DMMM: Data Management Maturity Model

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***Abstract*—The assessment of the digital transformation progress is essential to understand and undertake in order to evaluate the level of maturity of data-driven companies, and to plan for improvement actions. For this purpose, we developed a maturity model assessment. The value proposition is to evaluate the current maturity state of an enterprise from a data and information management point of view while envisioning an evolution path from the current state to the target state. In this paper, we present a new perspective on how to construct maturity models to assess companies' maturity in terms of data management and advanced analytics with a focus on building a set of tools to ease the application of our model and create a fact-based roadmap for evolution. Our Data Management Maturity Model (DMMM) was designed to support the digital transformation from an initial level to an optimized one. It covers the different aspects that can be encountered such as, the organizational structure, the systems, the data dimensions, and operations. This paper is also a representation of the technical tools we developed to ease their implementation through the DMMM user interface. It depicts the methodologies behind the development of the maturity scoring system, the model architecture, the assessment practice as well as the maturity levels resulting from the evaluation. Additionally, we set forth the technicalities behind the model capabilities, their mapping for a data-centric vision, and their linkage that brings consistency and traceability between the latter.**

Keywords-Maturity Assessment, Data Management, Maturity Model, Maturity Enablers, Data Capabilities, Maturity Roadmap

I. Introduction

Nowadays, organizations are more data-driven and are continuously striving towards full enablement and adoption of a digital transformation journey. This is because they face a massive influx of data and innovative technologies that need to be implemented. Moreover, they operate in an increasingly competitive and erratic global business environment, aligning data projects at the edge of technical and organizational projects. They, consequently, facing changes in IT organizations as well as changes in the operating models and organizational structure.

Furthermore, this digital transformation process is sensitive to complexity and untraceability in terms of knowing where to head, what should be done, and where to focus the first efforts, capabilities as well as resources. In this context, we have been supporting start-ups and international companies in their digital transformation in three ways: by implementing an ad hoc, scalable, and data-centric IT architecture, by developing tailor-made products, and, above all, by using machine learning to exploit data, derive maximum value from it and offer a competitive advantage.

We first exploited the state of the art of data management maturity models and then we consolidated it into a survey [1] where we also built a meta-model that we used as a baseline to design a new aggregated maturity model. The contributions of this paper are:

- Building an actionable model in the sense it allows being concretely used for defining a roadmap to reach a target maturity state by developing an exhaustive questionnaire to assess the current maturity state. Additionally, an architecture-based approach is provided to define the target maturity and a model to infer the concrete roadmap to get there.
- Building a model toolbox enabling mapping an entire business case catalog to the required maturity level and deriving the associated data program roadmap. This approach is based on the definition of a state of the art of functional data architecture and a dependency graph between the capabilities of the model from which a roadmap is inferred.

This paper is structured as follows: The first section covers the background for this specific initiative and presents an overview of the conducted research on maturity models in the field of data and information management and governance. The most referenced models in this study are mentioned as well. The second section is dedicated to the developed Data Management Maturity Model (DMMM). It describes the main concepts, characteristics, and components of the model such as the DMMM's conception and architecture. Moreover, the scoring system and assessment methodology are explained and the means of application of this model are clarified through a described set of tools. In the following section, the assessment process, the toolbox built around the model, and its means of presentation are provided. Lastly, a conclusion is drawn with mentions of future works.

II. Background

The DMMM was developed to assist organizations to exploit big data analytics successfully. This project started in the academic world. The rationale behind this research was to investigate maturity models' characteristics through the organizational effectiveness lens and understand how this theory could help organizations in implementing and sustaining data initiatives, leading to an effective analytics capability. As was demonstrated by many renowned organizations, many companies failed to manage to use analytics effectively. They rushed on big data/AI [2] but quickly found themselves struggling in getting their data initiatives off the ground and achieving the desired value from their investments. This is because enterprises are currently facing an increasingly competitive and erratic global business environment, aligning data projects at the edge of technical and organizational projects. They, thereby, encounter changes in IT organizations as well as in the business operating models and organizational structure. As a result, this has led us to study how organizational design has been impacting the implementation and utilization of data technologies in organizations. This model is constructed around a gap analysis methodology.

The value created for the customer is therefore three-fold: (1) understanding the customer's current analytical capabilities, (2) understanding a customer's core business functions analytical desire and willingness to adopt and implement, and (3) operational, tactical, and strategic view on how to reorganize the organization to successfully take advantage of the big data analytics technology.

To enable our critical and in-depth analysis on the subject of maturity models in data management and compare between them, we conducted a survey [1] in which our selection approach was based on a set of criteria, which included the identification of the different maturity models' strengths and weaknesses, their assessment methodologies and framework focuses. The different attributes served as guidelines for the classification and examination of the maturity models, through their structure, assessment processes, outputs, means of implementation, support details, and general features. An analysis [3] was conducted through these attributes, where each aspect is an important differentiator between the selected and most referenced academic as well as industrial maturity models, such as the Capability Maturity Model Integration (CMMI) [4], DAMA-DMBOK Data Management Maturity Model (DAMA-DMBOK2) [5], Gartner's Enterprise Information Management Maturity Model (EIM) [6], [7], [8], IBM data Governance Council Maturity Model (DGMM) [9], [10], [11], and data Management Capability Assessment Model (DCAM) [12], [13].

III. DMMM MODEL

A. *Metamodel Conception*

The aforementioned analysis allowed us to conduct a systematic comparison of the studied maturity models and develop a metamodel that serves as a framework to position and compare the different maturity models that have been selected. To enable these objectives, the metamodel we published in a dedicated survey [1] depicts a total of five main components. These components are a representation of the different chosen focus areas by maturity models, and each component underlines the set of attributed capabilities established by each model. Through this approach, the metamodel demonstrates the commonalities of the selected maturity models in terms of their shared practicalities, focus domains, and characterized functions. As a result, the conceptual differences between the subjects are also delineated.

B. *Model Architecture*

The model is designed around 4 building blocks: 4 data categories, 14 data capabilities, 5 maturity levels, and a scoring system. These components are essential to establish our assessment tool and base our maturity evaluation and gap analysis on a predefined set of criteria.

1) *Data categories*

By combining our extensive research results along with our clients' challenges, and as data and information are fundamental assets in any organization, we decided to go with 4 major categories that represent different aspects of businesses and data domains. Each of these categories encompasses a set of capabilities that will ensure that any organization reaches a top-level of data management processes.

a) *Category 1: Enterprise & intent*

This category revolves around the organization's set goals and the process of achieving them while progressing in the digital transformation journey and forging ahead with technology implementation. It also comprises the different cultural changes this journey brings with it, and how to achieve a data-driven culture.

b) *Category 2: Data management*

This category emphasizes that data and information are fundamental assets that every organization should constantly manage and monitor. It includes the different aspects to derive the most efficient value from data, while aligned with the business goals.

c) *Category 3: Systems*

This category highlights the significance of data in the implemented tools and their operations while preserving conservative standardized functions.

d) *Category 4: Data operations*

This category includes the methodologies behind the integrated processes across the organization, as well as their analytical deployment and contribution to the overall business process.

2) *Data capabilities*

To assess the maturity in terms of data management within an organization, we assume that a set of 14 capabilities must be checked to ensure that the organization reaches a top-level in data management. We classify these capabilities into the aforementioned 4 categories as described in Table 1.

Each of the 14 capabilities is put in place to answer a key question and to serve a specific purpose in data management. We explain this in the next subsections.

TABLE I. CATEGORIES & CAPABILITIES OVERVIEW

Categories	Capabilities
Category 1: Enterprise & Intent	Capability 1: Business Strategy Capability 2: Culture & People
Category 2: Data Management	Capability 3: Data Collection & Availability Capability 4: Metadata Management & Data Quality Capability 5: Data Storage & Preservation

	Capability 6: Data Distribution & Consumption Capability 7: Data Analytics/Processing/Transformation Capability 8: Data Governance Capability 9: Data Monitoring & Logging
Category 3: Systems	Capability 10: Architecture & Infrastructure Capability 11: Data Integration Capability 12: Security
Category 4: Data Operations	Capability 13: Processes Capability 14: Data Deployment & Delivery

a) Capability [1]: Business strategy

The business strategy defines the overall framework and provides the rationale for the investment in a data management program. It is structured to address the core principles of data management to highlight the importance of a data management program to critical stakeholders and how this program relates to their strategic goals.

b) Capability [2]: Culture & people

This capability is key to activating and engaging people in data management initiatives, policies, and procedures. Hence, organizational, and cultural change will lead to a smoother transition during the digital transformation journey.

c) Capability [3]: Data Collection & Availability

This capability helps to achieve interoperability in data collection and availability approaches while adopting the ideal approach that is aligned with an organization's capabilities to reduce limitations and costs.

d) Capability [4]: Metadata Management & Data Quality

This capability encompasses metadata management, data modeling at the business, logical and physical levels, data profiling, and data cleansing to establish the processes and infrastructure for specifying and extending clear and organized information about the structured and unstructured data assets under management, fostering and supporting data sharing, ensuring compliant use of data, improving responsiveness to business changes and reducing data-related risks.

e) Capability [5]: Data Storage & Preservation

Data storage or preservation ensures that the right relevant data has been collected and archived so it does not get lost or destroyed.

f) Capability [6]: Data Distribution & Consumption

This capability is to ensure accurate and low latency data as well as understanding the expected volatility and frequency with which data changes with the correct currency measurements.

g) Capability [7]: Data Analytics / Processing / Transformation

The purpose of this capability is to get insights from managing data to personalize the customer's experience, identifying the root cause of poor data management and business issues in real-time.

h) Capability [8]: Data Governance

Data governance formalizes and establishes how data management principles and guidelines should be followed and implemented. It is the set of best practices, procedures, rules, and guidelines to guarantee collection, availability, usability, integrity, and security of data. Data governance is a guide to managing data. It is the exercise of authority and control (planning, monitoring, and enforcement). It ensures the data asset is well managed within the organization.

i) Capability [9]: Data Monitoring & Logging

This capability serves the creation of an ongoing record of application events as well as a consecutive evaluation of application performance. There are mainly two aspects here: (1) Operation and maintenance (O&M) and (2) business activity monitoring, which can be especially useful when it comes to tracing business activities for legal compliance.

j) Capability [10]: Architecture & Infrastructure

This capability serves multiple purposes such as to define a consistent and common meaning of data, establish appropriate use of data throughout the organization, enable the appropriate means for data usage, define the current state of data in the organization, provide a standard business vocabulary for data and components, align data architecture with enterprise strategy and business architecture, express strategic data requirements, outline high-level integrated designs to meet these requirements, integrate with overall enterprise architecture roadmap, capture information requirements and transform them into the "what, where, when, and how" of data and focus on the physical IT infrastructure needed for operational deployment.

k) Capability [11]: Data Integration

Data integration ensures that data operations are functional, aligned with the enterprise's capabilities and strategy, and are supportive of the data management's lifecycle.

l) Capability [12]: Security

Data management operations are aligned with standards, privacy policies, and information security policies. These standards, policies, and procedures exist for all related data operations which are aligned with the technical aspect of the capabilities and are approved and verified by stakeholders.

m) Capability [13]: Processes

Processes ensure the adoption of a sustainable standard measurement and process methodology. Additionally, it will enable the organization the guidance of both strategy and tactics, as well as the measurement of impacts and progress.

n) Capability [14]: Data Deployment & Delivery

Data deployment and delivery guarantee the continuous understanding and evolution of high-level autonomy and product deployments.

3) Maturity levels

To evaluate the current maturity of organizations, a set of defined maturity levels have been defined, as described in Table 2.

TABLE II: MATURITY LEVELS DESCRIPTION

Level	Category	Description	Characteristics
0	No Capability	Not initiated	-Absence of Capability -No defined processes
1	Initial	Ad-Hoc	-Pre-Big data environment -Unstable performance -Lack of data management tools

			-Reactive process discipline
2	Developing	Awareness & Pre-Adoption	-Ad-hoc performance only at the implementation level of projects -A weak level of Analytics -Notable awareness of the importance of data management
STAGE	CHASM	Leap from level 2 to 3	All Capabilities are established and verified by stakeholders
3	Defined	Program Adoption	-Defined policies and standards -Improved operations and services integrated into processes -Increased formal processes embedding advanced analytics in operations
4	Managed	Corporate Adoption	-Achieved deployment & harmonization of data across business process areas -Standardized analytical programs in organizational operations innovation -Defined critical data elements -Sustainable revenue flow
5	Optimized	Mature/ Visionary	-Achieved data Culture -Optimized data management procedures -Optimized processes' performance -Continuous detection of improvement opportunities in processes and data supporting technologies -Continuous organizational innovation

4) Scoring system

For each capability, to calculate the score results of all the related questions, we follow the scores equivalence as shown below to be able to determine the maturity level for each capability. To calculate the different scores and the overall maturity, the model presents flexibility in its application by following the formulas below for each type of assessment:

- **At the Model Level:** For a holistic assessment of all categories: $Score_{Maturity} = Avg_{Score\ of\ Category}$
- **At the Category Level**: $Score_{Category} = Avg_{Score\ of\ Capability}$
- **At the Capability Level:** For a specific capability assessment; the assessment allows reflecting the score of maturity solely on a capability: $Score_{Capability} = Avg_{Score\ of\ Sub-Capability}$
- **At the Sub-capability Level**

$$Score_{Sub-Capability} = \frac{\Sigma\ Criteria}{N\ Criteria}$$

$$Score_{Criteria} = Score_{Answers}$$

- N criteria: number of criteria in its correspondent Sub-Capability

All the questions in the initial maturity assessment must be answered with one of the 5 choices. Based on the answers to each question, we will attribute scores as follows.
Table 3 explains how scores are attributed to the function of answers.

TABLE III: SCORING SYSTEM

Answer	Score
Not Applicable	--
I don't know	--
Absolutely No [ANO]	1
Not Really [NR]	2
Average [AVG]	3
Almost True [AT]	4
Absolutely Yes [AYE]	5

C. Assessment Methodology

The challenges faced by the company while implementing the Data Management Maturity Model depend on the scale, size, location, industry, culture, and attitude towards change. We address each phase with a set of activities needed, that depends on the challenges encountered, to identify the gaps and get the most efficient output by adopting a 3-phase approach as follows:

1) Phase 1: Current state assessment

The organization is assessed according to 14 business domains: the business strategy, the culture & people, data, the data collection & availability, the data quality & validation, the data storage & preservation, the data distribution & consumption, the data analytics, the data governance, the data monitoring & logging, the architecture & infrastructure, the integration within existing systems, security, the processes & methodology and finally the delivery & deployment.

The assessment is conducted through the selection and the interview of key representatives from each of those domains.

2) Phase 2: Targeted state assessment

The organization will be divided into departments and representatives will be selected for each of those departments. Those representatives come from key business departments.

The workshops are with key personnel across the business and information management teams. Thus, these workshops will enable us to discover the top-down and bottom-up short-term and long-term analytical desires, considering the strategic intents. Defining a target maturity state is not obvious since no one has a clear vision of which maturity level they need to reach. However, what we can establish is the list of strategic business cases to implement in the next 3 years. But how to derive the target maturity state from the cases? We describe our approach in the next section.

3) Phase 3: Evolution roadmap

The focus of this stage is to develop an organization's transformation roadmap for big data development. We provide digital initiatives to initiate the digital transformation and recommendations on how to leverage the current organizational capabilities to successfully adopt and implement big data analytics. The latter is achieved through the dependency relationship between our capabilities, as well as the mapping of our technical enablers. This determines the inference of a concrete and solid roadmap.

IV. MODEL TOOLBOX

The model can be applied using a set of tools to facilitate the application phase and help create a factual roadmap.

The DMMM toolbox encompasses (i) an assessment survey with an exhaustive list of questions to evaluate the company's maturity, (ii) a set of organizational enablers, technical enablers, and data governance artefacts to support a higher level of maturity, and (iii) a map and a grid to create a factual roadmap while taking into account the links between the 14 capabilities following a dependency graph we included in the toolbox.

A. Assessment Survey

The assessment survey allows clients to apply the model to their situation to measure their current maturity level. In this survey [14], questions were derived from the gathered industry best practices and were also elaborated based on the model's criteria. The questions were formulated as neutrally and objectively as possible for all 14 capabilities described by the model which also displays the level of maturity corresponding to every capability and category.

B. Organizational Enablers

For the "Enterprise & Intent" category, each capability encompasses a set of organizational enablers that deduce the business orientation and practices to support the strategic goals and the implementation of best practices. For the "Business Strategy" capability, the organizational enablers revolve around the implemented business model, its alignment with the embedded business strategy and goals, clearness in vision, and specified initiatives that would achieve incremental and adjacent processes. They also include the defined rules, processes, and metrics and how the business particularities are taken into account for conducting governance approaches and continuous improvements. Additionally, to ensure consistency of business terms and internal vocabularies, these enablers comprise the business glossary, as the essential means that defines the relationship between the data vocabulary and shares them across the entire organization.

For the second capability, "Culture & People", the organizational enablers involve the defined roles and responsibilities of the different professionals, the communication plan conducted within the organization, the availability of management resources and support, as well as those of systems. Moreover, they concern and promote all building-up knowledge-related programs and multi-disciplinary working culture.

C. Technical Enablers and Governance Artefacts

We have built our data-enabler vision around a set of technical enablers to be fully data-centric. To do so, we have compiled an exhaustive list of technical enablers. To be methodological, we organized this list of enablers into 4 phases to facilitate adopting a clear roadmap this segmentation into 4 phases is based on our experience from the field which will be refined with future projects. We suppose that for a company that has implemented nothing in terms of data i.e., has no data capability at all, following this roadmap should enable the 14 capabilities and help companies to reach an optimized maturity level. Our data-enabler roadmap encompasses 4 stages as follows.

In the first stage, we recommend implementing core features to start handling data by collecting it from multiple and variant data sources, ingesting it into a central data collector, store it and distribute it to multiple and variant data consumers. The data core guarantees to reduce the cost of all future use cases, shorten the time to market of these use cases and the company must be ready to support EDWH (Enterprise Data Warehouse) migration.

In the second stage, data can be exploited since we enabled core features in the previous stage, which means that the company can start enabling data science, BI (Business Intelligence), reporting, and emphasizing data quality. The technical enablers to ease data exploitation enable building a centralized 360° view around data, increase data efficiency, and initiate a business language model.

In the third stage, we should think about getting more control of the data by structuring the data to expose it to internal users and third parties, qualifying data, deploying engines such as a CEP (Complex Event Processing), and enabling self-service data and logging. These enablers speed up self-service data for business, enable real-time interaction between business users and the data management platform thanks to standardized data APIs and corporate KPIs reporting.

In the fourth and last stage, companies have implemented a data core (stage 1) exploited data (stage 2), and control data (stage 3), are now ready for servicing data through deploying customer engagement platforms and integrating microservice architecture. With such enablers, companies would have operational chatbots, customer engagement applications, operationalization strategy, and improved quality of experience.

D. Mapping Enablers x Capabilities

We consolidated all the material we constructed on technical data architecture enablers and capabilities. On this basis, we produced a capability map of functional enablers where we depict how each of the 20 enablers supports the 14 capabilities of the DMMM. In Table 4, we present the mapping for a limited number of enablers with capability 7. The complete mapping is accessible online [15] and encompasses the 20 enablers and their corresponding links to each of the 14 capabilities.

TABLE IV: EXAMPLE OF MAPPING A SET OF 3 TECHNICAL ENABLERS WITH CAPABILITY 7

	metadata management	data pipeline management	reference architecture
[Cap7] Data Analytics & Processing	- data modelling and metadata registration	- SQL-based real-time transformations - events enrichment	- data pipeline description - target data model description

E. *Grid Capabilities x Levels*

Starting from the mapping, explained in section 4.4., we chart the evolution of each DMMM capability from level 1 to 5. We produce a grid where we map the enablers for a capability C and showcase its evolution by explaining how adding a new set of enablers can enhance the capability and make it evolve from level N to level N+1. In Table 5, we depict the evolution of capability 7 "Data Analytics & Processing" as an example. We also made the full grid accessible online [16] for more details about the evolution of the 14 capabilities from level 1 to 5.

TABLE V. EVOLUTION OF CAPABILITY 7 FROM LEVEL 1 TO 5 (1 ROW OF THE GRID)

	Level 1: Initial	Level 2: Developing	Level 3: Defined	Level 4: Managed	Level 5: Optimized
[Cap7] Data Analytics & Processing	--	Batch processing	Data enrichment management: - SQL-based real-time data transformations - events enrichment	DSW accelerator: - 1-line access to collected data. - feature repository	CEP-CER: - wire business process or call µservice when a situation is detected
				CSL: - exposes data for operational or analytical purpose	µservice layer: - serves data in the application-driven data model - LoB self-service data
			L&M: - report data pipeline failures	CI/CD: - a toolchain to manage data pipelines	O&M: - treat issues & alarms

F. *Dependency Graph*

We suppose that our target is "level 5: optimized" then we list the links between the capabilities to form our last component in the DMMM toolbox. The dependency graph is illustrated in Figure 1.

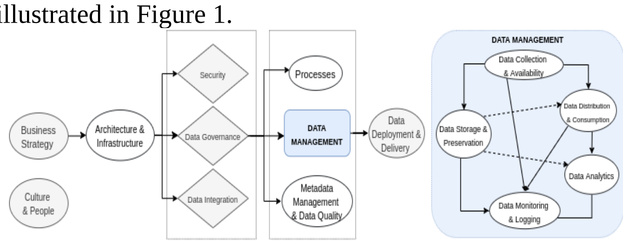

Figure 1. Dependency graph-optimized level

V. ASSESSMENT PRESENTATION

A. *Guidebook*

The guidebook [17] is a brief overview of the model and has only 10 pages. It provides an introduction to the model and its main components and concepts. Furthermore, it guides the reader through the assessment method and approach on how to evaluate the maturity level, while specifying the scope of data management categories and capabilities that suit the company's resources and ambitions. This book works together with the DMMM approach description report and the web application.

B. *DMMM Web Application*

The DMMM User Interface allows users to fill in the answers to the DMMM survey's questions for each customer representative (As-Is State & To-Be state). It should also be possible for the customer representatives to answer the questions themselves. Users can then visualize the results through the "Maturity Score" & "Evaluation" screens and get a roadmap based on answers provided in steps 1 & 2 (Path). We will use these categories to group the requirements. The DMMM UI is built using the Meteor framework. It is an open-source JavaScript web framework. Its main advantages are reactive programming out of the box, fast learning, many libraries available, seamless client-server communication, built-in authentication, and MongoDB native support.

VI. CONCLUSION & FUTURE WORK

Following a pragmatic research approach, we first conducted an exhaustive analysis of 22 existing maturity models that were selected based on a set of criteria we predefined. These models were then used to design the DMMM metamodel. This led us to have a full picture of the very best and most used maturity models in the industry as well as in the literature. We understood their commonalities and their differences, their strengths, and weaknesses. We also compared their approaches and assessment methodologies. From there, we noticed several limitations in the existing works. The most common one is related to being too specific or treating a narrow data domain. Companies that have several departments had to use more than one model to assess their different activities around information and data management. We also do not claim that the DMMM is the ultimate model that fits every company but the enhancements we brought to this newly born exercise came from a wide knowledge of the top existing models and assessment tools, combined with the conceived metamodel that helped us merge the strengths of 20 models and address their weaknesses.

Apart from the research methodology, we adopted a 3-phase assessment methodology where we assess the current maturity state first and before all, as we are convinced that no changes can be made without knowing where the company stands. We also allow time for sitting with the organization's stakeholders to understand their ambitions, help them translate their business needs into functional and technical requirements, and help them draw a short-term as well as a long-term roadmap. This phase is crucial to set a target maturity level to reach. As much as the first two phases are important, we believe that the third phase is one of the biggest DMMM strengths since it is about the evolution roadmap from the current state to the target state. The roadmap in question has an added value on our model because it is a factual one thanks to a set of tools, we built to support the DMMM application.

The first tool supports conducting the assessment by answering a survey of more than 500 questions that cover the 14 capabilities of the DMMM. Secondly, we included a set of more than 50 technical enablers and data governance artefacts. The enablers can support multiple data science and big data use cases' implementation following 4 evolution stages for adoption. We recommend starting by implementing a data core then start exploiting data to be able to control and qualify data that has been collected and stored in the company at a later stage. The last stage is about overhauling data, which means that the company has full control over its data and has reached an optimized level of managing it. We have granted importance to a set of organizational enablers as well, admitting that the organizational aspect is necessary to be able to adopt the aforementioned technical enablers.

To showcase how a roadmap can be created, we added 3 more tools: (1) the mapping between the 14 capabilities and the enablers to explain how exactly and factually each enabler can support the capability in question. (2) We then drew a grid to accurately explain the evolution of each capability from level 1 to level 5 and which set of enablers must be implemented at each level. (3) Last but not least, we generated a dependency graph to clarify the links between the capabilities. This graph helps to avoid focusing on some nodes by enhancing their corresponding capabilities while missing out on the parent nodes that must be enhanced first. This way, we have built multiple tools that serve at each phase of the DMMM application.

As we put a lot of effort into developing this model, we believe that the model itself cannot create awareness for decision-makers and stakeholders. A functional tool can bring value only when companies are convinced of its worth. Our mission at EURA NOVA includes working on this point by changing the mindset of our customers to go fully digital and by supporting them in adopting a data-centric approach. This can be achieved by deploying the DMMM and relying on our expertise as our biggest assets.

As a future work resulting from this paper, we concluded that most companies need to start from a data governance perspective to develop a governance model or framework that will facilitate the implementation of a data model later. As such, this model motivated us to develop a use case repository to add the business field as one of the DMMM dimensions and take it into account while creating the evolution roadmap. This repository would be a compilation of the most profitable businesses from digital transformation such as human resources, banking, insurance, IoT, and pharmaceutical industries.

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