Conceptual Model for SMEs' Data Maturity Assessment

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Abstract Digital transformation has brought about a rapid shift towards a completely digital enterprise, generating a huge amount of data. Most small and medium-sized enterprises (SMEs) have data stored in different places, formats, and systems, or are unaware that it exists (Dark Data). While digital technologies are at the root of rapid data growth within and outside organizations, sharing and exchanging data between organizations presents an additional challenge. We argue that one of the barriers to the successful digital transformation of SMEs is data immaturity. The concept of data maturity has been addressed from different aspects (data quality, governance,...), in specific domains (supply chain management, manufacturing companies,...) and from the perspective of the Capability Maturity Model. However, there has been no study that has addressed a comprehensive assessment of data maturity for the SME sector as a multi-criteria problem. In this research, we propose to combine the ideas of maturity models and multi-criteria decision modeling by using a design science research approach. The developed model will help SMEs assess their data maturity level and help them understand what aspects of data maturity they need to advance, what steps they need to take, and how to evaluate their progress.

Keywords: digital transformation, data, SMEs, data maturity, model

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1 Introduction

Digital transformation has caused the widespread creation of digital products and services and initiated the transformation from traditional business towards the completely digital one. Digital transformation refers to changes in the way companies operate and create value (new business models, products, and services) and the way they communicate, using digital technologies (Morakanyane et al., 2017; Vial, 2019). To digitally transform, companies need to respond and adapt to these changes by creating an appropriate organizational climate (open communication, experimentation, and agility), investing in digital capabilities, developing employees, and engaging in effective knowledge management supported by informed and timely decision-making (Kljajić Borštnar & Pucihar, 2021).

One of the important elements of digital transformation is data (Mitra et al., 2019), which is becoming an important strategic resource in the organization. The amount of data collected and generated is rapidly increasing within and outside organizations. Data can be a competitive advantage, if managed properly. On the other hand, data and data management technologies, when not managed properly, present high costs. With no identified added value in the end, data can end up being a frustration for the organization (Ahlstrom, 2019; Sharma, 2020). The ability to utilize internal and external data to its fullest potential affects the ability to digitally transform as a whole (Kotsev et al., 2020). »Data-driven« is so intertwined with digital transformation, that some authors use the term data-driven digital transformation (Capgemini, 2018), or even data-driven transformation (Someh & Wixom, 2017). In our thesis paper, we understand that data is an essential part of the digitalization process, which results in digital transformation. Further, we define a data-driven organization as an organization that collects, generates, stores, manages, uses, and controls its data in a comprehensive manner, to support its daily operations and decision-making. Such organizations can be referred to as data mature organizations.

We derive our proposition from the idea, that data maturity is crucial to achieve broader goals of digital transformation.

2 Previous literature

Research on data-driven transformation is growing, however, we have noticed a lack of literature that is more oriented towards data maturity of organizations, with a particular focus on data maturity models in relation to SMEs. The previous literature is mainly oriented on data-driven business model innovation (Cheah & Wang, 2017; Marcinkowski & Gawin, 2020), data analytics and its capabilities (Carvalho et al., 2019; Dremel et al., 2017; O'Donovan et al., 2016), and guidelines or directions, how to become a data-driven organization (Anderson, 2015; Berntsson Svensson & Taghavianfar, 2020). The data maturity models, observed in the literature are either focused on a specific area of data maturity, too generic or focused on large organizations. Nevertheless, most elements of the available models can be also applied to small and medium-sized enterprises, to provide them the starting point for data maturity assessment.

(Sen et al., 2006) focused on the maturity of the data warehousing process and the identification of the influencing factors following the Capability-Maturity Model (CMM), which could help characterize the corresponding maturity levels. They found that the most prevalent factors were data architecture, supported by online analytical processing (OLAP), business analytics and its alignment with business strategy, data quality, organizational readiness and resources (human, financial and technical), change management, and data warehouse size. Change management relates to changes and adaptations of data mechanisms and technologies, and OLAP refers to the analytical tool that enables analysts to gain meaningful information and insights from a vast and diverse variety of data, stored in databases (Moon et al., 2007). The results also showed that analytical culture is one of the most important factors to consider when assessing data warehouse maturity.

(Rivera et al., 2017) developed the data governance maturity model for micro-sized organizations and validated it on the case of a financial organization. The results showed that organizational culture, data processing and analysis, data integration, and interoperability are the main issues in micro-sized organizations, that should be given more emphasis to achieve greater data governance maturity.

(Sternkopf & Mueller, 2018) developed a model to help organizations assess their level of data literacy based on 3 main dimensions - data culture, data ethics and security, and level of data manipulation (retrieval, verification, analysis, visualization, evaluation, and its interpretation). Others, (Loshin, 2011) proposed the maturity model for assessing data quality. The proposed model assesses data quality based on eight dimensions (data expectations, measures, the level of established data policies, standards and procedures, applied data governance mechanisms, the level of technology and tools, data auditing, and reporting). Data expectations indicate, how much the organization emphasizes the importance of data quality. Similarly, (Al-Sai et al., 2020) developed a classification framework for the factors that organizations can consider when implementing Big Data analytics.

3 Problem definition

Data has been an important driver of change since expert systems in decision making (Mandinach et al., 2006; Power, 2008; Provost & Fawcett, 2013), but less attention has been paid to the role of data in assessing data maturity. Every organization, including small and medium-sized enterprises (SMEs), needs quality data and needs to know, how to manage it comprehensively, if they want to be competitive in the market. Most SMEs have their data scattered in different information systems and thus have a structure with a low level of interoperability, a low level of data governance applied, and a lack of good auditing and traceability of the data they collect and generate internally or externally.

Even though the organizations began to exploit the use of data more effectively in their digital transformation process, small and medium-sized enterprises (SMEs) are lagging behind. This is evident from the data provided by (Eurostat, 2021), which shows that more than half of SMEs do not use data analytics to analyze the data they collect and further extract the value that the data they collect could provide. This shows that most SMEs are not aware of the important role of data, nor do they have a defined approach to data management and governance that would address this issue in a systematic and comprehensive manner. It is important for SMEs to first identify what data they collect and generate, what quality of data they have, and for what purpose they are currently using it. To help them do this, various digital maturity models and tools have been developed. In addition, data maturity frameworks and models have been developed to help companies analyze the current state of the data they collect and generate, assess the level of their data usage and management, and serve as a guide for implementing the necessary steps towards becoming a data-driven organization and towards digital transformation in general.

We start from the proposition that it is possible to assess the data maturity of SMEs. This will help them to 1) better understand what to do with the data they have and collect and what steps to take to make better use of the data, and 2) to later assess their progress.

This dissertation will focus specifically on small and medium-sized enterprises and their assessment of data maturity. It will discuss the role of data as a key driver of change in digital transformation and as a foundation for quality-based data-driven decision-making.

The previous literature (Rivera et al., 2017; Sen et al., 2006; Sternkopf & Mueller, 2018) proposed a few data maturity models or frameworks, focusing on a specific area of data maturity (such as data warehouse maturity) or single aspects (data quality, data governance, data stewardship, etc.). None of the data maturity models examined, address the needs of SMEs. SMEs usually lack resources (financial, human, time, skills), so they need a comprehensive, systematic, and easy-to-use tool to help them assess the state of data and understand further steps towards data maturity. We need to consider that the problem of data maturity is multi-faceted. In order to assess the data maturity of an organization, we need to consider several criteria and address the problem by using multi-criteria decision modeling. The multi-criteria models are used to evaluate the alternatives (in this case, individual SMEs) (Mardani et al., 2015) and help us to set the proper criteria (in our case, criteria for data maturity assessment).

The aim of this paper is to develop a multi-criteria data maturity assessment model for small and medium-sized enterprises, to evaluate different levels of data maturity, and help SMEs to achieve a more systematic and comprehensive data management and governance, which will contribute to further digital transformation of SMEs. Based on the identified data maturity level, the proposed model will highlight the gaps in the areas they need to invest more, to raise their data maturity level, and start implementing the necessary steps to realize this issue. The results of the work will contribute to the modeling of decision knowledge in the field of data maturity assessment and will be useful for creating policies and strategies in the field of data science.

4 Methodology

We will use a design science research (DSR) approach (Hevner et al., 2004), within which we will develop an IT artifact - a multi-criteria data maturity model. Design science research relates to the iterative sequence of expert activities, to produce an innovative product (artifact). The artifacts can be constructs, methods, instantiations, or models. The evaluation of the artifact provides feedback and a better understanding of the problem, which allows us to improve the quality and the design of the artifact (Hevner et al., 2004, p. 78).

First, we will conduct a literature review with a focus on a data-driven digital transformation field, data maturity, data-driven decision making, data-driven organization, data governance models, and related fields. From the selected literature, we will in addition review the references in the reference list and selected those relevant for our research. In the next step, we will conduct interviews with selected small and medium-sized enterprises, to identify the actual problems the SMEs have in practice and are related to the data maturity problem. This will give us a deeper insight into what they have already achieved in the data maturity field and how they currently address this issue and feedback to our existing knowledge and literature.

In doing so, we will follow the three main cycles rooted in the DSR research, represented by the rigor, relevance, and design cycle (Figure 1). Based on the reviewed literature and conducted interviews, we will define the criteria needed for data maturity assessment, design data maturity levels, and develop a multi-criteria data maturity model (the design cycle), using DEX methodology and the gathered insights from the interviews. DEX (Bohanec et al., 2013) is a qualitative multi-attribute decision-making method, implemented in freely available software for multi-attribute decision making, DEXi (Bohanec, 2021).

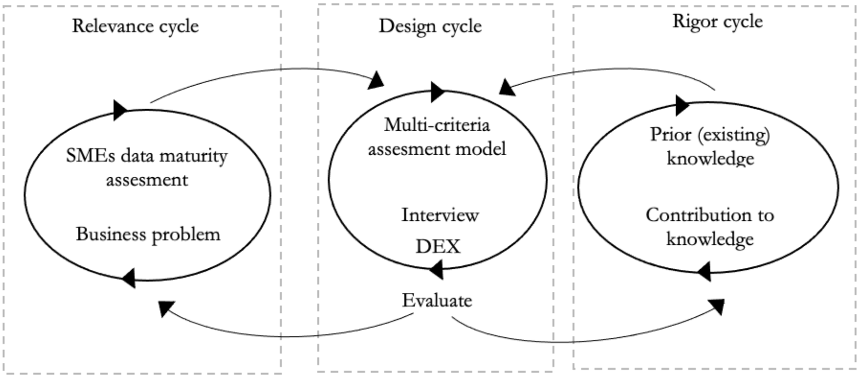

Figure 1: Methodology process - adapted from (Hevner, 2007)

The model will be validated on the real cases of SMEs. After the model validation, we will re-design the model, if needed, and extract the findings. Based on the current observation from the literature and the identification of a real (business) problem in practice, we will try to answer the following research questions: RQ1: "*What are the criteria that will allow us to assess the level of data maturity in SMEs?*" and RQ2: "*Is it possible to develop a sensitive multi-criteria model, that will well enough separate data maturity levels?*".

5 Preliminary/Expected results and future development

Future development in our research will focus on criteria identification, which will help us to develop the multi-criteria model to assess data maturity. We expect that the developed and validated model will be used in practice in the real environment and will thus represent a contribution to science and the real business environment. In addition, we expect that it will be possible to transfer the developed model to other businesses (not only to small and medium-sized enterprises) and to include the use of the questionnaire, which could increase the usability of the developed model for a larger number of organizations. In our next steps, we will validate the identified criteria from the literature with interviews in selected small and medium-sized enterprises. We expect that the findings from the interviews will contribute to a better understanding of the problem.

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