A Capability Maturity Model for Developing and Improving Advanced Data Analytics Capabilities

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Abstract

Background: *Advanced data analytics (ADA) is increasingly used in organizations to enhance decision-making, improve operational efficiency, and gain a competitive advantage. Yet, there is limited guidance available on the capabilities an organization should develop and improve on to effectively leverage ADA. To address this gap this study develops a capability maturity model answering the research question: "What are the key components of a capability maturity model that can effectively guide organizations in assessing and enhancing their advanced data analytics capabilities?"*

Methods: *A capability maturity model for advanced data analytics (ADA-CMM) was developed through a Delphi study using the design science research paradigm. To evaluate ADA-CMM for its utility interviews with practitioners were conducted on the use of ADA-CMM for assessing the maturity of a large company. To evaluate ADA-CMM effectiveness a nomological model was developed and tested using PLS-SEM based on a multi-company survey*

Results: *A comprehensive ADA capability maturity model prescribing necessary capabilities was presented. The model is deemed useful and effective and offers a method to assess ADA capabilities. The findings provide evidence supporting that ADA-CMM encompasses essential capabilities for creating value from ADA initiatives and can effectively measure an organization's ADA capability maturity.*

Conclusion: *This paper emphasizes the growing importance of ADA in enhancing business operations and competitiveness. Despite technological advancements, many organizations struggle to translate analytics efforts into tangible benefits. To address this, the paper proposes a Capability Maturity Model, ADA-CMM, to guide organizations in developing and improving ADA capabilities. This study contributes to literature by providing a well-structured and thoroughly evaluated capability maturity model for ADA, and to practice for navigating the challenges of ADA adoption and use.*

Keywords: *Advanced Data Analytics, Capability Maturity, Maturity Model, Survey, PLS-SEM*

1 Introduction

With the advances in digitalization, organizations are increasingly employing advanced data analytics to improve their processes, products, and services (Ghasemaghaei et al., 2017) and gain a competitive advantage in their markets (Seddon et al., 2017). While *traditional* data analytics focuses on descriptive and diagnostic analytics for developing insights, reports, and dashboards, *advanced* data analytics (ADA) extends this with the use of more sophisticated and computationally intensive techniques, such as machine learning, to discover deeper insights, make predictions, or generate recommendations (Debortoli et al., 2014; Gartner, 2022a). Research indicates that businesses can have higher performance with respect to their competitors by 4% to 10% in productivity and profitability when these analytical techniques are successfully applied (Dilda et al., 2017). Researchers have also claimed the potential of ADA to revolutionize and transform how we work, live, and think (Gupta & George, 2016).

Despite the opportunities brought by implementing ADA, many organizations struggle to generate business value from their analytics initiatives (Günther et al., 2017; Ransbotham et al., 2015). They face social, organizational, and technological challenges in adopting ADA and creating value from it (Radhakrishnan et al., 2022). Some key challenges include translating data into knowledge, making data available in the right form at the right location, and adapting the business to changing data usage patterns (Matthias et al., 2017; Seddon et al., 2017). Only 20% of analytic insights are estimated to deliver business outcomes (Herschel et al., 2018). Managers must be aware of the barriers to success and work to minimize them rather than eliminate them altogether (Yu et al., 2022).

However, current research suggests that most attention has been paid to the technical aspects of ADA, with limited focus on organizational change and the strategic implications (Mikalef et al., 2020). This has resulted in limitations concerning the implementation and exploitation of ADA (Brinch et al., 2020). To address this challenge, one approach for organizations is to understand and focus on the capabilities facilitating ADA value creation, enabling them to analyze and develop their composition of ADA capabilities (Gür et al., 2021). Thus, organizations need guidance on developing *capabilities* to implement ADA for business value creation and harvest the benefits of increased organizational performance.

An organizational capability represents how people and resources are brought together to accomplish work (Ulrich & Smallwood, 2004). Capability maturity models have emerged as an effective management tool to guide organizations in developing and improving organizational capabilities (Poeppelbuss et al., 2011). They are conceptual models that indicate the maturity levels of the capabilities required for a specific process or class of processes in one or more business domains (Röglinger et al., 2012; Tarhan et al., 2020). They represent an anticipated, desired, or typical evolutionary path for these processes (Becker et al., 2009). These models support assessing existing capabilities and the development of a path for their improvement (Tarhan et al., 2016). They also help enrich the academic discourse by offering a well-defined scope and common basis for a specific field (Kerpedzhiev et al., 2021).

It is essential that a maturity model should approach ADA from a holistic perspective, covering capabilities related to a broad range of aspects, including people, processes, and strategy regarding analytics (Comuzzi & Patel, 2016). Many of the existing maturity models adopt a narrow perspective and exhibit limited coverage of necessary capabilities by focusing primarily on specific industries or types of ADA techniques (Lahrmann et al., 2010). Furthermore, when developing an ADA maturity model, it is essential to empirically validate the model to ensure its effectiveness in practice (Röglinger et al., 2012). The maturity models developed in the existing literature are often not or weakly validated (e.g., Cosic et al., 2012), hindering their application in real-world business settings (Tarhan et al., 2016). Furthermore, previous literature has primarily investigated the relationship between the maturity level of organizational ADA capabilities, ADA value, and firm performance independently (e.g., Brinch et al., 2018; Elia et al., 2020; Gupta & George, 2016) and has not yet provided a maturity model that has been quantitatively evaluated for its effectiveness. In the current literature, there is a lack of comprehensive guidance for assessing and improving relevant capabilities (Menukhin et al., 2019).

This research seeks to address this research gap by developing a novel capability maturity model encompassing a wide array of ADA capability areas, providing a means to assess the maturity level of an organization with respect to ADA capabilities, and is evaluated for its utility and effectiveness. Hence, we address the following research question: *What are the key components of a capability maturity model that can effectively guide organizations in assessing and enhancing their advanced data analytics capabilities?* We developed a holistic, firm-level capability maturity model for organizations to assess their current state of ADA capabilities and help build a roadmap to improve them. It provides a descriptive tool for assessing the as-is ADA capabilities, which can also be used for prescriptive purposes to guide reaching higher maturity levels (Röglinger et al., 2012).

In developing the Advanced Data Analytics Capability Maturity Model (ADA-CMM), we followed the design science research paradigm (Gregor & Hevner, 2013), adopting the research process proposed by Peffers et al. (2007). Accordingly, we first reviewed the literature to identify the existing maturity models on ADA. Next, we designed an initial version of ADA-CMM based on the findings from the literature review. The model was refined and finalized through a Delphi study of three rounds with nine field experts, which strengthened the model's relevance. Next, ADA-CMM was used to assess the maturity of a large company and semi-structured interviews with model users were conducted to evaluate the model's utility as perceived by target users. The results indicate that organizations can use ADA-CMM as a tool to assess their ADA capabilities and create a roadmap for improving their relevant capabilities.

Furthermore, to evaluate ADA-CMM, we surveyed 48 companies to assess their ADA maturity, the business value they attain from ADA, and their firm performance. Our analysis demonstrates a significant relationship between the maturity of ADA capabilities (*as measured using ADA-CMM*) and firm performance, mediated by the business value of ADA. This provides evidence that ADA-CMM incorporates critical capabilities that are pivotal in generating business value from ADA initiatives, consequently leading to enhanced firm performance. It confirms that ADA-CMM can be an *effective* tool in assessing the maturity level of an organization's ADA capabilities.

This research article extends the initial conference paper of Korsten et al. (2022) with strengthened theoretical underpinnings, additional evaluation, and details regarding its research design, process, and evaluation. The remainder of this paper is structured as follows. Section 2 presents the theoretical background on ADA, discusses the impact of ADA on firm performance, and provides a brief review of the existing ADA maturity models. Section 3 describes the research process we followed in developing the model using a Delphi study. Section 4 presents the final version of the ADA-CMM. This is followed by the application of ADA-CMM and an evaluation using interviews in Section 5. Section 6 presents the survey we conducted, which is followed by a discussion and implications in Section 7. Finally, Section 8 concludes with its limitations and future research directions.

2 Background and Related Work

In this section, we first introduce the concept of ADA. We then follow with a discussion of the existing maturity models on ADA and related concepts.

2.1 Theoretical background on ADA

The abundance of data has emerged as a pivotal factor driving the growth of ADA. Firms often have multiple databases with terabytes of data available in structured and unstructured forms, usually indicated as *big data* referring to its volume, variety, velocity, veracity, and value (Akerkar, 2013). As digitalization continues to advance and more data becomes available, an increasing number of organizations are leveraging ADA to gain a competitive edge in their respective markets (Seddon et al., 2017). *Data analytics* techniques can be used to analyze the enormous amounts of data. These analytics techniques can be structured into four general categories: descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics (Davenport, 2013; El Morr & Ali-Hassan, 2019; Gartner, 2022b).

Traditional data analytics focuses on descriptive and diagnostic analytics for developing insights, reports, and dashboards. In this work, we consider *advanced data analytics* (ADA) as an overarching notion that builds upon the foundations of traditional data analytics, extending it with advanced techniques to support predictive and prescriptive analytics (Debortoli et al., 2014; Gartner, 2022b). ADA can be used for discovering deeper insights, making predictions, or generating recommendations. It covers a broader set of techniques, *often including* those of traditional data analytics (Brook & Arnold, 2019).

Within the notion of ADA, there are several research areas that focus on a specific topic of ADA. For example, *Big data analytics* which is primarily about managing large amounts of data and extracting insights from it, often including ADA components (Gandomi & Haider, 2015). *Business analytics*, on the other hand, includes various analytical techniques used to drive business success (Chen et al., 2012). In brief, ADA represents an evolution of data analytics that embraces traditional data analytics while incorporating advanced techniques and techniques (Chen et al., 2012). In this paper and the proposed model, we adopt a holistic view of ADA, including traditional data analytics.

2.2 Maturity models for ADA

Simpson & Weiner (1989) define maturity as the state of being complete, perfect, or ready. Maturity models often define an ordered set of maturity levels for processes or organizational capabilities in a specific domain (Becker et al., 2009). Maturity can result from shaping the needed organizational capabilities and investing in the performance of particular tasks. Maturity models can be used to assess the current situation, develop and prioritize improvements, and control the progress of the implementation (Tarhan et al., 2016). In this sense, they can serve a descriptive purpose to understand the 'as-is' situation and a prescriptive purpose to guide improving the current maturity level (Bruin et al., 2005).

While many organizations have recognized the potential benefits that ADA can offer, establishing business capabilities to fully leverage the value of ADA remains a significant challenge (Baijens et al., 2020). Organizations need guidance to execute ADA projects and implement such solutions (Saltz & Shamshurin, 2016). A maturity model could provide a roadmap for organizations to improve their maturity level for their analytics capabilities (Tarhan et al., 2016).

To obtain a comprehensive understanding of the current state-of-the-art regarding relevant maturity models, we conducted a thorough literature review encompassing models from academic research and industry practice in ADA and related areas (e.g., big data analytics, business intelligence). In our literature review, we adopted a wide perspective when considering ADA, and presumed that it encompasses traditional data analytics but often extends this with the use of more advanced techniques. This broad perspective allowed us to explore all maturity models used for ADA, including those rooted in traditional data analysis.

We took two systematic literature reviews as the departure point for our review. The first provides a comprehensive overview of the models specifically for big data and ADA (Al-Sai et al., 2019). The second comparatively analyzes the maturity models on ‘analytics’ (Król & Zdonek, 2020). These two review studies together identified 26 unique maturity models in areas related to ADA.

Following the technique proposed by Wohlin (2014), we used forward snowballing to locate relevant papers in Google Scholar that refer to these 26 maturity models. The papers of Al-Sai et. Al (2019) and Króld and Zdonek (2020) have included maturity models from the grey literature as well, because in the advanced data analytics domain, the majority of the models is developed in industry. Therefore, this paper has, besides the academic libraries, searched the grey literature. By including grey literature, we aimed to integrate the academic research with practical insights, which could lead to valuable results.

The inclusion criterium in our review was that the source proposed a maturity model in the ADA field; excluded were those that are patents and quotes. In addition, we excluded articles that propose models that apply only to specific industry domains, such as healthcare (e.g., Molina-Granja et al., 2022). We searched for contributions published until December 2021 and written in English. There were in total 41 maturity models identified. After applying the inclusion and exclusion criteria, 29 unique maturity models were identified in the area of ADA.

We further analysed the maturity models based on the following criteria:

(1) *Holistic perspective*: A maturity model is considered to have a holistic perspective to ADA, when it encompasses capabilities across various aspects such as people, processes and strategy (Comuzzi & Patel, 2016).
(2) *Empirical validation of usefulness*: It is important to conduct empirical validation of the model to verify its practical utility (Tarhan et al., 2016).
(3) *Empirical validation of effectiveness*: Empirical validation of the model to ensure its effectiveness can be important for its adoption in practice (Röglinger et al., 2012).
(4) *Assessment method*: A maturity model is expected to provide guidance for assessing related capabilities.
(5) *Documentation available*: Providing relevant documentation on the development and validation is considered important to ensure an unbiased perspective (Comuzzi & Patel, 2016).

Table 1 shows the list of the maturity models and the respective characteristics of each publication with regards to these criteria. Fifteen of these originate from industry, and the remaining fourteen are published in the academic literature. None of analyzed maturity models satisfy all five criteria. The absence of maturity models fulfilling all five criteria results in limitations to their effectiveness and usefulness.

Table 1. Comparison of existing Data Analytics Maturity Models

** (1) Holistic perspective, (2) Emprical validation of usefulness, (3) Empricial validation for effectiveness, (4) Assessment method, and (5) Documentation available*

ID	Model Name	Reference	Origin	(1)	(2)	(3)	(4)	(5)
1	TDWI Analytics Maturity Model	(Halper & Krishnan, 2014)	Practitioner	X			X	
2	Big Data Business Maturity Model Index	(Schmarzo, 2013)	Practitioner	X				
3	IDC MaturityScape Big Data and Analytics	(Vesset et al., 2015)	Practitioner	X				
4	Big Data Maturity Assessment Tool / Infotech Model	(Info-Tech Research Group, n.d.)	Practitioner	X			X	
5	Big Data Maturity Model / Malik –IBM- Model	(Malik, 2013)	Practitioner					X
6	Big Data Maturity Framework / El- Darwiche Model.	(Wef, 2014)	Practitioner	X				
7	A Maturity Model for Big Data and Analytics/IBM Model.	(Nott & Betteridge, 2014)	Practitioner	X				
8	Zakat Big Data Maturity Model / By Sulaiman.	(Sulaiman et al., 2015)	Academia					
9	Hortonworks Big Data Maturity Model.	(Dhanuka, 2016)	Practitioner	X			X	
10	Big Data Maturity Model / By Comuzzi.	(Comuzzi & Patel, 2016)	Academia	X				X

11	Big Data Maturity Model / By Adrian.	(Adrian et al., 2016)	Academia	X				
12	A Value Based Big Data Maturity Model/ By Farah.	(Farah, 2017)	Academia					
13	Analytic Processes Maturity Model (APMM)	(Grossman, 2018)	Academia					
14	Analytics Maturity Quotient Framework	(Piyanka, 2012)	Practitioner	X		X		
15	Blast Analytics Maturity Assessment Framework	(Sanatham, n.d.)	Practitioner	X		X		
16	DAMM	(King, 2017)	Practitioner	X		X		
17	DELTA Plus Model	(Davenport, 2018)	Practitioner	X				
18	Gartner's Maturity Model for Data and Analytics	(White & Oestreich, 2017)	Practitioner	X				
19	Logi Analytics Maturity Model	(Logi Analytics, n.d.)	Practitioner					
20	Big data capability maturity model	(Dremel et al., 2017)	Academia	X				X
21	CHROMA-SHADE	(Parra et al., 2019)	Academia		X	X		X
22	MM for big data analytics in airline network planning	(Hausladen & Schosser, 2020)	Academia		X	X		X
23	Enterprise intelligence capability maturity model	(Huffman & Whitman, 2011)	Academia					
24	Towards a business analytics capability maturity model	(Cosic et al., 2012)	Academia	X				X
25	A Maturity Model to Guide Analytics Growth	(Menukhin et al., 2019)	Academia	X				X
26	Towards a Global Big Data Maturity Model	(Mouhib et al., 2020)	Academia					X
27	DAMAF	(Gökalp et al., 2021)	Academia			X		X
28	Towards An Artificial Intelligence Maturity Model	(Alsheiabni et al., 2019)	Academia					X
29	AtScale Data & Analytics Maturity Model	(Mariani, 2021)	Practitioner			X		

Three commonly used practice-based maturity models are Al-Sai et al., (2019); Analytics Maturity Model (Halper & Krishnan, 2014), Big Data Business Model Maturity Index (Schmarzo, 2013), and IDC MaturityScapes (Vesset et al., 2015). These three models have been developed in the industry by technology vendors, professional educational institutes, or consulting companies. Documentation on their unbiased development and validation is missing - a common weakness of maturity models developed by the industry (Comuzzi & Patel, 2016).

Academic research has recently dedicated significant efforts toward developing maturity models that explicitly target ADA. For example, the Big Data Maturity Model aims to help organizations leverage big data and its value (Comuzzi & Patel, 2016). The model focuses on five general dimensions: strategy alignment, data, organization, governance, information technology, and nine sub-dimensions. The model focuses specifically on the broad business implications of big data technology, providing a high-level assessment of these aspects.

However, the model design and evaluation rely on second-hand data, limiting the ability to capture the relevant dimensions and factors that influence the maturity of the big data technology domain.

Another model originating from academic research is the "Value-Based Big Data Maturity Model" proposed by Farah (2017). The model focuses on data quality and argues that this is critical in gaining a competitive advantage. The model proposed by Dremel et al. (2017) follows a similar path and incorporates 34 generic capabilities necessary to leverage the potential of big data analytics. The model was developed using input from consultants working for a single company. Furthermore, the model has not been empirically validated. Similarly, Cosic et al. (2012) propose a business analytics capability model comprising 16 capabilities grouped under four areas: governance, culture, technology, and people. Parallel to the abovementioned models, this model also lacks a comprehensive empirical evaluation.

In conclusion, researchers and practitioners have proposed several maturity models for ADA and related domains. These models have several limitations. First, they often lack a holistic perspective and concentrate on specific aspects of ADA, e.g., data quality (Farah, 2017). Some models focus only on a fraction of necessary capabilities or provide limited guidance for organizations to employ the model for assessing maturity, making their use in practice difficult (e.g., Halper & Krishnan, 2014; Schmarzo, 2013; Vesset et al., 2015). Second, some models lack empirical validation to ensure their applicability in real-world business settings (e.g., Cosic et al., 2012). Third, several models lack guidance for assessing the maturity of the organization (e.g., Adrian et al., 2016). Finally, documentation on their development and validation is missing (e.g., Vesset et al., 2015). The limitations identified within such models lead to significant impediments, limiting their effectiveness and usufulness in assisting organizations in assessing and improving their ADA capabilities.

3 Research Design

The objective of this study is to develop a capability maturity model that will support organizations seeking to assess and enhance their ADA capabilities. This paper elaborates on the design, development, and evaluation of the model. For our research, we followed the design science research (DSR) paradigm to develop the proposed artifact (Gregor & Hevner, 2013). In design science research, an artifact refers to a thing that has or can be transformed into material existence as an artificially made object (e.g., model) or process (e.g., method or software) (Gregor & Hevner, 2013). DSR is seen as a rigorous research method which focusses on solving relevant practice problems by creating effective artifacts (Deng & Ji, 2018). We followed the design science research process proposed by Peffers et al. (2007), which consists of the following steps: problem identification, the definition of the solution objectives, design and development of the model, applying the model in a suitable context (i.e., demonstration), evaluating it in a real-life business setting and communication. This paper serves as the communication step of the research process. Accordingly, the research design depicted in Figure 1 was followed.

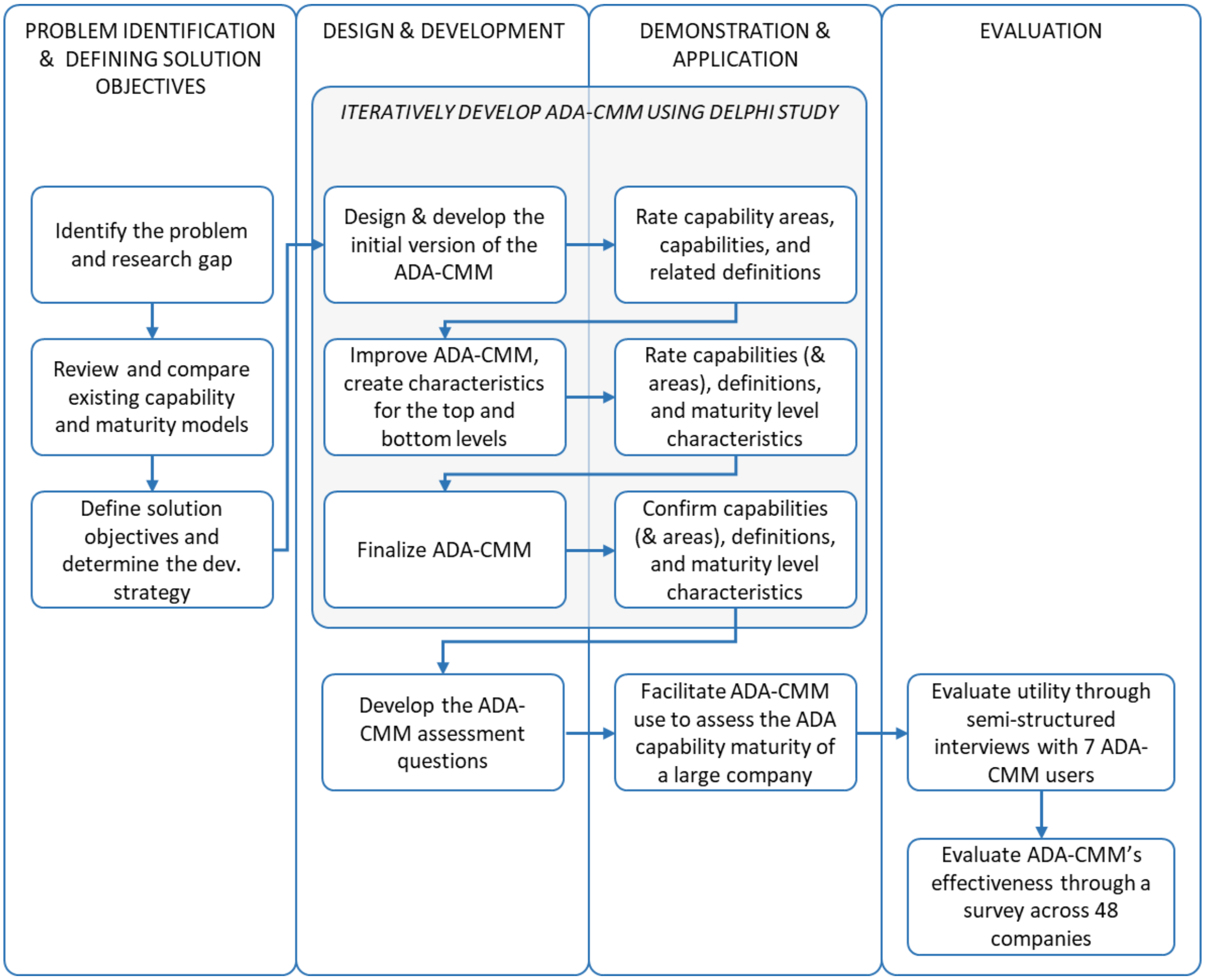


Figure 1. Research Design

Table 2 presents more details regarding the activities followed to address our research question. The development activities depicted in Figure 1 are aligned with the maturity model development process proposed by Becker et al. (2009). The mapping between these process steps and our research activity is also depicted in Table 2.

Table 2. Performed research activities and outputs in each DSR step

Step in the DSR Process (et al., 2007)	**Research Activity**	**Output and Corresponding Section**	**Maturity Model Dev. Process Phase** (Becker et al., 2009)
Problem identification & defining solution objectives	*Identify the problem and research gap* by reviewing the existing research on ADA challenges and related capability/maturity models	• Problem and research gap (Section 1) • Limitations of existing models (Section 2.2)	[1] Define the problem
	Review and compare existing capability and maturity models on ADA and related topics	Existing models on ADA and related areas (Section 2.2)	[2] Compare existing maturity models
	Define objectives for the proposed model and determine the development strategy	Solution objectives and research design (Section 3.1)	[3] Define the development strategy
Design & Development	*Iteratively develop the ADA-CMM using Delphi study*: • *Design & develop the initial version of the ADA-CMM* taking existing models as a basis • *Improve ADA-CMM and create characteristics for the top and bottom maturity levels* based on the feedback from Delphi expert panel (consisting of 9 experts) • *Finalize ADA-CMM* based on the feedback from Delphi expert panel	• ADA-CMM initial version (Section 3.2.1) • Model refinements (Section 3.2.1) • Final version of ADA-CMM (Section 4)	[4] Design and develop maturity model iteratively
	Develop the ADA-CMM assessment questions	ADA-CMM assessment questions (Section 3.2.2)	[5] Develop assessment method
Demonstration & Application	*Demonstrate the (improved) model to the Delphi expert panel* • *Rate capability areas, capabilities, related definitions and maturity level characteristics*	ADA-CMM (Section 3.3.1 & Appendix C)	[4] Design and develop maturity model iteratively
	Facilitate the use of ADA-CMM to assess the ADA capability maturity of a large company: • Self-assessment by 7 practitioners in the company	ADA-CMM capability maturity assessment of a large company (Section 3.3.2)	[6] Implement assessment method
Evaluation	*Evaluate ADA-CMM's utility through semi-structured interviews* with 7 practitioners that used ADA-CMM in the large company	Results of the semi-structured interviews regarding artifact's *utility* (Section 5)	[7] Evaluate
	Evaluate ADA-CMM's effectiveness as a maturity assessment tool through a survey across 48 companies and investigate the relationship between ADA capability maturity level, ADA value, and firm performance (using PLS-SEM)	Results of the analysis of survey data regarding artifact's *effectiveness* (Section 6)	

After identifying the problem by reviewing the extant literature, we have iteratively developed the solution objectives. Based on these objectives, we have developed the initial version of the ADA-CMM. Next, three Delphi rounds with a panel of nine experts from industry, consultancy, and academia have been conducted to design and validate the capability maturity model. With the help of feedback from Delphi rounds, we continually redefined the components in iterative build-and-evaluate loops, as suggested by Hevner et al. (2004), which helped increase the relevance and validity of the model.

Afterwards, the model underwent a series of explicit evaluation activities. First, it was applied in a large company to assess its ADA capability maturity. Then, we conducted semi-structured interviews with 7 model users in the company to evaluate the model's *utility* for its target users. Second, we conducted a survey across multiple companies to evaluate if ADA-CMM can be used as an *effective* measurement tool for assessing the maturity level of ADA capabilities (Sonnenberg & Vom Brocke, 2012). To this end, the survey investigated the relationship between the ADA maturity level -as measured using ADA-CMM, the business value that ADA generates, and firm performance.

The following subsections describe the details of the steps that were carried out, including the research methods applied in developing and evaluating ADA-CMM.

3.1 Problem identification and defining solution objectives

The sections above extensively discuss the problem, research gap, and research question our study aims to address. The objectives for the solution are determined based on the problem definition, literature review, and comparison of existing maturity models. The first objective relates to identifying the fundamental organizational capabilities and capability areas regarding ADA and the way these capabilities mature. Accordingly, the first objective can be stated as follows:

SO1: The artifact should comprise the key organizational capabilities and capability areas regarding ADA and their corresponding maturity levels.

The second objective focuses on the possibility of the artifact being used to self-assess the current maturity level of ADA capabilities. This could facilitate organizations in their identification and monitoring of ADA capabilities. Therefore, we state the following objective:

SO2: The artifact should allow companies to self-assess their maturity related to each ADA capability.

These solution objectives guided the development of the ADA-CMM and collectively presented the fundamental research objective that the ADA-CMM is expected to fulfill.

During the evaluation phase, we emphasized specific criteria to assess the effectiveness and usefulness of the ADA-CMM. One essential consideration pertains to the utility and usability of the artifact. The evaluation should focus on determining whether the model is not only functional but also user-friendly and beneficial to its intended audience (Hevner et al., 2004). Furthermore, an integral aspect of the evaluation involves investigating the potential impact of ADA-CMM on firm performance. Establishing a positive correlation between the maturity of ADA capabilities, assessed through the ADA-CMM, and the overall performance of a firm would provide evidence supporting the notion that the model incorporates critical capabilities for generating business value from ADA initiatives. These evaluation objectives collectively contribute to the assessment of ADA-CMM to ensure its utility for its intended users and its effectiveness, which is crucial in addressing the identified research gap and question.

3.2 Design and Development

3.2.1 Iteratively develop ADA-CMM using the Delphi study

As the extant literature suggests a substantial number and type of ADA capabilities for organizations, we base our initial model on the capabilities proposed in the literature. More specifically, the capabilities proposed by Brinch et al. (2020) provided the foundation for our model. We chose these capabilities as a basis since they are grounded on a thorough review of the literature on the capabilities in various related fields, such as big data analytics, data analytics, IT, and business process management. These capability areas are frequently identified in other ADA maturity models (available in *Appendix A*), and their relevance has been validated through a case study (Brinch et al., 2020). They underpin that data-driven performance does not rely only on IT and analytic capabilities but also requires various other capabilities, as confirmed by the literature. The list identifies the following six capability areas: IT, process, performance, human, strategic, and organizational capabilities.

Although the study by Brinch et al. (2020) provides definitions for ADA capability areas and related practices, it does not propose a maturity model for them; hence, it does not incorporate any structure or mechanism to assess the maturity level of these capabilities in organizations. Therefore, we explicitly adopted a maturity level structure and accordingly defined maturity level characteristics for the capabilities relevant to ADA.

We adopted the *maturity grid* structure inspired by the Process and Enterprise Maturity Model (PEMM) (Hammer, 2007). Maturity grid-based assessment methods represent the various concepts of the organization's practices and capabilities that are considered essential for success (Maier et al., 2012). A maturity grid approach typically contains a written description of the performance characteristics at each maturity level. It is often lightweight and of medium complexity, making it practical for assessments (Fraser et al., 2002). Hence, we selected this approach as it allows for self-assessment, is not tailored to a specific process or domain, and is considered easy to apply in practice (Tarhan, Turetken, & Reijers, 2015). Moreover, models developed with a maturity grid structure are often continuous models; that is, the maturity of the model's dimensions and components (i.e., capabilities) can be independently scored and determined (van Hillegersberg, 2019).

For the initial version of the ADA-CMM, we adopted the data analytical capabilities defined by Brinch et al. (2020) and created a maturity grid structure similar to PEMM. The initial capability maturity model consisted of six capability areas: infrastructure, governance, metrics, performers, leadership, and culture. Accordingly, we incorporated 24 *capabilities* categorized under six *capability areas*. Each capability is characterized by four maturity levels. The structure of the ADA-CMM is depicted in Figure 2. We developed the descriptions of capabilities based on the primary sources we used for ADA capabilities (Brinch et al., 2020; Hammer, 2007) and enriched them with other sources in the literature where necessary (the initial model is available in *Appendix A)*.

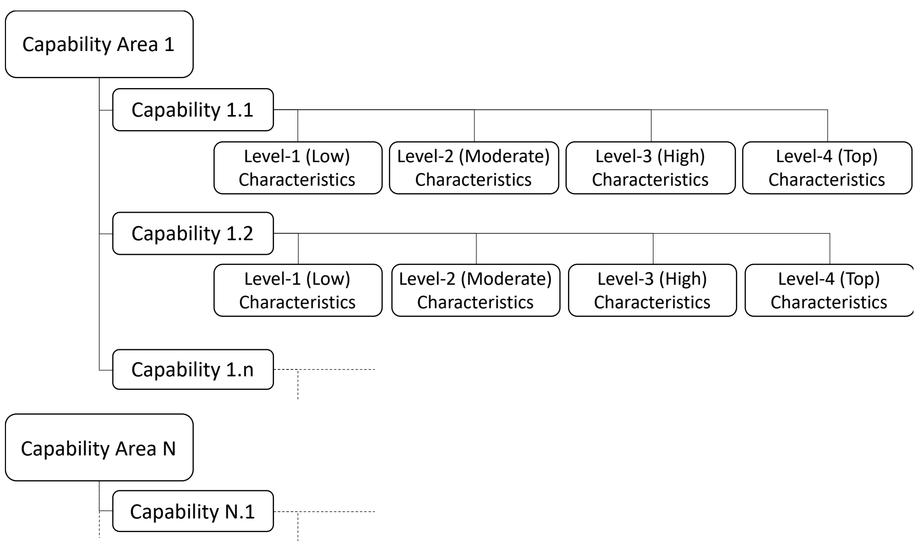


Figure 2. The structure of the ADA-CMM

Delphi study is a method for structuring a group communication process, where a panel of experts evaluates the content of the developed artifact. It is executed in multiple rounds of questionnaires moderated by a facilitator (Mahajan et al., 1976). The panelists do not directly face each other to prevent bias. We chose this method because it allows access to a broad range of domain experts and combines their views when there is a need to solve a practical problem (McMillan et al., 2016).

We selected the panelists based on their experience and knowledge of the ADA domain. More specifically, we expected panelists to possess expertise in one or more of the following domains: the technical aspects of ADA, its managerial or organizational aspects (such as strategy, team, governance), or related capability maturity models. Accordingly, we approached 15 experts via email, and nine accepted the invitation to participate in the panel. We aimed to have a heterogeneous group of panelists regarding their backgrounds to reduce single culture bias and provide diverse insights (Delbecq et al., 1975). Table 3 presents an overview of the composition of the expert panel. The panel included three academicians, three consultants, and three industry experts in ADA and related domains. Prior to the commencement of the Delphi rounds, separate introduction meetings were conducted to ensure their engagement, in which the objectives of the study and the responsibilities of the expert panel were explained.

Table 3. Overview of the Delphi expert panel

ID	Description	Origin	Area(s) of expertise	Years of expertise
Panelist 1	Managing director	Consultancy	Applied intelligence and data	> 10 years
Panelist 2	Director	Industry	Big data and advanced analytics	> 10 years
Panelist 3	Data scientist	Consultancy	Analytics and insights	Between 3-6 years
Panelist 4	Asst. professor	Academic	Software engineering, business process management, business models, maturity models	> 10 years
Panelist 5	Consultant	Consultancy	Hi-tech, media, and communications	Between 3-6 years
Panelist 6	Team lead	Industry	Technology and Innovation	Between 3-6 years
Panelist 7	Data engineer	Industry	Applied mathematics, data science management and information systems	Between 3-6 years
Panelist 8	Asst. professor	Academic	Algorithmic systems, business process management, information systems	> 10 years
Panelist 9	Asst. professor	Academic	Data governance and BDA for SMEs, supply chain management, and business process management, maturity models	> 10 years

An ideal Delphi study involves two or three rounds, as more rounds may result in a slower convergence among panelists' opinions (Gallego & Bueno, 2014). We asked the panelists to contribute to three rounds through online questionnaires. In the first round, an exploratory approach was adopted. For each capability area and capability, the panelists were asked to choose among three options: stay, change, or go (remove). In addition, they were asked to suggest additional capability areas and capabilities to the model. For the second and third rounds, a confirmative approach was adopted, where they were only asked to indicate if a model component should stay, change, or go. If they chose the latter two options, they had to justify their decision. In the rounds, we took percentage agreement as the measure of the level of consensus and set 80% as the threshold to decide whether the capability (areas) should stay (Diamond et al., 2014). If this was not the case, the capability (area) was changed or removed from the model and presented to the panelists in the following round.

3.2.2 Develop the ADA-CMM assessment questions

To conduct the maturity assessment, an online form was created consisting of 17 questions, each associated with a capability in ADA-CMM. The definitions of the capabilities were reformulated into a question format. Adhering to the structure of the model (as presented in Figure 2), the options for each question corresponded to the four maturity level characteristics. For each question, the participants were expected to select the maturity level that best characterizes their organization's current state for each ADA capability. (The ADA-CMM assessment questions are listed in *Table D1* in *Appendix D*).

3.3 Demonstration and Application

3.3.1 Demonstrate the (improved) model to the Delphi expert panel

The model evolved from an initial version to the final version in three Delphi rounds. Feedback from the first round led to changes in the model, including the addition of two capabilities (*Diversity* and *Talent Management*), the removal of three capabilities (*Organizational Structure, Process Standardization*, and *Process Governance*), and changes to the names and definitions. In the second round, the panelists received a report of changes and were presented with a revised model, including the definitions of maturity levels for each capability. The second round led to integrating two capability areas (*'People' and 'Culture'*) and name changes in other capability areas. The third round aimed to evaluate the descriptions of the maturity level characteristics to gather confirmation for all capability (areas). Changes (such as renaming *Data* to *Data & Governance* and renaming *Process Design* to *Process Design & Collaboration*) were made to capabilities areas, capabilities, and corresponding maturity level descriptions. We provide further details regarding this refinement process in *Appendix B.*

In brief, the model was extended in the areas of *People & Culture*, creating more awareness for capabilities such as *Diversity* and *Talent Management*. Furthermore, the process aspects have been emphasized more with the addition of the *Process Design & Collaboration* capability area. The changes in the capability area *Data & Governance* were limited, indicating that these aspects might have already been addressed sufficiently in the existing literature. The Delphi study supported the external validity of the ADA-CMM and ensured its relevance in terms of its coverage of the key organizational capabilities and their maturity levels regarding ADA, fulfilling solution objective SO1 and answering research question 1 (as stated in Section 3.1).

3.3.2 Facilitate the use of ADA-CMM to assess the ADA capability maturity of a large company

For the application of the ADA-CMM in a practical setting, we selected a large company operating in the semiconductor industry with about 32.000 employees. For the purpose of assessing the company's ADA capabilities, we focused on the company's customer supply chain department, which had a subdepartment dedicated to data analytics for the last five years. This provided a suitable context for the application of the model. Accordingly, we first introduced the model to a group of 20 employees. Following a brief introduction to the objective of the assessment and the model to be used, the participants were requested to perform a self-assessment of their department's ADA capability maturity using the *ADA-CMM's assessment questions* (as described in Section 3.2.2).

3.4 Evaluation

3.4.1 Evaluate ADA-CMM's utility through semi-structured interviews

After the assessment results were communicated and discussed with the participants, we asked the group to give in-depth feedback regarding the model and its use by participating in a semi-structured interview. Seven practitioners agreed to participate. The selection of participants was guided by several criteria, ensuring a diverse representation of expertise, experience levels, areas of expertise, and familiarity with maturity assessment practices. The aim was to capture a rich spectrum of perspectives that could contribute to a thorough evaluation of the model's effectiveness and utility. Table 4 presents more details regarding the participants' relevant profile.

Table 4. Profile of participants who took part in the utility evaluation

ID	Experience in the industry	Area(s) of expertise	Familiarity with assessing the maturity of organizations
Participant 1	2-4 years	Data science & supply chain management	Not at all familiar
Participant 2	4-7 years	Analytics, supply chain management	Slightly familiar
Participant 3	Less than 2 years	Process mining	Somewhat familiar
Participant 4	More than 10 years	Agile, project mng., change mng.	Slightly familiar
Participant 5	2-4 years	Business intelligence	Slightly familiar
Participant 6	Less than 2 years	Supply chain management	Not at all familiar
Participant 7	Less than 2 years	Data science	Moderately familiar

Before the interviews, we asked them to complete a questionnaire to express their view anonymously on the model's utility. The questionnaire was assembled using a set of statements based on the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh & Davis, 2000), a widely recognized framework in the literature for predicting and explaining the acceptance and utilization of technological design artifacts, including models (e.g. Dikici et al., 2018; Schriek et al., 2016), methods, and tools (Moody, 2003; Turetken et al., 2019). The questionnaire consisted of four items to assess perceived usefulness, four to assess perceived ease of use, and two to assess intention to use, as recommended by Venkatesh and Davis (2000). Each statement in the questionnaire was adapted to accommodate the characteristics of the proposed artifact. Table 5 presents the questions.

Table 5. Questionnaire for utility evaluation

Evaluation Construct	Nr.	Statement
Perceived usefulness	1	I think this approach provides an effective solution to assessing the maturity of advanced data analytics capabilities of organizations.
	2*	The capability maturity model for advanced data analytics capabilities designed in this way would be difficult for users (colleagues, stakeholders, etc.) to understand.
	3*	Using this approach would make it more difficult to communicate the maturity of our advanced data analytics capabilities to other stakeholders.
	4	Overall, I found the advanced data analytics capability maturity model (ADA-CMM) useful.
Perceived ease of use	5	Learning to use this model to assess the maturity of our advanced data analytics capabilities would be easy for me.
	6*	I found the structure of the ADA-CMM unclear and difficult to understand.
	7	It would be easy for me to become skilful at using the model to assess the maturity of advanced data analytics capabilities of organizations.
	8*	Overall, I found the ADA-CMM model difficult to use.
Intention to use	9	I would use this model to assess the maturity of advanced data analytics capabilities of organizations in the future.
	10	I would intend to use this way of assessing ADA capability maturity in preference to another assessment approach.

**Statements with '*' are presented in reverse form.*

We used a 5-point Likert scale to understand the level of agreement of a participant concerning a particular statement, for which "1" represents 'strongly disagree' and "5" represents 'strongly agree'. Some statements have been presented in reverse to prevent the participant from giving monotonous responses to questions. At the end of the questionnaire, an open-ended question was presented to participants to provide additional feedback about the model's strengths, weaknesses, and completeness.

Afterward, we conducted semi-structured interviews with participants to gather in-depth feedback regarding the model's utility. Accordingly, we conducted seven ex-post interviews. The interviews took around 30 minutes each and were recorded, transcribed, and coded following the interview analysis guidelines (Recker, 2013). We followed the structure of the questionnaire and asked them to elaborate on their view on the usefulness and ease of use of the model. The insights gained from the interviews are presented in Section 5.

3.4.2 Evaluate ADA-CMM's effectiveness as a maturity assessment tool through a survey

The maturity level of an organization's capabilities in ADA has been found to significantly impact the value created from ADA initiatives (Akter et al., 2016; Ghasemaghaei et al., 2017). The value created by advanced data analytics often extends beyond financial aspects, for example, by enhancing process cycle time or internal innovation (Afrah Ahmed et al., 2019). Research studies, such as Brinch et al. (2020) and Elia et al. (2020), provide evidence of the moderating effect of data analytics capabilities on value creation from big data. The former study found that data analytics capabilities are associated with greater value creation from big data. In addition, the latter study proposed a framework to support organizations in effectively utilizing ADA initiatives by disarticulating value-creation sources. These findings suggest that organizations with higher levels of ADA capability are better equipped to create value from big data by intelligently utilizing various sources of value creation. The ultimate goal of applying advanced technologies to large sets of data and information is to discover hidden information that can be strategically and operationally leveraged, highlighting the importance of organizational ADA maturity in generating more value from ADA projects (Mikalef & Krogstie, 2020). For example, ADA could facilitate greater agility in strategic decision-making by supporting firms in decision-making and recognizing business opportunities to gain a competitive landscape (Hyun et al., 2020). To explain the varying firm performances, the concept of *capability* has been used in the strategy literature, especially in the resource-based view (Eisenhardt & Schoonhoven, 1996).

Taking these findings as a point of departure, we hypothesize that the maturity level of an organization's ADA capabilities is positively related to the value generated from ADA projects, with the presumption that *a maturity assessment using an effective capability maturity model would confirm this relationship*. Accordingly, we propose the following hypothesis:

> *H1. An organization's ADA capability maturity, as measured using ADA-CMM, relates positively to the ADA value generated from its ADA initiatives.*

Firm performance refers to the extent to which a firm generates superior performance with respect to its competitors (Gupta & George, 2016). This can be in the form of operational performance, which reflects an organization's productivity, profit rate, return on investment, and sales revenue (Huang et al., 2020), and its market performance, i.e., its ability to enter new markets and improve its position in existing ones (Gupta & George, 2016). Differences in market or operational performance and, thus, firm performance can be explained by the utilization of capabilities. For example, when a firm is able to fully utilize its ADA capabilities, it can improve its performance (Akter et al., 2016). These studies demonstrate a positive relationship between an organization's maturity in ADA capabilities and its performance, with the value generated by ADA as a mediator. This is because the organization's ADA capabilities play a crucial role in generating value from ADA initiatives, which, in turn, impact the firm's overall performance. Following Gupta & George (2016), the firm performance can be attributed to its operational performance (i.e., how productive and effective it operates) and market performance (i.e., its ability to enter into new markets and introduce new products). Accordingly, we propose the following hypotheses:

> *H2a. An organization's ADA capability maturity, as measured using ADA-CMM, relates positively to a firm's operational performance, mediated by the ADA value generated from its ADA initiatives.*

> *H2b. An organization's ADA capability maturity, as measured using ADA-CMM, relates positively to a firm's market performance, mediated by the ADA value generated from its ADA initiatives.*

In line with our hypotheses, we pose the research model depicted in Figure 3.

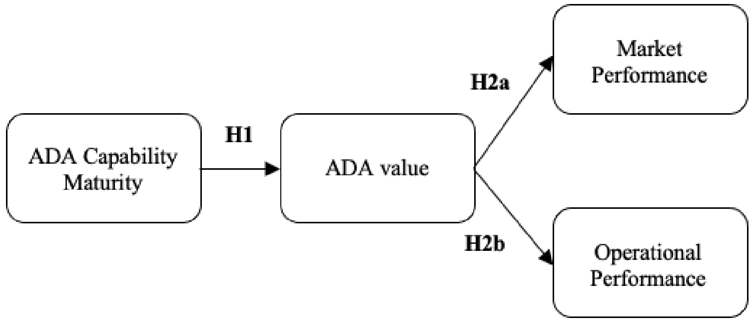


Figure 3. Research model

We designed an online survey to collect data on the maturity level of ADA capabilities of organizations, the value created by ADA, and firm performance. First, we describe the development of the measures, the units of measurement and the control measures. Next, we explain the sampling procedures. Finally, the analysis technique is addressed.

The survey consisted of four sections (which are presented in *Appendix D*). The first section of the survey consisted of the ADA-CMM assessment questions, which are used to assess the maturity level of ADA capabilities in accordance with the ADA-CMM (as described in Section 3.2.2). The second section focused on measuring the value created by ADA. Following Elia et al. (2020), we operationalized ADA value using five dimensions, namely informational, transactional, transformational, strategic, and infrastructural value. The third section measured firm performance in terms of its market and operational performance, for which we used validated items from Gupta & George (2016). Lastly, the fourth section collected general information about the participants and their organizations, including the sector and size of the organization.

The survey was distributed via social media and specifically targeted emails. According to Andrews, Nonnecke and Preece (2003), the combination of emails with web-based surveys is a valid vehicle for inviting individuals to participate in surveys. The target group was information managers, also known as data managers or knowledge managers, representing someone who is responsible for overseeing and optimizing an organization's data resources throughout their lifecycle. The survey was online for three weeks, and target groups were actively stimulated to fill in the survey by sending out invitations and reminders.

For our data analysis, there are several requirements. We need to test hypotheses, explore latent features such as capability areas, and develop a complex model with many indicators and relationships. The sample size is limited, and the data does not follow normal distributions. These factors require careful consideration of the analysis method to ensure the accuracy and reliability of our results. Taking into consideration these requirements, we have found Partial Least Squares - Structural Equation Modelling (PLS-SEM) analysis the most suitable method to test our research model (Figure 3) using the survey data. PLS-SEM allows for the investigation of unobservable or latent features measured by multiple observable variables (Rigdon, 2016). We chose this method because it can estimate complex models with many constructs, indicator variables, and structural paths without imposing distributional assumptions on the data. Furthermore, PLS-SEM can be used as an exploratory research method and is a causal predictive approach to SEM that emphasizes prediction in estimating statistical models (Hair et al., 2019). Finally, PLS-SEM is applicable with small sample sizes when models comprise many constructs and a large number of items (Hair et al., 2017). The software tool SmartPLS 3.3 was used to analyze the data. The results of the survey and analysis are presented in Section 6.

4 Advanced Data Analytics – Capability Maturity Model (ADA-CMM)

In this section, we briefly introduce the final version of the ADA-CMM. Table 6 presents the capability areas and capabilities of ADA-CMM, including their definitions. Each capability area encompasses a set of capabilities. The application domain of the ADA-CMM includes ADA projects related to business processes, IT, and business analytics. The capability maturity model aims at presenting the firm-level capabilities necessary to collect, manage, and use data using ADA to help organizations improve them. The target group includes firms using or planning to use ADA within their organization related to business processes, IT, and business analytics. The model allows for self-assessment of the current maturity and could be used for prescriptive purposes. Furthermore, it is a continuous capability maturity model; that is, it is based on scoring different capabilities at different maturity levels and weighing the individual scores (Tarhan, Turetken, & Ilisulu, 2015). Using a Delphi study, the model development involved close collaboration with academics, consultants in related fields, and industry experts in ADA projects. The knowledge of consultants and industry experts contributes to the relevance and practical applicability of the model.

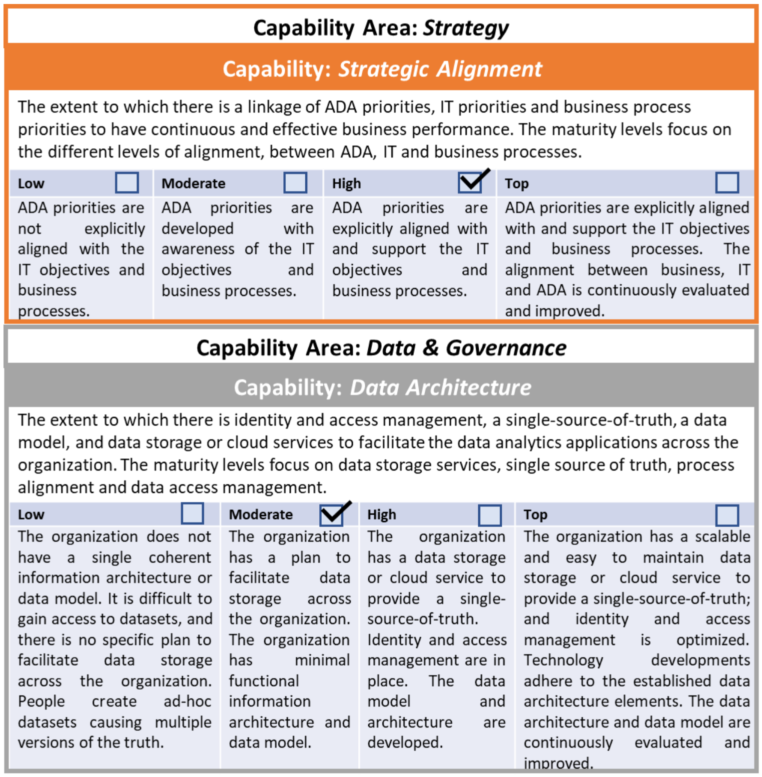
The capability area of *People & Culture* considers the knowledge and commitment of employees regarding ADA, the diversification of teams, and the adoption of analytical capabilities to improve business processes. *Performance & Value* focuses on metrics that show how ADA capabilities can turn data into value and innovation processes to develop best-in-class service operations. The *Strategy* capability area includes capabilities related to the definition of ADA vision, mission, and objectives and the linkage of ADA to business priorities. *Data & Governance* capability area relates to the data architecture, eliminating repetitive manual work, linking IT systems and operational processes, data governance, and available data analytics tools. Finally, *Process Design & Collaboration* emphasizes the capabilities regarding employees' competence and skill development, how they are informed about new technologies, how ADA projects are managed, and the extent of information sharing and functional project involvement.

ADA-CMM further includes the definition of capabilities and corresponding maturity level characteristics in four levels. There are 17 capabilities related to five capability areas, each representing an organizational capability necessary to create value from ADA. We provide the complete model in *Appendix C*.

Table 6. ADA-CMM capability areas and capabilities

Capability Area	Capability	Definition
Strategy	ADA Strategy	The degree to which the ADA department has a vision, mission, and objectives concerning data architecture, data governance, digital orientation and data investments to support the business processes.
	Strategic Alignment	The extent to which there is a linkage of ADA priorities, IT and business process priorities and business priorities for continuous and effective business performance.
Data & Governance	Data Architecture	The extent to which there is identity and access management, a single-source-of-truth, a data model, and data storage or cloud services to facilitate the data analytics applications across the organization.
	Automation	The extent to which ADA helps to eliminate repetitive manual work (e.g., data entry), thereby increasing data utilization and data driven decision making.
	Data Integration	The extent to which IT systems and operational processes are linked to facilitate information flows, intelligence sharing, and alignment.
	Data Governance	The extent to which there is an actively designed set of mechanisms (e.g., structure, policies, processes) to ensure that behaviours are consistent with the organization's ADA mission, strategy, and culture.
	Data Analytics Tools	The extent to which data analytics tools are integrated with the data platform and allow usersf to easily visualize and gain insights from ADA.
People & Culture	Knowledge	The extent to which employees and managers have knowledge regarding ADA and digitalization and are interested in learning about the application of ADA within the organization.
	Commitment	The extent to which employees and management make the investments (e.g., budget, effort, sponsorship) in ADA capabilities, execute the related projects and make the required changes in practice.
	Team Diversity	The extent to which a company is able to recruit the right talent, have balanced teams with diverse backgrounds and different levels of technical knowledge.
	Usage	The extent to which there are collective values and beliefs that stimulate data-driven decision making, employees and management make use of IT services, adopt analytical capabilities to improve business performance.
Process Design & Collaboration	Competence & Skills Development	The degree to which the company provides individuals and groups the opportunity to continually develop their skills and competences, by providing training and education.
	Communication	The extent to which employees are informed about new technologies within the area of ADA and stimulated to actively deploy these new technologies.
	Portfolio Management	The extent to which ADA projects are managed with clearly defined objectives, consistent portfolio management and cross-functional collaboration.
	Organizational Collaboration	The extent to which there is information sharing and functional project involvement across functions and expertise and a formal alignment between the focus of ADA teams.
Performance & Value	Performance Metrics	The extent to which metrics (e.g., process metrics, functional metrics, data quality metrics, financial metrics) are developed and standardized to show how ADA capabilities can turn data into value for its continuous development.
	Innovation Processes	The degree to which ADA is used to develop new products, improve and redesign processes to develop best-in-class service operations and deliver informational, strategic, transformational, transactional, and infrastructural value.

Taking the PEMM (Hammer, 2007) as a reference, we characterized each capability by four maturity levels and related characteristics: low, moderate, high, and top. An organization can be at a different level regarding each capability and weigh the individual scores into an average maturity score per capability area (as exemplified in Figure 4).



Capability Area: *Strategy*

Capability: *Strategic Alignment*

The extent to which there is a linkage of ADA priorities, IT priorities and business process priorities to have continuous and effective business performance. The maturity levels focus on the different levels of alignment, between ADA, IT and business processes.

Low ☐	Moderate ☐	High ☑	Top ☐
ADA priorities are not explicitly aligned with the IT objectives and business processes.	ADA priorities are developed with awareness of the IT objectives and business processes.	ADA priorities are explicitly aligned with and support the IT objectives and business processes.	ADA priorities are explicitly aligned with and support the IT objectives and business processes. The alignment between business, IT and ADA is continuously evaluated and improved.

Capability Area: *Data & Governance*

Capability: *Data Architecture*

The extent to which there is identity and access management, a single-source-of-truth, a data model, and data storage or cloud services to facilitate the data analytics applications across the organization. The maturity levels focus on data storage services, single source of truth, process alignment and data access management.

Low ☐	Moderate ☑	High ☐	Top ☐
The organization does not have a single coherent information architecture or data model. It is difficult to gain access to datasets, and there is no specific plan to facilitate data storage across the organization. People create ad-hoc datasets causing multiple versions of the truth.	The organization has a plan to facilitate data storage across the organization. The organization has minimal functional information architecture and data model.	The organization has a data storage or cloud service to provide a single-source-of-truth. Identity and access management are in place. The data model and architecture are developed.	The organization has a scalable and easy to maintain data storage or cloud service to provide a single-source-of-truth; and identity and access management is optimized. Technology developments adhere to the established data architecture elements. The data architecture and data model are continuously evaluated and improved.

Figure 4. An excerpt from ADA-CMM, containing two example capabilities and their maturity levels for the Strategy and Data & Governance capability areas

The structure of ADA-CMM, which consists of capability areas, capabilities, maturity levels, and related characteristics as depicted in Figure 2, ensures that organizations can use ADA-CMM to assess the current situation, develop and prioritize improvements, and control the progress of implementation (Poeppelbuss et al., 2011). Solution objective SO2 is fulfilled using this structure. The model can be used as a self-assessment tool for ADA capabilities. To gain a more reliable self-assessment, it is ideal that the assessment is conducted with multiple participants with different organizational roles, backgrounds, and motivations (Van Looy, 2015). The assessment can take place in a focus group or workshop setting where everyone can express their opinion and discuss each capability until a consensus is reached. Alternatively, it can be performed as an online survey, where participants express their opinions individually or as a group, and the results are aggregated.

The self-assessment results represent the current situation and unveil the areas of ADA capabilities in which the organization excels and which areas have room for improvement. The gap between the current and desired position can help prioritize ADA capability improvements. Conducting a regular self-assessment can facilitate monitoring the progress of improvements. Finally, the ADA-CMM can be used to benchmark and identify the organizational ADA performance compared to the ADA performance of other departments or organizations.

5 Results of the Evaluation of ADA-CMM for its Utility

This section describes the ex-post evaluation activities performed to evaluate ADA-CMM's utility for its target users. To this end, first, we facilitated an assessment of the ADA capability maturity of a large company using the ADA-CMM assessment questions via an online form. In total, 16 participants provided individual ratings for the maturity level of each capability in the model. The data was pre-processed by checking for missing values and investigating the data variance through boxplots. The boxplots showed that the capability area *Strategy* had the widest range of scores, ranging from 1 to 4. This suggests that respondents have varied opinions about the capability area *strategy*. On the other hand, the construct *Value* had a narrower range, from 2.4 to 3.4, with just one outlier at 3.8. The other capability areas (*Data & Governance, Performance & Value, People & Culture, and Process Design and Collaboration* fell somewhere in between these ranges.The pre-processing did not lead to any changes in the data. Finally, the results of the individual assessments were aggregated by taking the averages and medians at the general and capability levels, respectively. The results were presented to the participants in a meeting, allowing them to discuss the assessment process and findings. The process of using the assessment questions provided further confirmation for the fulfillment of solution objective SO2.

Next, we contacted a number of participants who had participated in the assessment and conducted semi-structured interviews with them. The goal was to elicit their view on ADA-CMM's usefulness and ease of use, and their intention to use it in assessing the ADA maturity. Table 7 illustrates the results of the responses to the questionnaire on the model's utility. In the following subsections, we describe the results of the evaluation of ADA-CMM for its utility.

Table 7. Responses to the questionnaire on the model's utility

Evaluation Construct	**Statement nr.**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
Perceived usefulness	1	0	0	1	4	2
	2*	0	2	2	3	0
	3*	0	1	1	4	1
	4	0	0	1	5	1
Perceived ease of use	5	0	0	2	5	0
	6*	0	2	0	5	0
	7	0	0	2	4	1
	8*	0	0	2	5	0
Intention to use	9	0	0	3	3	1
	10	0	0	5	2	0

The responses are reversed for statements indicated with a star (*).

5.1 Perceived usefulness

Concerning *perceived usefulness*, the results show that the participants considered the application of our model to be moderately useful, given that the majority selected 'Agree' as the answer to the related questions in the survey. During the interviews, participants mentioned that they appreciated the model's guidance in developing ADA capability, as indicated by some exemplary statements as below:

> *"Yes, I do think it is useful to have something like this … so that you can then have a kind of roadmap for an organization or department. From "okay, we are here now, so <we> must take this step to continue", so that you actually know a little bit of what you need to improve." [Participant 3]*

However, a topic that was recognized in four out of seven interviews is that the participants would prefer to receive more concrete actions for guidance in increasing the maturity. This relates to the prescriptive properties of the model. For example, participant 2 mentioned the following:

> *"A plan, so to speak. About these steps <would> contribute to these aspects, for example. In a joint analysis, which steps are the best together? The best combination to achieve a certain thing. But it is*

something, of course, just for every team is different, in every department is different, so something that is general enough to fill in yourself depending on the team." [Participant 2]

5.2 Perceived ease of use

Although with slightly fewer votes for 'Strongly Agree' or 'Agree' than for perceived usefulness, the results for the *perceived ease of use* indicate a positive view of the model. This is also reflected as one of the model's strengths identified in the interview. Participants 2 and 3 mentioned that the model is well described.

"Yes, I actually was just new at <Company X> …. I just had no idea about it. But I think I understood the description or something of the survey quite well. Especially the explanation, when you have a specific maturity level, what it includes and does not yet include." [Participant 3]

However, participants 1, 3, 5, and 7 indicated that the descriptions are sometimes perceived as too technical, formal, or wordy. This can affect the perception of ease of use of the method:

"The questions are quite technical… or at least detailed. So, you have to have some knowledge of a specific case to be able to answer." [Participant 1]

"If you ask me, I will split it and say, OK, either collect feedback from two separate teams: senior people and technical people. … Some people, I think they replied properly, but for some others, I think it's too vague or high level." [Participant 5]

5.3 Intention to use

Concerning *intention to use*, the results are generally neutral to positive. During the interviews, the most important topic of discussion was the target audience of the ADA-CMM. This was also motivated by participants 1, 3, and 5:

"And the only piece that is unclear to me is who exactly should be using this." [Participant 1]

Another topic suggested by participant 4 is that the model is focused on larger firms, so it would not be directly applicable to smaller firms.

But it's also modeled for big companies. And for smaller companies, not so much; smaller companies don't have as much portfolio management, organizational collaboration, or data governance. Those are terms that they may not have as strongly. I think it is catered more towards larger companies. [Participant 4]

Overall, the usefulness and ease of use of ADA-CMM have been positively assessed. The participants expressed a clear intention to use the model and perceived that it could help organizations assess the maturity of their ADA capabilities. However, the results also suggest that enhancing the model's prescriptive properties by providing concrete actions for improvement could increase its usefulness and ease of use. Additionally, the phrasing of the assessment questions could be improved to further enhance the ADA-CMM's ease of use. Section 7 presents further discussions on the feedback we gathered.

6 Results of the Evaluation of ADA-CMM for its Effectiveness

ADA-CMM has been developed as a joint effort of domain experts through a Delphi study, applied in a large company, and evaluated using interviews with target users. Yet, conducting a survey across multiple companies to confirm the relationship between ADA capability maturity as measured using ADA-CMM and firm performance provides insight into the effectiveness of ADA-CMM (Sonnenberg & Vom Brocke, 2012). It reveals if the model incorporates the key aspects of ADA that play a role in generating value from ADA initiatives and if the maturity level characteristics of ADA capabilities are valid measurement items. This section presents the design, conduct, and results of our survey.

6.1 Descriptive information

Prior to conducting any statistical analysis, the data underwent cleaning and preparation procedures. One response was removed due to straight-lining, and two responses due to missing data. We conducted univariate and multivariate outlier analyses, which did not result in any further data removal. After these cleaning procedures, the resulting dataset contained 48 observations, each corresponding to a firm's ADA maturity level as assessed using ADA-CMM, as well as the value created by ADA (ADA value) and the firm's market and operational performance.

The descriptive information on the experience of the participants and the size of the firms are shown in Table 8. The sector distribution showed that participants were mainly from the sectors of industrials (e.g., capital goods, transportation) (27%), IT (25%), financials (15%) and consumer staples (8%). The boxplots were generated for the aggregated maturity scores per capability area of the ADA-CMM (*Data & Governance*, *Performance & Value*, *Strategy*, *People & Culture*, *Process Design & Collaboration*), the overall score for ADA value, and the firm performance score aggregated for each organization (*Market Performance*, *Operational Performance*). The boxplots indicated that the *Performance & Value* capability area showed the widest range of scores, ranging from 1.5 to 4, indicating diverse responses. In contrast, the *People & Culture* area showed less variability, with scores ranging from 1.75 to 3.75. Among the constructs, *value*, *market performance* and *operational performance*, had *value* and *market performance* has a broader range of scores and more variability than *operational performance*.

Table 8. Descriptive statistics

Personal experience (years)	**0**	**0-2**	**2-5**	**5-10**	**>10**
Work		28%	35%	24%	13%
ADA	17%	21%	24%	29%	9%
Organization size (employee #)	**<10**	**11-50**	**51-250**	**251-1000**	**>1000**
	7%	29%	19%	21%	24%
Organization age (years)	**<5**	**6-15**	**>15**		
	21%	21%	58%		

6.2 Evaluation of ADA-CMM for its effectiveness using PLS-SEM Analysis

Taking the research model depicted in Figure 3 as a basis, a path model was created with the independent variables of ADA-CMM capability areas, ADA capability maturity, and ADA value. We defined ADA capability maturity level as a second-order construct with the five ADA-CMM capability areas as its formative indicators (i.e., first-order constructs) since the complete set of capability areas reflects this higher-order latent variable (Sarstedt et al., 2019). Each first-order latent variable (i.e., ADA-CMM capability area) was reflectively measured through indicators matching its capabilities, e.g., Data & Governance with five indicators (coded as D&G_1 to D&G_5). Similarly, the five items of ADA value were modeled as formative indicators. The *market* and *operational performance* items were also modeled as reflective indicators. The analysis was performed as a repeated indicator approach, meaning that the indicators of the first-order constructs were reused for the second-order construct (Sarstedt et al., 2019).

Following the guidelines for conducting PLS-SEM analysis (Benitez et al., 2020), we first report on the reliability and validity tests of the reflective measurement model. Next, as measures of fit for the reflective measurement models, we assessed the internal consistency reliability through Cronbach's Alpha (α) and composite reliability (CR) and convergent validity through Average Variance Extracted (AVE), as reported in Table 9. We assessed the discriminant validity through Heterotrait-Monotrait Ratio (HTMT), which resulted in a value below 1.0. We confirmed that all these variables match the suggested threshold values and, thus, the indicators of the reflective model are of sufficient quality (Benitez et al., 2020).

Table 9. Reliability and validity of reflective constructs

Construct	**α**	**CR**	**AVE**
ADA Capability Maturity	0.912	0.924	0.422
Market Performance	0.651	0.792	0.489
Operational Performance	0.848	0.897	0.687

As the data was collected through a single method (i.e., survey), common method bias (CMB) must be investigated. We performed two tests for CMB. First, Harman's single-factor test, the exploratory factor analysis (EFA) without rotation revealed that the total variance extracted by one factor is 32.54%, below the threshold of 50% (Kock, 2015). Second, we performed a full collinearity test. The VIF scores were below the threshold of 3.3 (Kock & Lynn, 2012). Therefore, CMB is unlikely to be a significant validity concern. For validating the formative model, first, we confirmed the lack of multicollinearity issues in the outer model by checking the outer VIF scores, which were below the threshold of 5. To check the significance of the indicators, bootstrapping was performed with a sample size of 5000 (Garson, 2016). An assessment of the outer weights revealed that all indicators were significant ($p<0.05$) except for D&G_1, S_1, P&C_2, P&C_4, PD&C_3, IMV, TCV, and TFV. The outer loadings of these indicators were all above 0.5. Thus, we decided to retain as suggested (Hair et al., 2013). We further confirmed that there are no multicollinearity issues for the structural model by checking the inner VIF scores to be 5 or more (Hair et al., 2013). Table 10 presents each latent construct and the corresponding indicator, outer weight, outer loading, and p-value.

*Table 10. Outer weights and loadings per indicator * denotes p<0.05*

Construct	Indicator	Outer weights (outer loadings)	P-value
Data & Governance	DG_1	0.159 (0.818)	0.244
	DG_2	0.221 (0.751)	0.024*
	DG_3	0.333 (0.776)	0.002*
	DG_4	0.313 (0.744	0.001*
	DG_5	0.311 (0.682)	0.001*
Performance & Value	PV_1	0.468 (0.820)	0.000*
	PV_2	0.672 (0.917)	0.000*
Strategy	S_1	0.516 (0.768)	0.077
	S_2	0.688 (0.877)	0.029*
People & Culture	PC_1	0.357 (0.811)	0.004*
	PC_2	0.248 (0.731)	0.073
	PC_3	0.371 (0.746)	0.008*
	PC_4	0.318 (0.797)	0.058
Process Design & Collaboration	PDC_1	0.276 (0.705)	0.018*
	PDC_2	0.413 (0.832)	0.014*
	PDC_3	0.242 (0.791)	0.109
	PDC_4	0.347 (0.778)	0.006*
ADA Value	IMV	0.332 (0.839)	0.190
	ISF	0.299 (0.750)	0.036*
	TCV	0.288 (0.785)	0.134
	TFV	0.009 (0.772)	0.955
	SV	0.352 (0.750)	0.029*

6.3 Results of the PLS-SEM analysis

The pathway coefficients for each relation are presented in Table 11. All relationships between the latent constructs are found to be significant ($p<0.001$). Each ADA-CMM capability area is shown to have a positive relationship with the ADA capability maturity level. Accordingly, a higher organizational *ADA capability maturity* as measured using ADA-CMM is seen to have a positive relationship with the *value* generated from ADA projects ($\beta=0.645$; $p<0.001$), thereby supporting H1. In other words, as the ADA maturity level of an organization increases, there is a corresponding increase in the value generated from ADA initiatives. Moreover, a higher organizational *ADA capability maturity* has a positive relation to the firm's *operational performance* ($\beta=0.643$; $p<0.001$) and *market performance* ($\beta=0.685$; $p<0.001$), mediated by *ADA value* generation, in support of H2a and H2b.

*Table 11. Pathway coefficients of model relationships * denotes p<0.001*

Relationship	Pathway coefficient
Data & Governance -> ADA Maturity	0.370*
Process Design & Collaboration -> ADA Maturity	0.272*
People & Culture -> ADA Maturity	0.260*
Performance & Value -> ADA Maturity	0.182*
Strategy -> ADA Maturity	0.121*
ADA Maturity -> ADA Value	0.645*
ADA Value -> Market Performance	0.685*
ADA Value -> Operational Performance	0.643*

Although all capability areas contribute significantly to the generation of ADA value and firm performance, the results from the analysis indicate a diverse impact of capabilities on ADA maturity (Table 10). The *Data & Governance* capability area has a relatively stronger contribution to *ADA maturity*, highlighting the technical aspects' importance in the overall ADA maturity of an organization. This finding suggests a slight deviation from the results of our Delphi study, which put more emphasis on the aspects related to the process, culture, and strategy. Although significant, the relationship between the *Strategy* and *ADA maturity* is relatively weaker. This result may be related to the evaluated companies, since they may not be at a maturity level where the aspects related to ADA strategy are the most critical.

The measures of structural model fit are presented in Table 12. The adjusted R^2 values of 0.400 to 0.458 indicate a moderate level of variance explained for dependent variables ADA value, market performance, and operational performance (Garson, 2016). The Q^2 values, which indicate the model's predictive relevance, are all above 0. Thus, the model can be considered to have medium to high predictive relevance (Hair et al., 2013).

Table 12. Model fit values per construct

Construct	**R^2**	**R^2 adjusted**	**Q^2**
ADA Value	0.416	0.403	0.236
Market Performance	0.470	0.458	0.193
Operational Performance	0.413	0.400	0.258

7 Discussions and Implications

ADA is increasingly used in organizations to improve their processes, products and services (Ghasemaghaei et al., 2017). Despite the opportunities, many organizations struggle to extract value from ADA (Günther et al., 2017; Ransbotham et al., 2015). Capability maturity models could guide organizations in developing their ADA capabilities (Poeppelbuss et al., 2011). This research seeks to adress the research question: *What are the key components of a capability maturity model that can effectively guide organizations in assessing and enhancing their advanced data analytics capabilities?* As shown in the comparison of existing data analytics maturity models in Table 1, the existing literature lacks a holistic and empirically validated capability maturity model for ADA, one that not only encompasses a holistic perspective but is also acknowledged for its effectiveness and practical utility. We adress this research question by developing a capability maturity model that could effectively assess an organization's advanced data analytics capabilities while also being considered useful. Following DSR, we present a comprehensive ADA capability maturity model prescribing necessary capabilities. ADA-CMM satisfies all five criteria presented in Table 1. The fulfillment of all five criteria results in holistic maturity model, which is deemed useful and effective, is well documented, and offers a method to assess ADA capabilities. This contribution falls under level 2 in the design science contribution types, representing a nascent design (Gregor & Hevner, 2013). The knowledge contribution involves providing a new solution for a known problem. We demonstrate the functional feasibility of ADA-CMM through a proof of concept by applying it to multiple companies and assessed its utility and effectiveness as proof of value (Nunamaker et al., 2015). In the next paragraphs, we will discuss the activities we performed for developing ADA-CMM, evaluating its usefulness, and evaluating its effectiveneess, along with contributions for each research activity.

We first identified what the key organizational capabilities for creating value from advanced data analytics are and how they matured. This study contributes to the literature by identifying the key capabilities necessary for creating value from ADA. Our findings provide insight into the specific capabilities that facilitate ADA value creation and confirm the findings of previous research by Brinch et al. (2020), who provided a holistic overview of firm-level capabilities required for big data value creation. We redefined these capabilities in the context of ADA and validated them empirically through a Delphi study. Additionally, we developed four maturity level definitions for each of these capabilities, which enables organizations to analyze their current composition of ADA capabilities and develop a roadmap for improving their maturity level. Furthermore, we took a capability improvement perspective compared to a process improvement-oriented approach, which aligns with the literature on organizational capabilities (Steininger et al., 2022). ADA-CMM contributes to the understanding of which organizational capabilities are important for ADA value creation. These findings underscore the importance of a coherent set of key capabilities in creating value from ADA. This would help create awareness among practitioners that gaining a competitive advantage from ADA requires capabilities beyond merely collecting large amounts of data and putting advanced technologies in place (Davenport, 2013). Among others, practitioners must strategically position ADA within their organization, ensure the availability of the right people and culture, foster a suitable collaboration environment, and establish effective performance and value management processes.

Second, we assessed whether the developed model was considered as useful. To evaluate the utility of ADA-CMM among its target users, we facilitated an assessment of the ADA capability maturity of a large company and conducted semi-structured interviews with a select group of participants who had used ADA-CMM. We focused on their perspective on the model's usefulness and ease of use, and their intention to use the model. The results show that the majority of participants rated the model positively in terms of its overall usefulness and ease of use and had a clear intention to use the model. ADA-CMM is a descriptive capability maturity model that organizations can use to assess their current situation, develop and prioritize improvements, and control the progress of these improvements (Poeppelbuss et al., 2011; Tarhan et al., 2016). Organizations can use ADA-CMM to self-assess the maturity of their current ADA capabilities and unveil the ADA capabilities that the organization excelled in, including areas with room for improvement. Assessment results can provide input to organizations to develop a roadmap for improving their maturity level of the specific ADA capabilities (Poeppelbuss et al., 2011). Conducting a regular self-assessment of the ADA capabilities can facilitate monitoring the progress of improvements. Finally, the ADA-CMM can be used to benchmark and identify the organizational ADA performance compared to the ADA maturity of other departments or organizations (Maier et al., 2012; Szelągowski & Berniak-Woźny, 2022).

Finally, we assessed the effectiveness of ADA-CMM. We analyzed the relationship between ADA maturity level and firm performance through a survey using ADA-CMM assessment questions as a measurement tool. The significant positive relationship between the ADA capability maturity, as assessed by ADA-CMM, and firm performance, mediated by ADA value, indicates that *ADA-CMM incorporates capabilities that are key in generating value from ADA initiatives*. Furthermore, it confirms that *it can be an effective measuring tool in assessing the maturity level of an organization's ADA capabilities*.

This research contributes to the literature by its use of PLS-SEM to evaluate how effective a maturity model is in incorporating critical aspects of its primary focus area, in our case, ADA capabilities. The research employs PLS-SEM as a statistical method of to reveal the relationship between the maturity level of organizational ADA capabilities as measured using ADA-CMM, ADA value, and firm performance. This contributes to the need of of investigating the relationship between ADA maturity and the performanceo of an organization by applying statistical analysis (Thordsen & Bick, 2023). Prior literature has primarily explored these relationships in isolation and has yet to quantitatively establish them (e.g., (Brinch et al., 2018; Elia et al., 2020; Gupta & George, 2016)). In that respect, our study extends the findings from existing research by exploring relevant ADA capabilities that are impactful in value generation from ADA (Elia et al., 2020).

This research has implications for also practitioners, such as executives and ADA managers. The findings underscore the importance of a coherent set of key capabilities in creating value from ADA. This would help create awareness among practitioners that gaining a competitive advantage from ADA requires capabilities beyond merely collecting large amounts of data and putting advanced technologies in place (Davenport, 2013). Among others, practitioners must strategically position ADA within their organization, ensure the availability of the right people and culture, foster a suitable collaboration environment, and establish effective performance and value management processes.

Our study is subject to several limitations and has various potential directions for future work. First, the advances in ADA would also impact the capabilities required to harvest value from it. Hence, the ADA-CMM should continue evolving, albeit at a slower pace than ADA and related technologies. Future research is needed to apply and validate ADA-CMM in specific contexts and domains, which may require modifications to accommodate their unique characteristics.

There are two main limitations in the evaluation of ADA-CMM. Firstly, the interviewees for the evaluation of utility were from a single company. Secondly, for the evaluation of ADA-CMM effectiveness, the selection of survey participants was non-random and some participants had limited experience in ADA. These two limitations pose risks to the internal validity, as the maturity assessment requires viewpoints of multiple participants with different backgrounds and motivations (Poeppelbuss et al., 2011). Future research should address these limitations by involving multiple participants from different organizations to capture a wider range of perspectives. Furthermore, a larger sample size should be used, and control variables, such as work and ADA experience, organization size, and sector, should be analyzed to confirm the robustness of the impact of ADA value on firm performance.

We aimed to evaluate ADA-CMM for its utility as perceived by the target users and effectiveness in generating its intended purpose. Future research should consider evaluating the model using objective performance measures, such as revenue. Evaluating the long-term impact of using ADA-CMM by a longitudinal study can also provide valuable insights since organizations struggle to justify the long-term benefits of ADA investments (Chen et al., 2012).

During the evaluation of the model, potential directions for future work have been identified. To further enhance the model, it can be extended to have a stronger prescriptive structure that explicitly guides organizations toward achieving higher maturity levels for their capabilities. Our model proposes four maturity levels for each capability. Future research can adopt a theoretically grounded model (e.g. Korsten et al., 2024) to enhance consistency and alignment across all capabilities and related levels. The descriptions of the maturity levels and questions used during the assessment can be improved to consider the perspectives of diverse organizational roles. Furthermore, the roles that would participate in the assessment and the target audience for the assessment results and improvement planning should be explicitly defined to facilitate effective model use in practice (Maier et al., 2012).

8 Conclusions

As technology improves, more companies use ADA to enhance their operations, offerings, and customer experiences (Ghasemaghaei et al., 2017). This can give them an advantage over competitors (Seddon et al., 2017). However, many businesses still have difficulty translating their analytics efforts into tangible business benefits (Günther et al., 2017; Ransbotham et al., 2015). Maturing in ADA can be challenging, particularly in the Asia Pacific region, where organizations often prioritize collective values over individual tools, which might overshadow the importance of data-driven decision-making (Anton et al., 2023). Despite the rise of ADA, many organizations in this region still rely on intuition rather than analytics for managerial decisions (Yu et al., 2022). Studies show that many companies need to be better aware of the necessary capabilities for successfully incorporating ADA (Brinch et al., 2020). They require guidance on building these capabilities to use analytics to drive business growth and improve overall performance (Günther et al., 2017). To address this gap, this paper proposes a capability maturity model for developing and improving ADA capabilities. By contributing to prevalent topics in the Pacific Asia Journal of the Association for Information Systems (PAJAIS), such as business intelligence, data analytics and design science (Jiang et al., 2019), this research aims to provide valuable insights into navigating the challenges of ADA adoption and utilization, particularly within the Asia Pacific context. Following DSR, we designed ADA-CMM using a Delphi study and evaluated it through interviews with target users and a survey across multiple companies. ADA-CMM is one of the maturity models encompassing a holistic perspective, providing a means for assessment, and is evaluated for its utility and effectiveness, which is called for in the field (Felch & Asdecker, 2020; Mettler, 2011; Santos-Neto & Costa, 2019; Tarhan, Turetken, & Reijers, 2015). ADA-CMM adds to the unbiased academic body of knowledge on ADA through a well-structured and thoroughly documented design and evaluation process.

Biographical statements

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References

Adrian, C., Abdullah, R., Atan, R., & Jusoh, Y. Y. (2016). Towards developing strategic assessment model for big data implementation: A systematic literature review. *International Journal of Advances in Soft Computing and Its Applications*, *8*(3).

Afrah Ahmed, A., Yusof, S. A. M., & Oroumchian, F. (2019). Understanding the Business Value Creation Process for Business Intelligence Tools in the UAE. *Pacific Asia Journal of the Association for Information Systems*, 55–88.

Akerkar, R. (2013). Big data computing. In *Big Data Computing*.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, *182*, 113–131.

Al-Sai, Z. A., Abdullah, R., & Husin, M. H. (2019). A review on big data maturity models. *JEEIT 2019*, 156–161.

Alsheiabni, S., Cheung, Y., & Messom, C. (2019). Towards An Artificial Intelligence Maturity Model: From Science Fiction To Business Facts. *Pacific Asia Conference Information Systems Proceedings*, 6–15. https://aisel.aisnet.org/pacis2019

Andrews, D., Nonnecke, B., & Preece, J. (2003). Conducting Research on the Internet : Online Survey Design , Development and Implementation Guidelines. *International Journal of Human-Computer Interaction*, *16*(2).

Anton, E., Oesterreich, T. D., Aptyka, M., & Teuteberg, F. (2023). Beyond Digital Data and Information Technology: Conceptualizing Data-Driven Culture. *Pacific Asia Journal of the Association for Information Systems*, *15*(3).

Baijens, J., Helms, R., & Iren, D. (2020). Applying Scrum in Data Science Projects. *Proceedings - 2020 IEEE 22nd Conference on Business Informatics, CBI 2020*, *1*, 30–38.

Becker, J., Knackstedt, R., & Pöppelbuß, J. (2009). Developing Maturity Models for IT Management. *Business & Information Systems Engineering*, *1*(3), 213–222.

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information and Management*, *57*(2), 103168.

Brinch, M., Gunasekaran, A., & Fosso Wamba, S. (2020). Firm-level capabilities towards big data value creation. *Journal of Business Research*, *July*.

Brinch, M., Stentoft, J., Jensen, J. K., & Rajkumar, C. (2018). Practitioners understanding of big data and its applications in supply chain management. *International Journal of Logistics Management*, *29*(2), 555–574.

Brook, R. J., & Arnold, G. C. (2019). 07. Data Science for Business: What You Need to Know about Data Mining and Data-Analytic Thinking. *Applied Regression Analysis and Experimental Design*.

Bruin, T. de, Freeze, R., Kulkarni, U., & Rosemann, M. (2005). Understanding the Main Phases of Developing a Maturity Assessment Model. *ACIS 2005*.

Buh, B., Kovačič, A., & ŠTemberger, M. I. (2015). Critical success factors for different stages of business process management adoption – a case study. *Economic Research-Ekonomska Istrazivanja* , *28*(1), 243–258.

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and Analytics: From big data to big impact. *MIS Quarterly*, *36*(4), 1165–1188.

Comuzzi, M., & Patel, A. (2016). How organisations leverage: Big Data: A maturity model. *Industrial Management and Data Systems*, *116*(8), 1468–1492.

Cosic, R., Shanks, G., & Maynard, S. (2012). Towards a business analytics capability maturity model. *ACIS 2012 : Proceedings of the 23rd Australasian Conference on Information Systems*.

Davenport, T. (2013). Analytics 3.0. *Harvard Business Review*, *DEC*.

Davenport, T. (2018). DELTA Plus Model & Five Stages of Analytics Maturity: A Primer. *International Institute for Analytics*, *August*.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3).

Debortoli, S., Müller, O., & Vom Brocke, J. (2014). Comparing business intelligence and big data skills: A text mining study using job advertisements. *Business & Information Systems Engineering*, *6*(5), 289–300.

Delbecq, A. L., Van de Ven, A. H., & Gustafson, D. H. (1975). Group techniques for program planning : a guide to nominal group and Delphi processes. In *Glenview, Illinois : Scott, Foresman and Company*. Scott, Foresman and Company.

Deng, Q., & Ji, S. (2018). A Review of Design Science Research in Information Systems: Concept, Process, Outcome, and Evaluation. *Pacific Asia Journal of the Association for Information Systems*, 1–36.

Dhanuka, V. (2016). *Hortonworks Big Data Maturity Model HORTONWO RKS BIG DATA MATURITY MODEL*. http://hortonworks.com/wp-content/uploads/2016/04/Hortonworks-Big-Data-Maturity-Assessment.pdf

Diamond, I. R., Grant, R. C., Feldman, B. M., Pencharz, P. B., Ling, S. C., Moore, A. M., & Wales, P. W. (2014). Defining consensus: A systematic review recommends methodologic criteria for reporting of Delphi studies. *Journal of Clinical Epidemiology*, *67*(4), 401–409.

Dikici, A., Turetken, O., & Demirors, O. (2018). Factors influencing the understandability of process models: A systematic literature review. In *Information and Software Technology* (Vol. 93).

Dilda, V., Mori, L., Noterdaeme, O., & Schmitz, C. (2017). Manufacturing: Analytics unleashes productivity and profitability. *McKinsey*.

Dremel, C., Overhage, S., Schlauderer, S., & Wulf, J. (2017). Towards a Capability Model for Big Data Analytics. *Wirtschaftsinformatik 2017*, 1141–1155.

Eisenhardt, K. M., & Schoonhoven, C. B. (1996). Resource-based View of Strategic Alliance Formation: Strategic and Social Effects in Entrepreneurial Firms. *Organization Science*, *7*(2).

El Morr, C., & Ali-Hassan, H. (2019). *Descriptive, Predictive, and Prescriptive Analytics*. 31–55.

Elia, G., Polimeno, G., Solazzo, G., & Passiante, G. (2020). A multi-dimension framework for value creation through Big Data. *Industrial Marketing Management*, *90*(March), 617–632.

Farah, B. (2017). A value based big data maturity model. *Journal of Management Policy and Practice*, *18*(1), 11–18.

Felch, V., & Asdecker, B. (2020). Quo vadis, business process maturity model? learning from the past to envision the future. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 12168 LNCS*.

Fraser, P., Moultrie, J., & Gregory, M. (2002). The use of maturity models/grids as a tool in assessing product development capability. *IEEE International Engineering Management Conference*, *1*, 244–249.

Gallego, D., & Bueno, S. (2014). Exploring the application of the Delphi method as a forecasting tool in Information Systems and Technologies research. *Technology Analysis and Strategic Management*, *26*(9), 987–999.

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, *35*(2).

Garson, G. D. (2016). *Partial Least Squares: Regression and Structural Equation Models* (2016 Ed.). Statistical Associates Publishers.

Gartner. (2022a). *Advanced Analytics - Gartner IT Glossary*. Gartner Glossary.

Gartner. (2022b). *Data and Analytics: Everything You Need to Know*. https://www.gartner.com/en/topics/data-and-analytics#q8

Ghasemaghaei, M., Hassanein, K., & Turel, O. (2017). Increasing firm agility through the use of data analytics: The role of fit. *Decision Support Systems*, *101*, 95–105.

Gökalp, M. O., Gökalp, E., Gökalp, S., & Koçyiğit, A. (2021). The development of data analytics maturity assessment framework: DAMAF. *Journal of Software: Evolution and Process*, e2415.

Gregor, S., & Hevner, A. R. (2013). Positioning and Presenting Design Science Research for Maximum Impact. *MIS Quarterly*, *37*(2), 337–355.

Grossman, R. L. (2018). A framework for evaluating the analytic maturity of an organization. *International Journal of Information Management*, *38*(1).

Günther, W. A., Rezazade Mehrizi, M. H., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *Journal of Strategic Information Systems*, *26*(3), 191–209.

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information and Management*, *53*(8), 1049–1064.

Gür, I., Guggenberger, T. M., & Altendeitering, M. (2021). Towards a data management capability model. *27th Annual Americas Conference on Information Systems, AMCIS 2021*.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods. *Journal of the Academy of Marketing Science*, *45*(5).

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance. *Long Range Planning*, *46*(1–2), 1–12.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review* (Vol. 31, Issue 1).

Halper, F., & Krishnan, K. (2014). Tdwi Big Data Maturity Model Guide. *RDWi Resarch*, *2013–2014*.

Hammer, M. (2007). The Process Audit Toolkit. *Harvard Business Review*, *April*.

Hammer, M. (2010). What is Business Process Management? *Handbook on Business Process Management 1*, 3–16.

Hausladen, I., & Schosser, M. (2020). Towards a maturity model for big data analytics in airline network planning. *Journal of Air Transport Management*, *82*.

Herschel, G., Brethenoux, E., Idoine, C., Kronz, A., Hunter, E., & Horvath, M. (2018). Predicts 2019: Analytics and BI Strategy. *Gartner Report: G00372971*.

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design Science in Information Systems Research. *MIS Quarterly*, *28*(1), 75.

Huang, C. K., Wang, T., & Huang, T. Y. (2020). Initial Evidence on the Impact of Big Data Implementation on Firm Performance. *Information Systems Frontiers*, *22*(2), 475–487.

Huffman, J., & Whitman, L. E. (2011). Developing a capability maturity model for enterprise intelligence. *IFAC Proceedings Volumes (IFAC-PapersOnline)*, *44*(1 PART 1).

Hyun, Y., Kamioka, T., & Hosoya, R. (2020). Improving Agility Using Big Data Analytics: The Role of Democratization Culture. *Pacific Asia Journal of the Association for Information Systems*, *12*(2), 35–63.

Info-Tech Research Group. (n.d.). *Big Data Maturity Assessment Tool*. Info-Tech Research Group. Retrieved June 16, 2022, from https://www.infotech.com/research/it-big-data-maturity-assessment-tool

Janssen, M., van der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. *Journal of Business Research*, *70*, 338–345.

Jiang, J., Liang, T. P., & Tsai, J. C. A. (2019). Knowledge Profile in PAJAIS: A Review of Literature and Future Research Directions. In *Pacific Asia Journal of the Association for Information Systems* (Vol. 11, Issue 1).

Kerpedzhiev, G. D., König, U. M., Röglinger, M., & Rosemann, M. (2021). An Exploration into Future Business Process Management Capabilities in View of Digitalization: Results from a Delphi Study. *Business & Information Systems Engineering*, *63*(2), 83–96.

King, D. (2017). *Plotting a Data Analytics Path for the Future Starts with Knowing Where You Are*. Association Analytics. https://associationanalytics.com/blog/plotting-data-analytics-path/

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration*, *11*(4), 1–10.

Kock, N., & Lynn, G. S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, *13*(7), 546–580.

Korsten, G., Aysolmaz, B., Turetken, O., Edel, D., & Ozkan, B. (2022). ADA-CMM: A Capability Maturity Model for Advanced Data Analytics. *HICSS*, *2022-January*.

Korsten, G., Ozkan, B., Aysolmaz, B., Mul, D., & Turetken, O. (2024). Understanding Capability Progression: A Model for Defining Maturity Levels for Organizational Capabilities. In *BPMDS/EMMSAD 2024* (pp. 355–371). LNCS-511. Springer, Cham. .

Król, K., & Zdonek, D. (2020). Analytics maturity models: An overview. *Information (Switzerland)*, *11*(3), 1–19.

Lahrmann, G., Marx, F., Winter, R., & Wortmann, F. (2010). Business Intelligence Maturity Models: An Overview. *Computer Science*.

Logi Analytics. (n.d.). *The 5 levels of analytics: from basic business intelligence requirements to sophisticated product differentiators,*. Retrieved June 16, 2022, from https://insightsoftware.com/resources/the-5-levels-of-analytics-maturity-from-basic-bi-to-sophisticated-differentiators/

Mahajan, V., Linstone, H. A., & Turoff, M. (1976). The Delphi Method: Techniques and Applications. *Journal of Marketing Research*, *13*(3), 317.

Maier, A. M., Moultrie, J., & Clarkson, P. J. (2012). Assessing organizational capabilities: Reviewing and guiding the development of maturity grids. *IEEE Transactions on Engineering Management*, *59*(1), 138–159.

Malik, P. (2013). Governing Big Data: Principles and practices. *IBM Journal of Research and Development*, *57*(3/4).

Mariani, D. (2021). *What Is the Data Analytics Maturity Model? | AtScale*. At Scale. https://www.atscale.com/blog/introducing-data-analytics-maturity-model/

Matthias, O., Fouweather, I., Gregory, I., & Vernon, A. (2017). Making sense of Big Data – can it transform operations management? *International Journal of Operations and Production Management*, *37*(1), 37–55.

McMillan, S. S., King, M., & Tully, M. P. (2016). How to use the nominal group and Delphi techniques. *International Journal of Clinical Pharmacy*, *38*(3), 655.

Menukhin, O., Mandungu, C., Shahgholian, A., & Mehandjiev, N. (2019). Now and Next: A Maturity Framework to Guide Analytics Growth. *Proceedings Of UKAIS 2019*.

Mettler, T. (2011). Maturity assessment models: a design science research approach. *International Journal of Society Systems Science*, *3*(1/2).

Mikalef, P., & Krogstie, J. (2020). Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities. *European Journal of Information Systems*, *29*(3), 260–287.

Mikalef, P., Pappas, I. O., Krogstie, J., & Pavlou, P. A. (2020). Big data and business analytics: A research agenda for realizing business value. In *Information and Management* (Vol. 57, Issue 1).

Molina-Granja, F., Bustamante Granda, W., Delgado Altamirano, J., & Ramos, P. L. (2022). Maturity Model for Data Analytics in Health Institutions. *Journal of Positive School Psychology* , *2022*(5), 4585–4590–4585–4590. https://journalppw.com/index.php/jpsp/article/view/7268

Moody, D. (2003). *The Method Evaluation Model: A Theoretical Model for Validating Information Systems Design Methods*. 1327–1336.

Moran, J. W., & Brightman, B. K. (2001). Leading organizational change. *Career Development International*, *6*(2), 111–119.

Mouhib, S., Anoun, H., Ridouani, M., & Hassouni, L. (2020). Towards a Global Big Data Maturity Model. *4th International Conference on Intelligent Computing in Data Sciences, ICDS 2020*.

Neubauer, T. (2009). An empirical study about the status of business process management. *Business Process Management Journal*, *15*(2), 166–183.

Nott, C., & Betteridge, N. (2014). *Big Data and Analytics Maturity Model*. IBM Big Data and Analytics Hub. https://whitehallmedia.co.uk/blog/2015/12/29/a-maturity-model-for-big-data-and-analytics/

Nunamaker, J. F., Briggs, R. O., Derrick, D. C., & Schwabe, G. (2015). The Last Research Mile: Achieving Both Rigor and Relevance in Information Systems Research. *Journal of Management Information Systems*, *32*(3), 10–47.

Parra, X., Tort-Martorell, X., Ruiz-Viñals, C., & Álvarez-Gómez, F. (2019). A maturity model for the information-driven SME. *Journal of Industrial Engineering and Management*, *12*(1).

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems*, *24*(3).

Piyanka, J. (2012). *The Analytics Maturity Quotient Framework*. Aryng. http://docplayer.net/37704650-The-analytics-maturity-quotient-framework.html

Poeppelbuss, J., Niehaves, B., Simons, A., & Becker, J. (2011). Maturity Models in Information Systems Research: Literature Search and Analysis. *Communications of the Association for Information Systems*, *29*.

Powell, C. (2003). The Delphi technique: Myths and realities. In *Journal of Advanced Nursing* (Vol. 41, Issue 4).

Radhakrishnan, J., Gupta, S., & Prashar, S. (2022). Understanding organizations' artificial intelligence journey: A qualitative approach. *Pacific Asia Journal of the Association for Information Systems*, *14*(6).

Ransbotham, S., Kiron, D., & Prentice, P. K. (2015). Minding the Analytics Gap. *MIT Sloan Management Review*, *Spring*, 63–68.

Recker, J. (2013). Scientific Research in Information Systems. In *Scientific Research in Information Systems*.

Rigdon, E. E. (2016). Choosing PLS path modeling as analytical method in European management research: A realist perspective. *European Management Journal*, *34*(6).

Rogers, E. M. (2009). Informatization, globalization, and privatization in the new Millenium. *Http://Dx.Doi.Org/10.1080/01292980009364785*, *10*(2), 71–92.

Röglinger, M., Pöppelbuß, J., & Becker, J. (2012). Maturity models in business process management. *Business Process Management Journal*, *18*(2), 328–346.

Saltz, J. S., & Shamshurin, I. (2016). Big data team process methodologies: A literature review and the identification of key factors for a project's success. *2016 IEEE International Conference on Big Data*, 2872–2879.

Sanatham, D. (n.d.). *Analytics Maturity Assessment - Understand Your Analytics Maturity Model*. Blast Analytics. Retrieved June 16, 2022, from https://www.blastanalytics.com/analytics-maturity-assessment

Santos-Neto, J. B. S. dos, & Costa, A. P. C. S. (2019). Enterprise maturity models: a systematic literature review. In *Enterprise Information Systems* (Vol. 13, Issue 5).

Sarstedt, M., Hair, J. F., Cheah, J. H., Becker, J. M., & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal*, *27*(3).

Schmarzo, B. (2013). Big Data: Understanding How Data Powers Big Business. In *Journal of Chemical Information and Modeling* (Vol. 53).

Schriek, M. H. J., Türetken, O., & Kaymak, U. (2016). A Maturity Model for Care pathways. *Undefined*.

Seddon, P. B., Constantinidis, D., Tamm, T., & Dod, H. (2017). How does business analytics contribute to business value? *Information Systems Journal*, *27*(3), 237–269.

Simpson, J. A., & Weiner, E. S. C. (1989). *The Oxford English Dictionary* (2nd ed. /). Clarendon Press ; Oxford University Press.

Sonnenberg, C., & Vom Brocke, J. (2012). Evaluations in the science of the artificial - Reconsidering the build-evaluate pattern in design science research. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *7286 LNCS*.

Steininger, D. M., Mikalef, P., Pateli, A., & Ortiz-De-guinea, A. (2022). Dynamic Capabilities in Information Systems Research: A Critical Review, Synthesis of Current Knowledge, and Recommendations for Future Research. *Journal of the Association for Information Systems*, *23*(2).

Sulaiman, H., Cob, Z. C., & Ali, N. (2015). Big data maturity model for Malaysian zakat institutions to embark on big data initiatives. *2015 4th International Conference on Software Engineering and Computer Systems, ICSECS 2015: Virtuous Software Solutions for Big Data*.

Szelągowski, M., & Berniak-Woźny, J. (2022). How to improve the assessment of BPM maturity in the era of digital transformation. *Information Systems and E-Business Management*, *20*(1), 171–198.

Tarhan, A., Garousi, V., Turetken, O., Soylemez, M., & Garossi, S. (2020). Maturity assessment and maturity models in health care: A multivocal literature review. *Digital Health*, *6*, 2055207620914772.

Tarhan, A., Turetken, O., & Ilisulu, F. (2015). Business Process Maturity Assessment: State of the Art and Key Characteristics. *Proceedings - 41st Euromicro Conference on Software Engineering and Advanced Applications, SEAA 2015*, 430–437.

Tarhan, A., Turetken, O., & Reijers, H. A. (2015). Do Mature Business Processes Lead To Improved Performance? -- A Review of Literature for Empirical Evidence. *ECIS 2015*.

Tarhan, A., Turetken, O., & Reijers, H. A. (2016). Business process maturity models: A systematic literature review. *Information and Software Technology*, *75*, 122–134.

Thordsen, T., & Bick, M. (2023). A decade of digital maturity models: much ado about nothing? *Information Systems and E-Business Management*.

Turetken, O., Ondracek, J., & IJsselsteijn, W. (2019). Influential Characteristics of Enterprise Information System User Interfaces. *Journal of Computer Information Systems*, *59*(3).

Ulrich, D., & Smallwood, N. (2004). Capitalizing on Capabilities. *Harv. Bus. Rev.* .

van Hillegersberg, J. (2019). The Need for a Maturity Model for Maturity Modeling. *The Art of Structuring*, 145–151.

Van Looy, A. (2015). An experiment for measuring business process maturity with different maturity models. *ECIS 2015*.

Venkatesh, V., & Davis, F. D. (2000). Theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science*, *46*(2).

Vesset, D., Girard, G., Feblowitz, J., Versace, M., Burghard, C., O'brien, A., Olofson, C. W., Schubmehl, D., Mcdonough, B., Woodward, A., & Bond, S. (2015). *IDC MaturityScape: Big Data and Analytics 2.0. IDC #255138*. https://www.cacp.ca/index.html?asst_id=1637

Wef. (2014). Big Data Maturity: An Action Plan for Policymakers and Executives. In *Weforum*. https://www3.weforum.org/docs/GITR/2014/GITR_Chapter1.3_2014.pdf

Weill, Peter., & Ross, J. W. (2004). *IT governance : how top performers manage IT decision rights for superior results*. 269.

White, A., & Oestreich, T. (2017). *ITScore for Data and Analytics*. Gartner. https://emt.gartnerweb.com/ngw/globalassets/en/information-technology/documents/benchmarks/gartner-it-score-for-data-analytics-sample-excerpt.pdf

Wohlin, C. (2014). Guidelines for Snowballing in Systematic Literature Studies and a Replication in Software Engineering. *EASE-2014*.

Yu, J., Taskin, N., Nguyen, C. P., Li, J., & Pauleen, D. J. (2022). Investigating the Determinants of Big Data Analytics Adoption in Decision Making: An Empirical Study in New Zealand, China, and Vietnam. *Pacific Asia Journal of the Association for Information Systems*, *14*(4).

Appendix A. Initial version of the ADA-CMM

Capability area	Capability	Definition	Reference
1. Performers	1a. Knowledge	The extent to which employees and managers have knowledge regarding business processes. digitalization, analytics capabilities.	(Brinch et al., 2020)
	1b. Usage	The extent to which employees adopt IT services, use informational insights in their decision making, and comply with process standardizations.	(Brinch et al., 2020)
	1c. Commitment	The extent to which employees and management make the investments, execute the related projects and make the required changes in practice.	(Brinch et al., 2020)
2. Infrastructure	2a. IT Architecture	The extent to which there is a single-source-of-truth and data storage service, data access and data analytics is facilitated across the organization.	(Brinch et al., 2020)
	2b. Informatization	The extent to which an organization utilises information and identifies value produced by data collection, data source integration, data analysis.	(Rogers, 2009)
	2c. IT Automation	The extent to which IT helps to eliminate manual data entry and increases the automated decisions and data utilization.	(Brinch et al., 2020)
	2d. IT Governance	The extent to which there are actively designed set of mechanisms (e.g., data standardization, policies) that encourages behaviours consistent with the organization’s mi(Weill & Ross, 2004) culture.	(Weill & Ross, 2004)
	2e. Software Applications	The extent to which there is data warehouse integration and users can easily incorporate this in data analytics engines to visualize the analytical insights.	(Brinch et al., 2020)
3. Culture	3a. Organizational Structure	The extent to which analytics competence centres and supportive competence centres are incorporated in the organizational structure and there is a clarity of roles, responsibilities and resources of the various departments	(Brinch et al., 2020)
	3b. Culture	The extent to which there are collective values and beliefs that shape digital-orientation, collaboration, process-related attitudes and behaviour to improve business performance.	(Hammer, 2010)
	3c. Human Resources	The extent to which human resource management skills and knowledge are used to recruit talent and provide talent management, and individuals and groups continually have the ability to develop their competences.	(Hammer, 2010)
	3d. Change Management	The extent to which there is employee involvement and communication with the employees in the process of continually renewing an organization's direction, structure, and capabilities.	(Moran & Brightman, 2001)
	3e. Organizational Collaboration	The extent to which there is information sharing, employee interaction and functional project involvement across functions and expertise.	(Brinch et al., 2020)
4. Metrics	4a. Performance Measurements	The extent to which metrics (e.g., process metrics, functional metrics, data quality metrics, financial metrics) are developed and standardized to show how analytics capabilities can turn data into value for its continuous development	(Brinch et al., 2020)
	4b. Innovation of Practices	The degree to which the processes are continuously improved and redesigned through the use of advanced analytics to develop best-in-class service operations.	(Brinch et al., 2020)
	4c. Project Management	The extent to which advanced analytics projects have clearly defined objectives, there is consistent portfolio management, business cases are developed, and there is cross-functional collaboration.	(Buh et al., 2015)
5. Governance	5a. Process Design	The extent to which processes are customer oriented, end-to-end processes toward IT systems and applications are defined and fit within the organization.	(Brinch et al., 2020)

	5b. Process Standardization	The extent to which business procedures are followed accurately and consistently, work descriptions and data inputs are defined, analytics standardization is applied, and there is real world compliance.	(Neubauer, 2009)
	5c. Process Integration	The extent to which IT systems and operational processes are linked facilitate information flows, intelligence sharing, and alignment.	(Janssen et al., 2017)
	5d. Process Governance	The extent to which there are decision-making and reward processes designed to guide process-related actions and appropriate and transparent accountability in terms of roles and responsibilities.	(Hammer, 2010)
6. Design	6a. Strategic Objectives	The extent to which there are IT and process-related domain objectives which promote the vision and mission and guide desired achievements	(Brinch et al., 2020)
	6b. Strategic Alignment	The extent to which there is a linkage of functional strategic priorities and IT business process priorities to have continuous and effective business performance.	(Hammer, 2010)
	6c. Business Process Strategy	The extent to which business processes emphasise the elements of standardization, performance measurements and continuous improvements in order to increase business process maturity.	(Brinch et al., 2020)
	6d. IT Strategy	The degree to which the IT department has a vision, mission, and objectives concerning the IT architecture, IT governance, digitalization and IT investments to support the business processes.	(Buh et al., 2015)

Appendix B. Summary of changes in the Delphi rounds

Delphi round 1 adopted an explorative approach to developing the structure of the model. This is a commonly suggested approach to initiate the Delphi rounds (Powell, 2003). To achieve this, we presented the structure of the model, capability areas and capabilities, and their definitions to the panelists and asked them to suggest additional capability (areas). In this first round, the maturity levels for each capability (area) were not presented to keep the focus on the definition of model capability (areas). The main feedback we received was on specifying the scope and focusing the model on ADA more explicitly through updating various capability areas and capabilities. We explicitly defined the scope of the model as *ADA projects* by emphasizing more on the descriptions of related terms. We also pointed out that the model aims to understand the capabilities necessary to collect, manage, and use data within organizations.

Several suggestions regarding the addition of capabilities were made, which resulted in some capabilities being added, changed, or removed. Two capabilities were added based on these suggestions. Panelists pinpointed the importance of multidisciplinarity and diversity of employees in terms of their expertise and roles. Relevant ones included technical experts, data storytellers, and subject matter experts who understand the business well. To address these points, the capability *Diversity* was added. It was also suggested to add an capability that focuses on the training of employees. Accordingly, we added a new capability of *Talent Management*. The capabilities *Organizational Structure*, *Process Standardization,* and *Process Governance* were considered less critical in creating value from ADA and were, therefore, removed from the model. The *Governance* capability area was considered unclear. Hence, its essential capabilities were moved to the capability area *Infrastructure*, which was renamed as *Data*. Various other changes were introduced in the names, definitions, or capabilities of five out of the six capability areas.

In *Delphi round 2*, the panelists received a report of changes in the initial model performed based on their feedback. They also received the revised model, including, this time also the definitions of the maturity level characteristics for each capability. The second round was confirmative in nature, i.e., it was used to gather information to either change or delete capability (areas) from the model. The panelists were not explicitly asked to propose new model capability (areas).

The discussions led to two changes in the capability areas of the model. It was suggested by two panelists to integrate the capability areas *People* and *Culture*. They suggested moving the capabilities *Change Management*, *Project Management,* and *Organizational Collaboration* to a new capability area named *Execution*. This was incorporated into the model, and the capability area was called *Process Design* inspired by the PEMM structure (Hammer, 2007). Furthermore, two panelists suggested renaming the capability area *Performance*. One of them suggested *Value* as a new name, and the other suggested to merge it with *Strategy* and rename it to *Strategy and Vision*. As a result, we renamed the capability area as *Performance and Value* relating *Metrics* to *Performance* and *Innovation* to the *Value*. Further changes in the positioning of the capabilities were also suggested. For example, panelists suggested moving the capabilities *Change Management*, *Project Management*, and *Organizational Collaboration* from *People & Culture* to the new capability area *Process Design*. Furthermore, several name changes were applied in the capability areas, content-related changes in capabilities, and corresponding maturity level characteristics.

In *Delphi round 3*, the goal was to evaluate the descriptions of the maturity levels to gather confirmation for all capability (areas). For the capability areas, *Data* was renamed to *Data & Governance* as the capability area was considered to entail more than data only. Similarly, *Process Design* was renamed to *Process Design & Collaboration*. Further, a few capabilities were renamed, and their descriptions and maturity level descriptions were improved. According to the feedback, the model was updated and finalized. As a result of round three, the final model was sent back to panelists for final confirmation.

Appendix C. ADA-CMM

Capability Area	Capability	Definition	Low	Moderate	High	Top
Strategy	ADA Strategy	The degree to which the ADA department has a vision, mission, and objectives concerning data architecture, data governance, digital orientation and data investments to support the business processes.	There is no explicit strategic ADA vision, mission or plan to support business processes.	A strategic ADA plan is present, focused on short-term goals.	A long-term ADA vision, mission and strategy concerning data architecture, data governance, digital orientation and data investments is present and well documented to support the business processes.	There is a well-documented long- term ADA vision, mission and plan concerning data architecture, data governance, digital orientation and data investments to support the business, which is continuously improved.
	Strategic Alignment	The extent to which there is a linkage of ADA priorities, IT and business process priorities, and business priorities for continuous and effective business performance.	ADA priorities are not explicitly aligned with the IT objectives and business processes.	ADA priorities are developed with awareness of the IT objectives and business processes.	ADA priorities are explicitly aligned with and support the IT objectives and business processes.	ADA priorities are explicitly aligned with and support the IT objectives and business processes. The alignment between business, IT and ADA is continuously evaluated and improved.
Data & Governance	Data Architecture	The extent to which there is identity and access management, a single-source-of-truth, a data model, and data storage or cloud services to facilitate the data analytics applications across the organization.	The organization does not have a single coherent information architecture or data model. It is difficult to gain access to datasets, and there is no specific plan to facilitate data storage across the organization. People create ad-hoc datasets causing multiple versions of the truth.	The organization has a plan to facilitate data storage across the organization. The organization has minimal functional information architecture and data model.	The organization has a data storage or cloud service to provide a single-source-of-truth. Identity and access management are in place. The data model and architecture are developed.	The organization has a scalable and easy to maintain data storage or cloud service to provide a single-source-of-truth; and identity and access management is optimized. Technology developments adhere to the established data architecture elements. The data architecture and data model are continuously evaluated and improved.
	Automation	The extent to which ADA helps to eliminate repetitive manual work (e.g., data entry), thereby increasing data utilization and data driven decision making.	The organization is unaware of the potential of automation. Manual labour is used to perform the repetitive work. There is no consistent data collection for automation.	There is an application of automation on an individual basis, the majority of decisions are not data driven. Standardized processes are in place for data collection.	Data driven decision making is implemented in processes throughout the whole organization. There is consistent data collection.	Consistent data collection and self-learning methods are in place to automate work processes throughout the whole organization. Machine learning and deep learning allow for adaptive automation. Processes are continuously evaluated and improved.
	Data Integration	The extent to which IT systems and operational processes are linked to facilitate information flows, intelligence sharing, and alignment.	IT systems are running mostly in silos; data sharing among them is limited.	IT systems are mostly integrated across functional silos; data is shared for cross-functional activities.	IT systems and operational processes are integrated and internally aligned. Data access and sharing is formalized.	IT systems and operational processes are integrated. They are internally and externally aligned. Data access and sharing is formalized and there is a functional transparency to increase BD & AA work efficiency. Data integration is continuously evaluated and improved.
	Data Governance	The extent to which there is an actively designed set of mechanisms (e.g., structure, policies, processes) to ensure that behaviours are consistent with the organization's ADA mission, strategy, and culture.	There are no formal mechanisms (e.g., structure, policies, processes etc.) in place for ADA projects. Responsibilities for ADA projects or data ownership is not formally defined.	There are limited formal mechanisms (e.g., structure, policies, processes, etc.) in place for ADA projects. It is clear who is functionally responsible for each ADA activity.	There are formal mechanisms (e.g., structure, policies, processes, etc.) in place for ADA projects. Responsibilities are integrated and aligned with the organizational structure and processes.	There are formal mechanisms (e.g., structure, policies, processes, etc.) that ensure behaviours are consistent with the organization's ADA mission, strategy, and culture. Responsibilities are integrated and aligned with organizational structure and processes, and in continuous development. It is ensured that there is consistent data access, collection and data quality. New technological developments adhere to the governance policy.

Capability Area	Capability	Definition	Low	Moderate	High	Top
	Data Analytics Tools	The extent to which data analytics tools are integrated with the data platform and allow users to easily visualize and gain insights from ADA.	There are no data analytics tools which are available and used throughout the organization.	A limited number of data analytics tools are available and functioning as separate systems.	Several data analytics tools are available and integrated; employees are actively encouraged to use these tools.	There is a set of data analytics tools available and used throughout the organization. The tools are integrated with the data platform and allow employees to visualize and gain insights from ADA. The available support tools are continuously evaluated and developed.
People & Culture	Knowledge	The extent to which employees and managers have knowledge regarding ADA and digitalization and are interested in learning about the application of ADA within the organization.	Employees and managers have limited knowledge regarding ADA. Employees and managers are not sufficiently triggered to learn about the application of ADA within the business.	Most employees and managers have basic knowledge regarding ADA and utilize this knowledge in a limited way to their specific role or function.	Employees and management understand how ADA can be applied or utilized at their specific role or function to increase work quality. Employees and managers have knowledge regarding business processes and analytical capabilities of the IT department.	Employees and management understand how ADA can be applied or utilized at their specific role or function to increase work quality. Employees and managers have knowledge regarding business processes and analytical capabilities of the IT department. Training is provided to continuously evaluate and improve employee knowledge regarding ADA.
	Commitment	The extent to which employees and management make the investments (e.g., budget, effort, sponsorship) in ADA capabilities, execute the related projects and make the required changes in practice.	There is no explicit commitment shown by the employees and management to make investments (e.g., budget, effort, sponsorship) in ADA.	Management and employees show commitment to make some investments in ADA (e.g., budget, effort, sponsorship).	Management and employees adopt ADA initiatives. They are committed to make investments (e.g., budget, effort, sponsorship) in ADA to develop the business and make the required changes in practice.	Management and employees show extensive adoption of ADA initiatives and they are committed to make investments (e.g., budget, effort, sponsorship) in ADA to develop the business. Management and employees actively motivate others to implement the required changes and embrace a digital culture.
	Team Diversity	The extent to which a company is able to recruit the right talent, have balanced teams with diverse backgrounds and different levels of technical knowledge.	People are hired and allocated to ADA project teams on an ad-hoc basis, the organization is unaware of the necessary team competencies. Diversification of team capabilities is not a priority.	The organization is aware of which competencies are necessary for ADA projects, these are not explicitly stated or acted upon	ADA project teams are carefully selected, in which the potential of existing employees is balanced with the competencies of new employees.	ADA teams are diversified in terms of their expertise, technical knowledge, and background and this is also considered in the recruitment of new employees. It is continuously evaluated whether teams still have the right skill set and adjusted if necessary.
	Usage	The extent to which there are collective values and beliefs that stimulate data-driven decision making, employees and management make use of IT services, adopt analytical capabilities to improve business performance.	Employees and management are sceptical about data-driven decision making, they rarely use ADA services and informational insights to make decisions. ADA is rarely used to innovate processes.	Employees and management are aware of the business value ADA can bring. ADA initiatives are implemented and used to make data-driven decisions.	There is a collective digital orientation. Employees and management use ADA services and informational insights to make data-driven decisions. ADA initiatives are used to innovate processes.	There is a collective digital orientation. Employees and management use ADA services and informational insights to make data-driven decisions. ADA initiatives are used to innovate processes and are aligned with the organizational strategy. The ADA usage is continuously evaluated and improved.
Process Design & Collaboration	Competence & Skills Development	The degree to which the company provides individuals and groups the opportunity to continually develop their skills and competences, by providing training and education.	There are no formal programs for competence and skills development; training on the topic of ADA is not provided.	There is a basic program for competence and skills development. No formal training on ADA is provided.	Employees benefit from an employee competence and skills development program. A number of training sessions on ADA and new technologies is available to all employees.	Employees benefit from an employee competence and skill development program; they are able to take training and are educated about ADA and new technologies. The talent programs are continuously evaluated and updated.

Capability Area	Capability	Definition	Low	Moderate	High	Top
	Communication	The extent to which employees are informed about new technologies within the area of ADA and stimulated to actively deploy these new technologies.	There are rarely communications about ADA projects. Managers have limited information to coach their employees to deploy these new technologies.	The organization infrequently shares stories about ADA outcomes among employees. Managers are aware that they should stimulate employees to deploy new technologies.	Inspirational stories about ADA projects are regularly shared. Management actively stimulates employees to deploy ADA projects on all levels.	There is a widespread communication about ADA project outcomes to inspire employees. Managers provide awareness towards new technologies within the area of ADA and create a collective innovation mindset. Outcomes of innovation management are measured, evaluated. and improved.
	Portfolio Management	The extent to which ADA projects are managed with clearly defined objectives, consistent portfolio management and cross-functional collaboration.	There is no explicitly defined portfolio management approach for ADA projects.	An explicit overview of all ADA projects is present and complete. Portfolio management is in line with the ADA strategy and organizational capabilities.	Portfolio management is based on the explicit and complete overview of all ADA. ADA projects are prioritized based on value, feasibility, and costs. Decisions are in line with the ADA strategy and organizational capabilities.	ADA projects are managed as a portfolio, have clearly defined objectives and a high implementation speed. ADA projects are prioritized based on value, feasibility, and costs and line with the ADA strategy and organizational capabilities. There is a regular analysis and renewal of the portfolio of projects. ADA projects take place across functions and expertise.
	Organizational Collaboration	The extent to which there is information sharing and functional project involvement across functions and expertise and a formal alignment between the focus of ADA teams.	Information sharing for innovation purposes takes place sporadically; professionals work in functional silos and do not share responsibilities.	Irregular contact, - based on informal internal connections- occurs between functions and departments. Some activities are aligned across functional silos in order to create cross-functional activities.	Information sharing is based on formal connections, such as the appointment of responsible employees and through knowledge sharing support tools. The ADA teams are informed about the focus of other teams.	Information sharing occurs explicitly across functions, expertise and responsibilities leading to improved decision making. ADA teams are aligned to have an optimal work efficiency. Organizational collaboration is actively promoted and supported throughout the organization.
Performance & Value	Performance Metrics	The extent to which metrics (e.g., process metrics, functional metrics, data quality metrics, financial metrics) are developed and standardized to show how ADA capabilities can turn data into value for its continuous development.	There are no explicitly defined metrics to measure the value ADA initiatives generate.	The organization has defined basic metrics which are relevant in each ADA project. Results of these ADA projects are stored.	ADA project related metrics (quantitative and qualitative) are defined, measured and stored in an integrated database. There is an easy-to-use and transparent performance dashboard available for appropriate employees.	ADA processes are continuously monitored through quantitative and qualitative metrics, which provide the basis for quantifying and improving the value that ADA initiatives generate. Metrics are stored in a database, and easily accessible in a performance dashboard for appropriate employees. The organization continuously reflects and updates the metrics and aligns them with the ADA strategy.
	Innovation Processes	The degree to which ADA is used to develop new products, improve and redesign processes to develop best-in-class service operations and deliver informational, strategic, transformational, transactional, and infrastructural value.	There are no explicitly defined ADA innovation processes in place.	ADA innovation processes are explicitly defined and documented. Decision criteria are based on transactional value an ADA project could generate.	ADA innovation processes are explicitly defined and documented. Decision criteria are based on the informational, strategic, transformational, transactional, and infrastructural value a ADA project could generate. Innovation processes are executed with expertise and aligned with other processes.	ADA innovation processes are explicitly defined and in place to improve and redesign processes throughout the company and develop best-class-service operations. An industrialisation process is defined in order to embed innovation into the organization. The innovation processes are constantly evaluated and improved.

Appendix D. Survey

We designed an online survey to collect data about the maturity level of ADA capabilities of organizations (as assessed using ADA-CMM), ADA value creation (ADA Value), and firm performance. The survey consisted of four sections.

The *first section* (Table D1) is based on the questions we used for the assessment of maturity in the large company (Section 3.3.2). Accordingly, we rephrased each capability in ADA-CMM in a question form and developed 17 questions. Adhering to the structure of the model (as presented in Figure 2), the options for each question corresponded to the four maturity level characteristics that are presented in Appendix C.

The *second* part of the survey focused on *ADA value creation* in a firm. Based on the framework of Elia et al. (2020), we defined five dimensions to measure the value created by ADA in an organization: informational, transactional, transformational, strategic, and infrastructural value. Informational value is the ability to extract new insights and knowledge from data, transactional value is the ability to automate and optimize business processes, transformational value is the ability to create new business models or services, strategic value is the ability to support decision-making and strategic planning, and infrastructural value is the ability to build and maintain the necessary technical and organizational infrastructure to support ADA initiatives. The statements had a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) (Table D2).

The *third* part of the survey referred to the *firm performance*, which consisted of four items related to market performance and four related to operational performance. These questions are based on the validated items from Gupta & George (2016). Operational performance was measured through productivity, profit rate, return on investment (ROI), and sales revenue. Market performance was measured by considering an organization’s entrance to new markets, the introduction of new products, the success rate of new products, and market share. The statements had a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) and included an option of “don’t know / not applicable” (Table D3).

The *fourth* and final part of the survey aimed at collecting general information about the participant and the organization being assessed. The participants were asked questions about their work position, general work experience, ADA experience, and the organization's sector and size. The organization's name and participant were not mandatory fields for enabling anonymity if preferred. The answer options of the sector were aligned with the Global Industry Classification Standard (MSCI & Standard & Poor’s, 1999) (Table D4).

Before reaching out to the target audience, we sent out a pilot survey to a number of practitioners to review the questions and completion time. Next, we distributed the survey via specifically targeted emails of practitioners in certain companies and social media. The target group was information managers of large companies and enterprises. The survey was online for three weeks, and the target group was actively stimulated to fill in the survey by sending out invitations and reminders.

Table D1: Survey Part 1 - Maturity Assessment Questions

ID	Variable	Question
DG_1	Data Architecture	To what extent is there is identity and access management, a single-source-of-truth, a data model, and data storage or cloud services to facilitate the data analytics applications across the organization.
DG_2	Automation	To what extent does ADA help to eliminate repetitive manual work (e.g., data entry), thereby increasing data utilization and data driven decision making.
DG_3	Data Integration	To what extent are IT systems and operational processes linked to facilitate information flows, intelligence sharing, and alignment.
DG_4	Data Governance	To what extent is there an actively designed set of mechanisms (e.g., structure, policies, processes) to ensure that behaviours are consistent with the organization's ADA mission, strategy, and culture
DG_5	Data Analytics Tools	To what extent are data analytics tools integrated with the data platform which allow users to easily visualize and gain insights from ADA.
PV_1	Performance Metrics	To what extent are metrics (e.g., process metrics, functional metrics, data quality metrics, financial metrics) developed and standardized to show how ADA capabilities can turn data into value for its continuous development.
PV_2	Innovation Process	To what extent is ADA used to develop new products, improve and redesign processes to develop best-in-class service operations and deliver informational, strategic, transformational, transactional, and infrastructural value.
S_1	ADA Strategy	To what extent does the ADA department have a vision, mission, and objectives concerning data architecture, data governance, digital orientation and data investments to support the business processes.
S_2	Strategic Alignment	To what extent is there a linkage of ADA priorities, IT priorities and business process priorities to have continuous and effective business performance.
PC_1	Knowledge	To what extent do employees and managers have knowledge regarding ADA and digitalization and are interested in learning about the application of ADA within the organization.
PC_2	Commitment	To what extent do employees and management make the investments (e.g., budget, effort, sponsorship) in ADA capabilities, execute the related projects and make the required changes in practice.
PC_3	Team Diversity	To what extent is the organization able to recruit the right talent, have balanced teams with diverse backgrounds and different levels of technical knowledge.
PC_4	Usage	To what extent are there collective values and beliefs that stimulate data-driven decision making, trigger the use of IT services, stimulate the adoption of analytical capabilities to improve business performance.
PDC_1	Competence & Skills Development	To what extent provides the organization individuals and groups the opportunity to continually develop their skills and competences, by providing training and education.
PDC_2	Communication	To what extent are employees informed about new technologies within the area of ADA and stimulated to actively deploy these new technologies.
PDC_3	Portfolio Management	To what extent are ADA projects managed with clearly defined objectives, consistent portfolio management and cross-functional collaboration.
PDC_4	Organizational Collaboration	To what extent is information shared, involvement across functions and expertise and a formal alignment between the focus of ADA teams.

* The options for each question corresponds to the four maturity level characteristics. For each question, the participants were expected to select the maturity level that best characterizes their organization's current state for each ADA capability. The maturity level characteristics for each capability are listed in Appendix C.

Table D2: Survey Part 2 - Value Framework [based on (Elia et al., 2020)*]*

ID	Variable	Statements
IMV	Informational Value	In our organization ADA allows for generating new information and discovering hidden knowledge, it reveals extremely useful information to support and enhance the quality of decision- making processes.
TCV	Transactional Value	In our organization ADA generates benefits by providing support to enhance the quality of outcomes, to increase revenues, to improve the operational and supporting processes, reaching better results and productivity.
TFV	Transformational Value	In our organization ADA enhances organizational performance by generating innovation in products, services, customer segments, markets or business models.
SV	Strategic Value	In our organization ADA allows for real-time processing of data to make the organization more market responsive, more ready and quicker to change, more oriented to improve products and services, more prepared to forecast customer needs and behaviours, more open to learn, enhance and manage internal capabilities and skills
ISV	Infrastructural Value	In our organization ADA allows for developing new applications, tools and architectures that increase the value of the existing infrastructure and prepare the ground (in terms of processes, people, and systems) for facing future technological challenges.

Table D3: Survey Part 3 – Firm Performance [based on (Gupta & George, 2016)]

ID	**Variable**	**Statement**
OP_1	Productivity	Our productivity has exceeded that of our competitors
OP_2	Profit Rate	Our profit rate has exceeded that of our competitors
OP_3	ROI	Our return on investment (ROI) has exceeded that of our competitors
OP_4	Sales revenue	Our sales revenue has exceeded that of our competitors
MP_1	New markets	We have entered new markets more quickly than our competitors
MP_2	New products	We have introduced new products or services into the market faster than our competitors
MP_3	Success rate	Our success rate of new products or services has been higher than our competitors
MP_4	Market share	Our market share has exceeded that of our competitors

Table D4: Survey Part 4 - Control Variables

ID	Question	Answer options
Sector	Please indicate in which sector your organization is active.	Energy, Material, Industrials (e.g., capital goods, commercial & professional services, transportation), Consumer discretionary (e.g., consumer services, media, non-food retailing), Consumer staples (e.g. food & staples retailing, household & personal products), Healthcare, Financials, Information technology, Telecommunication services, Utilities, Real estate, other
Work_BDA	Please indicate your working experience in the ADA field.	No experience, <2 years, 2-5 years, 5-10 years, >10 years
Org_Size	Please indicate the size of your organization in terms of employees	<10, 11-50, 51-250, 251-1000, >1000
Work_org	Please indicate how long you have been working in the current organization.	<2 years, 2-5 years, 5-10 years, >10 years
Org_age	Please indicate how long your organization exists.	<5 years, 6-15 years, >15 years