THE DATA ANALYTIC CAPABILITY WHEEL: AN IMPLEMENTATION FRAMEWORK FOR DIGITALIZATION

ALINDA KOKKINOU,[1,2] TON VAN KOLLENBURG,[2]
ALBERT MANDEMAKERS,[1] ERIC HOPSTAKEN,[1]
JAN VAN ELDEREN[1]

[1] Breda University of Applied Sciences, Academy of Built Environment and Logistics, Breda, Netherland
kokkinou.A@buas.nl, mandemakers.a@buas.nl, hopstaken.e@buas.nl, elderen2.j@buas.nl
[2] AVANS University of Applied Sciences, Center of Expertise Well-Being Economy and New Entrepreneurship, Breda, Netherland
ajc.vankollenburg@avans.nl

For mature organizations to engage in digital transformation, they first must engage in digitization and digitalization. Digitalization requires the organizations to possess data analytic capability: the ability to transform data into useful insights in a way that creates or maintains competitive advantage. The purpose of this study was to formulate a practical framework for the implementation of digitalization. For this, a qualitative approach was used. Relevant aspects of data analytic capability were identified, based on a review of the literature supplemented with semi-structured interviews with organizations currently implementing digitalization. With these findings a preliminary implementation framework entitled the "Data Analytic Capability Wheel" was formulated. The aspects encompassed by this framework included data quality, data analytics, IT infrastructure, processes, employee knowledge and skills, and management. Future research should refine and validate this framework and examine whether it leads to the successful implementation of DAC in organizations.

Keywords:
digitalization,
data,
analytic
capability,
change
management,
data,
implementation

University of Maribor Press

DOI https://doi.org/10.18690/um.fov.6.2023.5
ISBN 978-961-286-804-8

1 Introduction

In an increasing complex and globalized world, digital transformation has been recognized as an important avenue for organizations to create or at least maintain competitive advantage (Hess et al., 2016). Digital transformation has been linked to improved firm performance (Popovič et al., 2018), through increased organizational agility (Ghasemaghaei et al., 2017; Gong & Ribiere, 2023). Digital transformation is defined as "*a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies*" (Vial, 2019, p. 121), where entity refers to organizations, industries, or more generally, society.

Two related phenomena are confounded with digital transformation, namely digitization and digitalization, but for the purpose of this study they will be disentangled following Machado et al.'s (2019). Digitization is defined as "*the technical process of converting analog signals into a digital form, and ultimately into binary digits*" (Legner et al., 2017, p. 301). Digitalization is defined as "*the use of the technologies and data to improve and transform the business processes*" while digital transformation is broader, "*encompassing changes in the business models, activities, processes, and competences to enable to have all benefits of the full deployment of the new technologies*" (Machado et al., 2019, p. 1114). The scope of the present study is on the process of digitalization.

Organizations benefit from digitalization in two ways: (1) by increasing their internal efficiency (e.g. through more efficient product development and/or more efficient manufacturing) and (2) by adding value for customers and other stakeholders (e.g. through more sophisticated products and services) (Björkdahl, 2020). To achieve these outcomes, organizations need to develop their Data Analytic Capability (DAC), that is the ability to turn data into actionable insights by orchestrating data assets, IT infrastructure, and human talent in such a way that they create competitive advantage (Garmaki et al., 2016; Mikalef et al., 2018).

A variety maturity models have been developed to support organizations pursuing the development of DAC, digitization and/or digital transformation (Cosic et al., 2012; E. Gökalp & Martinez, 2021; Hein-Pensel et al., 2023; Korsten et al., 2022) from the perspective of diverse disciplines. From the Information Systems (IS) perspective, several models have been developed that stem from the Capability

Maturity Model (CMM), and include the Business Analytics CMM (BACMM) (Cosic et al., 2012), the Data Science CMM (DSCMM) (M. O. Gökalp et al., 2022), the Advanced Data Analytics CMM (ADACMM) (Korsten et al., 2022) and the Advanced Analytics CMM (Social Security Administration Analytics Center of Excellence, 2020). Other maturity models developed include those of Comuzzi and Patel (2016), and Grossman (2018). In the discipline of operations management, maturity models have been developed for digitalization and digital transformation (E. Gökalp & Martinez, 2022) and industry 4.0 (Ganzarain & Errasti, 2016; Mittal et al., 2018). These maturity models encompass a variety of aspects required for the organization to develop, including organization, infrastructure, data management, analytics, and governance (Comuzzi & Patel, 2016).

These maturity models have one to three complementary purposes, namely describing the current situation, prescribing guidelines for development, and enabling organizations to benchmark their development internally and externally (Hein-Pensel et al., 2023; Pöppelbuß & Röglinger, 2011). However, a common criticism of maturity models include the lack theoretical and empirical grounding of these models, having mostly been developed by consultants and software vendors (Comuzzi & Patel, 2016; Gupta & George, 2016; Mikalef et al., 2019) and their lack of actionability for organizations due to their descriptive/ comparative nature in combination with their complexity (Barton & Court, 2012; Hein-Pensel et al., 2023). Furthermore, the majority of maturity models examined do not consider all the aspects needed to develop capabilities related to digitalization (Hein-Pensel et al., 2023).

Existing research frequently takes an information technology (IT) perspective and focuses on issues of data quality, IT infrastructure and systems (Mikalef et al., 2017). Yet, a successful development of DAC is much more complex, involving factors such as people's knowledge and skills, processes, and organizational change (Ghasemaghaei et al., 2018; Mikalef et al., 2018). Studies that have embraced a more holistic view have also recognized the importance of organizational context (Mikalef & Krogstie, 2020). Thus, much remains unexplored about how organizations can develop their DAC, given their organizational context.

The purpose of this study was to formulate a practical framework for the implementation of digitalization, taking a multi-disciplinary approach and focusing on how organizations can "*configure, orchestrate and exploit competencies, assets, and data generated from digital technologies*" (Björkdahl, 2020). As many models are perceived to be too complex (Hein-Pensel et al., 2023), the point of departure for this framework was that it needed to be relatable for practitioners. A multi-disciplinary review of the literature was used to identify relevant aspects of DAC and formulate a preliminary framework (section 2). The qualitative research approach to collecting empirical data is presented in section 3 and the findings thereof in section 4. These led to the refinement of the preliminary framework and the formulation of an implementation framework: the Data Analytic Capability Wheel presented in section 5, followed by the discussion. Limitations and recommendations for future research are detailed in section 7.

2 Review of the Literature

Digitalization is a widely used term, both in academic and professional publications, leading to ambiguity (Bloomberg, 2018). For the purpose of this study, digitalization denotes an organizations' ability to improve its processes through the use of data and/or related technologies. However, this definition only reduces the ambiguity slightly, as digitalization has been defined and operationalized differently across disciplines. The present study therefore reviews literature from several disciplines, including management, manufacturing, supply chain, and business information systems to identify relevant aspects for the implementation of digitalization.

2.1 Digitalization, Data Analytic Capability, and Industry 4.0

In the context of manufacturing, digitalization has led to the concept of Industry 4.0 or Smart Industry (Rosin et al., 2020) and "*represents the current trend of automation technologies in the manufacturing industry*" (Shahin et al., 2020, p. 2928). From this perspective, digitalization is primarily concerned with improving the efficiency of processes, by improving cost, quality, lead time and flexibility (Khanchanapong et al., 2014). In the context of supply chain management, digitalization has led to the concepts of DAC and Big Data Analytic Capability (BDAC). DAC refers to an organization's capability to deploy data, technology and people to quickly access and analyze information to support complex decision-making (Yu et al., 2021) with some authors scoping this definition to big data (Dubey et al., 2019). While there are merits to distinguishing between the two, technological developments in this area are very rapid. Due to technological developments, what was considered big data and thus challenging to deal with in the past may no longer be considered challenging a few years later, thus broadening the applicability of DAC (Kokkinou et al., 2022a).

While digitalization, Industry 4.0, and DAC are related concepts, Industry 4.0 focuses more on the application of the technologies associated with digitalization (IoT, robotics etc.) whereas DAC encompasses the pre-requisites thereof (Garmaki et al., 2016; Mikalef et al., 2018). Furthermore, the concept of DAC is more comprehensively defined and is coupled with a sounder theoretical foundation. Therefore, the remainder of this paper will focus on DAC.

2.2 Theoretical Foundations

DAC has strong theoretical foundations in the contingent Resource-Based View of the firm (RBV) (Brandon-Jones et al., 2014; Mikalef & Krogstie, 2020; Wu et al., 2006; Yu et al., 2018). According to RBV, organization's resources can be a source of sustained competitive advantage if they are valuable, rare, cannot be imitated or substituted (Barney, 1991). However, according to the contingent perspective, the potential of capabilities to lead to competitive advantage will depend on their alignment with contextual factors such as national context and culture, firm size, strategic context, and other organizational context variables (Aragón-Correa & Sharma, 2003). Thus DAC can only become a source of competitive advantage for an organization if the organization is able to configure, orchestrate and exploit the tangible, intangible, and human aspects necessary in a way that fits its unique context (Björkdahl, 2020; Ghasemaghaei et al., 2018; Mikalef & Krogstie, 2020).

2.3 Data Analytic Capability Development

The topic of how DAC should be developed has been investigated from a variety of perspectives, including industry drivers and barriers, organizational enablers, organizational readiness, and organizational maturity (Nayernia et al., 2022). On an organizational level, which is the scope of our study, several ways exist to classify the aspects that make up DAC. Gupta and George (2016) distinguished between tangible, intangible, and human resources, where tangible resources included data, technology, basic resources such as time and investment. Intangible resources included a data-driven culture and the intensity of organizational learning, and human resources included managerial skills and technical skills. Mikalef et al. (2017, 2018) further elaborated on this classification. Their review of resources needed to build DAC formed the basis of the list of relevant aspects shown in Table 1.

Table 1: Relevant aspects for DAC implementation

Data	*Access to relevant data:* Organizations need to be able to identify, access, and if necessary, acquire relevant data (Behl et al., 2019) *Data Quality :* Data needs to be complete, accurate, timely, reliable and of value (Mikalef et al., 2017, 2018). *Data Governance*: Organizations need to put in place procedures to ensure that can create, capture, store, use, retrieve and delete data (Mikalef & Krogstie, 2018; Tallon, 2013) also referred to as *Data Management* (Jha et al., 2020) *Inductive vs. Deductive Approaches:* inductive approaches to data can result in insights that are new to the organization but require large investments in data and the ability to analyze it. Conversely, a deductive approach where data are collected, processed, and visualized for specific purposes can be more effective yet lead to tunnel vision (Günther et al., 2017)
Data Analytics	*Data Analytic Tools* are typically classified in descriptive, predictive and prescriptive tools (Ghasemaghaei et al., 2017) *Tool sophistication:* more sophisticated analytical tools (e.g. machine learning and artificial intelligence) enable organizations to conduct deeper analysis (Ghasemaghaei et al., 2018)
Technology	*IT Infrastructure:* Organizations need to have at their disposal an infrastructure that can collect, analyze, store and share data (Gupta & George, 2016; Mikalef et al., 2018). *Technical support from vendor:* organizations still rely on technology providers to support them (Behl et al., 2019)
Structure and Processes	*Centralized or Decentralized Structure:* Centralization seems to facilitate the development of DAC by pooling scarce resources whereas decentralization improved collaboration between domain experts and data scientists (Günther et al., 2017)
Organizational Learning	*Organizational learning* refers to the degree to which employees are open to extending their knowledge in the face of new emerging technologies. *Training and development of employees* is an important mechanism for organizational learning (Behl et al., 2019; Kokkinou et al., 2021)

Management	*Commitment and Support:* managers need to have a long-term orientation to investments and provide resources to data analytic teams (Tabesh et al., 2019) also referred to as *Attitude of top management* (Behl et al., 2019) *Effective communication and coordination:* managers should encourage cross-functional collaboration, disseminate data-driven insights, and create a common understanding of big data goals (Tabesh et al., 2019) *Gaining managerial analytics acumen:* managers need to gain relevant analytics knowledge and help and incentive their staff (Tabesh et al., 2019; Vidgen et al., 2017)
Employee Knowledge and Skills	*Domain knowledge:* employees need a deep understanding of the procedures, facts, and processes of the organization in order to be able to solve business problems of interest to the firm (Ghasemaghaei et al., 2018) *Talent and skills to analyze and interpret data:* Employees need to be able to generate business insights from the use of data analytics (Ghasemaghaei et al., 2018), also referred to as technical skills (Behl et al., 2019)

3 Methodology

Consistent with previous research, we used qualitative approach consisting of a combination of interviews with key informants, review of company documents and thematic analysis (Jha et al., 2020). The unit of analysis for our study was organizations' implementation of digitalization, a complex phenomenon affected by internal and external factors. A qualitative research approach was therefore deemed appropriate as it allowed for an in-depth understanding of the phenomenon with the purpose of analytic generalization (Yin, 2013). We used purposive homogeneous sampling (Gray, 2014) to identify four Dutch organizations in our network that were actively engaged in digitalization projects. We conducted individual and group interviews with key informants from each organization (Jha et al., 2020), supplemented with archival research of internal company documents for one organization (see table 2) and reviewed the websites of all organizations to collect additional information about relevant contextual variables.

The use of semi-structured interview guide based on open question interview protocols allowed important topics to be addressed while giving interviewees the possibility to express their emerging insights and comments. All interviews were recorded with participants' permission, freeing up the researchers to observe and take notes and thus improving their understanding of each interview's context (Ralston & Blackhurst, 2020). The semi-structured interview guide consisted of an introductory section, a general section about the organization and the respondent. The subsequent sections were about data and IT infrastructure, processes, employee skills and training, and the role of management.

Table 2: Overview of Data Collection

Org	**Type of Organization**	**Data Collection Methods**	**Duration**
1	Production Company (W)	Project Manager (I)	70 min
2	Retail (W)	Transportation Manager (I)	80 min
3	SME in High Tech Production (W)	Management Team (GI) Project Reports (Docs)	150 min
4	Production company in High Tech Sector (W)	Process Engineer & Continuous Improvement Specialist (GI)	120 minutes

(I: individual interview, GI: group interview, W: website review, Docs: internal document review)

The transcripts and notes were analyzed using the software Atlas.ti by applying the steps of thematic analysis (Jha et al., 2020) as recommended by Braun and Clarke (2006), namely familiarization with the data, generation of deductive codes based on the literature review (based on table 1), search for themes, revision of themes and selection of illustrative codes.

4 Findings

The purpose of the study was to formulate an implementation framework for digitalization, by exploring relevant aspects for the development of DAC. The numbers in brackets (e.g. [Org#1]) refer to the organizations listed in Table 2.

Theme 1: Knowledge and skills within the organization as a pre-requisite

The organizations we interviewed were all actively developing their DAC. However, three of the four organizations recognized that there were insufficient knowledge and skills within the organization to do so in a structured way. First, a lack of awareness about digitalization inhibited the urgency for the organization to pursue development in this area. Second, a lack of knowledge of data, data analytics and data management led to difficulties imagining how data could be used to improve decision-making. In the words of a respondent: "*we fell behind [in digitalization] in the sense that the need had not been recognized in our department, and the knowledge was not there to dive into it. Since my colleague and I started working on it, the need has been recognized,. Before, no one was busy with the idea that we had to become more data-driven.*" [Org#2]

To develop their DAC, the organizations first had to introduce knowledge and expertise about data and data analytics within the organization. For organizations 1 to 3 this happened by employing interns and/or recent graduates with an interest and affinity for data analytics and ensuring management gave them space to experiment. Organizations 1 and 2 also hired consultants to work for a longer period along their employees. Organizations 3 and 4 maintained close contacts with their software vendors who provided some of the knowledge.

Theme 2: Role of management to provide leadership, support and resources

In all four organizations, management's knowledge and skills about digitalization were limited. although their interest in the topic was increasing. In organizations 1 and 2, interested and knowledgeable employees receiving the time and resources to demonstrate its added value fueled the desire to increase digitalization. Management was also willing to invest in the IT infrastructure. As an interviewee stated: "*management sees that is really important and are prepared to invest in good systems. Think of a new supply chain application, a centralized department, employees for it, and capacity to manage all of this*" [#Org. 1]

Theme 3: Evolution of structure and processes

All four organizations seemed to be undergoing extensive developments in terms of structure, responsibilities, and processes related to digitalization. Organizations 1 and 2 saw the development of a centralized department, separate from IT, consolidating knowledge and expertise of DAC. In both cases, this department was in the process of taking ownership of the data management processes of the organization and supported departmental employees and teams in their choices of IT infrastructure. In organizations 1, 2 and 4 there was a concerted effort to inventory all the applications currently in use in the organization and formulate a plan to coordinate and manage them. For example, according to organization 4: "*our senior management has appointed a task force to review the application landscape within the organization and come up with a comprehensive data management plan*"[#Org 4]. In organization 3, the need for a data management plan was increasingly felt by senior management. However, due to a lack of knowledge and skills in this area within the organization, management was encountering difficulties in formulating a plan of action and deciding how to invest in IT infrastructure. In their words: "*we keep making small steps forwards with the best intentions, but we can't say 'this is where we are going' and make big steps.*" [#Org3]

Theme 4: Missing link to strategy

For organizations 3 and 4, the pressure to digitalize was external as it was imposed on them by customers and as a requirement to remain competitive. Despite a lack of skills and expertise on the topic of DAC, management was very committed to digitalization. For example, both organizations were actively seeking cooperations with universities by participating in student projects, providing internships, and by participating in academic research activities.

A striking finding was that none of the organizations involved formulated clear objectives for the implementation of digitalization were formulated beyond the departmental level. This translated to challenges deciding what data were relevant, and what projects should be prioritized. So while management was supportive and committed, it was not able to communicate in such a way that digitalization efforts were channeled in ways that supported the strategic objectives of the firm.

5 The Data Analytic Capability Wheel as a Metaphor

The above findings show that aspects of DAC do not operate independently. Instead, they are intertwined and thus require organizations to address them in a comprehensive manner. The findings of the literature review were combined with the empirical findings to formulate a preliminary implementation framework for digitalization, using a bicycle wheel as a metaphor. Bicycle wheels consist of three main parts: the hub, the spokes and the rim. The hub of a wheel is the part at its center that gives the wheel its integrity and allows it to rotate. The hub also attaches the wheel to the rest of the bicycle. The spokes of a wheel connect the hub to the rim and are meant to support the structure of the wheel. Their invention in 2000 BC was considered a revolution as they made wheels lighter and faster (Frithowulf, 2022). The rim and tire of the wheel make contact with the environment, absorbing shocks, keeping grip on the road, while transferring the wheel's speed without slipping. Applying the wheel metaphor to DAC creates a practical and relatable framework for the implementation of DAC, as explained below.

The hub of the DAC wheel is where an organization's DAC links to its organizational strategy (the bicycle). By clearly identifying and communicating how the organization's DAC contributes to its strategy, management can ensure that efforts to develop DAC are coherent. The hub is also the point around which the wheel revolves. This translates to decision-making about which resources to invest in and which projects to prioritize. The link to strategy is essential to ensure legitimacy and coherence to managerial decision-making, answering the "why pursue digitalization?" question.

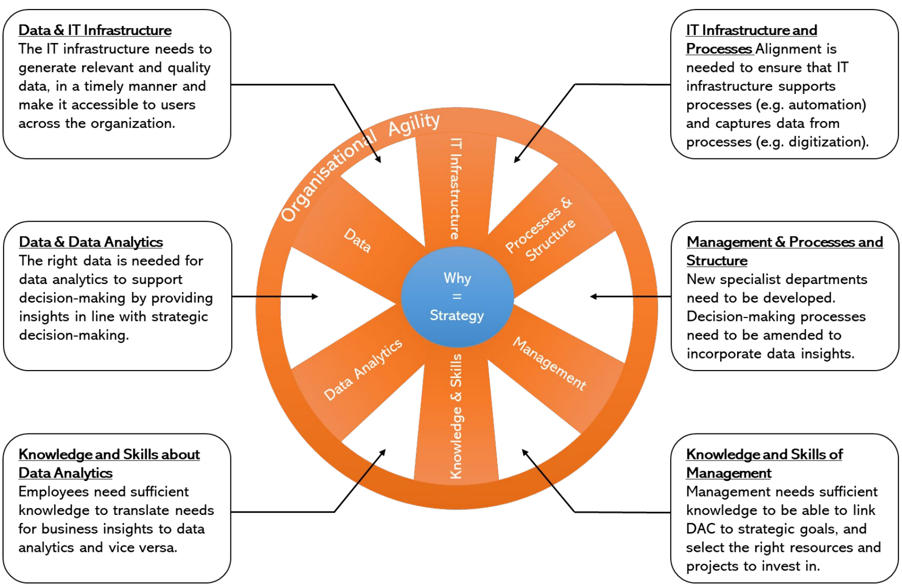

Figure 1: Implementation Framework

The spokes of the DAC Wheel are the six implementation aspects, namely Data, Data Analytics, Employee Knowledge and Skills, Management, Processes and Structure, and IT Infrastructure,. As the empirical findings show, these aspects are interrelated (see figure 1) and thus need to be considered holistically. Returning to the wheel metaphor, if spokes are of unequal length, the wheel will not turn properly and will be structurally unsound. Similarly, organizations' implementation of DAC will not be smooth or even functional if one aspect receives too much attention at the expense of the other aspects. For example, organizations that spend an outsize budget and effort on their data quality at the expense of knowledge and skills of employees will not be successful.

The rim and tire of the wheel are where the competitive advantage that DAC confers to the organization becomes apparent, by enabling the organization to sense its environment and respond quickly to changes in an effective way. The rim and tire of the DAC Wheel represent the organizational agility (Ghasemaghaei et al., 2017), defined as its "*ability to quickly respond and proactively embrace unanticipated changes in dynamic environments through effective resource reconfiguration and rapid decision-making*" (Gong & Ribiere, 2023, p. 5). Organizations that exhibit a high level of fit between different aspects such as analytical tools, data, and people will be able to better use DAC to generate organizational agility (Ghasemaghaei et al., 2017).

Just as different types of wheels are appropriate depending on the type and purpose of a bicycle, organizations will develop DAC in a way consistent with their strategy (e.g. cost leadership, customer engagement) (Sebastian et al., 2020).

5 Discussion

Despite the recognized importance of digitalization, there is a lack of understanding of how it should be implemented. Even when focusing on the better developed theoretical construct of DAC, there is a lack of empirical research focusing on implementation aspects. This is possibly due to the fact that academic research on the topic is typically conducted from the narrow perspective of a single discipline, most often information systems research (Gupta & George, 2016). Our findings show that a comprehensive perspective is necessary and that all three categories of DAC aspects defined by Gupta and George (2016) are relevant when implementing

DAC. Furthermore, our findings show that DAC aspects are strongly inter-related and thus the development of DAC needs to take a holistic approach.

Two aspects of DAC play a more prominent role, namely management and knowledge and skills. First, an initial seed of knowledge and skills within the organization is needed to create awareness and help the organization make the first steps towards developing DAC. Management plays an important role in acquiring this knowledge and expertise for the organization, and turning it into explicit and implicit organizational knowledge, either through hiring new employees, training existing employees by appealing to their intrinsic motivation (Pieters et al., 2022), or creating access to outside expertise (Behl et al., 2019; Kokkinou et al., 2021). Second, consistent with Tabesh et al. (2019), Mikalef et al. (2019) and Vidgen et al. (2017), we found that management plays an important role in orchestrating the necessary aspects of DAC. To be effective, management first need to acquire knowledge and skills themselves. Management needs to showing commitment and give support by allocating the right resources to the right people (Kokkinou et al., 2023). Furthermore, management needs to communicate the importance of DAC by linking it to the strategic objectives of the firm, a finding that parallels literature on continuous improvement implementation (Kokkinou et al., 2022b).

Consistent with IS research (Ghasemaghaei et al., 2017, 2018), we found that data and IT infrastructure received the most attention as organizations focused on collecting data of sufficient quality for data analytics projects. However, organizations were increasingly recognizing that processes and structure played an important role in ensuring that appropriate data were collected and shared across the organizations, leading to changes in the organizational structure and corresponding processes. Our study contributes to the notion that the implementation of digitalization, and specifically the development of DAC concerns complex socio-technical processes, requiring a multi-disciplinary perspective (Legner et al., 2017; Mikalef & Krogstie, 2020).

7 Limitations and Further Research

While the implementation framework presented in this paper is based on a multi-disciplinary review of the literature, this approach remains inferior to a structured review of the literature. It is therefore recommended to refine this framework through a structured review of the literature that encompasses more disciplines related to the use of data in decision-making. Similarly, four interviews are insufficient to validate the framework. Further research should adopt an action methodology to further test, validate, and refine the DAC Wheel. Finally, the study findings show similarities and overlap with literature on continuous improvement implementation. Further research should examine whether success factors of continuous improvement implementation could also apply to the implementation of digitalization.

References

Aragón-Correa, J. A., & Sharma, S. (2003). A Contingent Resource-Based View of Proactive Corporate Environmental Strategy. *The Academy of Management Review*, *28*(1), 71. https://doi.org/10.2307/30040690

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Barton, D., & Court, D. (2012). Making advanced analytics work for you. *Harvard Business Review*, *90*(10), 78–83.

Behl, A., Dutta, P., Lessmann, S., Dwivedi, Y. K., & Kar, S. (2019). A conceptual framework for the adoption of big data analytics by e-commerce startups: A case-based approach. *Information Systems and E-Business Management*, *17*(2–4), 285–318. https://doi.org/10.1007/s10257-019-00452-5

Björkdahl, J. (2020). Strategies for Digitalization in Manufacturing Firms. *California Management Review*, *62*(4), 17–36. https://doi.org/10.1177/0008125620920349

Bloomberg, J. (2018, April 29). Digitization, Digitalization, And Digital Transformation: Confuse Them At Your Peril. *Forbes*. https://www.forbes.com/sites/jasonbloomberg/2018/04/29/digitization-digitalization-and-digital-transformation-confuse-them-at-your-peril/?sh=62d90292f2c7

Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A Contingent Resource-Based Perspective of Supply Chain Resilience and Robustness. *Journal of Supply Chain Management*, *50*(3), 55–73. https://doi.org/10.1111/jscm.12050

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

Comuzzi, M., & Patel, A. (2016). How organisations leverage Big Data: A maturity model. *Industrial Management & Data Systems*, *116*(8), 1468–1492. https://doi.org/10.1108/IMDS-12-2015-0495

Cosic, R., Shanks, G., & Maynard, S. (2012). *Towards a business analytics capability maturity model.*

Dubey, R., Gunasekaran, A., & Childe, S. J. (2019). Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility. *Management Decision*, *57*(8), 2092–2112. https://doi.org/10.1108/MD-01-2018-0119

Frithowulf, H. (2022, September 4). Timeline of the Wheel: History and Invention. *Malevus*. https://malevus.com/how-the-wheel-was-invented-and-developed/

Ganzarain, J., & Errasti, N. (2016). Three stage maturity model in SME's toward industry 4.0. *Journal of Industrial Engineering and Management (JIEM)*, *9*(5), 1119–1128.

Garmaki, M., Boughzala, I., & Wamba, S. F. (2016). *The effect of Big Data Analytics Capability on Firm Performance*. 301.

Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2018). Data analytics competency for improving firm decision making performance. *The Journal of Strategic Information Systems*, *27*(1), 101–113. https://doi.org/10.1016/j.jsis.2017.10.001

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. https://doi.org/10.1016/j.dss.2017.06.004

Gökalp, E., & Martinez, V. (2021). Digital transformation capability maturity model enabling the assessment of industrial manufacturers. *Computers in Industry*, *132*, 103522. https://doi.org/10.1016/j.compind.2021.103522

Gökalp, E., & Martinez, V. (2022). Digital transformation maturity assessment: Development of the digital transformation capability maturity model. *International Journal of Production Research*, *60*(20), 6282–6302. https://doi.org/10.1080/00207543.2021.1991020

Gökalp, M. O., Gökalp, E., Kayabay, K., Koçyiğit, A., & Eren, P. E. (2022). The development of the data science capability maturity model: A survey-based research. *Online Information Review*, *46*(3), 547–567. https://doi.org/10.1108/OIR-10-2020-0469

Gong, C., & Ribiere, V. (2023). Understanding the role of organizational agility in the context of digital transformation: An integrative literature review. *VINE Journal of Information and Knowledge Management Systems*. https://doi.org/10.1108/VJIKMS-09-2022-0312

Gray, D. E. (2014). *Doing research in the real world* (3. ed). Sage.

Grossman, R. L. (2018). A framework for evaluating the analytic maturity of an organization. *International Journal of Information Management*, *38*(1), 45–51. https://doi.org/10.1016/j.ijinfomgt.2017.08.005

Günther, W. A., Rezazade Mehrizi, M. H., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *The Journal of Strategic Information Systems*, *26*(3), 191–209. https://doi.org/10.1016/j.jsis.2017.07.003

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*(8), 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

Hein-Pensel, F., Winkler, H., Brückner, A., Wölke, M., Jabs, I., Mayan, I. J., Kirschenbaum, A., Friedrich, J., & Zinke-Wehlmann, C. (2023). Maturity assessment for Industry 5.0: A review of existing maturity models. *Journal of Manufacturing Systems*, *66*, 200–210. https://doi.org/10.1016/j.jmsy.2022.12.009

Hess, T., Matt, C., Benlian, A., & Wiesböck, F. (2016). Options for formulating a digital transformation strategy. *MIS Quarterly Executive*, *15*(2).

Jha, A. K., Agi, M. A. N., & Ngai, E. W. T. (2020). A note on big data analytics capability development in supply chain. *Decision Support Systems*, *138*, 113382. https://doi.org/10.1016/j.dss.2020.113382

Khanchanapong, T., Prajogo, D., Sohal, A. S., Cooper, B. K., Yeung, A. C. L., & Cheng, T. C. E. (2014). The unique and complementary effects of manufacturing technologies and lean practices on manufacturing operational performance. *International Journal of Production Economics*, *153*, 191–203. https://doi.org/10.1016/j.ijpe.2014.02.021

Kokkinou, A., Mandemakers, A., & Mitas, O. (2022a). Data-analytic capability as a path to a resilient supply chain: An empirical investigation. *Presented at the 2022 EurOMA Conference*. EUROMA, Berlin, Germany.

Kokkinou, A., van Kollenburg, T., & Touw, P. (2022b). The road to operational excellence is scenic: Tales of continuous improvement journeys. Presented at the 2022 EurOMA Conference. European Operations Management Association (EurOMA), Berlin.

Kokkinou, A., Kollenburg, T. van, & Mandemakers, A. (2023). Development of data analytic capability in organizations. *Presented at the 2023 EUROMA Conference*. Leuven, Belgium

Kokkinou, A., van Kollenburg, T., & Touw, P. (2021). The Role of Training in the Implementation of Lean Six Sigma. *Presented at the 2021 EurOMA Conference*. European Operations Management Association (EurOMA), Berlin.

Korsten, G., Aysolmaz, B., Turetken, O., Edel, D., & Ozkan, B. (2022). *ADA-CMM: A Capability Maturity Model for Advanced Data Analytics*. Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2022.032

Legner, C., Eymann, T., Hess, T., Matt, C., Böhmann, T., Drews, P., Mädche, A., Urbach, N., & Ahlemann, F. (2017). Digitalization: Opportunity and Challenge for the Business and Information Systems Engineering Community. *Business & Information Systems Engineering*, *59*(4), 301–308. https://doi.org/10.1007/s12599-017-0484-2

Machado, C. G., Winroth, M., Carlsson, D., Almström, P., Centerholt, V., & Hallin, M. (2019). Industry 4.0 readiness in manufacturing companies: Challenges and enablers towards increased digitalization. *Procedia CIRP*, *81*, 1113–1118. https://doi.org/10.1016/j.procir.2019.03.262

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research*, *98*, 261–276. https://doi.org/10.1016/j.jbusres.2019.01.044

Mikalef, P., Framnes, V. A., Danielsen, F., Krogstie, J., & Olsen, D. (2017). *Big data analytics capability: Antecedents and business value. 136*.

Mikalef, P., & Krogstie, J. (2018). *Big Data Governance and Dynamic Capabilities: The Moderating effect of Environmental Uncertainty*. 206.

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. https://doi.org/10.1080/0960085X.2020.1740618

Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2018). Big data analytics capabilities: A systematic literature review and research agenda. *Information Systems and E-Business Management*, *16*(3), 547–578. https://doi.org/10.1007/s10257-017-0362-y

Mittal, S., Khan, M. A., Romero, D., & Wuest, T. (2018). A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs). *Journal of Manufacturing Systems*, *49*, 194–214. https://doi.org/10.1016/j.jmsy.2018.10.005

Nayernia, H., Bahemia, H., & Papagiannidis, S. (2022). A systematic review of the implementation of industry 4.0 from the organisational perspective. *International Journal of Production Research*, *60*(14), 4365–4396. https://doi.org/10.1080/00207543.2021.2002964

Pieters, J. J., Kokkinou, A., & van Kollenburg, T. (2022). Understanding Blockchain Technology Adoption by Non-experts: An Application of the Unified Theory of Acceptance and Use of Technology (UTAUT). Operations Research Forum, 3(1), 1. https://doi.org/10.1007/s43069-021-00113-9

Popovič, A., Hackney, R., Tassabehji, R., & Castelli, M. (2018). The impact of big data analytics on firms' high value business performance. *Information Systems Frontiers*, *20*(2), 209–222. https://doi.org/10.1007/s10796-016-9720-4

Pöppelbuß, J., & Röglinger, M. (2011). *What makes a useful maturity model? A framework of general design principles for maturity models and its demonstration in business process management*.

Ralston, P., & Blackhurst, J. (2020). Industry 4.0 and resilience in the supply chain: A driver of capability enhancement or capability loss? *International Journal of Production Research*, *58*(16), 5006–5019. https://doi.org/10.1080/00207543.2020.1736724

Rosin, F., Forget, P., Lamouri, S., & Pellerin, R. (2020). Impacts of Industry 4.0 technologies on Lean principles. *International Journal of Production Research*, *58*(6), 1644–1661. https://doi.org/10.1080/00207543.2019.1672902

Sebastian, I. M., Ross, J. W., Beath, C., Mocker, M., Moloney, K. G., & Fonstad, N. O. (2020). How big old companies navigate digital transformation. In *Strategic information management* (pp. 133–150). Routledge.

Shahin, M., Chen, F. F., Bouzary, H., & Krishnaiyer, K. (2020). Integration of Lean practices and Industry 4.0 technologies: Smart manufacturing for next-generation enterprises. *The International Journal of Advanced Manufacturing Technology*, *107*(5–6), 2927–2936. https://doi.org/10.1007/s00170-020-05124-0

Social Security Administration Analytics Center of Excellence (2020). https://www.ssa.gov/data/data_governance_board/ACE_A2CM2_for%20DGB.pptx.pdf

Tabesh, P., Mousavidin, E., & Hasani, S. (2019). Implementing big data strategies: A managerial perspective. *Business Horizons*, *62*(3), 347–358. https://doi.org/10.1016/j.bushor.2019.02.001

Tallon, P. P. (2013). Corporate Governance of Big Data: Perspectives on Value, Risk, and Cost. *Computer*, *46*(6), 32–38. https://doi.org/10.1109/MC.2013.155

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, *28*(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*, *261*(2), 626–639. https://doi.org/10.1016/j.ejor.2017.02.023

Wu, F., Yeniyurt, S., Kim, D., & Cavusgil, S. T. (2006). The impact of information technology on supply chain capabilities and firm performance: A resource-based view. *Industrial Marketing Management*, *35*(4), 493–504. https://doi.org/10.1016/j.indmarman.2005.05.003

Yin, R. K. (2013). Validity and generalization in future case study evaluations. *Evaluation*, *19*(3), 321–332. https://doi.org/10.1177/1356389013497081

Yu, W., Chavez, R., Jacobs, M. A., & Feng, M. (2018). Data-driven supply chain capabilities and performance: A resource-based view. *Transportation Research Part E: Logistics and Transportation Review*, *114*, 371–385. https://doi.org/10.1016/j.tre.2017.04.002

Yu, W., Wong, C. Y., Chavez, R., & Jacobs, M. A. (2021). Integrating big data analytics into supply chain finance: The roles of information processing and data-driven culture. *International Journal of Production Economics*, *236*, 108135. https://doi.org/10.1016/j.ijpe.2021.108135