Developing a Focus Area Maturity Model for Data-driven Decision-making

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Abstract

Context: As the global market becomes more competitive, data-driven organizations that excel at transforming data into meaningful actions, are gaining an increasing advantage. Companies strive to become data-driven to enhance efficiency, improve customer experiences, and make more informed and accurate business decisions. However, research suggests that organizations struggle with developing the capabilities necessary to become data driven. This challenge stems from a lack of maturity literature that offers a holistic approach to data-driven capability development.

Objective: In this research we present a Focus Area Maturity Model (FAMM) for Data-Driven Decision-Making (DDDM) as an artifact designed to assist practitioners with assessing and developing data-driven capabilities. Focus area maturity models can be used to assess the maturity level of an organization in specific domains and serve as a launchpad for the development of an improvement strategy. We present a model consisting of 12 focus areas and 54 capabilities that embody DDDM.

Method: The model is designed using established FAMM development methods, which are grounded in the design science research methodology. Model elements are derived from literature and practice through triangulation, consisting of a semi-systematic literature review, expert focus groups and a case study.

Results: The design process of the model and its components are described in detail and its application is illustrated using a case study.

Conclusions: We present the Data Driven Decision-making Focus Area Maturity Model (DDDMFAMM) and assessment instrument as tools for practitioners that provide actionable insights and a structured approach to enhance data-driven maturity iteratively. We propose that DDDM maturity development functions as a causal loop and provide intra- and interdependencies for capabilities across focus areas that illustrate how different aspects of DDDM are related. Model components are evaluated for their relevance and accuracy and our study shows that the DDDMFAMM is an effective tool that can help organizations incrementally improve their exploitation of data. We also propose a novel assessment method that improves assessment repeatability and institutionalization and offer various recommendations within the context of our case study and data-driven capability development in general.

Executive summary

As technology continues to evolve and our modern society generates more and more data, data-driven organizations gain an advantage over their competitors. The differentiating factor for innovative data driven organizations is that they use data and analytics to make better more accurate decisions, improve efficiency and develop new business opportunities. Data-driven decision-making is the act of making informed decisions based on the results of data analysis. Decisions that may benefit from this can be found at any level, be it strategic, tactical, or operational. Examples include, product development and market expansion, supply chain management and sales strategy adjustment, or production scheduling and inventory management. Data initiatives should not be seen as cost-centers, but instead as a means of generating new business value.

Research has identified that many organizations still struggle to extract value from their data due to a lack of knowledge about the capabilities necessary to become data driven. Data-driven capabilities describe how organizational assets should be used and practices applied to generate new data assets or support data-driven business activities. Examples of such assets and activities are applications, dashboards, performance metrics or prediction models, and financial administration, project management, sales, or product maintenance. To address this issue, we developed a maturity assessment framework for data-driven decision-making based on established best practice and academic research that organizations can use to assess how advanced their capabilities are in terms of utilizing data to support decision-making and develop an iterative improvement plan.

As part of this assessment, domain experts and data product users across various business functions of the organization were consulted using a questionnaire. Assessment results indicate the firm possesses a strong technical foundation for performing analytics and developing data products but doesn't utilize it effectively. The technical data-driven capabilities of the firm don't seem to translate properly to its use of data in decision-making processes by the business. This is likely resultant from a lack of clarity about the desired business value derived from data and results in a lack of commitment to data initiatives and poor data product adoption. Institutionalization of data activities and documentation in particular seem to suffer heavily, as there are additional costs associated with these tasks that don't directly add business value. To better align the maturity across different areas we recommend the following activities as part of an improvement strategy.

(1) Communicate to staff how data should add value to the business.
- Define clear objectives for the organizational use of data that add business value.
- Launch an awareness campaign to continually promote data initiatives and becoming data-driven to operational and management staff.

(2) Document critical data elements.
- Identify data elements that support critical business functions.
- Prioritize the documentation and inventorization of critical data elements for future data governance and architecture activities.

(3) Document business data definitions.
- Establish a common understanding of data and information across the organization.
- Create referenceable knowledge bases that provide information about data objects to both developers and users.

(4) Cross-functional collaboration for data product analysis and development.
- Develop data products in collaborative initiatives between IT, BI and business users.
- Design data products with clear goals that support specific value adding business activities.
- Embed the use of data products in the standard workflow of the business functions for which they were designed.

(5) Establish data (product) policies and standards and assign data classifications.
- Document agreed upon approaches that allow for consistent measurement, qualification and exchange of data and information.

(6) Data quality assessment and improvement.
- Fund a dedicated data quality assessment and remediation project, empowered with the necessary authority to make meaningful changes to data input processes.
- Launch a data quality awareness campaign that promotes the reporting of poor data quality among staff.

(7) Institutionalize the use of a maturity assessment.
- Monitor development progress through periodic assessments.
- Continually improve data-driven decision-making maturity.

Chapter 9 covers our recommendations in greater detail. Once these development steps have been taken and the organization can supply reliable accurate management information, monitor its business processes, and act based on descriptive metrics, we recommend they evaluate what level of data-driven decision-making maturity they wish to achieve based on an analysis of their competitive environment.

Academic research has demonstrated that being data-driven improves decision-making outcomes and organizational performance. On the other hand, publications by PwC and McKinsey report that up to 45% of work activities could be automated by current technologies and that data-driven organizations can outperform their competitors by up to 6% in profitability and 5% in productivity, while being 23 times more likely to beat their competitors in terms of new customer acquisition. Becoming data-driven is a challenging yet rewarding transformation that starts with assessing your current data-driven decision-making maturity and progressively developing the necessary organizational capabilities.

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1. Introduction

The digital transformation ushered in a new era of organizational change. As firms continue to digitize their processes, data becomes an asset that leading organizations leverage to improve their capabilities and generate value. As a consequence, the concept of a data-driven culture is continuously being adopted by more organizations that have become aware of its benefits (Assur & Rowshankish, 2022). This is keenly demonstrated by the increasing prevalence of business intelligence and analytics (BI&A) systems that improve decision-making (Visinescu et al., 2017) and its outcomes (Chaudhuri et al., 2021; Erjavec et al., 2017) by enhancing decision makers' knowledge. This in turn improves organizational performance (Popovič et al., 2019).

However, many organizations struggle to extract value from their data, due to a lack of knowledge about the capabilities necessary to become data-driven, how to develop them and adapt to them culturally (Bean, 2023; Crummenerl et al., 2023). Moreover, these challenges aren't new (Henke et al., 2016). Barriers to developing such capabilities are not limited to technical resources and information system (IS) quality, but also include organizational aspects such as incorporating data-driven insights into business processes, attracting or developing the necessary talent and creating a culture of data-driven thinking. As data, analytics and more recent advances in machine learning and AI provide a competitive advantage, the pressure on organizations to develop data-driven capabilities continues to increase.

These developments have stimulated a proliferation of scientific and especially practitioner literature on data driven capabilities. In particular, grey literature proposing capability maturity models (CMM) and assessment instruments (Celina M. Olszak, 2013; Chuah et al., 2011; Koenders, 2023; Król & Zdonek, 2020) that claim to guide organizations in the development of data driven capabilities. However, such literature and maturity models in general have long standing limitations (Bach, 1994; Pearce, 1994) and even more recently have received critiques (Adekunle et al., 2022; Albliwi et al., 2014; van Steenbergen et al., 2010). Information about the specific methodology used to create the model or the inner workings of the model are often proprietary, the model may not be peer reviewed, tested for accuracy or usability and no guidance for practical application of the model and its assessment instrument may be provided. These limitations are related to the fact that CMMs are often designed by practitioners based on experience, anecdotal evidence, and best practice to help organizations identify process weakness and improvement areas (Biberoglu & Haddad, 2002). CMMs can be considered staged or continuous fixed-level models as defined by van Steenbergen et al. (2010). Staged fixed-level models distinguish a fixed number of maturity levels and assign specific capabilities to each level, while continuous fixed-level models contain various focus areas – often referred to as dimensions or domains – in which each of the maturity levels are distinguished (Smits & Van Hillegersberg, 2015). Van Steenbergen et al. (2010) argue that a limitation of fixed-level models is that they don't express the interdependencies between the capabilities of different dimensions and therefore provide insufficient guidance relating to the order in which capabilities should be implemented (Biberoglu & Haddad, 2002), which limits the practical utility of the maturity model. Moreover, certain fixed-level models or frameworks may be perceived as too heavy and large to use or even comprehend for some organizations. We also share the view that the variation in levels between established fixed-level maturity models suggests that assuming the existence of generic maturity levels – like aware, reactive, proactive, managed, optimized – is an oversimplification.

To resolve these issues, van Steenbergen et al. (2010) propose the focus area maturity model (FAMM), which is built on the concept that various focus areas need to be developed to a certain level to achieve maturity in an overarching functional domain. Focus areas may include such things as: the implementation of certain processes, alignment between disciplines, and the development of certain competencies. FAMMs specify a number of maturity levels specific to each focus area based on a series of progressively mature capabilities unique to the focus area. This implies that focus areas in the model may each have a different number of maturity levels. Additionally, all capabilities across all focus areas are juxtaposed and both intra- and interdependencies are defined so that an incremental development path can emerge (Sanchez-Puchol & Pastor-Collado, 2017; van Steenbergen et al., 2010). Due to their practical utility, FAMMs continue to see development across various domains (Overeem et al., 2022; Smits & Van Hillegersberg, 2015; Yigit Ozkan et al., 2021).

However, even with the practical utility embedded in FAMMs, there appear to be surprisingly few of them relative to the maturity model types previously described (Sanchez-Puchol & Pastor-Collado, 2017). Moreover, the data-driven decision-making (DDDM) literature in particular, appears to be largely devoid of such artifacts. At the same time, it is startling that with the abundance of theoretical and practitioner DDDM related literature available, organizations still struggle to implement data-driven capabilities. This gap between the theoretical knowledge base and the practical environment spawns the need for an artifact that can bridge the gap between theory and practice and guide organizations through the data-driven maturity process. Therefore, this research attempts to answer the industry need for an integrated maturity model and comprehensible assessment instrument concerning DDDM. We develop a data-driven decision-making focus area maturity model (DDDMFAMM) and assessment instrument that is designed to help organizations identify their current maturity level in the data-driven evolution, understand the associations between the different aspects of data-driven maturity and provide actionable suggestions on how to incrementally develop the necessary capabilities needed to attain a higher level of data-driven maturity.

2. Method

The goal of this research is to develop an artifact that supports businesses in assessing their current maturity in the domain of data-driven decision making, and in the process, lays out a capability development path for incremental improvement based on theory and best practice. To achieve this, we apply the FAMM development process formalized by van Steenbergen et al. (2010), which is grounded in the Design Science Research Methodology (DSRM) (Peffers et al., 2007). The DSRM sets out a six-step process for IS research that aims to develop an artifact in order to answer an industry need (Figure 1).

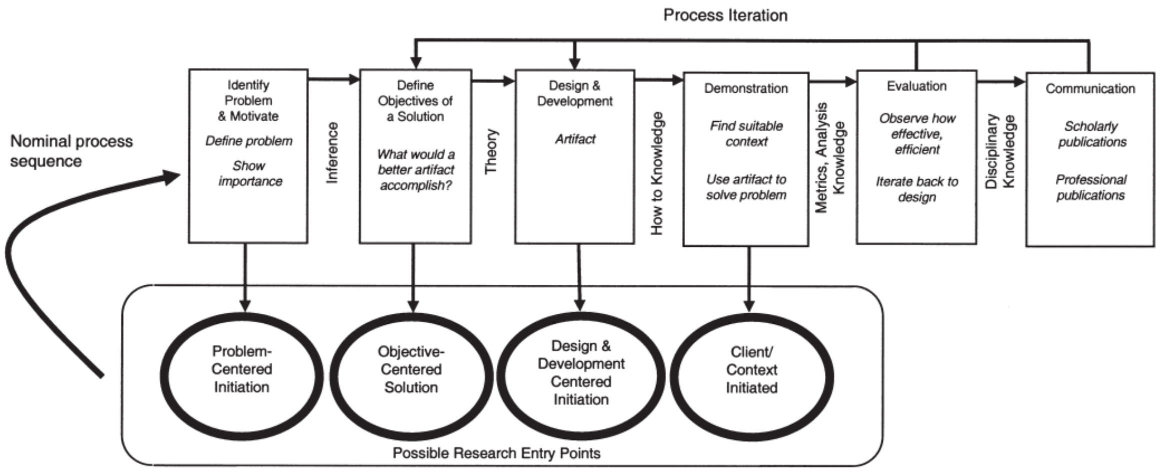

Figure 1. Six-step design science research process (Peffers et al., 2007)

2.1. FAMM DSRM development process

The nominal DSRM process begins with identifying a problem and showing the importance of creating a solution to motivate the research. Depending on the research objective, the DSRM process can be initiated from different stages. As this research covers the development of a new focus area maturity model and assessment instrument in response to an industry need, we initiate the design process from an objective-centered solution and proceed accordingly. Therefore, we begin the DSRM process in the second stage in which the objectives of the solution are defined. The objectives of the solution presented by this research – a focus area maturity model for data-driven decision-making – is to enable practitioners to assess organizational DDDM maturity within a reasonable timeframe and provide actionable suggestions to reach higher maturity levels through incremental improvement, based on extant literature and best practices.

In the third stage of the DSRM process, an initial design of the artifact can be generated. FAMM development utilizes both theoretical knowledge from extant literature and practical experience (Sanchez-Puchol & Pastor-Collado, 2017). In the design phase, the initial focus areas and their associated capabilities are identified through literature review and complimented with expert discussions. This triangulated approach enables the effective gathering of information for the creation of initial model components from multiple expert perspectives and provides internal validity by reducing potential bias introduced by the researchers during the development of the initial model. Capability dependencies are logically determined based on extant literature and capabilities positioned in the matrix based on their dependencies, best practice, and feedback from expert discussion. In addition to model design, the corresponding assessment instrument to measure DDDM maturity is developed and the recommended improvement actions are defined concurrently and evaluated through the same means.

This research effectuates expert discussions by collaborating with the Dutch branch of a large multinational engineering firm. A panel of 7 experts with expertise on the various facets of DDDM is assembled and each aspect of the model and assessment instrument discussed using a semi-structed discussion approach. The expert group is comprised of the CDO, the director of quality, customer satisfaction and business improvement (QCSBI), a master data specialist, BI solution manager, enterprise architect, an internal data governance manager and a former board member of the DAMA NL change management task force, we will refer to as a data governance consultant. Experts are requested to evaluate the model and assessment instrument in terms of covering all relevant facets of DDDM maturity, being understandable and applicable in an organizational setting, providing actionable improvement suggestions and capability levels having a progressing maturity. To ensure all topics are covered, we established a semi-structured discussion guide consisting of four statements for each focus area and five statements for each capability (Appendix 1: Expert discussion guide). During expert discussion participants are first asked to rate the statements using a Likert scale, ranging from 1; strongly disagree to 7; strongly agree, then discuss their reasoning for the provided score with the other participants and suggest potential improvements. Additionally, experts are asked to provide their preferred capability implementation order based on practical experience. The outcomes of the design phase are a maturity model and assessment instrument that can be applied in an organizational context.

The fourth and fifth phases of the DSRM process cover a demonstration of the generated artifacts in a practical setting and the evaluation of its effectiveness. The effectiveness of the DDDMFAMM is initially demonstrated through a case study at the collaborating firm. Next, per the definitions of the solution objectives, the DDDMFAMM must prove to be applicable in the destined context; have its assessment completable in a reasonable amount of time; accurately provide insight into the organization's current DDDM maturity; and provide actionable improvement suggestions (Yigit Ozkan et al., 2021). Therefore, participants are requested to complete an evaluation questionnaire with various statements, to which they can respond using a 7-point Likert scale (Appendix 2). Finally, in the sixth phase, the results of the DSRM process must be communicated. The problem addressed by this research, its importance, and the DDDMFAMM artifact's utility, novelty, design rigor and effectiveness are all communicated through the publishing of this paper and the development of a digital DDDMFAMM assessment tool within the case study firm's enterprise information management (EIM) department.

In the interest of providing a comprehensible description of the inner workings of FAMMs, Figure 2 depicts a visualization of the FAMM development process together with the components of the model and their relationships using UML notation. Additionally, Appendix 3 contains a description of the 10-step process for FAMM development as applied in this research.

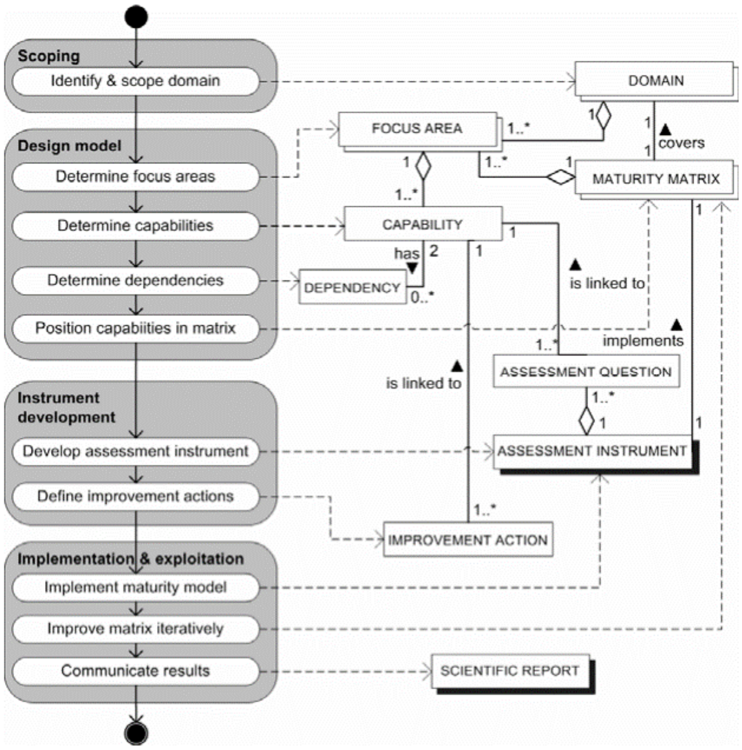

Figure 2. FAMM development process and component relations (van Steenbergen et al., 2010)

2.2. Research questions

To design a FAMM that provides organizations with the necessary information and recommendations to create an incremental change process, we must know what focus areas make up data-driven decision-making maturity, which capabilities a data-driven organization embodies, how these capabilities are related and through what actions they can be developed. This provides the desired state and recommended progression path on which a change management strategy can be built. Additionally, for the model to be applicable in an organizational setting it is paired with an assessment instrument that can measure the present state of maturity. To effectively measure this, we must know through which mechanisms the presence of a capability can be identified. In an attempt to formalize these research objectives, we define the following research questions:

1. What are relevant focus areas for data-driven decision-making maturity?
2. What capabilities make up each focus area?
3. How are these capabilities intra- and interrelated?
4. Through what actions can each capability be developed?
5. In which order should these capabilities be developed?
6. How can the presence of each capability be assessed?

Giving form to the focus areas and capabilities of the initial model starts with a review of existing maturity literature for the domains of DDDM to identify common best practices between different frameworks and models. This review also forms the basis for establishing effective means of developing each capability and an order in which they should be developed to improve data-driven decision-making.

2.3. Domain Scoping – Literature review

In order to define the focus areas and corresponding capabilities related to DDDM, we must identify its relevant components. In other words, what does data-driven entail; which dimensions does it cover; and how are these related? This is explored through a review of extant DDDM literature. Before a review can be performed, we must select an appropriate review methodology and define the scope of the domain of data-driven decision-making. To help us determine an appropriate review methodology, we performed an initial exploration of the DDDM domain by identifying the co-occurrence of different terms in academic DDDM literature on Scopus using text mining (Figure 3). This illustrates the different lenses through which DDDM has been studied and which areas of research have been focused on. For instance, in the purple cluster we encounter studies in the field of data governance and quality that investigate the importance of data handling and data quality in facilitating effective decision-making. Conversely, in the green cluster we see more of the organizational behavior and change management research that focuses on the impact of the human aspect, leadership and culture on the integration of data-driven practices and the human-machine learning process. Meanwhile, terms used by studies in the fields of information management and business intelligence (BI) – which encompasses the technology-driven processes for analyzing data and delivering actionable information to support informed decision-making (Ain et al., 2019) – are particularly dominant in the red cluster. Here, research revolves primarily around the tools and technologies for gathering, analyzing and visualizing data and the integration of BI in organizational processes. We also find more decision sciences related terms in the blue cluster, including risk assessment, uncertainty analysis, and decision theory. Lastly, the yellow cluster contains a majority of the terms predominantly ascribed to the fields of advanced analytics and machine learning. We observe that certain terms are similar or common across clusters and a very high frequency of inter-cluster co-occurrence for the general terms of data-driven and decision-making is present. This initial exploration emphasizes the broadness of the topic, its application in many areas of research and demonstrates that each tradition has its own conceptualization of aspects related to DDDM and uses different terminology.

Considering that DDDM is such a broad concept that has been studied through different lenses by researchers in diverse disciplines each with their own focus, this hinders a fully exhaustive systematic literature review. Therefore, we decided on a semi-systematic literature review (Snyder, 2019). More specifically, the meta-narrative review formalized by Wong et al. (2013). Meta-narrative review is a semi-systematic approach to literature review designed for topics that have been conceptualized differently and studied by different groups of researchers (Snyder, 2019). Wong et al. (2013) define these different research lenses as traditions and consider how these traditions have unfolded over time. The outcome of the semi-systematic literature review is then used to create a model for data driven maturity based on academic research. Afterwards, we collate the constructs of our model with components of the DDDM related maturity models we identified through our literature review, to establish the initial focus areas and capabilities.

The literature review is focused on identifying the different constructs of DDDM across the various research traditions in order to create a model for DDDM. Additionally, for each paper in the final collection, we determined which (if any) framework or model was used to describe the maturity of the covered DDDM components. Next, we collate the model and the various DDDM maturity models to establish the initial focus areas and their corresponding capabilities. In cases where no suitable maturity model for a respective focus area could be identified in the list of reviewed maturity models, we adapted an identified framework or consulted CMMs in grey literature. While grey literature sources may not all be peer reviewed, excluding this body of knowledge risks overlooking critical CMM based methods of measuring DDDM maturity. Additionally, due to grey literature not necessarily being peer reviewed, it is able to address more current topics, which is especially relevant in the context of recent developments around the organizational implementation of artificial intelligence (AI) technologies.

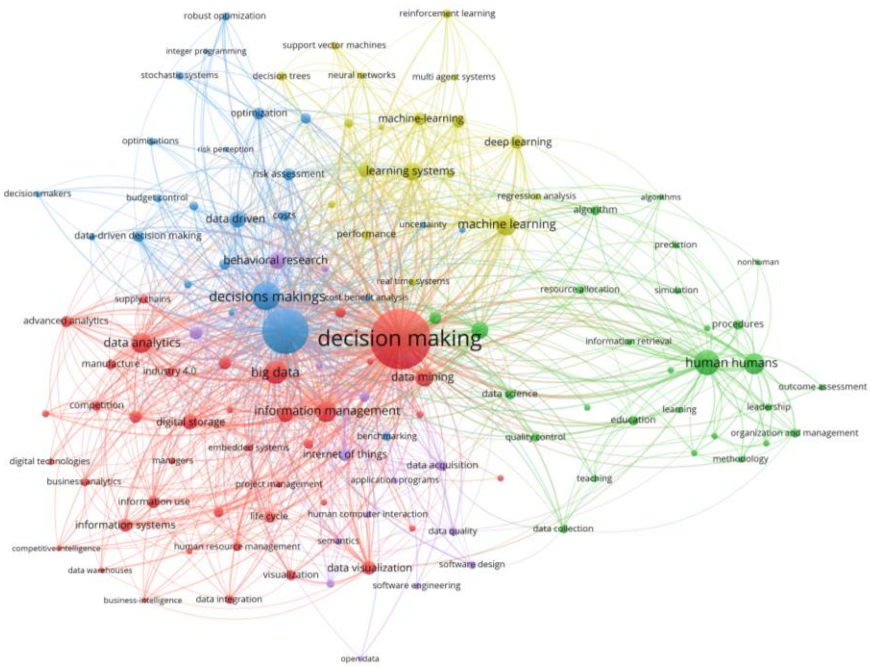

Figure 3. Text mining key-word analysis of extant literature DDDM from Scopus using Vos Viewer.

2.3.1. Scope & process

Before starting our systematic literature search, we performed an initial examination of extant literature reviews on the topics of BI, analytics and decision making to build on our own prior knowledge. As these domains each encompass a part of the broader concept of DDDM, this served the purpose of refining our search strategy by gaining an understanding of the overall literature. As a result of this exploration, the search scope was delimited to papers describing the following:

- Constructs or dimensions of DDDM.
- Causal relationships between DDDM constructs.
- Specific capabilities that when developed improve DDDM.
- Methods of measuring the presence of DDDM capabilities.
- Practices for DDDM capability development.
- Models or frameworks for measuring DDDM maturity.

Next, a systematic literature search was done on the world largest citation and abstract database Scopus between July and September 2023, using the following search term:

TITLE-ABS-KEY ((("data driven decision making" OR dddm OR ddd OR "business intelligence") W/1 (maturity OR mature OR "design principles" OR framework OR cmm OR "capability maturity model")) OR "data driven maturity" OR "data maturity") AND PUBYEAR > 2012 AND PUBYEAR < 2024

This search produced a collection of 358 documents, covering a range from 2013 to 2023. Furthermore, a set of 31 documents resultant from snowball searching and external recommendation were added to the document collection based on reader judgement.

2.3.2. Selection criteria

The complete collection was filtered down based on various selection criteria and consequently appraised to arrive at the final subset of 78 documents. Documents had to be written in English and be accessible. Publications in the initial database search had to be published in the past 10 years or earlier. Abstracts had to mention, to some extent, the dimensions or constructs of DDDM and their relations in the context of maturity. Abstracts that discussed best practice or theoretical mechanisms for DDDM capability development were also of particular interest. Highly technical literature that discusses the development of new technologies or the issues between extant technologies, without providing a description of the technology's position in its respective DDDM dimension's evolutionary progression, were also excluded. Additionally, strictly theoretical research without empirical or practical foundations was excluded. Lastly, abstracts that contained the search terms but lacked any other relevant information were also excluded.

2.3.3. Data extraction

From the final collection of documents, various data were extracted. These include publication and year, related DDDM constructs and causal models, CMMs and their assessment instruments.

2.3.4. Analysis and synthesis processes

We examined the final collection of documents and identified DDDM constructs and relationships from different traditions through in-depth reading of each paper. Next, we examined the dominant constructs of interest in more detail and discuss the findings from different publications to form the basis for an overall model for DDDM. Lastly, model components were collated with the dimensions and capabilities of the identified MMs and frameworks related to DDDM to establish the initial focus areas and capabilities for the FAMM and questions for the assessment instrument.

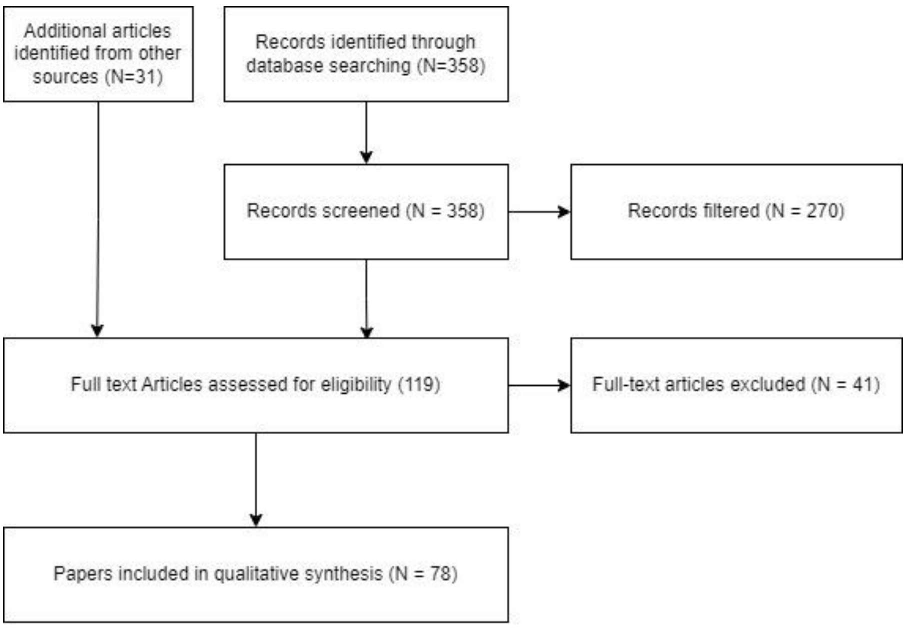

Figure 4. Document flow diagram of literature search

3. Literature review

3.1. Data-driven decision making

Data-driven decision-making is a broad concept that has been examined through different lenses by many scholars in many different fields. Extant research on managerial decision making defines DDDM as the practice of informing and enhancing human decision-making using algorithm-based systems and insights (Zaitsava et al., 2022). Simultaneously data science, BI and other research streams define it more generally as "the practice of basing decisions on the analysis of data rather than intuition" (Provost & Fawcett, 2013). The commonalities that all definitions share, are that decision-making is supported by data-driven insights and that the decision-making process still encompasses humans as the primary decision makers. In this it shares similarities to the practice of business intelligence (BI), which is more generally described as a process that presents historical information to users for analysis to enable effective decision-making and improve organizational performance. BI achieves this by combining data collection, storage and knowledge management to generate basic metrics for use in complex problem solving. As a result of the need for data in the decision-making process, issues arise in various areas. These include but are not limited to data and data source quality, system interaction, and user access (Isik et al., 2011). Data quality – which refers to the representation quality of facts relevant to the specific business use-case – is especially important to maintain, as it directly improves the quality of the information in BI&A products that reduce uncertainty by identifying alternatives or predicting outcome consequences, such as measures and analytical predictions (Wieder & Ossimitz, 2015). In turn information quality is positively related to decision-making quality (Wieder & Ossimitz, 2015) and further BI adoption and utilization (Guo et al., 2021). This is realized using what can be regarded as a two-stage process of identification, collection storage and maintenance of data in storage mediums – purpose built for the analytics data of the organization, such as a data warehouse, data marts or cubes – and the retrieval, processing and conveying of data in a way that is useful for the decision maker in the form of data products like reports, dashboards or data mining tools.

To ensure that the data quality is appropriate for its intended use-case and remains consistent, secure, and compliant, the data management process requires the implementation of data governance. The practice of data governance is consistent throughout the literature and is generally defined as a unifying planning, oversight, and control mechanism for data management and the use of data-related sources and products (DAMA International, 2017). However, the view on the topic in different research publications is fragmented, in the sense that research addresses data governance with a specific focus on certain domains, such as data quality, security (Abraham et al., 2019) or ownership. The purpose of data governance is to establish guidelines and controls for the data management process. Therefore, while the domains of data governance and management may be similar, data management encompasses the processes and practices involved in the creation, storage and use of data within an organization, while data governance lays out a set of practices and policies that ensure the data management process adheres to the standards defined by the organization. The expected benefits of data governance include optimization of data by aligning it with organizational data strategy, optimization of risks in regards to acquisition and use, exploitation and compliance of data, and optimization of the human and technological resources necessary to support the organization's various data-driven operations (Caballero et al., 2023).

Where DDDM and BI differ however, is the latter's emphasis on historical information. DDDM is a broader concept that also includes the prediction of likely future events in the decision-making process. This is where analytics comes in as the complementary asset for BI in BI&A. BI&A generates data-insights by utilizing analytical methods from the fields of data science, operations research, machine learning and statistics (Lepenioti et al., 2020), such as statistical modelling, process mining, neural networking, and simulation. BI&A can be categorized into 5 progressive stages each with a different level of difficulty and value. These include descriptive analytics, which answers the questions of "what has happened?" and "what is happening now?"; diagnostic analytics, answering the question of "why did it happen?"; predictive analytics, answering "what will happen and why"; prescriptive analytics, answering "what should you do?"; and cognitive analytics, which leverages AI technologies to automate or augment human decision-making (Król & Zdonek, 2020). This final stage of analytics is based on the human-machine interaction in which human capabilities are enhanced by the AI.

However, the implementation of BI&A systems and having quality data and metrics on its own does not make a data-driven organization. BI&A capabilities must be accompanied with complementary assets in order to be effective (Richards et al., 2019). This perspective is grounded in resource-based theory (RBT) which maintains that heterogeneity and immobility of organizational resources result in superior firm performance and distinguishes between two types of resources: assets and capabilities (Wade & Hulland, 2004). While assets are considered anything an organization can use in its processes, capabilities are workplace practices that make use of assets. A framework commonly referenced in the BI literature is that of Melville et al. (2004) who framed RBT in the context of IT in their integrative model of IT business value, that considers IT capabilities – which are the combination of IT-based assets and practices which add value to business processes – as the foundation of IT business value (Erjavec et al., 2017). Therefore, while data management products, such as databases, DBMS, DWH, analytics technologies including DSS, prediction models, dashboards and other BI tools may be considered valuable IT assets, they are to be accompanied with complementary assets and capabilities (Richards et al., 2019) such as appropriate organizational structure, policies, culture and workplace practices, to be effectively integrated into the firm's existing processes and add business value. This in turn, presents training, leadership (Korherr et al., 2022) and adoption challenges which must be overcome, the latter being a topic to which BI scholars have more recently called research attention (Ain et al., 2019). In consideration of BI&A system success's dependance on organizational assets that complement the systems, these facets should be considered during FAMM development.

Internal organizational drivers heavily impact the extent of DDDM adoption. As such, leadership is a crucial factor in successfully becoming data driven as an organization. Upper management has the best chance of changing the decision-making to be data driven (Heubeck & Meckl, 2022) and ultimately managerial cognition serves as the basis for decision-making within firms. Moreover, management BI&A championing improves BI system capability – improving workflow support, feature development and scenario exploration – by promoting user participation and data-driven decision-making orientation (Kulkarni et al., 2017). This implies that the characteristics, attitude and activities of management dictate the shape and success of organizational decision-making and its supporting processes. As such, data-driven adoption and transformation is most successful when organization leaders are committed to data (Sleep et al., 2019) and have the relevant management and leadership skills to actively manage the change (Korherr et al., 2022).

Culture and user behavior have also been found to significantly influence data-driven decision-making. The presence of an analytical decision-making culture has long been found to extensively affect the use of information in business processes (Popovič et al., 2012) and having a data driven culture improves process performance and innovation (Chaudhuri et al., 2021). However, as the conceptualization of data-driven culture has tended to vary across research, its exact characteristics and development process are still a topic of further research (Anton et al., 2023) and practitioners tend to rely heavily on popularized best-practices. What is known, is that the adoption of business analytics and the corresponding acquisition of tools and data has a major impact on the development of a data-driven culture (Chatterjee et al., 2021), as does organizational strategy and employee behavior and skill (Berndtsson et al., 2018). Interestingly, research findings (Popovič et al., 2012), suggest a feedback-loop in which an initial adoption of data-driven capabilities and resources promotes the development of a data-driven culture, which in turn promotes further adoption and utilization. Additionally, a large body of literature built on the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003), has expanded our understanding of BI&A technology adoption to include the impact of user expectations. For instance, the organizational usage and adoption of data-driven capabilities and products has been found to be dependent on the disposition of decision makers towards data-driven capabilities such as BI&A (Ain et al., 2019; Al-Okaily et al., 2021). Moreover, when we consider that BI systems are designed to inform and assist in decision-making, it is evident that the impact of such systems and the expectations of users becomes inherently tied to the interpretative and analytical abilities of said users (Ain et al., 2019; Shao et al., 2022). In an environment with employees that lack BI experience or analytics skill, it stands to reason that the value captured by DDDM efforts will be low, regardless of the maturity of the technologies and data within the organization. Decision makers may either draw the wrong conclusions from data insights due to a lack of understanding, prefer to make decisions based on personal experience or simply have a negative disposition towards data analytics. The effects of certain end-user characteristics (Erjavec et al., 2019) and perceived BI effectiveness on decision-making quality (Ain et al., 2019) have similarly been identified. More recent research by Zaitsava et al. (2022) highlights the connection between human cognitive characteristics and errors in DDDM on the basis of dual-process theory, which argues that humans rely on two distinct types of reasoning. Type 1 reasoning focuses on unconscious and intuitive thinking, making it faster but leaving it susceptible to bias, while type 2 reasoning is rule-based, more deliberate and slower. The research adopts the parallel competitive theory lens – that assumes both types of reasoning work in parallel to effectuate decision-making – and shows that even rule-based methodical thinking is susceptible to data bias and trust issues. This emphasizes the impact of individual user's skill with using data and analytics as part of the decision-making process and the importance of their disposition towards data and analytics.

3.2. Model conceptualization

The literature review revealed DDDM development in organizations to be a complex dynamic process that requires iterative development of strategy, attitude and techniques paired with the acquisition of new resources and skills. To better illustrate the way in which the identified constructs are interrelated, we adopt a systems thinking approach to model design, which looks at social systems holistically and stresses the dynamic interrelationships among system components (Fang et al., 2018). Based on our review of the literature on DDDM, we constructed the model depicted in Figure 5.

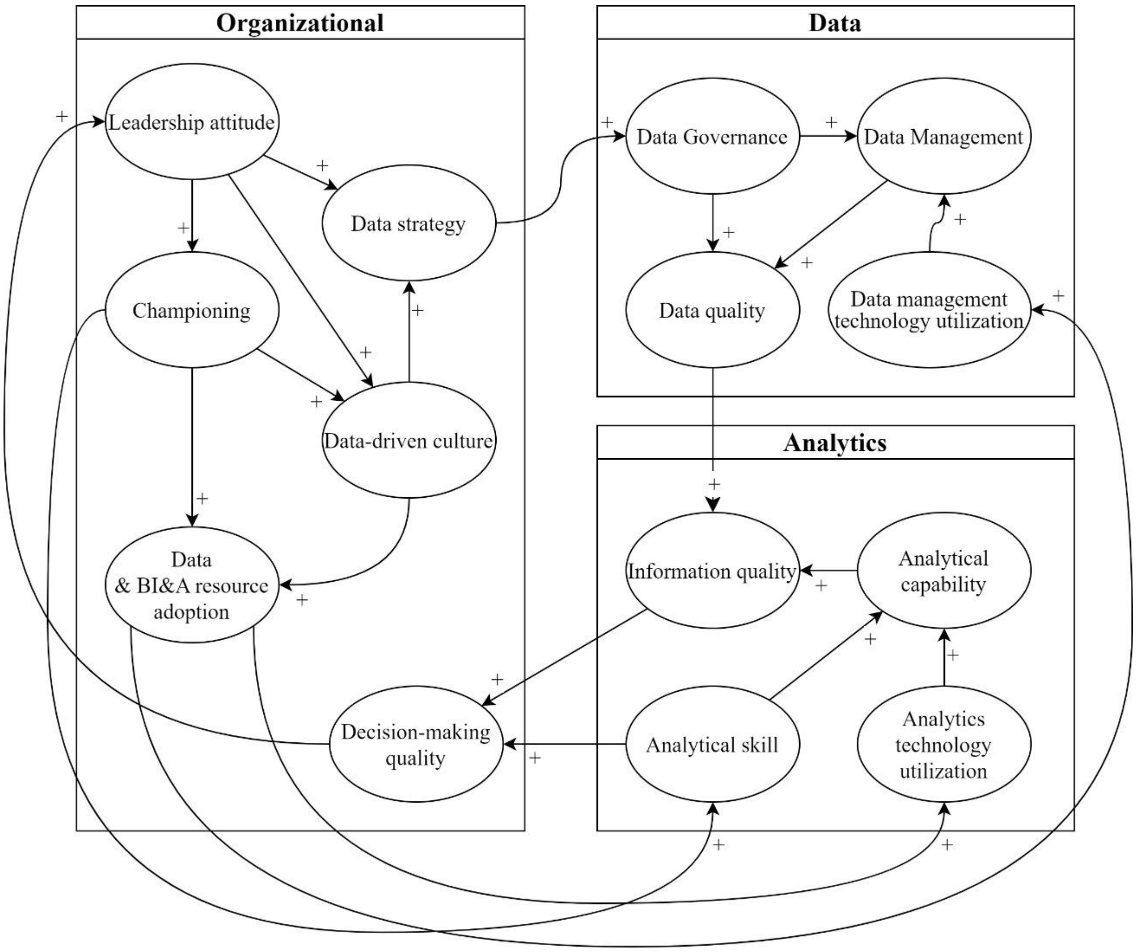

Figure 5. Causal loop diagram for data-driven decision-making

The causal loop consists of various constructs for which extant research proposes different measurement variables and methods. However, the aim of our literature review is to capture the different facets of DDDM in which capabilities may be developed so that we can map them to focus areas of extant DDDM related maturity models, not to measure the effect of relationships between constructs. Therefore, this causal loop diagram should be considered as a conceptual basis on which our focus areas will later be based. In this section, we briefly explain the diagram, its constructs, their relationships in this conceptualization and the choices made during creation.

During model development, data security – as a preventative measure to protect data from outside threats – was considered for model inclusion. However, this construct was eventually excluded, since by this definition it doesn't necessarily contribute to the data-driven decision-making process. Whilst data security is undoubtedly imperative to ensure the safe and proper use of data, any form of data or information security – other than that effectuated by the governance program to ensure effective data use – does not positively affect any of the other facets of data-driven decision-making. One could even argue that it affects data-driven decision-making negatively, by reducing data accessibility and transparency.

Becoming data-driven is a change process and organizational change often comes from those in charge. The construct "leadership attitude" expresses the attitude towards the development and use of data-driven decision-making from executive management and members of organizational leadership. The "championing" construct covers the extent to which management is or attempts to become data-driven, promotes the adoption of data-driven capabilities, and stimulates the development of data and analytics skills amongst employees. Leadership sets the tone and direction for the organization and supports initiatives through their actions by championing their cause, giving it a positive causal relationship with championing. Organizational culture can be defined as *"the set of shared attitudes, values, goals, and practices that characterizes an institution or organization"* (Merriam Webster, n.d.). The construct "Data driven culture" captures the extent to which the use of data and analytics in the decision-making process has become part of standard procedure and how data and analysis has become an intrinsic part of the organization and its members. Organizational leadership has a major hand in shaping corporate culture. A positive leadership attitude towards data and analytics, backed up by actions that stimulate its adoption and reduces resistance, results in being data-driven to become a bigger part the organization's culture. This implies a positive effect of leadership attitude and championing on data-driven culture.

"Data & BI&A resource adoption" covers the extent to which an organization acquires and adopts new data management and analytics resources, such as technologies, techniques and staff. By championing data-driven adoption through the acquisition of new tools and technologies, training employees, and promoting the development of relevant skills, organizations can more effectively adopt new data and analytics resources. Similarly, having a data-driven culture in place already improves the further adoption of new data and analytics resources by lower the barrier to entry and reducing resistance to change. This indicates a positive effect of championing and data-driven culture on data & BI&A resource adoption. While the adoption of data and BI&A resources is one thing, utilization is another. "Analytics technology utilization" and "data management technology utilization" cover the extent to which data management and analytics technologies are utilized and incorporated into processes. This includes both the range and complexity of technologies in use. As an organization must adopt technologies before utilization, it stands to reason that an increase in data and BI&A resource adoption positively affects data management and analytics technology utilization.

The construct "analytical skill" captures the analytics knowledgebase present within the organization. In other words, it addresses the ability of employees to effectuate an analytics process of the desired complexity. Organizations may increase this by training employees, promoting development in the area of analytics or by hiring new specialized staff. Championing data driven capabilities and promoting skill development helps improve the analytical skill present in the organization, indicating a positive relationship. The "analytical capability" of an organization dictates the kind of analyses it can perform to generate useful information, these can range from descriptive analytics using simple statistics, to prescriptive or even cognitive analytics that use data science and machine learning. Different forms of analytics require their own special technologies and skills, which must be acquired and effectively utilized. As an organization adopts and start utilizing more advanced analytics technologies and improves their analytical knowledge base, their analytical capability increases. As such a firm's analytical capability is positively affected by analytical skill and analytics technology utilization.

In addition to supporting data-driven decision-making capabilities through championing, organizations create a data strategy and align it with their business strategy. The construct "data strategy" expresses how comprehensive the data strategy of the organization is and how aligned it is with its business strategy. This includes setting objectives, describing how value is to be generated from data, and how resources are allocated. The more positive leadership's attitude is towards becoming data-driven, the more comprehensive its data-strategy will be, indicating a positive relationship. Similarly, having a data-driven culture also positively affects the development and refinement of the data strategy by being able to collect and reference internal stakeholder feedback.

In this conceptualization "data governance" is defined as the set of practices and policies that enable data collection, enforce the quality of data, and ensure its proper use. It involves defining and implementing processes and standards, specifying roles, and assigning responsibilities and ownership of data and data products, to ensure data is accurate, consistent, secure and complies with organizational policy and business needs throughout its lifecycle. The organization's data strategy lays the foundation for its data governance program by establishing overarching objectives and guidelines. A more comprehensive the data strategy in this context leads to better data governance processes, implying a positive relationship.

The "data management" construct embodies the extent of practices for data collection and processing, storage and architecture that describe how data is managed from collection through to transformation, distribution, and consumption. Including the types of tools and technologies applied during this process. The data governance program establishes the guidelines for how data should be managed within an organization and dictates the extent of the data management activities, indicating a positive relationship. Similarly, having a more comprehensive portfolio of data management tools or utilizing more advanced technologies positively affects data management.

"Data quality" is conceptualized as a measure of how data adheres to an organization's definitions of quality for its specific use cases, as a result of its data governance and data management activities. As such, better governance and management practices result in better data quality, indicating a positive relationship. Unlike data, which refers to individual statistics or raw facts and requires examination and analysis to result in actionable insights, information has context, is organized and purposeful, and is what helps decision-makers decide. Such information may include key performance indicators (KPI) such as customer sentiment and server uptime or actionable metrics like price comparisons or investment signals. Information is the outcome of an analytical process that uses data as fuel. The higher the quality of the data used in this process results in a higher quality outcome, which indicates a positive relationship between data quality and information quality. Similarly, the better the analytical process that generates this information, the higher the quality of the result. As such, having greater analytical capability improves information quality.

The construct "decision-making quality" represents a measure of decision-making process effectiveness. How well the outcome of the decision-making process served the organization's objectives and how beneficial the outcome was. Decision-makers having improved analytical skills can streamline the decision-making process and reduce cognitive biases, thereby improving the decision-making quality. Similarly, improving the quality of information used in the decision-making process increases the likelihood of making better decisions. Therefore, information quality and analytical skill are both positively related to decision-making quality. Additionally, as data-driven decision-making outperforms traditional decision making in terms of outcome quality and thereby improves the organizational performance (Erjavec et al., 2017; Richards et al., 2019), it stands to reason that as decision-making quality continues to increase as a result of iterative improvement to the DDDM development cycle we propose, organizational leadership would adopt a more positive attitude towards becoming data-driven. Lastly, the proposed causal loop diagram serves as an example of the previously mentioned feedback-loop between BI&A resource adoption and data-driven culture, where an initial adoption of data-driven capabilities and resources promotes the development of a data-driven culture, which in turn promotes further adoption and utilization.

3.3. Identified maturity models

For each paper in the final collection, we determined which (if any) framework or model was used to assess DDDM maturity. Table 1 shows the maturity models identified in the literature review. Appendix 6: Identified maturity frameworks contains a breakdown of the maturity levels, categories and dimensions of each framework. Most of the identified models have their roots in practitioner literature. It stands to reason that the practitioner domain generates the majority of maturity assessment artifacts, as these are predominantly used in practice to assess the domain maturity of one's own organization or that of a client. However, documentation on the process and criteria for assessing DDDM maturity for several of these models is not openly accessibly and therefore difficult to verify or even examine. The exceptions are the DAMA-NL maturity scan, which is based on the knowledge areas of the Data Management Book of Knowledge (DMBoK), the ISACA CMMI Data Management Maturity model (DMM) and the EDM council's Data Management Capability Assessment Model (DCAM). Additionally, the models from academic sources are publicly accessible and supporting documentation can be found in their respective publications or research group webpages.

Framework	**Abbreviation**	**Model Type**	**Source**	**Assessment Accessibility**	**Doc. Avail.**	**Date updated**
DAMA - Data Management Book of Knowledge	DMBoK	Continuous fixed CMM	Practitioner	Public	Yes	2022
EDM Council - Data Management Capability Assessment Model	DCAM	Continuous fixed CMM	Practitioner	Commercial	Yes	2017
CMMI - Data Management Maturity model	DMM	Continuous fixed CMM	Practitioner	Commercial	Yes	2017
Alarcos' Model for Data Maturity	MAMD	Staged fixed CMM	Academic	Public	Yes	2023
TDWI – Data Management Maturity Model	TDWI – DMMM	Continuous fixed CMM	Practitioner	Public	No	2023
TDWI – Analytics Maturity Model	TDWI - AMM	Continuous fixed CMM	Practitioner	Public	No	2023
Master Data Management Maturity Model	MD3M	Continuous fixed CMM	Academic	Public	Yes	2015
Circumplex Hierarchical Representation of Organization Maturity Assessment - Simplified Holistic Approach to DMP Evaluation	CHROMA - SHADE	Continuous fixed CMM	Academic	Commercial	Yes	2019
Business Analytics Capability Maturity Model	BACMM	Continuous fixed CMM	Academic	Commercial	Yes	2015

Table 1. Identified DDDM related maturity models and frameworks.

4. Maturity model design

The components of the model and identified MMs were collated and the initial focus areas established based on an examination of the identified maturity literature. Afterwards, capabilities from established maturity literature were adapted to the DDDMFAMM or new capabilities constructed using on the identified frameworks.

4.1. Focus areas & capabilities

The constructs of our model (Figure 5) were collated with the components of the various maturity models and frameworks identified (Table 1) to establish the initial focus areas of the DDDMFAMM. Additionally, each focus area was grouped into one of three over-arching categories – Organizational, Data, or Analytics – that indicate its general theme. The capabilities for each focus area are adopted from established maturity models, scientific or best practice frameworks (Table 2).

4.1.1. Analytics

Analytics Applications & Tools: Applications and tools form the backbone of an organization's analytics capabilities. This focus area describes the capabilities powered by the tools and technologies available within the organization for analyzing, visualizing, and presenting data. They also and supporting their capacity to evolve and allow for specialized analysis. Applications may range from spreadsheet programs and dashboards to prescriptive analytics software such as decision-support systems and AI powered analysis tools.

Analytics Techniques & Analysis: Analytics applications must be paired with complementary techniques that enable the generation of metrics, insights and predictions. This focus area covers the procedures, standards and protocols applied and their level of sophistication in performing data analysis. Additionally, it articulates the purposes for and approach under which the various types of analytics are applied to contribute to decision-making throughout the organization.

4.1.2. Data

Data Governance structure: Before any data governance processes can be established, an initial data governance structure should be designed and charted. The aim of the data governance structure is to identify and organize key stakeholders and link them to the required data governance components. The data governance board interacts with executive management to ensure that adequate funding is allocated for data initiatives and to ensure effective data governance. In order to implement data governance, a formal deployment plan must be established that details the data governance processes and oversight mechanisms to ensure these will work in the business environment. This focus area covers the development of the organizational data governance structure, executive ownership, plans to develop a data governance mechanism, and an integration of the data governance function throughout the organization. The presence of these capabilities – that indicate the level of formalization and scope of the governance function – are used to express its maturity.

Data Policy & Standards: Formalizing data policy is the core activity of data governance. Policies and standards word together to address how data is collected, stored, maintained, delivered, and used throughout the organization. Data policy sets the strategic direction by describing the overall goals and guidelines, while standards express how this will be operationally achieved. These rules and standards are developed through a collaborative effort between the governance body, executive management and business and IT stakeholders to ensure they are complete, verified and align with the data management strategy and business objectives. To ensure effective policy, it must be enforced and be auditable.

Content Governance: Content governance focuses on identifying and managing the data assets that are critical to business operations and specific processes. Data is grouped in domains such as "customers" and "products" and related to specific business functions like HR or Finance to support data use by business stakeholders. Additionally, content governance ensures a common definition and language of data across and outside the organization and supports data analysis, risk analysis and reporting by establishing standardized data identification methodologies.

Data Quality Program: A data quality program describes the strategy and approach that encompasses the "what, who, and how" of data quality. Ensuring data quality requires organizational change and commitment, therefore it is critical that the data quality strategy is communicated to relevant stakeholders, that their feedback is incorporated to increase awareness and buy-in, and that responsibilities are assigned, and individuals held accountable for maintaining the desired data quality.

Data Quality Assessment and Remediation: Data quality is critical to ensuring valuable data insights. Poor quality data could distort the outcomes of analytical processes and provide an incorrect representation of reality. In order to begin managing data quality, the scope of the data under the quality management program must be identified and the processes for assessing and remediating data quality established. This focus area describes the capabilities necessary to identify which data should be assessed, assess and document the data quality, resolve data quality issues across the organization and ensure proper data quality maintenance and continuous improvement across business-lines.

Data Architecture: Data architecture considers the design, definition, management, and control of data and information. This focus area covers aspects such as the identification and management of logical data domains, repositories, metadata, and data models. A data architecture establishes consistency in the definition of data throughout the organization, documents where specific data is stored and comes from, and ensures users have the required access. Documenting and communicating this information supports self-service BI and data democratization which enables all members of an organization to work with data comfortably, regardless of their know-how.

Data Infrastructure and Operations: The data storage infrastructure forms the backbone of an organization's data operations capabilities and dictates the volume, variety and velocity of data that can be collected, processed and stored. This focus area covers data collection, processing and storage infrastructure and operations, including data sharing, ETL, enterprise data warehousing, and big data.

4.1.3. Organizational

Data Management Strategy (DMS): The primary objective of data collection and analysis is to support the organization in achieving its business objectives. A data management strategy defines the organization's motivations for implementing data management and how its components fit together. The data management strategy should determine how data management is defined, organized, funded, governed, and embedded into business operations. It defines the long-term vision and description of key stakeholder functions that must be aligned, while demonstrating the business value the program aims to achieve. In a sense, it becomes the blueprint for evaluating, defining, planning, measuring, and executing the data management program. Additionally, it communicates the organization's approach to data management training and improving awareness of data management throughout the organization.

Decision-making process (DMP): Decision-making is a daily occurrence and an integral part of strategic, tactical, and operational business activities. Making informed and systematic decisions improves decision outcome and business performance. The decision-making process describes the elements that must be present for decision-making to be carried out accurately, objectively and efficiently, thereby promoting the development of an information driven business strategy and data-driven decision-making process that serves to effectively manage the risks associated with decision outcomes.

Data Driven Culture: Corporate culture sets the general tone for how organization members interact with each other, how they use the resources at their disposal, and how they are motivated to pursue certain activities. Culture is abstract and challenging to change. In order to overcome a cultural change management process, resistance must be managed, and the desired cultural workplace practices promoted. This focus area covers awareness creation, participation encouragement, skill development and training to eventually establish a culture in which data-driven practices are the norm.

Leadership & Empowerment: Executive management and other leadership set the tone for the rest of the organization. The behavior of managers and executives and their attitude towards the use of data and analytics dictates for a large part how members of the organization will engage with new technologies and practices. At the same time, it heavily influences the corporate culture. Having a comprehensive business case for data management, expresses the importance of data to members of the organization and motivates managers to achieve data related objectives and strengthen data skills. This focus area covers leadership attitude, empowerment, decision-making delegation, and the extent to which the data management and analytics business case motivates adoption.

4.1.4. Mapping

Each model construct was mapped to a specific focus area where applicable (Table 2) or otherwise integrated into a combination of focus areas. Additionally, the model constructs "Leadership attitude" and "Championing" were consolidated into the singular focus area Leadership & Empowerment, to reduce the overall complexity of the FAMM.

Several model constructs were not directly mapped, due to them not being expressible by any single focus area or combination thereof. These include "Data & BI&A resource adoption", "Analytical skill", and "Information quality". "Data & BI&A resource adoption" was instead integrated into the focus areas Analytics Applications & Tools, and Data Storage Infrastructure and Operations. These specific focus areas include a progressive development of data and BI&A application adoption over its capability levels and thereby reflect the effects of increasing data and analytics resource adoption. Similarly, the constructs "Analytical capability" – which represents the level of complexity of techniques applied in analyses – and "Analytics skill" – which encompasses the skills required to execute such techniques – were consolidated into the focus area Analytics Techniques & Analysis. Lastly, we cannot express the capabilities necessary for the construct "Information quality" using one or more specific focus areas or express this construct in terms of focus area maturity as it is instead a measure of the effectiveness and maturity of other focus areas in the DDDMFAMM. For instance, information quality relies on a combination of data quality management, content governance, data architecture and analytics techniques. As such, this model construct can be considered loosely integrated into the other focus areas.

	Model Construct	Focus Area	Reference Framework
Analytics	Analytical capability Analytical skill	Analytics Techniques & Analysis	(Parra, 2018; Parra et al., 2019)
	Analytics technology utilization	Analytics Applications & Tools	(Parra, 2018; Parra et al., 2019)
Data	Data Governance	Data Governance Structure	(EDM Council, 2014, 2020)
		Policy & Standards	
		Content Governance	
	Data Management Data Management technology utilization	Data Storage Infrastructure and Operations	(Halper, 2023; Larson, 2023; Parra, 2018; Parra et al., 2019)
		Data Architecture	(DAMA International, 2017; EDM Council, 2014, 2020)
	Data Quality	Data Quality Program	(EDM Council, 2014, 2020)
		Data Quality Assessment and Remediation	
Organizational	Data Strategy	Data Management Strategy	(DAMA International, 2017; EDM Council, 2014, 2020)
	Decision-making quality	Decision-making process	(Parra, 2018; Parra et al., 2019)
	Data & BI&A resource adoption	Analytics Applications & Tools	(Parra, 2018; Parra et al., 2019)
		Data Storage Infrastructure and Operations	
	Leadership attitude Championing	Leadership & Empowerment	(EDM Council, 2014, 2020; Parra, 2018; Parra et al., 2019)
	Data-driven culture	Data-Driven Culture	(Cosic et al., 2012; Halper, 2023; Larson, 2023; Spruit & Pietzka, 2015)

Table 2. Model Construct - Focus Area mapping

4.1.5. Expert discussions

The initial focus areas and capabilities developed based on literature, were examined in-depth during expert discussion. At this time, quantitative and qualitative data were collected through the survey – as part of the semi-structured discussion guide – and the provided feedback from experts. The survey served primarily to identify – and allow for detailed discussion of – problematic model components, and secondarily to quantitatively assess the validity of each theoretical model component. The qualitative feedback enabled the iterative improvement of focus areas, capabilities, improvement actions or their respective descriptions.

Unfortunately, due to external commitments, two of the original expert discussion group members were unable to attend all sessions. While both members still attended most sessions and were able to contribute by providing qualitative feedback, this absence resulted in their survey data being incomplete. Due to the amount of missing data, the small sample size and the potential loss of variability in responses, it was determined that the remaining data was not suitable for imputation. Therefore, their responses were excluded from the quantitative analysis. Additionally, due to the small sample size, the data was not suitable for the application of inferential statistics. Therefore, we only report the descriptive statistics of the focus area and capability analyses.

Q: The description of this focus area is clear								
Focus Area	CDO	Master Data Specialist	Enterprise Architect	Governance Manager	Governance Consultant	Mean	Std. Dev.	Range
1	5	6	6	6	7	6.0	0.63	
2	5	5	7	7	5	5.8	0.98	
3	5	5	5	6	6	5.4	0.49	
4	6	5	7	6	6	6.0	0.63	
5	6	6	6	4	6	5.6	0.80	
6	7	6	7	6	6	6.4	0.49	
7	7	6	7	5	5	6.0	0.89	
8	6	6	5	6	6	5.8	0.40	
9	7	6	7	6	5	6.2	0.75	
10	6	6	6	5	6	5.8	0.40	
11	7	6	6	5	6	6.0	0.63	
12	7	6	7	7	7	6.8	0.40	
13	7	6	7	7	5	6.4	0.80	

Table 3. Descriptive statistics for focus area description clarity from expert discussion guide survey.

Q: This focus area is a relevant part of data-driven decision-making.							
Focus Area	CDO	Master Data Specialist	Enterprise Architect	Governance Manager	Governance Consultant	Mean	Std. Dev.
1	7	7	6	7	6	6.6	0.49
2	7	7	7	7	6	6.8	0.40
3	7	7	7	7	7	7.0	0.00
4	6	7	7	7	7	6.8	0.40
5	6	7	7	7	7	6.8	0.40
6	7	7	7	7	6	6.8	0.40
7	7	3	7	4	7	5.6	1.74
8	6	7	7	7	7	6.8	0.40
9	7	7	7	7	6	6.8	0.40
10	7	7	7	7	7	7.0	0.00
11	7	7	7	7	7	7.0	0.00
12	6	7	7	7	7	6.8	0.40
13	7	6	7	7	6	6.6	0.49

Table 4. Descriptive statistics for focus area relevance from expert discussion guide survey.

Q: The order of capabilities within this focus area demonstrates a progressive evolution of the focus area.							
Focus Area	CDO	Master Data Specialist	Enterprise Architect	Governance Manager	Governance Consultant	Mean	Std. Dev.
1	6	7	6	7	6	6.4	0.49
2	7	7	7	7	6	6.8	0.40
3	5	5	4	6	6	5.2	0.75
4	6	7	6	6	6	6.2	0.40
5	6	7	5	5	6	5.8	0.75
6	5	5	5	5	6	5.2	0.40
7	6	7	7	4	6	6.0	1.10
8	7	7	6	5	6	6.2	0.75
9	7	7	4	7	6	6.2	1.17
10	6	7	5	6	6	6.0	0.63
11	6	7	5	6	6	6.0	0.63
12	6	7	5	7	6	6.2	0.75
13	6	7	5	7	6	6.2	0.75

Table 5. Descriptive statistics for focus area maturity progression from expert discussion guide survey.

Q: The combination of its capabilities provides a complete representation of this focus area.							
Focus Area	CDO	Master Data Specialist	Enterprise Architect	Governance Manager	Governance Consultant	Mean	Std. Dev.
1	7	7	7	7	6	6.8	0.40
2	7	7	5	7	6	6.4	0.80
3	7	4	6	6	6	5.8	0.98
4	6	6	6	6	6	6.0	0.00
5	7	7	7	5	6	6.4	0.80
6	6	7	6	6	6	6.2	0.40
7	5	7	7	4	5	5.6	1.20
8	6	7	6	5	6	6.0	0.63
9	6	7	4	7	6	6.0	1.10
10	6	7	4	5	5	5.4	1.02
11	4	7	5	6	6	5.6	1.02
12	6	7	5	7	7	6.4	0.80
13	6	7	5	6	6	6.0	0.63

Table 6. Descriptive statistics for focus area completeness from expert discussion guide survey.

Accounting for the standard deviation in response among expert discussion participants, we find an average score above 4 – indicating a positive sentiment – for all focus areas in Table 3, Table 5, and Table 6. Similarly, there is a positive sentiment for all focus areas based on the data in Table 4, except for focus area focus area 7 “Data Quality Program”. The qualitative feedback allowed us to further explore the issues with this focus area. While experts noted that the content of this focus area was very relevant and critical for establishing an effective data quality program, experts indicated that focus area 7 may lack sufficient content to constitute its own focus area. Moreover, the argument was made that assigning data stewards and data quality ownership separate from the established data governance structure, would drastically undermine the authority of data owners. Suggestions were made to discard this focus area and transfer its capabilities into focus areas 3, 5, 6 or 8. Based on this feedback, capability 7C, which only consisted of communicating data quality program roles and responsibilities to the wider organization, was integrated into the focus area’s other capabilities. Capability 7B on the other hand, constituted assigning data stewards throughout the business and providing them with the corresponding authority and responsibilities – which in practice is an extension of the data governance structure – meant that it lent itself to be transferable to focus area 3 “Data Governance Structure”. Lastly, capability 7A was consolidated into capability 8A that covers the scoping and planning of the data quality program and its activities.

Q: The description of this capability is clear.							
Capability	CDO	Master Data Specialist	Enterprise Architect	Governance Manager	Governance Consultant	Mean	Std. Dev.
1A	6	7	6	7	6	6.4	0.49
1B	3	5	5	6	3	4.4	1.20
1C	6	7	7	7	5	6.4	0.80
1D	6	7	5	7	5	6	0.89
1E	6	6	7	6	5	6	0.63
2A	7	7	7	7	6	6.8	0.40
2B	6	7	7	6	6	6.4	0.49
2C	7	7	7	7	6	6.8	0.40
2D	4	3	3	5	5	4	0.89
3A	6	2	7	6	6	5.4	1.74
3B	6	5	7	7	6	6.2	0.75
3C	7	3	6	7	6	5.8	1.47
3D	4	2	3	3	5	3.4	1.02
3E	6	6	7	7	6	6.4	0.49
4A	7	6	3	6	6	5.6	1.36
4B	7	4	7	6	6	6	1.10
4C	7	4	7	6	5	5.8	1.17
5A	6	6	7	6	5	6	0.63
5B	6	6	7	4	6	5.8	0.98

5C	7	6	7	4	6	6	1.10
5D	6	6	6	3	5	5.2	1.17
5E	7	6	7	3	6	5.8	1.47
6A	6	6	6	5	6	5.8	0.40
6B	6	6	6	5	6	5.8	0.40
6C	6	6	5	6	6	5.8	0.40
6D	6	6	7	5	6	6	0.63
6E	6	6	6	6	6	6	0.00
6F	6	6	7	6	6	6.2	0.40
6G	6	6	6	5	6	5.8	0.40
7A	7	6	6	4	6	5.8	0.98
7B	7	6	7	4	6	6	1.10
7C	7	6	7	4	6	6	1.10
8A	6	6	7	3	6	5.6	1.36
8B	6	6	4	4	6	5.2	0.98
8C	6	6	6	7	6	6.2	0.40
8D	6	6	7	6	6	6.2	0.40
8E	6	6	7	3	5	5.4	1.36
9A	6	6	6	6	5	5.8	0.40
9B	6	6	6	7	6	6.2	0.40
9C	6	5	7	6	6	6	0.63
9D	6	6	7	6	5	6	0.63
10A	6	6	7	4	6	5.8	0.98
10B	6	3	6	5	6	5.2	1.17
10C	6	4	6	5	6	5.4	0.80
10D	6	6	5	6	4	5.4	0.80
11A	5	6	7	7	6	6.2	0.75
11B	5	6	5	7	5	5.6	0.80
11C	7	6	7	7	6	6.6	0.49
11D	7	6	5	7	4	5.8	1.17
12A	7	6	7	6	6	6.4	0.49
12B	6	6	4	6	6	5.6	0.80
12C	6	6	6	6	5	5.8	0.40
12D	6	6	7	6	6	6.2	0.40
13A	5	4	7	7	4	5.4	1.36
13B	7	6	7	7	5	6.4	0.80
13C	6	6	7	6	6	6.2	0.40
13D	7	6	7	7	6	6.6	0.49
13E	5	6	5	7	5	5.6	0.80

Table 7. Descriptive statistics for capability description clarity from expert discussion guide survey.

When analyzing the data in Table 7 we find that when accounting for the standard deviation, the average score for description clarity of capabilities is above 4, indicating an overall positive sentiment. The exceptions are capability 1B, 2D, 3A, and 3D, which indicate a negative sentiment. Additional qualitative feedback allowed us to further explore the reasons for this negative sentiment. Firstly, Capability 1B originally included the term "low-cost" in its description when referring to the types of domain targeted data input and reporting applications, such as ERP, MIS, CRM or ERM systems. Experts argued that using a term referring to cost or simplicity was confusing, as this is context dependent. Additionally, the CDO remarked that the description was overly conceptual for a management audience. Based on this feedback, the mention of low-cost was removed and the capability description was adjusted to include several examples of data input and reporting tools. Secondly, regarding capability 2D, experts commented that the concept of prescriptive analytics was confusing to an audience with less analytics experience and not sufficiently explained as part of the capability. Additionally, the description lacked an emphasis on decision-making. This sentiment – while not as extreme – was also expressed for the earlier capabilities in the focus area. The terms, descriptive, diagnostic, predictive and prescriptive – while known to experts with sufficient domain knowledge – may not be familiar to a general audience. To account for these issues, a more comprehensive explanation of the concept and workings each type of analytics was added to each capability description, with an emphasis to capability 2D. Thirdly, the description of Capability 3A originally limited the responsibilities of the DMO to "championing" the data program. The master data specialist commented that while this captured the essence of the capability, "championing" as a singular responsibility for the DMO was vague. In agreement with other experts, the capability was expanded to also include the design and steering of the data management program, in addition to allocating resources and coordinating resource sharing for data projects. This addition is further related to the changes made to capability 3D. Lastly, the critique and changes made to capability 3D were more comprehensive as this capability also had negative sentiments in terms of its relevance to the focus area (Table 8) and its development action accuracy (Table 10) and clarity (Table 9). Capability 3D originally covered the development of a data program management office (PMO). This organizational entity was intended to serve as a managing body for data related projects and facilitate necessary resource sharing, in contrast to the data management office (DMO), which serves more as a governing body that designs, steers and champions data governance initiatives. However, experts noted that the separate inclusion of the PMO, in addition to the DMO, is excessive and dilutes the model. It was noted that in practice, the organizational body the model defines as the DMO should reasonably be able to execute data project coordination and facilitate resource sharing. Alternatively, the tasks of coordinating and sharing data resources would be delegated to an existing department like project management, BI or IT, or data stewards. While the essence of the capability is of clear importance, in order to reduce model complexity, capability 3D was consolidated into capability into capability 3A based on expert feedback. Additionally, a new capability 3D was developed that covers the development of a decentralized governance structure combined with the corresponding data governance roles and responsibilities. This capability incorporates the content of the previously defunct capability 7B.

Q: This capability is relevant to its corresponding focus area.

Capability	CDO	Master Data Specialist	Enterprise Architect	Governance Manager	Governance Consultant	Mean	Std. Dev.
1A	7	7	7	7	7	7	0.00
1B	7	7	4	7	6	6.2	1.17
1C	7	7	7	7	6	6.8	0.40
1D	7	7	7	7	6	6.8	0.40
1E	7	7	7	7	6	6.8	0.40
2A	7	7	7	7	6	6.8	0.40
2B	7	7	7	7	6	6.8	0.40
2C	7	7	7	7	6	6.8	0.40
2D	6	7	7	7	6	6.6	0.49
3A	7	7	7	7	6	6.8	0.40
3B	7	7	7	7	6	6.8	0.40
3C	7	4	7	7	6	6.2	1.17
3D	5	2	3	4	6	4	1.41
3E	6	7	7	7	6	6.6	0.49
4A	6	7	5	7	6	6.2	0.75
4B	6	7	7	6	6	6.4	0.49
4C	6	7	7	7	6	6.6	0.49
5A	7	7	7	7	6	6.8	0.40
5B	7	4	7	7	6	6.2	1.17
5C	7	7	6	7	6	6.6	0.49
5D	7	7	6	5	6	6.2	0.75
5E	7	7	7	6	6	6.6	0.49
6A	7	7	6	7	6	6.6	0.49
6B	7	7	6	7	6	6.6	0.49
6C	7	4	6	5	6	5.6	1.02
6D	7	7	7	7	6	6.8	0.40
6E	7	7	7	7	6	6.8	0.40
6F	7	7	7	7	6	6.8	0.40
6G	7	7	7	6	6	6.6	0.49
7A	7	7	7	4	6	6.2	1.17
7B	7	7	7	4	7	6.4	1.20
7C	7	7	7	4	6	6.2	1.17
8A	7	7	1	7	7	5.8	2.40
8B	7	7	6	7	7	6.8	0.40
8C	7	7	7	7	7	7	0.00
8D	7	7	7	7	7	7	0.00
8E	7	7	5	3	6	5.6	1.50
9A	7	7	5	7	6	6.4	0.80
9B	7	7	7	7	6	6.8	0.40
9C	7	7	7	7	6	6.8	0.40
9D	7	7	7	7	6	6.8	0.40

10A	7	7	7	4	7	6.4	1.20
10B	6	7	4	6	7	6	1.10
10C	7	7	5	7	7	6.6	0.80
10D	7	7	7	6	7	6.8	0.40
11A	7	7	7	7	7	7	0.00
11B	6	7	6	7	7	6.6	0.49
11C	7	7	7	7	7	7	0.00
11D	7	7	7	7	6	6.8	0.40
12A	7	7	7	6	7	6.8	0.40
12B	6	7	6	6	6	6.2	0.40
12C	6	7	6	6	6	6.2	0.40
12D	7	7	7	6	6	6.6	0.49
13A	7	7	7	7	6	6.8	0.40
13B	7	7	7	6	6	6.6	0.49
13C	7	7	7	6	6	6.6	0.49
13D	5	5	5	6	7	5.6	0.80
13E	5	4	5	5	5	4.8	0.40

Table 8. Descriptive statistics for capability relevance to focus area from expert discussion guide survey.

A similar analysis of the data from Table 8 shows an overall positive sentiment for all capabilities in terms of their relevance to their focus area when accounting for the standard deviation. However, capability 3D and capability 8A are the two exceptions. As the qualitative feedback and changes to capability 3D were previously discussed, we instead focus on capability 8A. Capability 8A is a unique exception, as the discrepancy in expert scores stems from a faulty description in the original capability documentation. The enterprise data architect noted that the capability goal was likely incorrect as it appeared to closely resemble that of capability 7A. Experts also noted that one of the development actions for this capability was likely extraneous as this action was already covered by capability 5C. Consequently, the capability goal description was rectified to express the correct goal of the capability, that being to prioritize and determine the scope of the data quality program. Additionally, the extraneous capability development action was removed, and the other capability development actions were rephrased to better express their intent. Lastly, the capability name was adjusted to “data prioritization and scoping” to better indicate the emphasis on these aspects instead of identification, which was already covered by CDE definition in capability 5C.

Q: The actionable suggestions for achieving this capability are clearly communicated and comprehensible.

Capability	CDO	Master Data Specialist	Enterprise Architect	Governance Manager	Governance Consultant	Mean	Std. Dev.
1A	5	7	7	6	6	6.2	0.75
1B	5	7	6	6	6	6	0.63
1C	5	7	4	7	6	5.8	1.17
1D	6	7	7	7	6	6.6	0.49
1E	5	6	6	6	6	5.8	0.40
2A	7	7	6	7	6	6.6	0.49
2B	6	7	7	6	6	6.4	0.49
2C	6	7	7	7	6	6.6	0.49
2D	5	5	6	6	6	5.6	0.49
3A	6	7	4	6	6	5.8	0.98
3B	6	7	6	7	6	6.4	0.49
3C	6	7	6	6	6	6.2	0.40
3D	6	2	6	6	6	5.2	1.60
3E	6	6	5	7	6	6	0.63
4A	6	6	6	7	6	6.2	0.40
4B	6	6	6	6	6	6	0.00
4C	6	6	4	7	6	5.8	0.98
5A	6	6	5	6	6	5.8	0.40
5B	6	6	6	5	6	5.8	0.40
5C	6	6	7	6	6	6.2	0.40
5D	6	6	7	6	6	6.2	0.40
5E	6	6	7	6	6	6.2	0.40
6A	6	6	6	5	6	5.8	0.40
6B	6	6	5	6	6	5.8	0.40
6C	6	6	5	5	6	5.6	0.49
6D	7	6	3	6	6	5.6	1.36
6E	7	6	7	7	6	6.6	0.49

6F	7	6	4	6	6	5.8	0.98
6G	7	6	6	6	6	6.2	0.40
7A	7	6	6	4	6	5.8	0.98
7B	7	6	5	4	7	5.8	1.17
7C	7	6	7	4	7	6.2	1.17
8A	6	6	5	5	7	5.8	0.75
8B	6	6	3	4	7	5.2	1.47
8C	6	6	7	6	7	6.4	0.49
8D	6	6	7	6	7	6.4	0.49
8E	6	6	7	5	6	6	0.63
9A	6	6	5	7	6	6	0.63
9B	6	6	6	7	6	6.2	0.40
9C	6	6	6	7	6	6.2	0.40
9D	6	6	7	7	6	6.4	0.49
10A	5	6	6	4	7	5.6	1.02
10B	6	6	6	5	7	6	0.63
10C	5	6	5	5	7	5.6	0.80
10D	6	6	6	6	6	6	0.00
11A	5	6	5	7	6	5.8	0.75
11B	6	6	5	7	6	6	0.63
11C	7	6	6	7	6	6.4	0.49
11D	7	6	6	7	6	6.4	0.49
12A	7	6	7	6	6	6.4	0.49
12B	6	6	7	6	6	6.2	0.40
12C	6	6	6	6	6	6	0.00
12D	6	6	6	6	6	6	0.00
13A	6	6	4	6	6	5.6	0.80
13B	7	6	7	6	6	6.4	0.49
13C	6	6	5	6	6	5.8	0.40
13D	6	6	6	6	6	6	0.00
13E	6	6	6	6	6	6	0.00

Table 9. Descriptive statistics for capability development action clarity from expert discussion guide survey.

Except for capabilities 3D and 8B, analysis of the data from Table 9 indicates a positive sentiment from expert discussion participants for all capabilities. As the issues with and changes to capability 3D were previously described we won't cover them here. The enterprise data architect and data governance manager both similarly remarked that the first capability development action was expansive but still lacked clarity. Notably it was commented that this capability required data business rules and standards to be present before profiling could be performed. Additionally, the original third development action concerning grading and cataloging in-scope data was deemed too vague without further explanation. In response to this feedback, the requirement for data standards and business rules to be present before profiling can be performed was expressed in the model by adding a dependency on policy and standards related capability 4A to an earlier capability that is a prerequisite for capability 8B. Additionally, the third development action was expanded to provide a more detailed description.

Q: The actionable suggestions for reaching this capability level are accurate.

Capability	CDO	Master Data Specialist	Enterprise Architect	Governance Manager	Governance Consultant	Mean	Std. Dev.
1A	6	7	7	7	6	6.6	0.49
1B	5	7	5	7	5	5.8	0.98
1C	6	7	6	7	5	6.2	0.75
1D	6	7	6	7	6	6.4	0.49
1E	5	7	5	7	6	6	0.89
2A	7	7	7	7	6	6.8	0.40
2B	7	7	7	7	6	6.8	0.40
2C	7	6	5	7	6	6.2	0.75
2D	6	6	5	7	6	6	0.63
3A	7	6	7	6	5	6.2	0.75
3B	7	7	7	6	6	6.6	0.49
3C	7	6	7	6	6	6.4	0.49
3D	4	3	4	6	5	4.4	1.02
3E	6	6	7	7	6	6.4	0.49
4A	7	6	7	6	6	6.4	0.49
4B	7	6	6	6	6	6.2	0.40
4C	7	6	5	7	6	6.2	0.75

5A	6	6	6	6	5	5.8	0.40
5B	6	6	5	5	6	5.6	0.49
5C	6	6	6	6	6	6	0.00
5D	6	6	7	6	5	6	0.63
5E	6	6	7	6	6	6.2	0.40
6A	7	6	7	5	6	6.2	0.75
6B	7	6	6	6	6	6.2	0.40
6C	6	6	4	5	5	5.2	0.75
6D	6	6	7	6	6	6.2	0.40
6E	6	6	7	7	5	6.2	0.75
6F	6	6	6	6	6	6	0.00
6G	7	6	7	6	6	6.4	0.49
7A	6	6	6	4	6	5.6	0.80
7B	6	6	7	4	6	5.8	0.98
7C	6	6	7	4	6	5.8	0.98
8A	6	6	6	4	7	5.8	0.98
8B	6	6	6	5	7	6	0.63
8C	6	6	7	6	6	6.2	0.40
8D	6	6	7	5	7	6.2	0.75
8E	6	6	6	4	6	5.6	0.80
9A	6	6	7	7	6	6.4	0.49
9B	6	6	6	7	6	6.2	0.40
9C	6	5	7	7	6	6.2	0.75
9D	6	6	7	7	6	6.4	0.49
10A	6	7	7	4	6	6	1.10
10B	4	4	5	4	6	4.6	0.80
10C	6	4	6	6	6	5.6	0.80
10D	5	4	5	6	5	5	0.63
11A	5	6	4	7	5	5.4	1.02
11B	6	6	6	7	6	6.2	0.40
11C	7	6	4	7	6	6	1.10
11D	7	6	5	7	6	6.2	0.75
12A	7	6	7	6	6	6.4	0.49
12B	6	6	5	6	6	5.8	0.40
12C	7	6	7	6	5	6.2	0.75
12D	6	6	6	6	6	6	0.00
13A	6	6	5	6	6	5.8	0.40
13B	6	6	6	6	6	6	0.00
13C	6	6	5	6	6	5.8	0.40
13D	6	6	5	6	6	5.8	0.40
13E	5	6	4	6	6	5.4	0.80

Table 10. Descriptive statistics for capability development action accuracy from expert discussion guide survey.

Analysis of the data in Table 10 indicates a positive sentiment for all capabilities in terms of the accuracy of their development actions, except for capabilities 3D and 10B. Capability 3D was completely altered as previously described; hence we will only discuss the issues and changes regarding capability 10B. Experts commented the terminology used in the original development actions only described performing the indicated practices for data attributes, thereby essential skipping metrics and data entities when moving from capability 10A to 10B. As this was not the intended meaning of the capability, the descriptions of the development actions were altered to also include the practice of defining business definitions for entities and metrics and creating an inventory of metrics, the related entities, and their respective attributes.

In addition to the changes made based on the quantitative data, various other alterations were made to model components based on qualitative feedback. For instance, the order of capability 12C and 12D was reversed as experts deemed the development of an agile or scalable data storage solution to be of greater importance and a more logical next maturity stage than the integration of external data sources, since not all organizations will require the use of external data, while the need for a scalable storage solution may very well be present. Similarly, capability 10B and 10C also had their order reversed, as development of data and analytical skills through training was argued to be necessary for employees to effectively participate in the use and development of an organization's data and analytics environment. Capability 10C concerning metadata capture and inventorization was extended to include the process of establishing common organizational definitions for each metadata type, since this was noted to be missing from capability 10B which only covered this for entities and their attributes. Capability 6C and 6E had their positions swapped, as including the need for specifying enterprise data governance in the data management strategy was deemed of greater importance than the consecutive focus area capabilities by experts. Consecutively the new capability 6E was removed completely since including it as part of the strategy focus area was considered excessive, as the practices it described were predominantly justifying the need to perform certain tactical governance activities, which could be consolidated into capability 5A and reduce model complexity. Capability 6F and 6G also had their order reversed, as experts deemed it more practical to first develop a clear education and training program based on established governance policies, before quantitatively assessing the data management program's effectiveness. Additionally, due to the removal of capability 6E, capability 6F and 6G became the new capability 6E and 6F. Lastly, several capability descriptions and improvement actions received minor changes to better express their intended meaning.

Appendix 4 contains a complete collection of the final focus areas, their capabilities, the various capability descriptions and development actions after all changes were made.

4.2. Dependencies & matrix placement

While all model capabilities – with exception of the first – have intra-dependencies within their respective focus area, various capabilities have cross-focus area interdependencies as they require that one or more other capabilities are implemented first. These dependencies are either axiomatic or based on best practices that ensure effective alignment between functions. A dependency being axiomatic implies that is self-evident and can be logically deduced. An example of an axiomatic dependency would be that using predictive analytics techniques to develop data products, by definition requires predictive analytics tools to be available. Next, the capabilities were positioned in the maturity matrix as per the design rules proposed by (van Steenbergen et al., 2010) and shifted based on feedback gathered during expert discussion. The blue arrows in Figure 6 visually show the dependencies. Capabilities without specific dependencies can be developed independently. Table 11 contains a list of all 33 dependencies of the DDDMFAMM. In this section, we explain the dependencies and present a matrix that visualizes the dependencies Figure 6.

Establishing data driven capabilities begins with management commitment and assembling an initial steering committee that can spearhead data-driven development and supply funding to data initiatives, combined with an exploration of the possible organizational applications of data. However, before analytics practices can be applied, the technologies must be in place that can facilitate them. This constitutes a dependency for Analytics Techniques & Analysis A on Analytics Applications & Tools A. Similarly, Data Driven Culture B requires there be an established set of analytics techniques users should aim to develop, making it dependent on Analytics Techniques & Analysis A. Decision-making process (DMP) A requires that initial descriptive data analysis techniques are in place that produce data products to be used in decision-making; therefore, it is dependent on Analytics Techniques & Analysis A. Additionally, it requires that leadership is committed to becoming data driven so that decision-makers are motivated to use data products to inform decision-making, making it dependent on Leadership & Empowerment A. Policy & Standards A needs a governance body to be present that can establish policies, standards and guidelines for data and its use, which constitutes a dependency on Data Governance Structure A.

Before logical data domains can be inventoried and assigned to authorized data domains as part of Data Architecture A, there must be an understanding about which data categories support which business function. Therefore, it is dependent on Content Governance A. Data Driven Culture A requires that a general data management strategy is place to describes how data-driven business analytics contributes to organizational decision-making and generate awareness amongst employees, making it dependent on Data Management Strategy (DMS) A. Content Governance D requires data policies and standards are present before classifications can be established and assigned to data elements, constituting a dependency on Policy & Standards A. Similarly, the practice of assigning classifications to metadata as part of Data Architecture C can only be performed once policies & standards for metadata are in place.

Data Architecture B requires that data taxonomies and ontologies are in place that describe how conceptual data domains and are related, before the semantics of logical data domain can be defined, therefore, it is dependent on Content Governance B.

In order to develop and maintain a centralized data storage and management solution as part of Data Storage Infrastructure and Operations B, the sources of different logical data elements must be identified. This constitutes a dependency on Data Architecture A. Data Governance Structure C requires the goals, objectives and desired structure of an enterprise data governance program are defined as part of the organization's strategy, before a formal governance plan can be developed, making it dependent on Data Management Strategy (DMS) C. In turn, Policy & Standards B requires that relevant data governance stakeholders are identified before they can review the developed data policies and standards, creating a dependency on Data Governance Structure C. Data Quality Assessment and Remediation A requires that logical data elements which support critical business functions are identified and have clearly defined semantics in order to prioritize data in need of quality control, this constitutes dependencies on Data Architecture B and Content Governance C. In turn, Content Governance C, is also dependent on Data Architecture B, as the logical data elements must be inventoried before they can receive a priority based on their importance to critical business functions. Similarly, Data Governance Structure D requires that data assets such as metrics, entities and attributes are inventoried, before responsibilities for their quality can be assigned to data stewards, constituting a dependency on Data Architecture B.

For the outcomes of diagnostic analytics to be utilized in or help improve decision-making processes as part of Decision-making process (DMP) B, the techniques to perform such analyses must be present in the organization, making it dependent on Analytics Techniques & Analysis B. In turn Decision-making process (DMP) C requires that predictive analytics techniques are used to develop prediction models that may be referenced as part of decision-making, constituting a dependency on Analytics Techniques & Analysis C. Additionally, it requires that the DMS is aligned with data architecture, IT and operations objectives in order to develop consistent reliable decision-making strategies that realize business objectives, which makes it dependent on Data Management Strategy (DMS) D. Data quality Assessment and Remediation B requires that metadata is being inventoried and that data elements receive a classification indicating which policies and standards apply to it in order to perform an assessment and assign a quality grade as metadata. This constitutes dependencies on Data Architecture C and Content Governance D.

In order to establish quality control points across the data supply chain and detect issues with data input processes as they emerge, Data Quality Assessment and Remediation D requires an established governance structure consisting of data stewards that are responsible for the quality of data assets. This makes it dependent on Data Governance structure D. Data Driven Culture C requires that employees are aware of and act in compliance with the guidelines for the data management program and possess the necessary skills, before they can effectively participate in the development of the organization's data driven environment. This constitutes a dependency on Data Management Strategy (DMS) E. Similarly, Leadership & Empowerment C requires that both organization leaders and employees are versed in the organization's data strategy, in order to participate in collaborative data initiatives and improve the data and analytics business case, making it also dependent on Data Management Strategy (DMS) E.

	Prerequisite Capability	Dependent Capability	Source
1	Analytics Applications & Tools A	Analytics Techniques & Analysis A	Axiomatic
2	Analytics Techniques & Analysis A	Data Driven Culture B	(Cosic et al., 2015)
3	Analytics Techniques & Analysis A	Decision-making process (DMP) A	Axiomatic
4	Data Governance Structure A	Policy & Standards A	(DAMA International, 2017)
5	Content Governance A	Data Architecture A	(EDM Council, 2014, 2020)
6	Data Management Strategy (DMS) A	Data Driven Culture A	(Larson, 2023)
7	Leadership & Empowerment A	Decision-making process (DMP) A	(Heubeck & Meckl, 2022)
8	Policy & Standards A	Content Governance D	(EDM Council, 2014, 2020)
9	Policy & Standards A	Data Architecture C	(EDM Council, 2014, 2020)
10	Content Governance B	Data Architecture B	(EDM Council, 2014, 2020)
11	Data Architecture A	Data Storage Infrastructure and Operations B	(DAMA International, 2017)
12	Data Governance Structure C	Policy & Standards B	(DAMA International, 2017)
13	Data Management Strategy (DMS) C	Data Governance Structure C	Axiomatic
14	Data Architecture B	Data Quality Assessment and Remediation A	(EDM Council, 2014, 2020)
15	Data Architecture B	Content Governance C	(DAMA International, 2017)
16	Data Architecture B	Data Governance Structure D	Expert Feedback
17	Analytics Techniques & Analysis B	Decision-making process (DMP) B	Axiomatic
18	Content Governance C	Data Quality Assessment and Remediation A	(EDM Council, 2014, 2020)
19	Data Management Strategy (DMS) D	Decision-making process (DMP) C	(Parra, 2018; Parra et al., 2019)
20	Data Governance Structure D	Data Quality Assessment and Remediation D	(EDM Council, 2014, 2020)
21	Content Governance D	Data Quality Assessment and Remediation B	Axiomatic
22	Data Management Strategy (DMS) E	Data Driven Culture C	(Cosic et al., 2015)
23	Data Management Strategy (DMS) E	Leadership & Empowerment C	(Parra, 2018)
24	Data Architecture C	Data Quality Assessment and Remediation B	(EDM Council, 2014, 2020)
25	Analytics Applications & Tools D	Analytics Techniques & Analysis C	Axiomatic
26	Analytics Techniques & Analysis C	Decision-making process (DMP) C	Axiomatic
27	Leadership & Empowerment C	Data Driven Culture D	(Korherr et al., 2022; Sleep et al., 2019)
28	Analytics Applications & Tools E	Analytics Techniques & Analysis D	Axiomatic
29	Analytics Techniques & Analysis D	Decision-making process (DMP) D	Axiomatic
30	Data Governance Structure E	Data Quality Assessment and Remediation E	Expert feedback
31	Data Quality Assessment and Remediation E	Leadership & Empowerment D	(Wieder & Ossimitz, 2015)
32	Decision-making process (DMP) D	Data Driven Culture D	Axiomatic
33	Data Driven Culture D	Leadership & Empowerment D	(Parra, 2018)

Table 11. DDDMFAMM capability dependencies.

In order to develop predictive models as part of Analytics Techniques & Analysis C, the technologies must be in place to support these techniques, which constitutes a dependency on Analytics Applications & Tools D. Data Driven Culture D requires that leaders active engage in the development and use of the data-driven environment so that data insights contribute for a large part to decision-making, in order to establish data-driven as the new norm, making it dependent on Leadership & Empowerment C and Decision-making process (DMP) D. Analytics Techniques & Analysis D requires that the technologies needed to develop prescriptive analytical models are present, constituting a dependency on Analytics Applications & Tools E. Similarly, Decision-making process (DMP) D requires such prescriptive analytics products to be available before they can be used in decision-making processes, making it dependent on Analytics Techniques & Analysis D. Performing tiered data quality audits across business lines as part of Data Quality Assessment and Remediation E, requires that business lines have dedicated individuals in charge of data asset quality whom are able to report directly to the DMO or their business leaders. This constitutes a dependency on Data Governance Structure E. Lastly, delegating decision making activities to employees or automated systems as part of Leadership & Empowerment D, requires the highest level of trust in data and data product quality, creating a dependency on Data Quality Assessment and Remediation E. Additionally, decision-making based on data insights and working with data must be the default operating procedure to ensure a similar decision outcome, constituting a dependency on Data Driven Culture D.

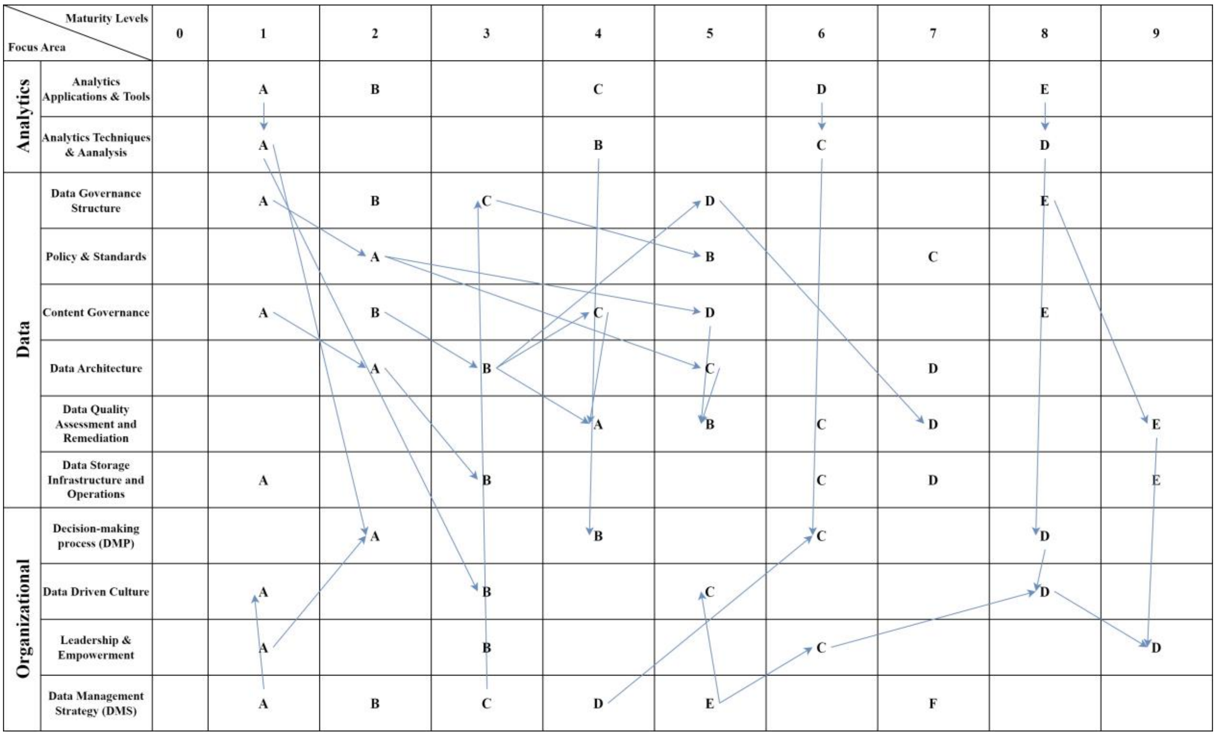

Figure 6. Capability dependencies visualized: The letters represent the capabilities; arrows signify the dependencies.

The dependencies determine the placement of each capability in the matrix. Each focus area in the maturity matrix was originally populated with all its capabilities and a minimum maturity level assigned to each capability. Afterwards, the maturity level for each capability with one or more prerequisites was increased by one, until its level was at least one higher than that of the prerequisite capability with the highest maturity level. This resulted in an initial theoretical maturity matrix. Finally, the theoretical maturity matrix was examined during expert discussion. During this examination, expert participants were able to provide indepth qualitative feedback about capability dependencies and matrix placement based on their experience. By incorporating this feedback dependencies were altered, removed or added and the maturity levels of specific capabilities were changed with respect to their dependencies in order to better allign with their practical implementation order. As part of this process, capabilities were moved either right or left in the matrix – thereby increasing or decreasing their corresponding maturity level – so long as each capability with dependencies remained at a maturity level the same or higher than its prerequisites. This iterative process resulted in the final maturity matrix that considers all dependencies and practical implementation order preferences (Figure 7).

	Focus Area \ Maturity Levels	0	1	2	3	4	5	6	7	8	9
Analytics	**Analytics Applications & Tools**		Basic Analytics Applications	Targeted Applications		Business intelligence tools		Analytics tool integration		Self-service & Prescriptive tools	
	Analytics Techniques & Aanalysis		Descriptive Analytics			Diagnostic analytics		Predictive analytics		Prescriptive analytics and automation	
Data	**Data Governance Structure**		Data Management Office (DMO)	Executive ownership	Data governance plan		Data quality roles and responsibilities			Enterprise-wide governance	
	Policy & Standards			Establishing Policy & Standards			Stakeholder review & approval		Data governance policy integration		
	Content Governance		Establish Authorized data domains (ADD)	Data taxonomies and ontologies		Critical data elements (CDE)	Data classification			Standardized identifiers and relational models	
	Data Architecture			Entity identification	Data semantics and relationships		Metadata definition, capture and inventorization		Business & Technology Alignment		
	Data Quality Assessment and Remediation					Data prioritization and scoping	Data profiling, analysis, and grading	Data remediation	Data quality control		Data quality audit
	Data Storage Infrastructure and Operations		Collection and sharing		Centralized storage and management			Agile & scalable storage solution	External data integration		Big Data
Organizational	**Decision-making process (DMP)**			Ad-hoc data-driven decision-making		Systematic data-driven decision-making		Embedded data-driven decision-making		Strategic data-driven decision-making	
	Data Driven Culture		Awareness creation		Training & Skill development		Adoption & Participation Encouragement			Data-driven standardization	
	Leadership & Empowerment		Leadership attitude		Empowerment & Business case			Leadership collaboration			Delegation, alignment, and innovation
	Data Management Strategy (DMS)		DMS specification and sharing	Business requirements	Enterprise data governance	Architecture, IT and Operations alignment	Communication and Training		Data Management Measuring and Evaluation		

Figure 7. Focus areas and capabilities in the DDDMFAMM maturity matrix. Shaded areas indicate the maximum maturity in the corresponding focus area.

The focus area with the lowest maturity determines the overall maturity score. In practice, matrix squares for each focus area may be filled until the square before the level corresponding to the first capability that isn't reached. This way, focus areas that only see development at later maturity stages, don't reduce the overall maturity score. This also implies that when the final capability in focus area is present, the matrix squares for that focus area may be filled until the model's maximum level.

5. Assessment instrument development

The maturity model is paired with an instrument that can be used to assess the presence of the various capabilities. Capability maturity models and assessment frameworks often propose various means of assessment, leaving the choice of assessment method up to the assessor (DAMA International, 2017; EDM Council, 2014). These may include questionnaires, interviews with key organization members, analyses of work products or processes or investigations of organizational information systems. In FAMMs this instrument usually takes the form of a list of assessment statements (Smits & van Hillegersberg, 2019; van Steenbergen et al., 2010; Yigit Ozkan et al., 2021). Each capability may have one or more assessment statements that when answered positively, ascertain whether an organization has developed the associated capability.

5.1. Assessment statements

The assessment statements of the DDDMFAMM are derived from the capability descriptions and development actions, as these describe the requirements for the capability. Experts were given the opportunity to comment on each assessment statement and provide qualitative feedback on how to improve its accuracy, comprehensibility and legibility. Additionally, the extent to which experts agreed that the combination of assessment statements for each capability reflected it fully, was quantitatively examined (Table 12). Note that this examination was done after changes were made to the original focus areas and capabilities. This implies that focus area 7 and capability 6G were not covered. To maintain internal consistency, focus area 7 and capability 6G are absent from Table 12 and numbering has not been altered.

Q: The capability assessment statements together fully reflect the capability.

Capability	CDO	Master Data Specialist	Enterprise Architect	Governance Manager	Governance Consultant	Mean	Std. Dev.
1A	7	5	6	7	6	6.2	0.75
1B	5	5	6	7	6	5.8	0.75
1C	7	5	6	7	6	6.2	0.75
1D	6	4	6	7	6	5.8	0.98
1E	5	5	6	6	6	5.6	0.49
2A	6	6	6	7	6	6.2	0.40
2B	6	6	6	7	6	6.2	0.40
2C	6	6	6	7	6	6.2	0.40
2D	6	6	6	7	6	6.2	0.40
3A	6	6	6	7	5	6	0.63
3B	7	7	7	7	6	6.8	0.40
3C	6	7	6	7	5	6.2	0.75
3D	7	7	7	7	6	6.8	0.40
3E	6	7	7	7	6	6.6	0.49
4A	7	7	7	7	6	6.8	0.40
4B	6	6	6	6	6	6	0.00
4C	7	6	7	7	6	6.6	0.49
5A	7	5	6	6	6	6	0.63
5B	6	5	6	6	6	5.8	0.40
5C	7	7	7	7	6	6.8	0.40
5D	7	7	7	7	6	6.8	0.40
5E	6	6	6	6	6	6	0.00
6A	7	5	6	7	6	6.2	0.75
6B	7	5	6	7	6	6.2	0.75
6C	7	5	6	7	6	6.2	0.75
6D	7	5	6	7	6	6.2	0.75
6E	7	5	6	7	6	6.2	0.75
6F	7	5	6	7	6	6.2	0.75
8A	6	6	6	7	6	6.2	0.40
8B	7	6	7	7	6	6.6	0.49
8C	6	7	7	7	6	6.6	0.49
8D	7	7	7	7	6	6.8	0.40
8E	6	7	7	7	6	6.6	0.49
9A	6	7	7	7	6	6.6	0.49
9B	7	7	7	6	6	6.6	0.49
9C	6	6	6	5	6	5.8	0.40

9D	6	6	6	6	6	6	0.00
10A	4	7	4	7	6	5.6	1.36
10B	6	6	6	7	6	6.2	0.40
10C	6	3	5	7	6	5.4	1.36
10D	6	6	6	7	6	6.2	0.40
11A	6	6	5	7	6	6	0.63
11B	6	6	6	6	6	6	0.00
11C	6	6	7	7	6	6.4	0.49
11D	7	6	7	6	6	6.4	0.49
12A	7	6	7	7	6	6.6	0.49
12B	6	6	6	7	6	6.2	0.40
12C	7	6	5	7	6	6.2	0.75
12D	6	6	5	6	6	5.8	0.40
13A	7	6	3	7	5	5.6	1.50
13B	7	6	6	6	6	6.2	0.40
13C	7	6	4	7	6	6	1.10
13D	7	6	4	6	6	5.8	0.98
13E	7	6	5	7	6	6.2	0.75

Table 12. Descriptive statistics for capability completeness in assessment statements from expert discussion guide survey.

When analyzing the data in Table 7 we find that when accounting for the standard deviation, the average score for description clarity of capabilities is above 4, indicating an overall positive sentiment for all capabilities in terms of their assessment statements together reflecting the capability. The full list of DDDMFAMM assessment statements can be found in Appendix 5: Capability assessment statements.

5.2. Assessment method

It is important to note that the interpretation of the assessment statements is key to answering them accurately, as these may be quite technical. Therefore, it is common for both CMM's and FAMM's that the assessment is conducted by a model expert. Additionally, when the assessment method involves gathering information from non-model experts, this is generally done in an interview setting (Smits & van Hillegersberg, 2019) or contains some opportunity for participants to enquire about the model context and provide additional feedback. The DDDMFAMM similarly allows for this type of assessment to be conducted by using the assessment statements to guide interviews. However, while the DDDMFAMM's assessment statements function as an instrument – like all FAMMs – that allows a model expert to perform an assessment of an organization's DDDM capabilities, the need for a model expert limits the viability of the DDDMFAMM as a potential self-assessment tool. In practice, organizations may wish to conduct an initial assessment to measure their DDDM maturity, followed by a repeat assessment after having further developed their DDDM capabilities. Alternatively, organizations may wish to conduct periodic assessments to ensure capability development is progressing as intended. In this context, the need for a model expert to perform the assessment limits the DDDMFAMM's practical applicability.

During expert discussion, the means of establishing an appropriate assessment method was extensively discussed, and a novel assessment method was conceived. First, to ensure repeatability as a self-assessment tool, the DDDMFAMM assessment method utilizes a questionnaire containing the various assessment statements. Second, to prevent the results from being an isolated representation of the organization, the questionnaire is administered among a cross functional respondent pool. Third, to bolster model accuracy, the respondent pool is carefully selected among organization members in specific functions and the various focus areas of the model are divided over specific respondent groups based on the alignment of their expertise and organizational knowledge to the focus area. Additionally, during the questionnaire respondents are asked to indicate their perceived level of expertise pertain to a specific topic ranging from 1 to 7 before and after answering the related questions to allow for post-questionnaire response filtering and future assessment group refinement. Fourth, in order to improve assessment statement comprehensibility and reduce the chance of respondents misinterpreting their meaning, the assessment statements are altered to include simpler terminology, brief explanations of unavoidable terms and one or more context specific examples that apply to the organization. This is achieved through the use of an organization specific model glossary and link table.

Using this method, a model expert first selects various organization members with knowledge relating to the DDDMFAMM's 12 focus areas and collaborates with them to develop the model glossary and select the eventual target groups for the questionnaire. This can be effectuated through either individual interviews or focus group discussions. Using the model glossary, the terminology of the default assessment statements is altered to better fit the organization's lexicon and context. The altered assessment statements are then connected to the original statements using the link table. Next, a questionnaire using the organization specific assessment statements is developed and conducted among the target audience. Finally, the questionnaire results are analyzed, visualized, and communicated using the DDDMFAMM reporting tool.

This method allows for repeat periodic assessment of the DDDM capabilities of organizations. Another benefit of this method is that both the questionnaire and the visualization of the results can be developed in or adapted to the preferred survey and BI tools of the organization, allowing for easier institutionalization of the self-assessment.

5.3. Assessment results processing

The responses to the assessment statements are processed and reported in a visualization that displays the achieved capabilities and their corresponding maturity score (Figure 7). The original FAMM design methodology requires all assessment statements be answered positively before a capability can be deemed achieved (van Steenbergen et al., 2010). However, more recent implementations of the design approach have argued that this requirement is too stringent (Yigit Ozkan et al., 2021) and have designed alternative approaches to score calculation using weighted maturity scores. We share the opinion that the requirement to have all assessment statements be positively answered to achieve a specific capability is too stringent as it doesn't allow for any derivation from the model guidelines. However, we consider the use of a scoring system as proposed by (Yigit Ozkan et al., 2021) to deviate too much from the original design principles of focus area maturity modelling. When a weighted maturity score is assigned based on the maturity level of each capability, it disproportionately promotes the development of late-stage capabilities and reduces the relevance of dependencies. Instead, we designed a method that allows some flexibility, but retains the power of dependencies.

To achieve a capability in the DDDMFAMM, only the majority of its assessment statements are required to be answered positively and in the case of tie, the presence of the subsequent capability determines whether the score of the previous capability may be assigned. To prevent users from misinterpreting a partially achieved capability as a fully achieved one, presentation of assessment results emphasizes the result for each assessment statement.

6. Case study results

In order to assess the practical viability of the DDDMFAMM assessment instrument, a case study was conducted at a large Dutch engineering firm. In collaboration with the organization's enterprise information management department, the model glossary and organization specific questionnaire were developed, the target audience selected, and the relevant focus areas assigned to each respondent group based on their expertise. Table 13 contains a list of all respondent groups and their assigned focus areas.

Respondent Group	Assigned focus areas
Country & Domain process owners	Data management strategy, Decision-making process, Data driven culture, Leadership & empowerment
BI subject matter experts & Top 20 BI users	Analytics applications & tools, Analytics techniques & analysis, Data quality assessment and remediation, Data driven culture
Legal, Security & Trade compliance	Data governance structure, Policy & standards, Data driven culture
Enterprise Architects & Product Manager Business Applications	Analytics applications & tools, Analytics techniques & analysis, Data governance structure, Policy & standards, Content governance, Data quality assessment and remediation, Data architecture, Data driven culture, Data infrastructure and operations
Enterprise Information Management	All

Table 13. Assessment respondent groups & assigned focus areas.

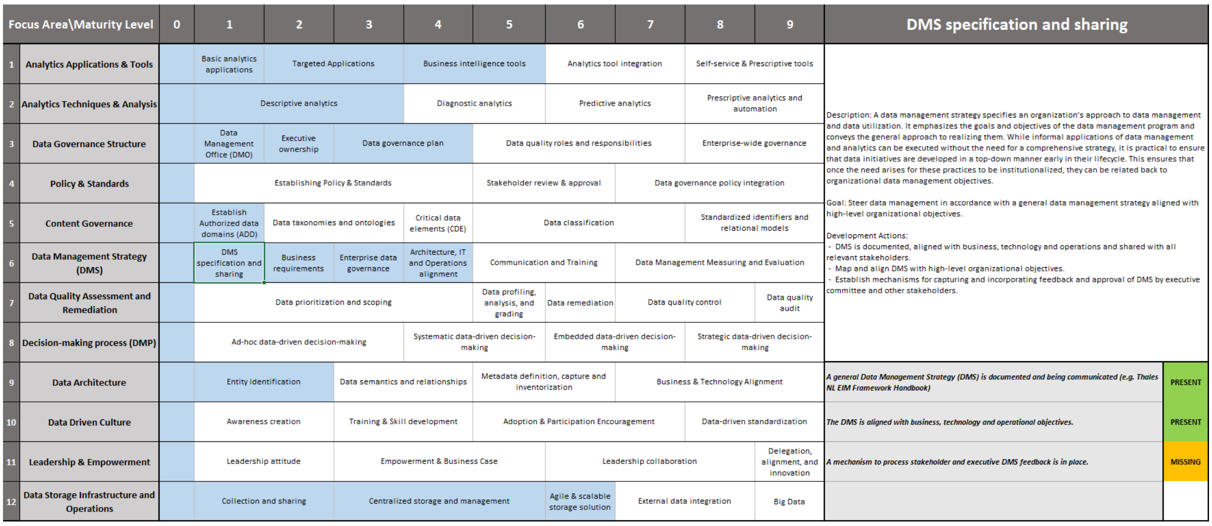

Figure 8. Example of DDDMFAMM assessment tool result report.

After assessment completion, the assessment results were analyzed and processed into a visualization that dynamically provides informational descriptions for each selected focus area or capability, which contain the capability goals, potential development actions, and the majority response to each capability assessment statement (Figure 8). Additionally, the visualization displays the achieved capabilities and the corresponding maturity score for each focus area in both a matrix and radar view. Appendix 7: DDDMFAMM assessment tool result report (Enlarged) contains an enlarged view of Figure 8. From the case study, we also found that respondents desired a mechanism to provide their reasons for a given answer.

In order to assess the accuracy of the DDDMFAMM as an assessment tool, the original focus group that developed the organization specific model glossary in collaboration with the model expert, was asked to indicate the accuracy of the results for each focus area and the overall assessment. In the case of this initial case study, the focus group is the same as the expert discussion group. The assessment was performed after changes were made to the model based on expert feedback. As a result, the post assessment evaluation doesn't include the original focus area 7 "Data Quality Program", since this focus area was removed at an earlier stage in the design process, limiting it to only 12 focus areas down from

13. The focus area numbering in Table 14 remains consistent with Figure 8 and the list of focus areas and capabilities in Appendix 4.

Q: I recognize my organization in the maturity results for this focus area.									
Focus Area	CDO	Master Data Specialist	Enterprise Architect	Governance Manager	Governance Consultant	BI Solution Manager	Director QCSBI	Mean	Std. Dev.
1	6	6	6	7	6	6	6	6.1	0.35
2	7	6	7	7	6	6	6	6.4	0.49
3	7	5	5	6	5	6	5	5.6	0.73
4	7	5	6	7	6	6	5	6.0	0.76
5	6	6	5	6	5	5	6	5.6	0.49
6	7	7	5	5	5	6	6	5.9	0.83
7	7	6	7	5	7	6	7	6.4	0.73
8	6	4	5	7	7	6	6	5.9	0.99
9	6	5	6	7	7	6	6	6.1	0.64
10	6	6	6	6	6	6	7	6.1	0.35
11	6	6	7	7	7	6	7	6.6	0.49
12	6	7	6	6	5	6	6	6.0	0.53

Table 14. Descriptive statistics for focus area assessment results accuracy from post assessment survey.

Accounting for the standard deviation in response, we find an average score above 4 for all focus areas in Table 14, indicating a generally positive sentiment from the original focus group participants in terms of the accuracy of the assessment results per focus area. Similarly, data from Table 15 indicates a positive sentiment towards the accuracy of the overall assessment results.

Q: I recognize my organization in the overall assessment results.								
CDO	Master Data Specialist	Enterprise Architect	Governanc e Manager	Governance Consultant	BI Solution Manager	Director QCSBI	Mean	Std. Dev.
7	6	6	6	6	6	6	6.1	0.35

Table 15. Descriptive statistics for overall assessment results accuracy from post assessment survey.

To test the viability of the DDDMFAMM as an assessment instrument, all respondents from the chosen assessment groups were asked to indicate if the purpose of the assessment was clear, if it can be completed is a reasonable amount of time, and whether it will help their organization become more data driven as described in Appendix 2. Additionally, respondents were asked whether the adjusted assessment statements based on the organization specific model glossary were comprehensible. These responses were analyzed, and the results are reported in Table 16.

As this respondent group is significantly larger than the expert discussion group, we are able to make statistical inferences from this data. For all post assessment questions, we find a p-value of the chi-square statistic lower than the minimum alpha value of 0.05 and a majority positive sentiment for each post assessment question. This indicates that the positive sentiment to the post assessment questions is statistically significant. In turn this implies that the DDDMFAMM achieves its original design objectives and can serve as a tool to help organizations develop data-driven capabilities.

H_0: Response is evenly distributed, indicating a neutral sentiment. *H_a: Response is not evenly distributed, indicating a preferential sentiment.*						
Question	Distribution				N = 19	α = 0.05
	-	o	+	Sentiment	p-value	p ≤ α
The assessment statements were comprehensible.	3	2	14	+	0.008	True
The purpose of the DDDMFAMM assessment is clear.	3	4	12	+	0.020	True
The DDDMFAMM assessment can be performed in a reasonable amount of time provided that conditions are suitable.	1	3	15	+	< 0.001	True
The DDDMFAMM assessment can help my organization incrementally improve its exploitation of data for generating business value.	4	2	13	+	0.029	True

Table 16. Chi-squared test for post assessment survey response.

7. Discussion

Our study has demonstrated that the DDDMFAMM can help organizations with the development of both technical and organizational data-driven capabilities which can improve its exploitation of data for generating business value. We will briefly discuss some additional aspects of the model and address how the DDDMFAMM compares to other maturity assessment frameworks.

As the DDDMFAMM assessment instrument is only intended to measure the presence of capabilities based on a quantitative analysis of the respondents' answers, the option to provide qualitative feedback or reasons for an answer was not included in the assessment questionnaire. However, adding a mechanism that provides respondents the opportunity to offer their motivations for each given answer, as our case study participants requested, may enable us to drill down into each response and gleam similar information as one would from an interview. This could result in a more in-depth analysis of capability presence and offer a launchpad for more detailed analyses. Additionally, the reporting application of the assessment instrument can be further developed to provide additional information, such as general descriptions for each overall maturity level and automatic recommendations about which capabilities an organization should focus its development on based on assessment results and dependencies.

The primary motivation for this research, was to close the gap between DDDM research and practice. We found that academic research tends to focus its attention on the relationships between DDDM constructs, while practitioner literature focusses on the application of technical and organizational assets and practices to help organizations develop DDDM capabilities. Both aspects are valuable for organizations. For example, knowing how data quality and data governance can be measured and which effect one has on the other is critical to understanding how these concepts are related. At the same time, organizations must also understand how they should use assets and apply practices to effectuate good data governance and data quality management. When comparing academic and practitioner DDDM maturity literature we found that academic frameworks often don't address the organizational capabilities necessary to perform DDDM and the associated challenges with implementing them, whereas practitioner frameworks often don't specify explicit relationships between capabilities across dimensions or categories, only alluding to them or disregarding them entirely. The first leaves practitioners guessing about how to implement effective DDDM capabilities, while the latter makes them question which aspects they should prioritize and where to focus their improvement efforts. To address these concerns, the DDDMFAMM specifies capabilities organizations should develop to become data driven based on referenceable academic and best practice frameworks that consider organizational implementation challenges. Additionally, it defines dependencies between capabilities across its focus areas that together provide a recommended capability development order.

Additionally, the DDDMFAMM is uniquely positioned as an assessment framework for organizational data-driven decision-making maturity. This is in contrast to existing maturity frameworks don't cover the full breadth of data driven decision making. Instead, they are limited to one or more of its various aspects, such as data management, analytics, governance or change management. As part of this research, we attempted to consolidate all aspects of DDDM into one holistic model.

On another note, one critique against maturity assessments, particularly CMMs, is that, while they are exhaustive, many can be perceived by practitioners as too heavy and large to use or even comprehend (Smits & Van Hillegersberg, 2015). This often stems from the depth and complexity of the framework or the time and resource intensive nature of the proposed assessment method. Alternatively, many maturity assessments exist that offer quick self-assessment at low or no cost. However, these often suffer from a lack of depth and don't provide actionable improvement recommendations. In this way, we find that the complexity of extant maturity assessments is often located at either extreme of too complex to perform in a reasonable amount of time or too simplistic to derive actionable insights from. As opposed to some extant data management maturity assessments (CMMI Institute, 2014; EDM Council, 2014), which suggest the use of interviews or work product analysis as a method for conducting an assessment, our model recommends surveying the organization's domain experts using a questionnaire that is tailored to the context of the organization. In this manner, the DDDMFAMM addresses both concerns by providing actionable recommendations for developing each capability and utilizing a relatively fast and repeatable assessment method.

8. Conclusions

This research has examined the domain of data-driven decision-making maturity, identified its constructs and how these are related through a literature review of extant DDDM literature. Furthermore, the goal of our research was to help practitioners by closing the identified gap between DDDM research and practice through the development of an artifact that organizations can use to assess their current level of data-driven decision-making maturity and create an incremental improvement strategy. We argue that the development of data-driven decision-making is a causal loop in which its various components build on each other through an iterative improvement process. In order to understand which practices contribute to the development of each component, we performed an in-depth examination of DDDM related maturity models and best-practice frameworks which specify the organizational capabilities required to increase the value of each construct. Based on this, we developed a focus area maturity model and assessment instrument for data-driven decision-making.

Using the constructs in our proposed causal loop diagram we compiled 13 relevant focus areas pertaining to DDDM, derived from extant maturity models. Based on expert feedback, the total number of focus area was eventually reduced to 12 with the following focus areas being validated for their relevance and included in the final model.

Analytics
- Analytics Applications & Tools
- Analytics Techniques & Analysis

Organizational
- Data Management Strategy
- Decision-making process
- Data Driven Culture
- Leadership & Empowerment

Data
- Data Architecture
- Data Governance Structure
- Content Governance
- Policy & Standards
- Data Quality Assessment and Remediation
- Data Storage Infrastructure and Operations

Each focus area contains various capabilities that form a progressing maturity of the focus area. The capabilities are adapted from the maturity literature from which each focus area is derived. For each we provide various actionable recommendations based on best practice that serve to support organizations in developing the associated capability. Appendix 4 contains a full list of all capabilities within their corresponding focus areas.

To express the way in which capabilities are intra- and interrelated, we established dependencies based on the need for one or more capabilities to be present before implementation of the dependent capability. Except for some axiomatic dependencies, dependencies were assigned based on extant literature or expert feedback. The intra-dependencies provide a clear order on how to develop the data-driven capabilities within each individual focus area. However, the addition of interdependencies that cross focus area boundaries allow for a holistic approach to data driven maturity progression that considers a combination of technical and organizational aspects such as analytics and data management, but also decision-making processes, culture, and empowerment.

For organizations to make use the DDDMFAMM as a maturity framework, they must be able to assess their current maturity within the context of the model. Therefore, an assessment instrument was developed that consists of various assessment statements for each capability – based on the development recommendations – which together assess the presence of their respective capability. This instrument can be used by an expert assessor to evaluate an organization's DDDM maturity, but also by as self-assessment tool by expert practitioners with considerable knowledge about the topic of DDDM. Alternatively, we propose a novel method that allows the DDDMFAMM assessment to be institutionalized and repeatable after the development of some context specific components and an initial expert assessment.

All these are elements are combined and put into practice through the developed DDDMFAMM, assessment instrument, reporting tool and proposed assessment method.

Finally, the results of our study (Chapter 6) show that the DDDMFAMM achieves its original design objectives, as stated in paragraph 2.1, to provide practitioners with an instrument to assess organizational DDDM maturity within a reasonable timeframe and provide actionable suggestions to reach higher maturity levels through incremental improvement.

9. Recommendations

This section will cover our recommendations for the case study firm based on the assessment results, will outline a more general development path for organizations that wish to become data driven and cover some guidelines on how organizations can use the DDDMFAMM as an assessment tool.

9.1. Becoming data-driven

Our case study results indicate low maturity for the assessed organization in the areas of leadership and empowerment, data quality, operational governance, data-driven culture, and decision-making processes. Furthermore, formal documentation of data semantics, policy, and standards, was found to be lacking, instead the firm relies heavily on the expertise of responsible governance, IT and BI staff, which inhibits institutionalization, scalability and presents knowledge retention challenges. The low maturity scores for the softer organizational focus areas are in stark contrast to the median maturity scores achieved in the technical focus areas dealing with data and analytics applications and infrastructure. This suggests that the firm does possess a strong foundation to develop data products but doesn't utilize it effectively.

The assessment results indicate that the organization particularly struggles with adapting processes and culture to be data driven. This seemingly stems from difficulties with expressing the value the firm derives from data and analytics, resulting in a lack of commitment to data-driven transformation from both management and employees. It stands to reason, that when the perceived value data contributes to decision-making is low and data products aren't being utilized effectively, that the commitment to documentation, data quality and standards will also be lacking, as this presents an additional cost without financial benefits.

Based on the DDDMFAMM assessment results we make the following recommendations to improve the data-driven maturity of the case study firm. We intentionally do not provide a timeframe for the implementation of these recommendations, as the development timeline for data driven capabilities can vary severely depending on organization size, its culture and present maturity or its budget assigned to data initiatives, and many other factors. However, it is safe to assume a timeline on the scale of years.

(1) Communicate how data adds value to the business.
Incremental improvement should begin with executive management clearly communicating to staff why the organization should be data driven and in what way they expect it to support the core business activities. In doing so, clear objectives for the use of data should be defined and communicated. Data and analytics serve to support business activities; therefore, data products must be designed with the end goal of supporting some specific business activity that generates value. If data product development doesn't follow this initial premise, an organization cannot justify spending resources on it. This desired utilization of data should be continually expressed to operational and management staff through an awareness campaign to promote data initiatives, data-driven adoption and data insight utilization as part of decision-making.

(2) Document critical data elements.
Data governance personnel must examine and document which data elements support critical business functions to create a prioritization for future governance and architecture activities.

(3) Document business data definitions.
Data elements, such as entities, attributes, metrics, KPIs, metadata, etc. must receive documented business definitions and these must be communicated to and referenceable by developers and users alike. Preferably this information should be made accessible through some type of internal knowledge base, such as a corporate wiki. This is an absolute necessity to ensure that all stakeholders involved in the development and use of data products have a common understanding of the data. We wish to emphasize the importance of this step. When data products are developed by IT or BI engineers in a vacuum or users on the business side have a different interpretation of the data, these data products are likely to not be used as they don't align with the users' expectations. Based on the

assessment, we deem that this issue is likely the root cause for the firm's lacking utilization of data in decision-making.

(4) Cross-functional collaboration for data product analysis and development.

Data definition documentation should be followed by a call to action for management and operational staff to increase cross-functional collaboration with BI and data teams to analyze the organizations current data products for effectiveness. These existing data products must be designed to be effectively integrated into decision-making processes or new data products must be developed that can be integrated into workflows to support decision-making. Staff with domain knowledge such as operational staff or domain experts, must be involved in the development of data products to ensure they accurately reflect reality. Having effective data products in place will gradually increase adoption, foster commitment, and improve future collaboration efforts.

(5) Establish data (product) policies and standards and assign data classifications.

In tandem with the development of data products, clear policies and standards must be established that express how data elements – be it entities, attributes, metrics, data products, or anything else – should be used and which approaches are agreed upon to ensure consistent measurement, qualification, or exchange. These policies and standards must then be assigned to specific data assets through classification and be communicated to and made referenceable by developers and users.

(6) Data quality assessment and improvement.

Once the use of one or more data products has been integrated into the standard workflow of a business function, initial data quality assessment and remediation initiatives should be funded to increase the reliably of and trust in critical data products. Complete and reliable data forms the foundation of trust. If users don't trust the insights provided by data products, they will not use them. We recommend this is initially done by a central body that oversees the quality of critical data assets, until data quality activities can be integrated into business lines through a decentralized network of data stewards.

Once these capabilities are in place, the organization assessed as part of our case study will have achieved its desired median maturity score across most focus areas. At this stage, the firm can consider itself reasonably data driven to the extent that it possesses the technical and organizational foundation to supply reliable accurate management information, can monitor its business processes, and act based on descriptive metrics.

It important to note that the DDDMFAMM is designed to apply to any organization. However, the desired DDDM maturity of an organization is dependent on its context, such as its sector, competitive market position and other factors. Therefore, organizations that don't rely heavily on data to support their core business activities, don't necessarily require a high maturity score in all focus areas. Alternatively, organizations that operate in environments which require a competitive edge, may wish to progress beyond the level of descriptive analytics and adopt a fully data-driven strategy.

Progressing beyond the point of simply managing business activities using descriptive reporting, also requires increased maturity in other areas to ensure advanced data products are reliable and continue to add business value. For instance, to improve operational efficiency or project market opportunities using diagnostic and predictive analytics respectively, requires that operational processes are systematically performed, and large amounts of data are stored. Moreover, personnel must be trained in the use of data tools and the established policies and standards. At the same time, cross functional collaboration between data product users and development teams must be very high or entirely embedded to ensure the necessary data is provided and sufficient domain knowledge is available to develop advanced data products, such as prediction models. Moreover, as decision-making continues to rely more on data insights and less on expert opinion, in turn, trust in data must be absolute, requiring institutional data quality assessments to ensure data insights reflect reality. Once these levels of maturity are reached, organizations can begin considering the use of big data and machine learning technologies to develop institutional prescriptive analytics tools suited to their specific needs. Of course, organizations can experiment with applying advanced analytics applications for business use, but it's important to remember that the quality of data products can only ever be as high as the quality of the data used.

While the desired maturity level an organization wishes to achieve is up to them. We do recommend organizations aim to achieve the highest level of maturity in the long-term and preferably begin sooner rather than later. As markets mature and quickly become more congested, being data driven will provide a valuable competitive advantage. Pair this with the long timeline for data-driven capability development, and by the time you decide to commit to achieving full maturity, you'll be playing catch-up with your closest competitors for years.

9.2. Model use

The DDDMFAMM is designed to function as a guide for data-driven capability development. The accompanying assessment instrument serves to measure the current DDDM maturity and record one's progress. Organizations are recommended to begin with an initial assessment to position themselves on the model. The preferred method of assessment is open to the organization. For instance, they may perform and assessment through the examination of work products, by conducting interviews or by consulting an external model expert as an assessor, so long as the questions in the assessment instrument are answered accurately. However, when using our novel assessment method described in paragraph 5.2, the assessment process can be institutionalized and periodically repeated to monitor progress.

Once positioned on the model, organizations may develop whichever capabilities they desire. However, we recommend that they prioritize focus areas with low maturity scores to ensure that all DDDM activities are properly aligned, and especially focus on the prerequisites for the capabilities they eventually wish to develop. Having a model expert serve as the assessor performing the initial assessment may help with analysis and the interpretation of the results. Lastly, we strongly recommend organizations institutionalize the use of a maturity framework and assessment to performing period assessments and monitor development progress, as this enables the continuous improvement of data-driven capabilities.

10. Limitations & Future work

This research applied triangulation by using a combination of literature review and expert discussion as part of model development. While quantitative data was gathered during model development and instrument evaluation, the small sample size of the expert group at n=5 limited our ability to make statistical inferences. Instead, we relied primarily on qualitative feedback from a multi-disciplinary group of domain experts. Future research can seek to validate the DDDMFAMM components and the instrument's applicability using quantitative methods with a larger participant population of experts of organizations. Similarly, due to the time constraints on our study, we were unable to make longitudinal observations. Developing data driven capabilities is a comprehensive undertaking, and reaching full data-driven maturity as per our model requires a large effort spanning several years. This limits our ability to examine the long-term effectiveness of the model. Future work could include longitudinal studies of the effectiveness of the DDDMFAMM.

On another note, as the DDDMFAMM is designed to be a tool used by current practitioners, it stands to reason that over time the artifact may become outdated due to new developments in the field and therefore no longer be an accurate representation of the full range of DDDM maturity. For instance, we foresee a need for future model adjustments related to the organizational use of artificial intelligence (AI) in DSS and BI&A technologies. This is because the organizational challenges around the adoption of advanced BI&A technologies and the potential ways of resolving them are areas that have received comparatively little attention in the extant literature (Ain et al., 2019). This is understandable, as we are only recently seeing more widespread organizational adoption of AI technologies due to the technical developments and commercialization efforts in the field. Instead, research in this area has mainly focused on the development, optimization, or application of different methods for both predictive and prescriptive analytics (Lepenioti et al., 2020; Yalcin et al., 2022). With the development and implementation of more complex analytics and decision support systems, organizations may face new barriers for adoption. Recent research by Wijnhoven (2022) explored the process of organizational learning within the context of intelligence amplification (IA) – which aims to make people smarter through the use of AI – and identified several barriers that inhibit the organizational learning process as it relates to the use of AI decision support systems in a clinical setting. Future research building on such findings is required to establish new best practices, which may then be integrated into the DDDMFAMM. Additionally, we'd like to draw more academic research attention to into the organizational challenges and barriers to becoming data driven in general. It is because of the characteristic of FAMMs being based on best practices, that the model development process emphasizes the need for iterative matrix improvement.

Lastly, future research could build on the DDDMFAMM to increase the measurement level to provide a more detailed overview of capability maturity. As it stands, the DDDMFAMM's assessment instrument measures maturity on the focus area level, by assessing the presence of relevant capabilities using a dichotomous response variable. Maturity measurement could be extended to the capability layer by for instance, using an ordinal response variable or by assigning specific completeness levels to each capability. This provides greater granularity to the assessment data, which may be beneficial during analysis.

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Appendix 1: Expert discussion guide

Model & assessment validity and viability metrics (1; Strongly disagree – 7; Strongly agree)

For each focus area:

- The description of this focus area is clear.
- This focus area is a relevant part of data-driven decision-making.
- The order of capabilities within this focus area demonstrates a progressive evolution of the focus area.
- The combination of its capabilities provides a complete representation of this focus area.

For each capability:

- The description of this capability is clear.
- This capability is relevant to its corresponding focus area.
- The actionable suggestions for reaching this capability level are accurate.
- The actionable suggestions for achieving this capability are clearly communicated and comprehensible.
- The capability assessment statements together fully reflect the capability.

Appendix 2: Post assessment evaluation

Assessment accuracy metrics (1; Strongly disagree – 7; Strongly agree)

For each focus area:

- I recognize my organization in the maturity results for this focus area.

Overall assessment:

- I recognize my organization in the overall assessment results.

Assessment instrument practical viability metrics (1; Strongly disagree – 7; Strongly agree)

Overall assessment:

- The purpose of the DDDMFAMM assessment is clear.
- The DDDMFAMM assessment can be performed in a reasonable amount of time provided that conditions are suitable. (Refers only to the time necessary for filling out the questionnaire)
- The DDDMFAMM assessment can help my organization incrementally improve its exploitation of data for generating business value.

Appendix 3: FAMM design process application

1	Identification of the functional domain scope.	The DDDMFAMM is scoped to the construct and dimensions of data-driven decision-making. Within this context the scope is limited to the organizational practices and assets involved in the DDDM process, where DDDM is defined as an approach to decision-making that relies on the systematic use of data and statistical analysis.
2	Determination of maturity focus areas.	Focus areas are established based on literature review and deducted from extant frameworks and maturity models, critical success factors identified in prior research or derived anew from expert discussion.
3	Determination of capabilities for each focus area.	The capabilities are based on theoretical and best practice literature and complimented with expert discussion in a panel of 7 BI, data governance and management experts and managers.
4	Determine dependencies.	Determination of intra-dependencies between capabilities within the same focus area and inter dependencies between capabilities in different focus areas is achieved by stating the prerequisites of each capability. Each capability's prerequisites and implementation order is addressed during expert discussion.
5	Positioning capabilities in matrix.	Focus area capabilities are assigned to maturity scale levels based on their dependencies, best practice, logical order and experience. Capabilities dependent on other capabilities are positioned further to the right and those not dependent on each other may be placed at the same level. Capability matrix position may be influenced by capability implementation order preferences resultant from expert discussion.
6	Develop assessment instrument.	A questionnaire is developed based on capability descriptions and practices derived from literature. All questions associated with a capability must be answered positively to achieve said capability. We assess whether the assessment questions fit the associated capability through expert discussion.
7	Definition of improvement actions.	Each capability has one or more improvement actions to guide practitioners in how to achieve said capability. Improvement actions consist of recommended practices that may be implemented to realize the capability. Due to the situation specific nature of improvement actions, these are not necessarily prescriptive and instead serve as a guide or recommendation. Improvement actions are be based on literature or expert feedback.
8	Maturity model implementation	The model's practical viability is validated through a case study at the Dutch branch of a multinational engineering firm. During the case study, data will be collected by distributing the assessment questionnaire electronically to select assessors within the organization. Afterwards, participants are presented with their assessment results and are requested to provide feedback on the assessment process through an assessment evaluation questionnaire.
9	Iterative matrix improvement.	The DDDMFAMM is initially qualitatively evaluated during expert discussion and quantitatively evaluated using assessment evaluation questionnaire. Key points of focus on are question comprehensibility, the accuracy of the overall DDDMFAMM assessment and its ability to provide an incremental improvement path.
10	Communication of results.	We contribute to the scientific and practitioner community by communicating our research process and results through this paper and the case-study organization deploying a digital assessment tool to be used for periodic DDDM maturity assessment.

Table 17. Application of the FAMM design process of van Steenbergen et al. (2010) (left column) in this study (right column)

Appendix 4: Focus Areas and Capabilities

	1. **Analytics Applications & Tools**	
A	**Basic analytics applications**	
	Goal:	Establishment of an initial generic process for business analytics using data for reporting.
	Actions:	- Adoption of generic spreadsheet programs for general use in analytics processes - Manual reporting for data visualization through for instance, e-mail, pdf documents, presentations. - Adoption of performance metrics.
	Prerequisite:	
	References:	(Parra, 2018; Parra et al., 2019)
	Description:	Performing data analytics can be a daunting task that people often assume requires advanced skill and experience working with complex applications. However, even the most rudimentary data tools used in the right way can provide deeper insight and result in actionable information. The most common tool for data analytics is the spreadsheet. Adopting rudimentary tools for basic data analysis and manually reporting and sharing results is the first step to developing analytics capabilities.
B	**Targeted Applications**	
	Goal:	Standardization of reports through the adoption of domain targeted analytics applications.
	Actions:	- Domain specific reporting tools are acquired, such as management information system (MIS), enterprise resource planning (ERP), customer relationship management (CRM), enterprise resource management (ERM). - Tailored solutions for information reporting and visualization are acquired or developed. - Reports are standardized within each application.
	Prerequisite:	
	References:	(Parra, 2018; Parra et al., 2019)
	Description:	Once a generic process for data analytics is in place, the next step is the standardization of reports and data sharing. While the spreadsheet is a simple yet powerful data manipulation and analysis tool, issues often arise when sharing files or collaborating with multiple users. Relying only on basic spreadsheet applications, can have the undesirable consequence that users may each be working with different versions of the same dataset or basing decisions on an outdated analytical report. Adopting data processing and reporting tools for specific business functions such as CRM, ERM, or ERP systems, combined with developing standardized data reports or visualizations, can support collaboration and data sharing, streamline data input processes, and ensure users are referencing the same reported information.

C	**Business intelligence tools**	
	Goal:	Improving analytics through the adoption of full-service BI tools and the development of dashboards.
	Actions:	- Acquisition of BI, OLAP, data discovery or analytics tools in an unintegrated state. - Develop data visualizations such as dashboards and scorecards.
	Prerequisite:	
	References:	(Parra, 2018; Parra et al., 2019)
	Description:	Organizations can seek to enhance their analytics proficiency by adopting comprehensive BI tools and creating dynamic dashboards. These technologies allow for more advanced data analysis and automated updating, ensuring users are always referencing the latest data. Procuring diverse data discovery and analytics tools, builds a robust technological foundation, that enables users to craft artifacts to visualize data effectively, facilitating informed decision-making, and performance tracking.
D	**Analytics tool integration**	
	Goal:	Integrate analytics tools across the business and expand analytics capability to include predictive analytics.
	Actions:	- Data insight solutions are integrated into workflows and various applications. - Use of analytics tools is embedded into various business processes. - Adoption of applications for predictive analytics. (e.g. data science applications, machine learning tools, scenario modelling software) - Development of dynamic graphs and dashboards.
	Prerequisite:	
	References:	(Parra, 2018; Parra et al., 2019)
	Description:	Providing the right information at the right time and place is crucial to support decision-making. By leveraging predictive analytics tools and integrating data insights into applications that are part of the standard workflow of employees, intelligence is delivered pre-emptively and where it's needed most.
E	**Self-service & Prescriptive tools**	
	Goal:	Enable self-service analytics and fully integrate and embed analytics tools throughout the organization.
	Actions:	- Integrate analytics applications to ensure same source referencing. - Embed analytics application use in processes throughout the entire organization. - Adopt prescriptive analytics applications. (e.g. decision-support systems, neural network builders, AI powered analysis tools, etc.) - Provide self-service BI with controlled data-use.
	Prerequisite:	
	References:	(Parra, 2018; Parra et al., 2019)
	Description:	Empowering data literate employees to create their own BI solutions enables immediate information delivery where needed and reduces the strain on the BI department. However, it is important to ensure all sources of intelligence are based on managed collections of data to ensure information integrity. Additionally, supporting employees with data-driven suggestions during decision-making serves to increase operational efficiency.

	2. Analytics Techniques & Analysis	
A	**Descriptive analytics**	
	Goal:	Steer process performance based on quantitative metrics using historic data.
	Actions:	- Use of descriptive analytics to describes performance of processes using historic data. - Metrics describe past process performance. - Use of KPIs to provide insights for decision-making. - Analytics is focused on accuracy, consistency, and timeliness.
	Prerequisite:	Analytics Applications & Tools A
	References:	(Parra, 2018; Parra et al., 2019)
	Description:	Descriptive analytics is the first type of analytics and seeks to identify "what" has happened in the past. It uses historical data to provide an account of past performance by leveraging quantitative metrics. Such metrics, known as KPI's, are utilized to offer actionable insights and guide decision-making processes. Amongst other things, the emphasis of descriptive analytics techniques is often to monitor the accuracy, consistency, and timeliness of processes, thereby enabling the organization to steer process performance effectively and make informed decisions.
B	**Diagnostic analytics**	
	Goal:	Optimize processes by identifying why certain things are happening.
	Actions:	- Diagnostic analytics is used to examine causality between events or the relationships between data objects to identify why something happened or which factors that led to specific outcomes. - Use of root cause analysis, data mining, text-mining, correlation analysis or other diagnostic analytical techniques. - Focus includes cost reduction or process optimization.
	Prerequisite:	
	References:	(Parra, 2018; Parra et al., 2019)
	Description:	As opposed to descriptive analytics that looks at "what has happened", diagnostic analytics seeks to explain "why something happened". This second form of analytics is used to examine the root causes of events. Identifying what events led to specific outcomes, allows organizations to optimize their practices and reduce costs by altering processes to prevent bottlenecks or other undesirable outcomes.

C	**Predictive analytics**	
	Goal:	Proactively identify and predict the impact of process improvement or business development opportunities using data to support innovation initiatives.
	Actions:	- Decision-making processes are proactively reported on to solve business problems. - Predictive analytics is applied to predict the likelihood of outcomes for a specific process, process gain, and optimization. - Forecasting with trend analysis, statistical algorithms, regression analysis or machine learning models. - Focus includes business transformation through analytics.
	Prerequisite:	Analytics Applications & Tools D
	References:	(Parra, 2018; Parra et al., 2019)
	Description:	Unlike the previous two types of analytics, predictive analytics looks towards the future and seeks to predict "what will happen". It combines the use of metrics from descriptive analytics and the relationships between process steps identified from diagnostic analytics and research, to predict the outcome and impact of certain events. This technique has many different applications, ranging from risk analysis to forecasting process improvement and business development opportunity outcomes, thereby supporting innovation initiatives. This way, it empowers an organization's analytics function to directly contribute to driving business transformation.
D	**Prescriptive analytics and automation**	
	Goal:	Develop systems to automate innovation and decision-making across various business processes.
	Actions:	- Develop predictive and prescriptive models for risk analysis and mitigation, scenario modelling, and recommendation systems based on developed knowledge bases of actions and rules. - Ensure new data can easily be incorporated into existing model assets. - Focus includes innovation leveraging and business opportunity search and development.
	Prerequisite:	Analytics Applications & Tools E
	References:	(Parra, 2018; Parra et al., 2019)
	Description:	Prescriptive analytics, seeks to identify "what should happen". Whereas the previous types of analytics still relied on a user to interpret the results of a given analysis, prescriptive analytics automates this stage of the decision-making process. Prescriptive analytics builds on the results of predictive models and utilizes advanced techniques and knowledgebases with recommendation actions for specific data values to evaluate the outcomes of various potential events and recommend one or more optimal courses of action. Programs that provide such recommendations are known as decision-support systems and reduces the need for decision-makers to have advanced analytical interpretive skills.

<table>
<tr><td></td><td colspan="2">3. Data Governance structure</td></tr>
<tr><td>A</td><td colspan="2">Data Management Office (DMO)</td></tr>
<tr><td></td><td>Goal:</td><td>Creation of a centralized organizational body responsible for designing, steering and championing the data management program and coordinating, allocating and sharing resources to and between data projects.</td></tr>
<tr><td></td><td>Actions:</td><td>- Design and plan a DMO.
- Ensure a DMO is approved by executive management and structurally charted.
- Create the DMO.
- Coordinate data projects and resource allocation.</td></tr>
<tr><td></td><td>Prerequisite:</td><td></td></tr>
<tr><td></td><td>References:</td><td>(EDM Council, 2014, 2020)</td></tr>
<tr><td></td><td>Description:</td><td>The data management office (DMO) serves as the primary governing body that oversees the organization’s data initiatives and can take many different forms. From steering committees comprised of executives to small governance or analytics teams. It’s the responsibility of the DMO to develop the organization’s data initiatives and innovate its data management program. Therefore, the creation of a DMO is an essential first step for organizations to organize and develop and approach to become data driven.</td></tr>
<tr><td>B</td><td colspan="2">Executive ownership</td></tr>
<tr><td></td><td>Goal:</td><td>Appointment of an executive officer (e.g. Chief Data Officer) to run the DMO with full authority and board sponsorship.</td></tr>
<tr><td></td><td>Actions:</td><td>- Recognize, socialize and communicate need for executive ownership of the DMO.
- Have board or leading organizational body appoint executive officer.
- Communicate duties and authority of executive data officer to all relevant stakeholders across the organization.</td></tr>
<tr><td></td><td>Prerequisite:</td><td></td></tr>
<tr><td></td><td>References:</td><td>(EDM Council, 2014, 2020)</td></tr>
<tr><td></td><td>Description:</td><td>The executive data officer is responsible for the activities of the DMO and is a key player in determining the organization’s data strategy and governance initiatives. The executive data officer must be able to appropriate funding for the organization’s data activities and contribute to shaping organizational strategy as it relates to data. By appointing an executive data officer, the DMO gains legitimacy and is empowered to utilize resources to develop the organization’s data-driven capabilities.</td></tr>
</table>

C	**Data governance plan**	
	Goal:	Creation of a formal governance plan on how to manage the availability, usability, integrity and security of data in collaboration with critical business and IT stakeholders.
	Actions:	- Draft data governance plan that is aligned to operational and strategic objectives and priorities and reflects the desired culture. - Assign appropriate roles to key data governance stakeholders (e.g. data owners, data stewards, etc.) - Communicate established data governance plan to relevant stakeholders. - Review and incorporate stakeholder feedback.
	Prerequisite:	Data Management Strategy (DMS) C
	References:	(EDM Council, 2014, 2020)
	Description:	To establish effective data governance, an organization requires a detailed data governance plan that ensures all stakeholders have a common understanding of the organization’s approach. The data governance plan should indicate the design of the organization’s governance mechanisms, which may include identifying key stakeholders, the required structure, necessary processes, oversight mechanisms and data governance roles. This does not include the actual governance content.
D	**Data governance roles and responsibilities**	
	Goal:	Establish the governance structure and mechanisms necessary to capture, process and deliver data through a network of data stewards and subject matter experts.
	Actions:	- Identify and assign individual employees as data stewards to be accountable for the quality of specific data assets. (e.g. specific IT or business domain experts.) - Delegate data quality authority and responsibilities while stimulating data stewards to uphold the data quality function performance. (e.g. performance metrics, annual reviews and compensation considerations) - Communicate data quality roles and responsibilities to the wider organization.
	Prerequisite:	Data Architecture B
	References:	(EDM Council, 2014, 2020)
	Description:	The primary objectives of data governance are to support knowledge sharing, drive value through collaboration, eliminate uncertainty and instill a sense of trust in data. To achieve this, the established guidelines, protocols, processes and rules, must be translated into action through data management by assigning employees as data stewards which are responsible for upholding the quality of specific data assets. This includes the quality of the data itself, but can also pertain to the quality of metadata, master and reference data, architecture, data development, database operations, security, storage solutions and BI, documents and other content. Finally, the roles, responsibilities and authority of individual data stewards must be communicated to the wider organization, to ensure that employees have a clear understanding about who is responsible for which data assets.

E	**Enterprise-wide governance**	
	Goal:	Appoint organization members in business lines or control functions that take ownership and responsibility of data management within their verticals and report to their business leader or the CDO.
	Actions:	- Define, document and communicate enterprise-wide governance structure in collaboration with relevant stakeholders. - Implement organizational governance structure. - Establish working committees with written charters approved by the DMO. - Communicate stakeholder roles and responsibilities. - Hold stakeholders accountable for data management program participation via performance reviews and compensation considerations.
	Prerequisite:	
	References:	(EDM Council, 2014, 2020)
	Description:	While initially limiting the execution of data management roles, such as data ownership and stewardship to specific IT, data management or BI stakeholders is acceptable, for an organization to become truly data-driven, it must embed these roles and responsibilities in its business lines. Data management and business intelligence are disciplines in service of an organization's core business activities and are designed to support the generation of business value. Employees that are part of the core business have the best understanding of how and when data initiatives contribute to value generation and when they fail to do so. Assigning data roles to core business employees with direct reporting lines to their business leaders ensures that data quality issues are swiftly identified and that data initiatives support accomplishing business objectives.

	4. Policy & Standards	
A	**Establishing Policy & Standards**	
	Goal:	Define standards for how business, technology and operations control, acquire, manage, maintain and deliver data throughout the organization.
	Actions:	- Develop policy and standards for aspects such as data ownership, data definition, data lineage, metadata and data quality management, data access, permissible use, data sourcing and data controls in collaboration with business and IT stakeholders. - Align policy and standards with data management strategy.
	Prerequisite:	Data Governance structure A
	References:	(EDM Council, 2014, 2020)
	Description:	In order to perform data management and analytics tasks, there must be clearly defined standards and policy guidelines that express the agreed upon methods for organizing and using data to ensure consistent measurement, quality, and exchange of information. This may include the definition of what constitutes appropriate data quality, the methods for ensuring compliance with data protection regulations, or the approach to safely collecting and sharing data with other parties, among other things.

B	**Stakeholder review & approval**	
	Goal:	Ensure agreement, alignment and buy-in with the established data management policy and standards across all business lines and programs.
	Actions:	- Share and review policy and standards documentation with all relevant data governance stakeholders. - Continually incorporate stakeholder feedback in policy and standards development.
	Prerequisite:	Data Governance Structure C
	References:	(EDM Council, 2014, 2020)
	Description:	While having data governance personnel establish the initial policies and standards for data management and use is common and acceptable, this activity should preferably not take place in a vacuum. It is essential that data related policies and standard are shared with and reviewed by the relevant stakeholders, and feedback incorporated to ensure regulatory compliance and alignment with business strategy.
C	**Data governance policy integration**	
	Goal:	Integration of data governance policies and standards with the existing enterprise governance structure. Senior executive management recognition and support of data policy and standards.
	Actions:	- Policy and standards are submitted to the organizational governance mechanism for evaluation. - Data management policy and standards are approved by organizational governance body.
	Prerequisite:	
	References:	(EDM Council, 2014, 2020)
	Description:	Data governance and its respective policy development is a subset of the corporate governance discipline that is commonly performed by data management professionals in collaboration with end users. However, as an organization's use of data matures, it becomes essential that the corporate governance body and executives review data policy, as they are better positioned to evaluate whether it addresses the organizations broader goals and obligations. This involvement ensures proper alignment with corporate strategy, regulatory compliance, validation of the approach to risk-mitigation and serves to promote transparency and improve resource allocation and change management.

	5. Content Governance	
A	**Establish Authorized data domains (ADD)**	
	Goal:	Identify and inventory conceptual data categories that support specific business functions for use in applications and processes. (e.g. customer information, financial information, employee information, product information, etc.)
	Actions:	- Identify, document and declare ADDs in collaboration with business stakeholders. - Establish ADD inventories (e.g. compilation of necessary ADDs per business function.)
	Prerequisite:	
	References:	(EDM Council, 2014, 2020)
	Description:	ADDs are defined as data concepts specific to a business function, while data entities are logical system specific implementations of such data domains. The two differ in that data entities are identifiable unique objects within an information system, whereas ADDs are the overarching data concepts. For example, the data domain EMPLOYEE encompasses all data pertaining to employees within an organization – such as employee information, employment history and performance evaluations – whilst the data entity EMPLOYEE represents individual data records that refer to each employee, such as employee ID, name, address, position and salary. Data entity identification and inventorization is covered in capability 10A.
B	**Data taxonomies and ontologies**	
	Goal:	Define formal relationships and structural alignment between ADDs and their entities and model relationships between taxonomies into a business ontology.
	Actions:	- Define data taxonomies and business ontology. - Verification of taxonomies and ontology by business subject matter experts. - Publish and use taxonomies in up- and downstream systems in cross process data sharing. - Use established taxonomies in new business developments.
	Prerequisite:	
	References:	(EDM Council, 2014, 2020)
	Description:	Establishing taxonomies for data domains and their entities, modelling the relationships between these taxonomies across functional domains in a business ontology and mandating adherence to these taxonomies for all information systems, creates a single representation of data domain and entity structure and relationships across the organization's information systems. This ensures a common understanding of the structure and relationships between data elements throughout the organization and supports the development and use of data products

C	**Critical data elements (CDE)**	
	Goal:	Identify and catalogue data elements that support critical business functions, to allow for data prioritization.
	Actions:	- Identify and inventory CDEs. - Document CDE sources. - Approve assigned business definitions to each CDE.
	Prerequisite:	Data Architecture B
	References:	(EDM Council, 2014, 2020)
	Description:	This capability involves examining the inventoried data and creating a catalogue of data elements which are critical to specific business functions. This allows for the development of priority targeted data management initiatives, such as data quality and remediation, policy compliance monitoring, data lineage tracking and metadata registration. Note that this capability does not cover the identification, documentation and inventorization of data attributes, as these are established its prerequisite capability 10B.
D	**Data classification**	
	Goal:	Formalize the policy and standards for data (entities, attributes, files, etc.) across the organization's information systems through classification.
	Actions:	- Establish and assign data classifications (policy & standards categories) to data elements (ADDs, entities, attributes, cubes, databases, files, etc.) and have stakeholder verify them. - Assign established policies and standards to data classifications that dictate how data is to be handled (e.g. privacy treatment, info-security treatment, masking, encryption, risk analysis, etc.) - Adopt and describe data classifications in documentation (e.g. data catalogue) and applications.
	Prerequisite:	Policy & Standards A
	References:	(EDM Council, 2014, 2020)
	Description:	While data policies and standards describe how data should be structured, what it should adhere to and how it should be interacted with, developing and assigning classifications enables the binding of policies and standards to specific data elements. Correctly linking policies and standards to data classifications and assigning them to different data elements is imperative to ensuring that data is reliable and used in an appropriate manner through the organization.

E	**Standardized identifiers and relational models**	
	Goal:	Establish standard entity identifiers and align identifier format and data schemas to industry standards (e.g. UUID, Microsoft CDM).
	Actions:	- Ensure the definition of unique identifiers for business entities (e.g. product; customer; account; etc.) - Assign, publish and use internal entity IDs across information systems. - Align internal IDs with industry standard identifiers. - Align internal schemas with globally recognized schemas.
	Prerequisite:	
	References:	(EDM Council, 2014, 2020)
	Description:	Data identification schemes are used to identify data factors of input. Establishing common internal ID methodologies is critical for data activities such as integration, classification and analysis of data across different information systems, as this allows us to more easily identify and differentiate between different records. Aligning identifiers and relational schemas with globally recognized standards allows for easier processing of external data. Internally, organizations may continue to use business or surrogate keys to refer to data entities, while each record receives an additional industry standard unique identifier.

	6. Data Management Strategy (DMS)	
A	**DMS specification and sharing**	
	Goal:	Steer data management in accordance with a general data management strategy aligned with high-level organizational objectives.
	Actions:	- DMS is documented, aligned with business, technology and operations and shared with all relevant stakeholders. - Map and align DMS with high-level organizational objectives. - Establish mechanisms for capturing and incorporating feedback and approval of DMS by executive committee and other stakeholders.
	Prerequisite:	
	References:	(EDM Council, 2014, 2020)
	Description:	A data management strategy specifies an organization's approach to data management and data utilization. It emphasizes the goals and objectives of the data management program and conveys the general approach to realizing them. While informal applications of data management and analytics can be executed without the need for a comprehensive strategy, it is practical to ensure that data initiatives are developed in a top-down manner early in their lifecycle. This ensures that once the need arises for these practices to be institutionalized, they can be related back to organizational data management objectives.

B	**Business requirements**	
	Goal:	Data management strategy includes business requirements to align data-strategy with business objectives.
	Actions:	- Incorporate business requirements for critical business lines and functions in DMS. - Have stakeholders regularly review, prioritize and approve DMS business requirements.
	Prerequisite:	
	References:	(EDM Council, 2014, 2020)
	Description:	Data management and business intelligence are disciplines in service of an organization's core business activities and are designed to support the generation of business value. This makes it essential for the data management strategy to specify the business objectives and requirements each data initiative is designed to meet.
C	**Enterprise data governance**	
	Goal:	Expressing the need to enforce compliance through enterprise data governance and role and responsibility assignment.
	Actions:	- Define the purpose, objectives and expected outcomes of an established enterprise data governance program. - Describe the target-state for the data governance structure in the DMS. - Describe the roles, responsibilities and relationships of data management stakeholders as well as business-line data executives.
	Prerequisite:	
	References:	(EDM Council, 2014, 2020)
	Description:	This capability is centered on integrating a robust data governance program within the data management strategy in a top-down manner, to enforce compliance, clarify role and responsibility assignments and ensure strategic alignment. This involves clearly defining the purpose, objectives, and desired target-state for the data governance program. Additionally, it includes a general description of the roles, responsibilities, and relationships of data management stakeholders, ensuring a cohesive and accountable approach to data governance throughout the organization that is aligned to the data management strategy, business requirements and objectives.

D	**Architecture, IT and Operations alignment**	
	Goal:	Align the DMS with data architecture, IT and operations capabilities.
	Actions:	- Define and incorporate data architecture concepts into the DMS and align them with stakeholder plans and roadmaps. (e.g. design, definition, management and control of data content, ADD's, metadata descriptions, taxonomies, ontologies, data transformation, distribution, and consumption) - Incorporate technology concepts, such as the strategy, design and implementation of physical infrastructure into the DMS and align them with stakeholder plans and roadmaps. (e.g. servers, cloud solutions, platforms, tools, etc.) - Incorporate operational concepts into the DMS and align them with stakeholder plans and roadmaps. (e.g. uptime requirements, business continuity planning, retention and archiving guidelines, privacy standards, etc.)
	Prerequisite:	
	References:	(EDM Council, 2014, 2020)
	Description:	Before the data management strategy is formalized, it must be aligned to the organization's other capabilities by including relevant architecture, IT and operations concepts, such as data consumption, use of cloud solutions or business continuity planning. This ensures that the various components of the data management program are designed to effectively support, but also utilize the organization's other capabilities. This improves program effectives and can contribute to cross-functional collaboration.
E	**Communication and Training**	
	Goal:	Develop and promote education and training initiatives within a defined program and increase organizational awareness, understanding, buy-in and compliance to the data management program.
	Actions:	- Describe the need for a communication strategy to stimulate data management program awareness, goals, objectives, scope, priorities, policies and standards. - Detail the need for education and training programs and the desired methodologies for ensuring understanding, buy-in and compliance. - Address the approaches, methodologies, core components, scope and reach of the communications and data management training programs.
	Prerequisite:	
	References:	(EDM Council, 2014, 2020)
	Description:	Once a comprehensive data management strategy is in place and being maintained, it is essential that its content is communicated to members of the organization. Employees must be made aware of data management program aspects that are relevant to their business function and receive training that enables them to effectively deliver on expectations. It is also imperative that a continuous awareness campaign and training initiatives are in place, such that both current and future employees are aware of the data management program and their role in executing the data management strategy. A communication and training strategy that delivers on these points, needn't require employees develop general or specific data related skills. Instead, it should express how employees are informed and trained to perform their job in accordance with the data management strategy.

F	**Data Management Measuring and Evaluation**	
	Goal:	Expressing the need to develop qualitative measurement metrics for monitoring the data management program progress and evaluating its effectiveness.
	Actions:	- Define the need to plan how the data management program progress will be quantitatively measured in collaboration with relevant stakeholders. (program categories may include governance, policies, standards and implementation, stakeholder buy-in, etc.) - DMS defines the need to develop outcome metrics for measuring the data management program effectiveness in collaboration with relevant stakeholders. (outcome metrics may include data quality, operational failures, improved discovery, critical data access, etc.) - Define how adherence to the DMS will be measured and tracked in collaboration with relevant stakeholders. (strategy adherence items may include data management program resource appointment, adoption of standards, policy compliance, etc.)
	Prerequisite:	
	References:	(EDM Council, 2014, 2020)
	Description:	With a formal data management strategy and program in place that is continuously being maintained, a data-driven organization will strive to monitor the performance of the program through quantitative metrics. This involves planning how to measure program progress as it relates to the data management strategy objectives across categories such as governance, policy, and data product development. Additionally, it concerns the development of outcome metrics to evaluate program effectiveness, including aspects such as data quality, operational failures, improved discovery, and critical data access. Monitoring these metrics ensures ongoing improvement and alignment with organizational goals.

	7. Data Quality Assessment and Remediation	
A	**Data prioritization and scoping**	
	Goal:	Prioritize data components in need of quality control and establish the scope of the data quality program.
	Actions:	- Prioritize data for the data quality program based on established CDEs in alignment with the data management strategy. - Establish the scope of data quality program.
	Prerequisite:	Content Governance C, Data Architecture B
	References:	(EDM Council, 2014, 2020)
	Description:	Data quality assessment and remediation is a comprehensive activity that doesn't always provide a clear benefit. Moreover, poor data quality is notoriously difficult to identify due to the common behavior of end-users to either ignore the faults in the data due to a lack of awareness or ignore the data-insights altogether due to a lack of trust and neglect to provide feedback. As a results, data quality must often be actively investigated. With the vast amounts of data in modern organizations, critical data elements that support key business functions which rely on high quality data to make informed decisions, should therefore be prioritized.

B	**Data profiling, analysis, and grading**	
	Goal:	Profile, analyze and grade data based on quality within the scope of the DQ management program and ascribe this grade to the data asset inventory (e.g. data catalogue).
	Actions:	- Profile and statistically analyze data within the scope of the DQ management program. Profiling may include quality dimensions such as completeness, timeliness, coverage, conformity, reference integrity, consistency, duplication, and redundancy. Analysis should be both column and row-based and identify statistical column properties to ensure record accuracy. - Review metadata and perform gap analysis to ensure proper definition of intended use. - Assign a quality grade to analyzed data elements (fields, records and tables) and document grades as metadata in the data-asset inventory (e.g. data catalogue) or metadata repository.
	Prerequisite:	Data Architecture C, Content Governance D
	References:	(EDM Council, 2014, 2020)
	Description:	Once the scope and priority of the data quality program is established, all relevant data must be profiled, analyzed, and graded. These grades must then be documented and communicated to end-users. Clearly expressing the quality grade of the data underpinning performance metrics and its implications to end-users, allows them to make more informed decisions and fosters trust in data products.
C	**Data remediation**	
	Goal:	Develop and implement plans to improve quality of in-scope data by remediating/cleaning CDEs based on the performed current state analyses and establish timelines for ongoing DQ evaluation and maintenance.
	Actions:	- Perform and prioritize data remediation based on business process objective priorities. - Perform a high priority data cleaning process. - Establish timelines for ongoing DQ evaluation and remediation.
	Prerequisite:	
	References:	(EDM Council, 2014, 2020)
	Description:	While, analyzing and communicating the quality of specific data is an effective approach to preventing potentially biased decision-making, data remediation is the next step in improving data quality and supporting better decision-making outcomes. Data in need of cleaning, should be prioritized based on its importance to key business processes and mechanisms for remediation should be established. These may be comprised of altering data input activities to improve future data intake or performing data cleaning activities on current datasets.

D	**Data quality control**	
	Goal:	Quantitatively measure the quality of data as it flows through business processes, determine root-causes for poor data quality, remediate data gaps and hold stakeholders accountable for achieving the established data quality standards.
	Actions:	- Establish data quality control points across the data supply chain. - Document and clearly communicate control and remediation procedures. - Routinely capture and report data quality metrics across the business-lines to executive management to drive data quality remediation improvement. - Perform root-cause analysis and implement corrective measures to business or IT processes.
	Prerequisite:	Data Governance structure D
	References:	(EDM Council, 2014, 2020)
	Description:	As an organization becomes more information driven, maintaining acceptable data quality becomes essential. At this stage, it may be necessary to actively monitor the quality of data records as they travel across information systems and alter business processes to improve data quality at its source. Data quality control and remediation procedures should be documented to create a knowledge base and improve awareness across the organization.
E	**Data quality audit**	
	Goal:	Continually maintain and improve data quality across the organization through data quality audits across business lines, ensuring compliance with internal and best practice policies and standards.
	Actions:	- Data stewards and subject matter experts perform a quality assurance (QA) self-assessment of business-line data quality and processes. - DMO performs facilitated quality control (QC) assessments of business-line data quality operations. - Routinely examine business-line data quality procedures in corporate audits and generate formal issues where gaps are discovered. - Empower DMO to force operational teams to solve gaps found in their data quality processes.
	Prerequisite:	Data Governance Structure E
	References:	(EDM Council, 2014, 2020)
	Description:	With a comprehensive data quality management program in place, periodic audits can be performed at various levels to assess both the quality of specific data products and the effectiveness of the data quality management program itself. The outcomes of such assessments can be used to iteratively improve aspects of the data management program. While data quality audits can absolutely be performed at an earlier stage, it is the embedded nature of such audits in the data quality program as part of a continuous improvement cycle that differentiates it as a fully mature approach to data quality management.

	8. **Decision-making process (DMP)**	
A	**Ad-hoc data-driven decision-making**	
	Goal:	Become aware of the need to be data-driven and make deliberate coordinated ad hoc decisions based on data and metrics.
	Actions:	- Create initial awareness of the need to become data-driven amongst leadership. (e.g. data value, data-driven business opportunities, risk mitigation, etc.) - Incorporate referencing descriptive analytics insights in the decision-making process for specific/important cases. - Begin defining performance metrics for decision-making outcomes.
	Prerequisite:	Analytics Techniques & Analysis A, Leadership & Empowerment A
	References:	(Parra, 2018; Parra et al., 2019)
	Description:	Organizational decision-making doesn't become data-driven from one day to the next. This is an iterative process that requires the commitment and determination to not only develop the capabilities required to deliver data-insights, but also rely on them as part of decision-making processes. Creating and using descriptive metrics, like performance indicators, for specific processes or projects is the first step to steering an organization using data. Since those in leading positions are often responsible for decision outcomes, they are also the ones to decide whether referencing data insights is deemed necessary. This makes it essential that leaders and managers are aware of the organization's desire to become data driven and genuinely commit to using data-insights to inform decision-making.
B	**Systematic data-driven decision-making**	
	Goal:	Establish systematic coordinated deliberate decision-making processes for specific business functions on the basis of available data.
	Actions:	- Establish, document, and communicate a systematic decision-making process for select business functions and processes. - Establish goals and metrics to measure decision-making outcome at the department or business-line level. - Insights from diagnostic analytics provided in reports or dashboards are referenced during decision-making.
	Prerequisite:	Analytics Techniques & Analysis B
	References:	(Parra, 2018; Parra et al., 2019)
	Description:	Data analytics can help businesses to not only monitor performance but also identify improvement opportunities. Establishing systematic decision-making processes for specific business functions, supports the development of informational metrics for each specified process step. Systematic processes combined with clear goals and metrics to measure decision outcome quality and the use of diagnostic analytics, enables organizations to iteratively improve decision-making processes on both the operational and tactical level.

C	**Embedded data-driven decision-making**	
	Goal:	Standardize and institutionalize a clearly articulated decision-making process throughout the organization that is driven by data insights.
	Actions:	- Develop and implement a comprehensive decision-making strategy in collaboration with DMO, IT, and operations stakeholders on the basis of objective, reliable and relevant data that aligns with business objectives and the DMS. - Integrate goals and metrics for continuous organization-wide measurement of decision-making outcomes. - Proactively consider and manage risks by leveraging predictive analytics outcomes as part of the decision-making process.
	Prerequisite:	Data Management Strategy D, Analytics Techniques & Analysis C
	References:	(Parra, 2018; Parra et al., 2019)
	Description:	An organization can't truly call itself data-driven, when only certain areas of its business are supported by data or when decision-making outcomes are only assessed retroactively. To progress further, decision-making outcomes should be proactively assessed using predictive analytics and the use of data-driven insights expanded across the enterprise. This requires the development of a comprehensive strategy that establishes data-driven decision-making processes for each part of the business.
D	**Strategic data-driven decision-making**	
	Goal:	Continuously improving data-driven insight development becomes part of an information-driven business strategy.
	Actions:	- Embed the systematic data-driven decision-making process into business strategy and its objectives. - Apply analytics-based risk management as a differentiator for decision-making. - Establish continuous improvement cycle of the decision-making process and performance metrics. - Use prescriptive analytics to provide actionable recommendations and partially automate the decision-making process.
	Prerequisite:	Analytics Techniques & Analysis D
	References:	(Parra, 2018; Parra et al., 2019)
	Description:	For an organization to be fully data driven, implies data lies at the root of its business strategy and that data insights are the key differentiators in decision-making. When reaching this point, an organization is not only supported by its data, but truly reliant on it to improve and innovate. Therefore, having a continuous improvement cycle in place for all data-driven decision-making, is essential to business development. When reaching this point, organizations may wish to adopt prescriptive analytics technologies and techniques, such that systems can provide recommendations to automate parts of decision-making processes.

	9. Data Architecture	
A	**Entity identification**	
	Goal:	Identify, document and inventory logical data domains – also known as entities – (e.g. Customer, Product or Project) and their underlying sources (e.g. databases, cubes, specific applications) for each ADD.
	Actions:	- Collaborate with subject matter experts to identify and prioritize data entities. - Link data sources to entities. - Inventory and actively maintain identified repositories.
	Prerequisite:	Content Governance A
	References:	(DAMA International, 2017; EDM Council, 2014, 2020)
	Description:	Names of entities can vary across information systems. Identifying, documenting, and creating an inventory of the organization's data and its sources, must be done for each established Authorized Data Domain (ADD) to ensure a common understanding of what specific data is, what it's used for and where it comes from. Entities are the logical data object representations of ADDs. Where ADDs represent everything to do with the subject it describes, an entity represents a specific concept pertaining to the ADD. For example, the ADD EMPLOYEES includes all information related to employees, such as their performance history, their name, place of residence, etc., while the EMPLOYEE entity may only include attributes that describe the employee, such as their name, department and function. As such, entities can be considered the building blocks for ADDs. ADD identification and inventorization is addressed in capability 5A.
B	**Data semantics and relationships**	
	Goal:	Define semantics and relationships of data and information in the form of non-technical descriptions based on contractual, legal or business facts.
	Actions:	- Document business definitions of entities, attributes and metrics in collaboration with domain experts (e.g. business glossary). - Map entities and their attributes with business data definitions in collaboration with domain experts. - Create an inventory of metrics, entities and their corresponding data attributes (e.g. data catalog).
	Prerequisite:	Content Governance B
	References:	(DAMA International, 2017; EDM Council, 2014, 2020)
	Description:	Data is often complex. The interpretation of entities, attributes and metrics can vary wildly between people. Moreover, the ways in which data elements are related is rarely apparent. For an organization to work effectively with data, semantic definitions must be established for preferably all data elements that contribute to a data product. By collaborating with business users to document clear business definitions of entities, attributes and metrics and describing how the various elements are related to one another, employees gain a referenceable repository that promotes a common understanding of data semantics. This can improve data product development efficiency and greatly supports self-service business intelligence.

C	**Metadata definition, capture and inventorization**	
	Goal:	Establish common definitions and capture metadata of data elements from their sources and inventory it to ensure usability by all relevant teams.
	Actions:	- Document common definitions of metadata across information systems. (e.g. metadata glossary) - Capture and use metadata from data sources (e.g. timestamps, activity logs, source systems, data lineage). - Rationalize metadata across data taxonomies. - Inventory metadata for fully attributed logical models in metadata repositories (e.g. entity associated ADDs and relationships, enrich data catalog with metadata). - Ensure metadata adheres to the established relevant data policies and standards.
	Prerequisite:	Policy & Standards A
	References:	(DAMA International, 2017; EDM Council, 2014, 2020)
	Description:	Metadata is data that describes the properties of other data. Capturing, inventorying, and documenting metadata definitions and relationships ensures all relevant users can access and work with metadata to improve their analytics experience and data product quality. Metadata can be used to make working with specific data easier, supports data lineage tracking and cost management, improves data discovery and quality management, and helps build additional trust among users.
D	**Business & Technology Alignment**	
	Goal:	Ensure continuous alignment of data architecture with business processes and technology.
	Actions:	- Ensure data architecture is aligned to business processes. (e.g. semantic data definitions, operation procedures, and 3rd party contract specifications) - Enforce technology development (e.g. dashboard development, application adoption) to follow data architecture standards and use established data architecture elements. (ADDs, data entities, taxonomies)
	Prerequisite:	
	References:	(DAMA International, 2017; EDM Council, 2014, 2020)
	Description:	In addition to inventorying and documenting data definitions and relationships to support users, it is essential that an organization's data architecture is aligned with its business processes and that the various technologies of the organization adhere to the established data architecture. This implies both current and new information systems should be designed to use the entities, attributes, relationships, and definitions described in the enterprise data architecture. In doing so, different sources systems can more easily be integrated, and data discovery and transformation becomes more efficient.

	10. Data Driven Culture	
A	**Awareness creation**	
	Goal:	Generate awareness about the potential value generated by data and analytics tools and techniques for decision-making to mitigate resistance to change.
	Actions:	- Express the value and demonstrate the utility of data-driven BA and decision-making to business and IT users. - Encourage data-driven BA technology and participation adoption.
	Prerequisite:	Data Management Strategy (DMS) A
	References:	(Cosic et al., 2015; Halper, 2023; Larson, 2023; Spruit & Pietzka, 2015)
	Description:	Supporting decision-making with data analysis takes additional time and resources that could reasonably be used elsewhere. People are logical creatures that require reasons to act. The decision for people to commit their time to developing data analyses and practice informed decision-making holds true to this principle. Communicating how your business benefits from using data and analytics, allows employees and managers to justify their effort spent using analytics tools and basing their decisions on data. This is the first step in creating a data-driven culture, promotes the adoption of data-driven technologies and reduces resistance to working with data.
B	**Training & Skill development**	
	Goal:	Develop an environment in which employees are motivated to use the organization's data and analytics capabilities and support further development of their related skills.
	Actions:	- Develop trust in data and the BA tools used in data analytics processes. - Promote data stewardship and data use from authorized repositories. - Establish training initiatives or compensation programs for the development of select data and analytics related skills.
	Prerequisite:	Analytics Techniques & Analysis A
	References:	(Cosic et al., 2015; Halper, 2023; Larson, 2023; Spruit & Pietzka, 2015)
	Description:	Developing data and analytics skills is one of the primary ways employees can contribute to a data-driven organization. Developing advanced analytics skills improves awareness and fosters increased trust in data insights. By creating training programs or compensation structures to finance data related skill development and promoting data use and stewardship, reduces resistance to change and allows employees to gradually adapt to a new way of working.

C	**Adoption & Participation Encouragement**	
	Goal:	Have employees actively participate in the use and development of the organization's data and analytics environment.
	Actions:	- Encourage users to actively participate in data-driven environment development. - Ensure employees are provided access and directions to required data and information. - Establish a knowledgebase on who is using which data.
	Prerequisite:	Data Management Strategy (DMS) E
	References:	(Cosic et al., 2015; Halper, 2023; Larson, 2023; Spruit & Pietzka, 2015)
	Description:	While having users contribute to the organization's decision-making processes by developing data products does contribute to the creation of a data-driven culture, organization's that value data-insights also value those that provide them. Monitoring and establishing a knowledge base of which employees use what data allows for easier information exchange, collaboration and data delivery. Moreover, encouraging analytics users to participate in the development of new data initiatives, helps increases the adoption rate of data and analytics technologies and fosters affective commitment.
D	**Data-driven standardization**	
	Goal:	Create a culture where using data in day-to-day operations is the norm and generating or consuming data is the default behavior of employees.
	Actions:	- Establish data collection from all relevant organizational processes as the new norm. - Encourage decisions-making based on data at all levels of the organization, through function descriptions, compensation structures and promotion requirements. - Make analysis reporting a standard element of meetings on the operational, tactical, and strategic level.
	Prerequisite:	Leadership & Empowerment C, Decision-making process (DMP) D
	References:	(Cosic et al., 2015; Halper, 2023; Larson, 2023; Spruit & Pietzka, 2015)
	Description:	Employees in truly data-driven organizations operate in an environment where working with data and reporting data-driven insights is a near daily occurrence. At the same time, data collection, processing and reporting is a part of all organizational processes that can benefit from it or support the information needs of another process.

	11. Leadership & Empowerment	
A	**Leadership attitude**	
	Goal:	Establish the importance of data and analytics amongst management and communicate this mentality to organization members.
	Actions:	- Leadership communicates a recognition of the importance of data in decision-making processes and encourages its use. - Establish a data management and analytics funding model in collaboration with stakeholders and communicate it to the organization. - Review and enhance data management and analytics funding model on an annual basis.
	Prerequisite:	
	References:	(EDM Council, 2014, 2020; Parra, 2018; Parra et al., 2019)
	Description:	Leadership sets the tone and direction for the organization and supports initiatives through their actions by championing their cause. Therefore, it's essential that executives and managers have a positive attitude towards data and analytics to contribute to its development. One of the first steps for any organization with data-driven ambitions is to ensure that leaders recognize the importance of becoming data driven and champion the transformation by communicating its importance to the rest of the organization and establishing a funding model that provides a budget for data management and analytics activities.
B	**Empowerment & Business case**	
	Goal:	Establish business case for data management and analytics and empower employees to contribute to decision-making processes.
	Actions:	- Strengthen leadership and management analytical skills. - Establish select data-driven decision-making support activities to be delegated to employees with differentiated degrees of autonomy and responsibility. - Improve the funding model to a data management business case, mapped to drivers and requirements for achieving objectives for each line of business and communicate it.
	Prerequisite:	
	References:	(EDM Council, 2014, 2020; Parra, 2018; Parra et al., 2019)
	Description:	Establishing a clear business case for the data management and analytics solidifies the business value derived from data. This stresses the importance of data to members of the organization and motivates those in leadership positions to achieve data related objectives and strengthen their data skills. Establishing activities that support decision-making and delegating these to employees, allows them to contribute to decision-making, thereby fostering commitment and reducing resistance.

C	**Leadership collaboration**	
	Goal:	Encourage business case development participation and communicate goals across the organization.
	Actions:	- Leadership engages actively and sets an example in collaborative data and analytics initiatives that include members from different levels of the organization. - Collaborate with operational and tactical business and IT stakeholders to validate and improve the data and analytics business case.
	Prerequisite:	Data Management Strategy (DMS) E
	References:	(EDM Council, 2014, 2020; Parra, 2018; Parra et al., 2019)
	Description:	By actively engaging in data initiatives, leaders demonstrate the importance of data and related skills to other organization members, stimulating adoption and skill development. Additionally, collaborating with employees at the operational and tactical levels to improve the data and analytics business case, empowers them to contribute to data management and analytics development.
D	**Delegation, alignment, and innovation**	
	Goal:	Delegate decision-making to lower levels of the organization, align data management analytics objectives to specific business lines, and promote autonomous innovation of business case.
	Actions:	- Fully delegate decision-making based on data throughout the organization with a focus on innovation and business opportunity development. - Data management and analytics funding is allocated by business lines. - Empower DMO to review and approve budgets and enforce the business line data management and analytics funding allocation to be in accordance with data strategy objectives.
	Prerequisite:	Data Driven Culture D, Data Quality Assessment & Remediation E
	References:	(EDM Council, 2014, 2020; Parra, 2018; Parra et al., 2019)
	Description:	By allowing data initiative funding to be determined autonomously by business lines and fully delegating opportunity development and innovation related decision-making to employees supported by data analytics and decision support systems, business development can rapidly improve without the intervention of executive or senior leadership. Additionally, to ensure the different business line data initiatives adhere to established guidelines and continue to support achieving organizational objectives, the DMO may be empowered to approve budgets and enforce policy.

	12. Data Storage Infrastructure and Operations	
A	**Collection and sharing**	
	Goal:	Collect, store and share (internal) data across multiple teams or a department.
	Actions:	- Share (internal) data as a collaborative activity. - Store (internal) data in datasets or (siloed) data warehouses at minimally the team or department level.
	Prerequisite:	
	References:	(Parra, 2018; Parra et al., 2019; Larson, 2023; Halper, 2023)
	Description:	Enabling data storage and sharing are the primary goals of developing data infrastructure. Enabling data storage at minimally the team or department level, makes data readily accessible to users and enables data sharing, which contributes to cross functional collaboration.

B	**Centralized storage and management**	
	Goal:	Centrally store and manage data used for analytical purposes.
	Actions:	- Create a centralized repository for all (internal) structured data. (e.g. Enterprise data warehouse) - Collect and transform data according to an established ETL process that is aligned with business data definitions and rules. - Establish managed shared datamarts for use across the entire business.
	Prerequisite:	Data Architecture A
	References:	(Parra, 2018; Parra et al., 2019; Larson, 2023; Halper, 2023)
	Description:	Any organization that is aiming to become data-driven requires some form of centrally managed data storage and data processing method that is aligned with the business's data definitions and adhere to established business rules for data transformation. Storing analytical data in a centralized location, allows data management activities to ensure that aspects like data lineage, compliance, and quality control, can be applied to all relevant data. When sharing centrally managed data through analytical repositories like datamarts or cubes, end-users can be certain that the data they access is as reliable as the organization's data management processes.
C	**Agile & scalable storage solution**	
	Goal:	Make the established data storage solution scalable and flexible to support seamless integration of new data.
	Actions:	- Implement a flexible scalable data storage infrastructure that allows for seamless integration of new structured data (e.g. data vault, data fabric) - Absorb new sources of data as they emerge within the organization without a need for a storage model redesign.
	Prerequisite:	
	References:	(Parra, 2018; Parra et al., 2019; Larson, 2023; Halper, 2023)
	Description:	Whereas in the past, analytical data storage was characterized by the data warehouse, over the past several years both data storage and organizations have changed a lot. Databases have become significantly cheaper; SQL has adapted to reduce ETL workload and business can no longer afford to wait for database developers to create a perfect data warehouse. As the intake of data increases and the enterprise data storage solution grows with the needs of the business, there will come a point where it must be altered to accommodate more new categories or types of data. As the amount of data in circulation continues to rise, so will the need for alternations of generic data storage solutions. For this reason, data-driven organization of a certain scale must invest in agile scalable storage solutions that can adapt to the changing needs of the business and continue to support its analytical processes.
D	**External data integration**	
	Goal:	Collect and store relevant data from external sources (outside the organization) as they emerge. (e.g. supplier price lists, commercial address lists)
	Actions:	- Capture data from external data sources where relevant. - Integrate external data with internal data architecture and storage solution.
	Prerequisite:	
	References:	(Parra, 2018; Parra et al., 2019; Larson, 2023; Halper, 2023)
	Description:	In addition to data captured in an organization's own information systems, there may be a desire to integrate data from third parties to enrich analytical models or provide more accurate or advanced performance metrics in support of core business activities. This requires the enterprise data storage solution be capable of seamlessly integrating external data sources.

E	**Big Data**	
	Goal:	Collect, process and store large volumes of data of a wide variety (e.g. structured, unstructured, real-time, metadata) at a high velocity for analytical purposes.
	Actions:	- Integrate unstructured data storage solutions into the enterprise data storage infrastructure (e.g. data lake, NoSQL database) - Collect, store and process data of various types in large amounts for use in big data analytics (e.g. process mining, text mining, regression analysis, machine learning).
	Prerequisite:	Content Governance E
	References:	(Parra, 2018; Parra et al., 2019; Larson, 2023; Halper, 2023)
	Description:	Mature data-driven organizations rely on vast amounts of data to perform complex analytics, build data models, feed AI algorithms and much more. These datasets may be unstructured and of such enormity that they require specialized data storage solutions. While not necessarily needing to be managed in the same way as other data, depending on the needs of the business, the enterprise storage solution must be able to support the intake of potentially billions of records of structured, unstructured, geospatial, open source, or logging data. This requires specialized data storage solutions that support the use of Big Data applications.

Appendix 5: Capability assessment statements

1. Analytics Applications & Tools		
Capability Maturity	**#**	**Capability Assessment Statement**
A	1.	Spreadsheet programs are used in data analysis.
A	2.	Data insights are manually visualized and reported.
B	1.	Data is reported in domain specific applications.
B	2.	Data reporting is standardized within these applications.
C	1.	Data can be analyzed and visualized using dedicated BI or data discovery tools.
C	2.	Data insights are visualized using dashboards and/or scorecards.
D	1.	Data insights are presented in applications that are part of the daily workflow.
D	2.	There are tools present for making prediction models to support decision-making.
D	3.	Dashboard visualizations include predictive model outcomes.
E	1.	Analytics tools use and provide access to the same underlying data.
E	2.	Applications are in place that automatically prescribe specific improvement actions based on provided data.
E	3.	BI is self-service with controlled data-use.

2. Analytics Techniques & Analysis		
Capability Maturity	**#**	**Capability Assessment Statement**
A	1.	Current and past process performance is described with metrics.
A	2.	Data analytics is used to monitor process accuracy, consistency and timeliness among other things.
B	1.	Diagnostic data techniques are used to identify the causes of process outcomes or bottlenecks.
B	2.	Data analytics is used for cost reduction and process optimization among other things.
C	1.	Analytics techniques are used to predict outcomes.
C	2.	Data analytics supports business improvement and innovation.
D	1.	Optimal process actions and rules are documented in referenceable knowledgebases.
D	2.	Analytical data models are in place to automatically provide recommendations based on knowledgebases.

3. Data Governance Structure		
Capability Maturity	**#**	**Capability Assessment Statement**
A	1.	There is a steering committee or department responsible for designing and championing data initiatives.
A	2.	This committee or department coordinates resource allocation and sharing between data projects.
B	1.	The steering committee or department is headed by an executive officer with board sponsorship.
C	1.	The data governance design, structure and oversight mechanisms are formalized in a data governance plan.
C	2.	The data governance plan incorporates stakeholder feedback.
D	1.	Data stewards are assigned and empowered to uphold the quality of specific data.
D	2.	It is documented and communicated which data stewards are responsible for the quality of which data.
E	1.	Data owners are assigned to manage all aspects of specific data assets.
E	2.	Data owners have a direct reporting line to their business leaders or the CDO.

E	3.	The roles and responsibilities of data owners are documented and communicated.

4. Policy & Standards		
Capability Maturity	**#**	**Capability Assessment Statement**
A	1.	Standards and policies are in place that describe how the organization controls, acquires, manages, maintains, and shares data.
A	2.	Data policies and data standards are aligned with the data management strategy.
B	1.	Data policies and data standards are shared with and reviewed by data governance stakeholders.
B	2.	Standards and policies continually incorporate governance stakeholder feedback.
C	1.	Data governance policies and standards are integrated into the overall organizational governance structure.

5. Content Governance		
Capability Maturity	**#**	**Capability Assessment Statement**
A	1.	There is a documented inventory of data domains relevant to each business function.
B	1.	Data taxonomies describe how data entities are categorized within data domains.
B	2.	The relationships between taxonomies are modelled into domain ontologies.
B	3.	Data taxonomies and ontologies are verified by domain experts from inside the business.
B	4.	All information systems adhere to the established data taxonomies and business ontology.
C	1.	The critical data elements that support core business functions are documented.
D	1.	Data receives a classification that determines which policies and standards apply to it.
E	1.	Data entities receive unique industry aligned identifiers.
E	2.	Data schemas are aligned with common industry schemas.

6. Data Management Strategy (DMS)		
Capability Maturity	**#**	**Capability Assessment Statement**
A	1.	A general Data Management Strategy (DMS) is documented and being communicated.
A	2.	The DMS is aligned with business, technology and operational objectives.
A	3.	A mechanism to process stakeholder and executive DMS feedback is in place.
B	1.	The DMS contains specific data related business requirements.
B	2.	These business requirements are regularly reviewed by relevant stakeholders.
C	1.	The purpose, objectives and structure of the data governance program are described in the DMS.
C	2.	The DMS specifies the importance of data stewards, owners and business-line data executives.
D	1.	Relevant architecture, technology and operations elements are included in the DMS.
E	1.	The DMS specifies the need for a communication strategy that informs and promotes awareness.
E	2.	There is a data education and training program as described in the DMS.
F	1.	The DMS expresses the need to quantitatively monitor the data management program progress and effectiveness.

F	2.	The DMS describes how adherence will be measured and monitored.

7. Data Quality Assessment and Remediation		
Capability Maturity	**#**	**Capability Assessment Statement**
A	1.	Data in need of quality control is prioritized.
A	2.	There is a data quality program with a clear scope.
B	1.	Data is statistically analyzed, profiled and assigned a grade that defines the quality level.
B	2.	The data quality grade is stored as metadata.
C	1.	Data quality is remediated based on established priority.
C	2.	There are timelines for ongoing data quality evaluation and data remediation.
D	1.	Data quality control points are established throughout the data supply chain.
D	2.	Data quality is routinely measured across business-lines and reported.
D	3.	Corrective measures are implemented into processes to resolve data quality issues.
E	1.	Data stewards and subject matter experts perform quality assessments of their business-line related data.
E	2.	Data quality processes are routinely audited for effectiveness.

8. Decision-making process (DMP)		
Capability Maturity	**#**	**Capability Assessment Statement**
A	1.	Organization leadership is aware of the need to become data driven.
A	2.	KPI's and historic data is referenced during decision-making.
B	1.	A systematic decision-making process is in place for specific business functions and processes.
B	2.	Decision-making outcome quality is quantitatively measured.
B	3.	Referencing diagnostic analytics results is part of decision-making processes.
C	1.	There are documented standard decision-making processes for the entire organization.
C	2.	Decision-making outcomes are proactively assessed using predictive analytics.
D	1.	Data-driven decision-making is embedded in the business strategy and objectives.
D	2.	The decision-making process and outcome metrics are continuously improved.
D	3.	Decision-making is partially automated by software systems that provide actionable recommendations.

9. Data Architecture		
Capability Maturity	**#**	**Capability Assessment Statement**
A	1.	Data entities and their sources are being identified, prioritized, and inventoried.
B	1.	Data entities and attributes receive clear documented non-technical business definitions.
B	2.	Relationships between different entities and attributes are being established and registered in collaboration with business subject matter experts.
C	1.	Utilized metadata receives a documented common definition across the enterprise.
C	2.	Metadata in dedicated repositories is being inventoried.
C	3.	Metadata is stored and used to support working with specific data.
D	1.	Technology developments use the defined and agreed upon data architecture.
D	2.	The data architecture is continuously being aligned to business processes.

10. Data Driven Culture		
Capability Maturity	**#**	**Capability Assessment Statement**
A	1.	The value of data-driven decision-making is being communicated to users within the organization.
A	2.	The adoption of data analytics technology is encouraged.
B	1.	Data stewardship and trust in data driven insights are being promoted.
B	2.	There are training initiatives to help develop data and analytical skills.
C	1.	Users are encouraged to participate in the use and development of the data-driven environment.
C	2.	If someone needs access to data or information, it's clear where to find or request it.
C	3.	It is documented or known which data and information different users or user groups frequently use.
D	1.	Collecting and using data is the norm for all organizational processes.
D	2.	Decision-making based on data-driven insights is stimulated at all levels of the organization.
D	3.	Reporting of analytical insights is a standard part of decision-making meetings.

11. Leadership & Empowerment		
Capability Maturity	**#**	**Capability Assessment Statement**
A	1.	Organization leadership communicates the importance of data and encourages its use in decision-making.
A	2.	A data management and analytics funding model is established and periodically reviewed in collaboration with stakeholders.
B	1.	People in leadership and managerial positions have developed data analytics skills.
B	2.	Employees can contribute to tactical or strategic decision-making by providing data-driven insights, regardless of seniority.
B	3.	The business case for data management is documented and communicated.
C	1.	Leaders participate in collaborative data and analytics initiatives across the organization.
C	2.	The data management business case is continually improved in collaboration with business and IT stakeholders.
D	1.	Data-driven decision-making is fully delegated throughout the organization.
D	2.	Data management and analytics funding is allocated autonomously by business lines or departments, under supervision of the organization's data management committee.

12. Data Storage Infrastructure and Operations		
Capability Maturity	**#**	**Capability Assessment Statement**
A	1.	Data is collected, stored and shared across or within teams or departments.
B	1.	There is a centralized repository for analytical data.
B	2.	The process of extracting, transforming and loading data into the enterprise data storage solution is aligned with business data definitions and rules.
B	3.	Data is shared through centrally managed data stores.
C	1.	The data storage solution is scalable and can integrate new structured data without structural design changes.

D	1.	Relevant data acquired from external parties is stored and integrated.
E	1.	Large volumes of data can be stored in the enterprise storage solution.
E	2.	Unstructured data is stored for use in advanced analytics.

Appendix 6: Identified maturity frameworks

Framework	Levels	Categories	Dimensions	Reference
DAMA - DMMA	0: Absent 1: Initial 2: Repeatable 3: Defined 4: Managed 5: Optimized	N.A.	Data Modeling & Design Data Storage & Operations Data Security Data Integration & Interoperability Document & Content management Reference & Master Data Data Warehousing & BI Data Quality Data Architecture Data Governance Data Ethics	(DAMA International, 2017; DAMA NL, 2022)
EDM Council - DCAM	0: Not Initiated 1: Conceptual 2: Developmental 3: Defined 4: Achieved 5: Enhanced	Data Management (DM) Strategy	DM Strategy Specification and Sharing Business Requirement Capture, Prioritization, and Integration Definition of Identification, Prioritization, and Assuring of Authorized Data Domains DM Strategy Alignment with Architecture, IT and Operations Description of Data Governance Program DM Program Measurement and Evaluation DM Communication and Training Program	(EDM Council, 2014, 2020)
		Data Management Business Case and Funding Model	Data Management Business Case Alignment Data Management Funding Model Funding Model Measurement and Evaluation	
		Data Management Program	Data Management Program Data Management Program Roadmap Stakeholder Engagement Communication Program Design and Operation Data Management Routines	
		Data Governance	Data Governance Structure Policy and Standards Program Controls Program Governance Operationalization Content Governance Technology Governance Cross-Organizational Enterprise Data Governance	
		Data Architecture	Data Identification Data Definitions Data Architecture Governance	

		Technology Architecture	Data Platform Strategy Data Technology Tool Stack Data Storage Management Strategy IT Operational Risk Planning	
		Data Quality	Data Quality Program Data Quality Assessment Data Quality Program Operationalization	
		Data Operations	Data Operations EDM and Strategy Alignment Data Management Lifecycle Cross-Organizational Control Function Alignment	
CMMI - DMM	1: Performed 2: Managed 3: Defined 4: Measured 5: Optimized	Data Management Strategy	Data Management Strategy Communications Data Management Function Business Case Program Funding	(CMMI Institute, 2014; ISACA, 2017)
		Data Governance	Governance Management Business Glossary Metadata Management	
		Data Quality	Data Quality Strategy Data Profiling Data Quality Assessment Data Cleansing	
		Data Operations	Data Requirements Definition Data Lifecycle Management Provider Management	
		Platform & Architecture	Architectural Approach Architectural Standards Data Management Platform Data Integration Historical Data, Archiving and Retention	
		Supporting Processes	Measurement and Analysis Process Management Process Quality Assurance Risk Management Configuration Management	
MAMD	0: Incomplete 1: Performed 2: Managed 3: Established 4: Predictable	Data Management	Data Requirements Management Technological Architecture Management Historical Data Management Data Security Management Configuration Management	(Caballero et al., 2023; Carretero et al., 2017)

	5: Innovating		Master Data Management Data Design Establishment of Data Sources and Targets Data Integration	
		Data Quality Management	Data Quality Planning Data Quality Control and Monitoring Data Quality Assurance Data Quality Improvement	
		Data Governance	Establishment of Data Strategy Data Lifecycle Management Data Value Management Standards, Policies and Procedures Definition Human Resources Management Organizational Data Strategy Monitoring Financial Resources Management Data Strategy Change Management	
TDWI – DMMM	1: Nascent 2: Developing 3: Established 4: Managed 5: Optimized	Organization	Executive Sponsorship Culture Strategy Metrics Data Ethics	(Larson, 2023)
		Resources	Funding Talent/Skills Roles and Responsibilities Education Literacy	
		Architecture	Diversity, Volume, Speed Data Access Data Integration and Management Technical Infrastructure Business Architecture Alignment	
		Data Life Cycle	Scope of Capabilities Automation/Augmentation Deployment and Delivery Approaches Curation Value of Analytics Storage and Operations	
		Governance	Data Governance Processes and Tools Model Governance Processes and Tools Governance Roles	

			Security/Privacy Quality Sovereignty	
TDWI - AMM	1: Nascent 2: Early 3: Established 4: Mature 5: Visionary	Organization	Leadership Culture Impact Strategy	(Halper, 2023)
		Resources	Funding Talent/Skills Roles/responsibilities Training	
		Data Infrastructure	Diversity, Volume, Speed Data Access Data Integration and Management Data Architecture	
		Analytics	Scope of Capabilities Automation/Augmentation Deployment and Delivery Approaches Innovation	
		Governance	Data Governance Processes and Tools Model Governance Processes and Tools Governance Roles Security/Privacy	
MD3M	1: Initial 2: Repeatable 3: Defined Process 4: Managed & measurable 5: Optimized	Data Model	Definition of Master Data Master Data Model Data Landscape	(Spruit & Pietzka, 2015)
		Data Quality	Assessment of Data Quality Impact on Business Awareness of Quality Gaps Improvement	
		Usage & Ownership	Data Usage Data Ownership Data Access	
		Data Protection	Data Protection	
		Maintenance	Storage Data Lifecycle	
CHROMA - SHADE	1: Uninitiated 2: Awareness 3: Proactive Adopting	Data Availability	Infrastructure Governance Properties	(Parra, 2018; Parra et al., 2019)
		Data Quality	Quality & Standardization	

	4: Integral embracement 5: Completely embedded		Technology & Methods Skills & Expertise	
		Data Analysis & Insight	Applications & Tools Techniques & Analysis Skills & Expertise	
		Information Use	Requirements & Use Knowledge Management Information Governance	
		Decision Making	Goals & Outcomes Decision-making Process Leadership & Empowerment	
BACMM	0: Non-existent 1: Initial 2: Intermediate 3: Advanced 4: Optimized	Governance	Decision Rights Strategic Alignment Dynamic BA Capabilities Change Management	(Cosic et al., 2012, 2015)
		Culture	Evidence-Based Management Embeddedness Executive Leadership and Support Flexibility and Agility	
		Technology	Data Management Systems Integration Reporting BA Technology Discovery BA Technology	
		People	Technology Skills and Knowledge Business Skills and Knowledge Management Skills and Knowledge Entrepreneurship and Innovation	

Appendix 7: DDDMFAMM assessment tool result report (Enlarged)

	Focus Area\Maturity Level	0	1	2	3	4	5	6	7	8	9
1	Analytics Applications & Tools		Basic analytics applications	Targeted Applications		Business intelligence tools		Analytics tool integration		Self-service & Prescriptive tools	
2	Analytics Techniques & Analysis		Descriptive analytics			Diagnostic analytics		Predictive analytics		Prescriptive analytics and automation	
3	Data Governance Structure		Data Management Office (DMO)	Executive ownership	Data governance plan		Data quality roles and responsibilities			Enterprise-wide governance	
4	Policy & Standards		Establishing Policy & Standards				Stakeholder review & approval		Data governance policy integration		
5	Content Governance		Establish Authorized data domains (ADD)	Data taxonomies and ontologies		Critical data elements (CDE)	Data classification			Standardized identifiers and relational models	
6	Data Management Strategy (DMS)		DMS specification and sharing	Business requirements	Enterprise data governance	Architecture, IT and Operations alignment	Communication and Training		Data Management Measuring and Evaluation		
7	Data Quality Assessment and Remediation		Data prioritization and scoping				Data profiling, analysis, and grading	Data remediation	Data quality control		Data quality audit
8	Decision-making process (DMP)		Ad-hoc data-driven decision-making			Systematic data-driven decision-making		Embedded data-driven decision-making		Strategic data-driven decision-making	
9	Data Architecture		Entity identification		Data semantics and relationships		Metadata definition, capture and inventorization		Business & Technology Alignment		
10	Data Driven Culture		Awareness creation		Training & Skill development		Adoption & Participation Encouragement			Data-driven standardization	
11	Leadership & Empowerment		Leadership attitude		Empowerment & Business Case			Leadership collaboration			Delegation, alignment, and innovation
12	Data Storage Infrastructure and Operations		Collection and sharing		Centralized storage and management			Agile & scalable storage solution	External data integration		Big Data

DMS specification and sharing

Description: A data management strategy specifies an organization's approach to data management and data utilization. It emphasizes the goals and objectives of the data management program and conveys the general approach to realizing them. While informal applications of data management and analytics can be executed without the need for a comprehensive strategy, it is practical to ensure that data initiatives are developed in a top-down manner early in their lifecycle. This ensures that once the need arises for these practices to be institutionalized, they can be related back to organizational data management objectives.

Goal: Steer data management in accordance with a general data management strategy aligned with high-level organizational objectives.

Development Actions:
- DMS is documented, aligned with business, technology and operations and shared with all relevant stakeholders.
- Map and align DMS with high-level organizational objectives.
- Establish mechanisms for capturing and incorporating feedback and approval of DMS by executive committee and other stakeholders.

A general Data Management Strategy (DMS) is documented and being communicated (e.g. Thales NL EIM Framework Handbook)	PRESENT
The DMS is aligned with business, technology and operational objectives.	PRESENT
A mechanism to process stakeholder and executive DMS feedback is in place.	MISSING