organisation and determining the likelihood of these threats compromising the organisation.
- *Security initiatives* (*AF15*): Data security can only be guaranteed through initiatives. This concerns suitable organisational and technical initiatives.

6. *Organisation of the master data management* (*DL6*): This level is about the design of the master data management through organisational measures. The level includes the following *AF*.

- *Ownership* (*AF16*): Ownership is the assignment of a business system to functional units deliberately created by the organisation on the basis of defined criteria in order to be able to subsequently derive responsibilities for the master data.
- *Responsibilities* (*AF17*): Accountability means that a person (or functional unit) is assigned responsibility for the maintenance of master data.
- *Data access* (*AF18*): Data access includes all measures to make selected data accessible to a selected user field so that it can be reused.
- *Data utilisation* (AF19): Data utilisation is the basis for the use of master data in processes and for decisions on the way to a data-driven company. An essential part of this is the adaptation or conversion into a more readable format.

7. *Resources in master data management* (*DL7*): This level is about the design of the socio-technical system to support master data management in business systems. The level includes the following *AF*:

- *Personnel/labour* (*AF20*): To fulfil operational tasks, personnel should be motivated and have a broad set of relevant skills (competencies) related to master data.
- *Technology/systems* (*AF21*): Technologies are tools, machines and devices that help people to do things. An application system is a system that includes all programme functions that are developed, implemented and used as application software for machine support in master data management.

8. *Controlling in master data management* (*DL8*): This level is about the design of the continuous monitoring and maintenance of master data. The level includes the following *AF*:

- *Metrics/key performance indicators (KPIs)* (*AF22*): Metrics/KPIs are quantitative measurement values that can be used to monitor and evaluate the success or failure of processes and decisions in master data management.
- *Data analysis* (*AF23*): Data analysis describes the process of extracting valuable information in master data management from raw data and their evaluation.

4.5. Maturity levels

For the definition of the maturity levels (ML), the paper orientated itself on the "capability maturity model" developed by Paulk et al. (1993). In contrast to Spruit and Pietzka (2015), the most used maturity model, a level with a non-existent ML (level 0) was explicitly taken into account, as the lack of knowledge of master data management in business systems — not in its entirety, but in its parts — is assumed to be quite realistic. This assumption was confirmed in the discussion with the experts. At level 1, master data management is initial, i.e., reactive and controlled on an *ad hoc* basis. Anomalies in the master data management serve as the starting point for solution action. When level 2 (isolated) is reached, master data management initiatives are established, but in isolation without internal coordination or overarching integration. Master data management is carried out in the functional units according to their own best practice. At level 3 (established), standard processes in master data management are established throughout the organisation and at level 4 (foresighted), measurement takes place in master data management. At level 5 (optimized), the focus is on a continuous improvement process in order to maximise the benefits. Achieving each maturity level means that all the capabilities of that level have been fulfilled. The following maturity levels can be summarised:

- *ML0* (non-existent): The organisation has not identified any problems or issues in master data management.
- *ML1* (initial): Action in master data management is controlled in an *ad hoc*, uncontrolled and reactive manner.
- *ML2* (isolated): Action in master data management is isolated, and solutions are communicated from the bottom up.
- *ML3* (established): Master data management standard processes are defined and documented.
- *ML4* (foresighted): Master data management is measured and process capability is determined.
- *ML5* (optimised): The focus of master data management is on the continuous improvement of process performance.

5. DISCUSSION

Despite the consideration of current research findings in master data management and data governance, the proposed maturity model still has some points of contention.

This model is relatively rigid in its predefined stages and maturity levels. This can lead to organizations feeling forced to adapt their unique processes and structures to the proposed model, rather than tailoring the model flexibly to their individual requirements. Introducing more dynamism into the model could help overcome this issue.

Despite the detail in the design levels and assessment criteria, the model could encourage a strong focus on achieving formal maturity levels, which can lead to "tick-box" thinking in organizations, where achieving a certain level becomes more important than actually improving process quality. To overcome this, the focus should be on achieving goals and results at the individual design levels. The question "Why are we doing this?" should be clearly answered to ensure that each measure has a clear benefit and impact. Key performance indicators should be developed that reflect actual results and improvements.

The practical feasibility and measurable benefits of the development paths proposed in the model can also be questioned. The implementation and regular application of the maturity model involve the use of resources, which can be a challenge, especially for smaller operational systems. Consideration should be given here to combining the maturity model with measurable performance indicators.

Finally, there is a risk that the dynamic and rapidly changing nature of modern business processes and thus the complexity in the data as a result of increasing digitalization and the use of diverse IT systems (with often heterogeneous data storage) is not sufficiently taken into account. The proposed model could potentially quickly become outdated and no longer meet current requirements. This point can also be addressed by making the model more dynamic.

These points must be the subject of future research.

6. CONCLUSION

Master data management is a systematic process for managing critical business objects in business systems, the master data, including customers, products, suppliers and accounts, which are used in multiple systems and applications. The goal of master data management is to ensure a unified, accurate and consistent view of this data across the entire business system. The maturity model proposed in this study provides support in this regard and consists of eight design levels with a total of 23 assessment factors on six maturity levels, framed by six organisational aspects.

The maturity model for master data management proposed in this study makes a significant theoretical contribution by providing a structured framework that enables organizations to systematically assess the maturity and effectiveness of their processes, technologies and organizational structures. The proposed model defines different levels of maturity and provides detailed descriptions of the characteristics expected at each level. In this way, it supports organizations in identifying weaknesses and developing targeted improvement strategies in master data management. It not only serves as a diagnostic tool but also provides a roadmap for continuous improvement in master data management by promoting best practices and standards. The theoretical basis is based on assumptions that organizations can achieve sustainable performance improvements by systematically progressing from lower to higher maturity levels. This enables standardized assessment and comparability across different industries and organizations, which contributes to the dissemination of knowledge and the implementation of best practices and fosters the application and implementation of data governance.

The proposed model further has a significant impact on management by providing a structured method for assessing and improving organizational processes and capabilities. By applying the model, managers can determine the current maturity level of their organization in terms of specific master data management capabilities and processes. This enables targeted identification of strengths and weaknesses and prioritization of improvement measures. It promotes systematic and continuous improvement by providing clearly defined development stages and the corresponding characteristics of each stage. This supports management in creating roadmaps for process optimization and resource allocation. In addition, the model facilitates communication and understanding of complex improvement initiatives within the organization by creating a common language and understanding. Overall, the proposed maturity model helps to increase the efficiency and effectiveness of management decisions and improve the long-term performance of the organization.

Despite the consideration of current research findings in master data management and data governance, the proposed maturity model also has limitations (limits of research). As it is a new (theoretically based) model, it has not yet been empirically tested (i.e., there is currently a lack of valid data). It is intended to apply the maturity model to organizations of different sizes and from different industries in order to validate its effectiveness and adaptability in different contexts. Longitudinal studies are also planned to provide insights into how the maturity level of an organization's master data management develops over time and how optimization strategies affect business results (performance measurement). New technologies (artificial intelligence, machine learning) are to be examined in this context in order to evaluate their contribution to improving master data management processes and overcoming identified challenges. Another limitation is that the selection of criteria, dimensions, and metrics in the model is subjective and influenced by the assumptions and perspectives of the researcher, which can lead to different interpretations and applications. Finally, models often have to integrate different disciplines and perspectives, which poses challenges in terms of the consistency and coherence of theoretical assumptions. Each empirical application contributes to overcoming this limitation and generalizing the model.

Future research on the maturity model will focus on several key areas to further improve the effectiveness and applicability of the model. One focus is on the development towards a dynamic and thus more flexible model to better adapt to the specific and constantly changing needs of operational organizations. Master data management can be interpreted as a viable system, and management cybernetics provides helpful support for its tools. This could include the integration of artificial intelligence and machine learning to create personalized maturity paths and provide continuous feedback. Another approach is to adapt the maturity model to different industries and organizational sizes to expand its relevance and application possibilities. Longitudinal studies should provide data here. In addition, research into combining the maturity model with agile methods should open up new ways of finding the balance between structured processes and the necessary flexibility in fast-moving business environments. Finally, the focus is on investigating the long-term effects of applying the maturity model on the organizational performance and innovative capacity of operational systems in order to gain deeper insights into the sustainability and actual benefits of the model.

REFERENCES

Abraham, R., Schneider, J., & vom Brocke, J. (2019). Data governance: A conceptual framework, structured review, and research agenda. *International Journal of Information Management, 49*, 424–438. https://doi.org/10.1016/j.ijinfomgt.2019.07.008

Arthofer, K., & Girardi, D. (2017). Data quality- and master data management: A hospital case. In *Studies in health technology and informatics* (Vol. 236, pp. 259–266). IOS Press. https://doi.org/10.3233/978-1-61499-759-7-259

Becker, J., Knackstedt, R., & Pöppelbuß, J. (2009). Dokumentationsqualität von Reifegradmodellentwicklungen (Report No. 123). In J. Becker, B. Hellingrath, S. Klein, H. Kuchen, U. Müller-Funk, & G. Vossen (Eds.), *Arbeitsberichte des Instituts für Wirtschaftsinformatik*. Westfälische Wilhelms-Universität Münster, Institut für Wirtschaftsinformatik. https://www.wi.uni-muenster.de/sites/wi/files/publications/ab123.pdf

Beckmann, H. (2019, April 8). Stammdatenmanagement. In *Enzyklopädie der Wirtschaftsinformatik*. https://wi-lex.de/index.php/lexikon/informations-daten-und-wissensmanagement/informationsmanagement /informationsmanagement-aufgaben-des/stammdatenmanagement/

Benker, T., & Jürck, C. (2016). Das betriebliche Informationssystem. In T. Benker, C. Jürck, & M. Wolf (Eds.), *Geschäftsprozessorientierte Systementwicklung: Von der Unternehmensarchitektur zum IT-System* (pp. 25–32). Springer. https://doi.org/10.1007/978-3-658-14826-3

Bitkom. (2022). *Datenschutz-Reifegradmodell. Reifegradmodell zur Abbildung von technisch-organisatorischen Maßnahmen bei der Auftragsverarbeitung. Betaversion zum Review.* https://www.bitkom.org/sites /main/files/2022-08/220802_LF_Datenschutz-Reifegradmodell%20Betaversion.pdf

Bley, K., Schön, H., & Strahringer, S. (2020). Overcoming the ivory tower: A meta model for staged maturity models. In M. Hattingh, M. Matthee, H. Smuts, I. Pappas, Y. K. Dwivedi, & M. Mäntymäki (Eds.), *Responsible design, implementation and use of information and communication technology* (Vol. 12066: Lecture notes in computer science, pp. 337–349). Springer. https://doi.org/10.1007/978-3-030-44999-5_28

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Cambridge University Press. (n.d.). Headcount. In *Cambridge dictionary*. https://dictionary.cambridge.org /de/worterbuch/englisch/headcount

DAMA International. (2017). *DAMA-DMBOK: Data management body of knowledge* (2nd ed.).

DSMM. (n.d.). *Data security maturity model*. https://docs.datasecurity.org/

Dyché, J., & Levy, E. (2007). *The baseline on MDM: Five levels of maturity for master data management*. Baseline Consulting Group. http://download.101com.com/tdwi/ww29/Baseline_The_Baseline_on_MDM.pdf

Fink, A. (2019). *Conducting research literature reviews: From the Internet to paper*. SAGE Publications.

Firican, G. (n.d.). *Stanford data governance maturity model*. LightsOnData. https://www.lightsondata.com/data-governance-maturity-models-stanford/

Gamero, A., Garcia, J., & Raymundo, C. (2019). Reference model with a lean approach of master data management in the Peruvian microfinance sector. In *Proceedings of the 2019 8th International Conference on Industrial Technology and Management* (pp. 56–60). IEEE. https://doi.org/10.1109/ICITM.2019.8710697

Gartner. (2015). *Use the Gartner MDM maturity model to create your MDM roadmap*. https://www.gartner.com/en /documents/3044517

Grande, M. (2011). Reifegradmodelle. In *100 Minuten für Anforderungsmanagement: Kompaktes Wissen nicht nur für Projektleiter und Entwickler* (pp. 113–116). Vieweg+Teubner. https://doi.org/10.1007/978-3-8348-8135-9_15

Grant Thornton. (2019). *Data protection maturity model*. https://www.grantthornton.ie/globalassets/1.-member-firms/ireland/insights/publications/grant-thornton-data-proctection-model-brochure.pdf

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly, 28*(1), 75–105. https://doi.org/10.2307/25148625

IBM. (2007). *IBM master data management: Effective data governance*. https://public.dhe.ibm.com/software/data/sw-library/mdm/whitepaper/mdm-data-governance.pdf

Iqbal, R., Yuda, P., Aditya, W., Hidayanto, A. N., Handayani, P. W., & Harahap, N. C. (2019). Master data management maturity assessment: Case study of XYZ company. In *Proceedings of the 2019 2nd International Conference on Applied Information Technology and Innovation* (pp. 133–139). IEEE. https://doi.org/10.1109 /ICAITI48442.2019.8982123

Jacobs, S. (2019, April 8). Reifegradmodell. In *Enzyklopädie der Wirtschaftsinformatik*. https://wi-lex.de/index.php /lexikon/entwicklung-und-management-von-informationssystemen/systementwicklung/reifegradmodelle/

Kampker, A., Schuh, G., Schittny, B. (2011). Unternehmensstruktur. In G. Schuh & A. Kampker (Eds.), *Strategie und Management produzierender Unternehmen: Handbuch Produktion und Management 1.* (pp. 133–229). Springer. https://doi.org/10.1007/978-3-642-14502-5_3

Kaur, D., & Singh, D. (2023). Master data management maturity evaluation: A case study in educational institute. In J. Choudrie, P. Mahalle, T. Perumal, & A. Joshi (Eds.), *ICT with intelligent applications* (Vol. 311: Smart innovation, systems and technologies, pp. 211–220). Springer. https://doi.org/10.1007/978-981-19-3571-8_22

Kitchenham, B. (2004). *Procedures for performing systematic reviews* (Keele University Technical Report TR/SE-0401). https://www.inf.ufsc.br/~aldo.vw/kitchenham.pdf

Krismawati, D., Ruldeviyani, Y., & Rusli, R. (2019). Master data management maturity model: A case study at statistics business register in statistics Indonesia. In *Proceedings of the 2019 International Conference on Information and Communications Technology* (pp. 931–936). IEEE. https://doi.org/10.1109 /ICOIACT46704.2019.8938482

Kumar, S. (2010). MDM maturity model. *Information Management Newsletters*.

Larson, D. (2023). *TDWI data management maturity model assessment guide.* TDWI. https://tdwi.org/research/2023/03/diq-all-tdwi-data-management-maturity-model-guide.aspx
Loshin, D. (2010). *MDM components and the maturity model* (A DataFlux White Paper). DataFlux Corporation. https://www.knowledge-integrity.com/Assets/MDMComponentsMaturityModel.pdf
Mecca, M. (2014). *Data management maturity model introduction.* CMMI Institute. https://cdn.ymaws.com/www.globalaea.org/resource/collection/68814379-BF7E-41C8-B152-18A617F9C0AA/Data_Management_Maturity_Model_Introduction_-_Dec_12_2014.pdf
Merkus, J. (2015). *Data governance maturity model* (Master's thesis, Open Universiteit). https://datagovernancematurity.wordpress.com/wp-content/uploads/2016/03/datagovernancematuritymodel_thesis_janrutgermerkus_nov2015.pdf
Oracle. (2011). *Oracle MDM maturity model* (An Oracle White Paper). https://de.scribd.com/document/82739843/Mdm-Maturity-Model-Wp-414600
Otto, B., & Hüner, K. M. (2009). *Funktionsarchitektur für unternehmensweites Stammdatenmanagement* (Report No. BE HSG/CC CDQ/14). University of St. Gallen, Institute of Information Management. https://www.alexandria.unisg.ch/server/api/core/bitstreams/59668dee-4f9d-4928-94b2-c4624e080176/content
Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, Article 71. https://doi.org/10.1136/bmj.n71
Paulk, M. C., Curtis, B., Chrissis M. B., & Weber, C. V. (1993). Capability maturity model, version 1.1. *IEEE Software, 10*(4), 18–27. https://doi.org/10.1109/52.219617
Peffers, K., Rothenberger, M., Tuunanen, T., & Vaezi, R. (2012). Design science research evaluation. In K. Peffers, M. Rothenberger, & B. Kuechler (Eds.), *Design science research in information systems: Advances in theory and practice* (Vol. 7286: Lecture notes in computer science, pp. 398–410). Springer. https://doi.org/10.1007/978-3-642-29863-9_29
Pratama, F. G., Astana, S., Yudhoatmojo, S. B., & Hidayanto, A. N. (2018). Master data management maturity assessment: A case study of organization in ministry of education and culture. In *Proceedings of the 2018 International Conference on Computer, Control, Informatics and its Applications* (pp. 1–6). IEEE. https://doi.org/10.1109/IC3INA.2018.8629524
Qodarsih, N., Yudhoatmojo, S. B., & Hidayanto, A. N. (2018). Master data management maturity assessment: A case study in the supreme court of the republic of Indonesia. In *Proceedings of the 2018 6th International Conference on Cyber and IT Service Management* (pp. 1–7). IEEE. https://doi.org/10.1109/CITSM.2018.8674373
Rahman, A. A., Dharma, P. G., Fatchur, R. M., Freedrikson, A. N., Ari, B. P., & Ruldeviyani, Y. (2019). Master data management maturity assessment: A case study of a Pasar Rebo Public Hospital. *International Journal of Emerging Trends in Engineering Research, 7*(5), 15–20. https://doi.org/10.30534/ijeter/2019/02752019
Rishartati, P., Rahayuningtyas, N. D., Maulina, J., Adetia, A., & Ruldeviyani, Y. (2019). Maturity assessment and strategy to improve master data management of geospatial data case study: Statistics Indonesia. In *Proceedings of the 2019 5th International Conference on Science and Technology* (Vol. 1, pp. 1–6). IEEE. https://doi.org/10.1109/ICST47872.2019.9166400
Saunders, M. N. K., Lewis, P., & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson.
Schewe, G. (2018a). Aufgabenanalyse. In *Gabler Wirtschaftslexikon.* https://wirtschaftslexikon.gabler.de/definition/aufgabenanalyse-31803/version-255354
Schewe, G. (2018b). Aufgabensynthese. In *Gabler Wirtschaftslexikon.* https://wirtschaftslexikon.gabler.de/definition/aufgabensynthese-30797/version-254373
Schmuck, M. (2024). Relevance of master data management as part of data governance and a critical factor for corporate success: A scientometric analysis. In *Proceedings of the EU FInance, REgulation and Business International Conference.* https://doi.org/10.2139/ssrn.4964064
Siemon, D. (2022, February 10). *Methods in design science research.* Design Science Research. https://design-science-research.de/en/post/methods-in-dsr/
Simon, H., Clausen, G., Tacke, G., & Dautzenberg, N. (2018). Umsatz. In *Gabler Wirtschaftslexikon.* https://wirtschaftslexikon.gabler.de/definition/umsatz-48634/version-271885
Spruit, M., & Pietzka, K. (2015). MD3M: The master data management maturity model. *Computers in Human Behavior, 51*, 1068–1076. https://doi.org/10.1016/j.chb.2014.09.030
Statistisches Bundesamt. (n.d.). *Arbeitsmarkt: Wirtschaftszweig.* https://www.destatis.de/DE/Themen/Arbeit/Arbeitsmarkt/Glossar/wirtschaftszweig.html
Venable, J., Pries-Heje, J., & Baskerville, R. (2016). FEDS: A framework for evaluation in design science research. *European Journal of Information Systems, 25*(1), 77–89. https://doi.org/10.1057/ejis.2014.36
Zimmermann, F.-O. (1999). *Betriebliche Informationssysteme in virtuellen Organisationen.* Deutscher Universitätsverlag Wiesbaden. https://doi.org/10.1007/978-3-322-92389-9
Zúñiga, D. V., Cruz, R. K., Ibañez, C. R., Dominguez, F., & Moguerza, J. M. (2018). Master data management maturity model for the microfinance sector in Peru. In *Proceedings of the 2018 2nd International Conference on Information System and Data Mining* (pp. 49–53). https://doi.org/10.1145/3206098.3206127

APPENDIX

Table A.1. List of papers guiding the research questions

Reference(s)	Document type	Questions				Own maturity model	Industry	Industry details	Comment(s)
		1	2	3	4				
Rahman et al. (2019)	Conference Paper		×	×	×	No	Healthcare	Pasar Rebo Public Hospital	Application of MD3M (Spruit & Pietzka, 2015)
Arthofer and Girardi (2017)	Article	×					Healthcare	LeiVMed	
Gamero et al. (2019)	Conference Paper		×	×	×	No	Finance	Peruvian Microfinance Sector	Application of DMBOK (DAMA International, 2013)
Iqbal et al. (2019)	Conference Paper		×	×	×	No	Provider	Provider of infrastructure networks for banks	Application of MD3M (Spruit & Pietzka, 2015)
Kaur and Singh (2023)	Conference Paper		×	×	×	No	Education	Government educational institute	Application of MD3M (Spruit & Pietzka, 2015)
Krismawati et al. (2019)	Conference Paper		×	×	×	No	Statistics	Statistics Indonesia (Statistical Business Register)	Application of MD3M (Spruit & Pietzka, 2015)
Pratama et al. (2018)	Conference Paper		×	×	×	No	Education	Ministry of Education and Culture	Application of MD3M (Spruit & Pietzka, 2015)
Qodarsih et al. (2019)	Conference Paper		×	×	×	No	Justice	Supreme Court of Indonesia Republic	Application of MD3M (Spruit & Pietzka, 2015)
Rishartati et al. (2019)	Conference Paper		×	×	×	No	Statistics	Statistics Indonesia (Geospatial Data)	Application of MD3M (Spruit & Pietzka, 2015)
Spruit and Pietzka (2015)	Article	×	×		×	Yes, MD3M	Energy sector	Trading company	./.
Zúñiga et al. (2018)	Conference Paper	×	×		×	Yes	Finance	Microfinance sector in Peru	./.
Oracle (2011)	White Paper	×	×		×	Yes	./.	./.	./.
Loshin (2010)	White Paper	×	×		×	Yes	./.	./.	./.
Kumar (2010)		×	×		×	Yes	./.	./.	./.
Gartner (2015)	White Paper	×	×		×	Yes	./.	./.	./.
Dyché und Levy (2007)	White Paper	×	×		×	Yes	./.	./.	./.
Larson (2023)	White Paper	×	×		×	Yes	./.	./.	./.
Mecca (2014)	Presentation	×	×		×	Yes	./.	./.	./.
DAMA International (2013)	Presentation	×	×		×	Yes	./.	./.	./.
IBM (2007)	White Paper	×	×		×	Yes	./.	./.	./.
Merkus (2015)	Master Thesis	×	×		×	Yes	./.	./.	./.
Firican (n.d.)	White Paper	×	×		×	Yes	./.	./.	./.
Bitkom (2022)	White Paper	×	×		×	Yes	./.	./.	./.
Grant Thornton (2019)	White Paper	×	×		×	Yes	./.	./.	./.
DSMM (n.d.)	Article					Yes	./.	./.	./.

Source: Author's elaboration