A Framework for Corporate Artificial Intelligence Strategy

Kajetan Schuler and Dennis Schlegel(✉)

Reutlingen University, Reutlingen, Germany
dennis.schlegel@reutlingen-university.de

Abstract. In recent years, artificial intelligence (AI) has increasingly become a relevant technology for many companies. While there are a number of studies that highlight challenges and success factors in the adoption of AI, there is a lack of guidance for firms on how to approach the topic in a holistic and strategic way. The aim of this study is therefore to develop a conceptual framework for corporate AI strategy. To address this aim, a systematic literature review of a wide spectrum of AI-related research is conducted, and the results are analyzed based on an inductive coding approach. An important conclusion is that companies should consider diverse aspects when formulating an AI strategy, ranging from technological questions to corporate culture and human resources. This study contributes to knowledge by proposing a novel, comprehensive framework to foster the understanding of crucial aspects that need to be considered when using the emerging technology of AI in a corporate context.

Keywords: Artificial intelligence · Strategic alignment · Organization · Capabilities · Governance

1 Introduction

Since its first appearance in the 1950s, artificial intelligence (AI) has experienced ups ("AI springs") and downs ("AI winters") over the course of the decades [1, 2]. With the rapid advancements of computing power, storage and data availability, AI is on the rise again, getting meaningful traction within corporations [3]. Studies and reports show that companies are increasingly infused with AI, with 50% of them using an AI application in at least one business function [4, 5]. The new AI applications help organizations to increase their productivity and customer experience as well as enhancing the decision making process by providing essential and relevant information [6].

Despite AI being regarded as an important strategic technology [7] and the fact that companies are investing heavily in AI applications, only about 17% have formulated a clear AI strategy [5]. The discrepancy between the number of companies that are adopting AI and those that have a clear AI strategy suggests that many companies are approaching AI opportunistically rather than strategically. Therefore, companies need to establish an AI strategy to systematically exploit the emerging opportunities of the

R. Jallouli et al. (Eds.): ICDEc 2021, LNBIP 431, pp. 121–133, 2021.
https://doi.org/10.1007/978-3-030-92909-1_8

technology. So far, however, there has been little discussion in the academic community about how to build such a strategy.

The aim of this study has therefore been to develop a holistic framework for corporate AI strategy to provide organizations with guidance in terms of important aspects that have to be considered in the formulation of an AI strategy.

To address this aim, a combination of different research methods was used. First, a systematic literature review [8–10] was conducted to extract relevant factors from prior studies. Next, to develop a conceptual framework, the findings from the literature were analyzed according to the codes-to-theory-model for qualitative inquiry [11] that is based on based on Grounded Analysis [12].

This study makes an original contribution by proposing a novel conceptual framework for corporate AI strategy, derived by means of a scientific procedure. The framework provides important insights for both scholars and practitioners regarding relevant questions and design parameters that have to be considered in the formulation of an AI strategy.

2 Background

2.1 Artificial Intelligence (AI)

AI is seen as a disruptive technology and, in some cases, as the fifth industrial revolution [13]. In the past years, the technology has become increasingly relevant and now permeates both economic and social everyday life [14]. Despite its importance, no uniform definition has yet emerged. This is partly due to the fact that the term intelligence itself is difficult to define [6]. The broad scope of the term leads to an inclusion of different techniques such as machine learning and statistics [15]. Researchers agree that AI is a field of research in computer science and is concerned with the development of intelligent agents that can solve problems independently [6]. To set a context for this study, the definition by Kaplan and Haenlein [16] is used. They define AI as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation."

While defining AI, the distinction between strong and weak AI is important. AI applications available today, e.g. speech recognition, belong to the class of weak AI. These programs are characterized by the fact that they were developed for a very specific task and can only perform this task [17]. In contrast, the concept of strong AI tries to reproduce human cognitive abilities in detail to develop an AI that is not specialized in individual tasks but has a general intelligence in a wide variety of subject areas [6, 17]. Since strong AI is not available today and it is questionable when it will be achieved [18], the following paper focuses on application of weak AI.

2.2 AI Strategy

The term strategy has been used by Henderson [19] to refer to a plan of action that generates a competitive advantage for the business and the execution of these actions. In other words, a strategy is an action plan that addresses current and future developments in an organization's environment and represents decisions about financial and human resources to drive performance and achieve long-term goals [20].

The widespread introduction of information systems and their increasing complexity has led to companies deriving distinct IT strategies from the existing business strategies [21]. Various studies have examined the importance of strategic alignment between business and IT in the past [22].

In a similar vein, also an AI strategy that is aligned with the general business strategy and the IT strategy can be developed. Different studies argue, that technology is not the only challenge when adopting AI in a company context [23–25]. Instead, an AI strategy must encompass more than the technology perspective. Based on the previously mentioned terminological definitions, this paper defines AI strategy as a holistic action plan for current and future adoption of artificial intelligence on an organizational level with the goal of gaining a competitive advantage.

3 Current State of Research

3.1 Previous Studies

There are several studies that have investigated challenges and success factors of the adoption of AI [24–29]. A survey with participants across different Australian industries showed, that the biggest barriers for AI adoption are unclear business cases, lack of top management support and lack of skills, and in fact not technological [23]. Bauer et al. [24] focus on the challenges of using machine learning in SMEs. Their survey and interviews of C level and managing directors finds that mostly acceptance, knowledge and data availability are enabling the adoption of machine learning.

Another stream of research focuses on readiness and maturity models [30–35]. For example, Pumplun et al. [34] expanded the technological-organizational-environmental (TOE) framework to cover specific characteristics of AI. The exploratory study based on interviews revealed several specific organizational readiness factors like data or culture. Lismont et al. [35] used a survey approach to identify maturity indicators for analytics applications. Based on the findings, four levels of maturity were identified which help to categorize companies efforts. Similar to that, Grossman [32] developed a framework to evaluate the analytic maturity of a company which can be considered a subfield within AI.

3.2 Research Gap

Although the papers provide interesting results for the area of AI adoption, a significant research gap exists. As described above, previous studies have been limited to specific technologies e.g., machine learning, or specific steps in the life cycle of AI applications. However, an AI strategy must take a holistic view of AI and related factors. It can be argued that the mentioned maturity models take a more holistic approach to the topic. Nevertheless, the goal of these models is to categorize companies' efforts to levels instead of creating a strategy to pursue. To the authors' best knowledge, there are no prior studies that developed an AI strategy or similar framework. Therefore, the factors and their relationships important to AI strategy are poorly understood.

4 Research Approach and Methods

4.1 Systematic Literature Review

The procedure of the systematic literature review is based on the suggestions by Webster and Watson [9], vom Brocke et al. [8] and Kitchenham [10]. The overall research aim was broken down into four related review questions that encompassed the following aspects: success factors and challenges for the introduction of AI, characteristics of digital or IT strategies, maturity models for AI, and readiness models for AI. The review questions were subsequently transformed into search strings with logical operators that also considered synonyms of the relevant search terms, as shown in Table 1.

Table 1. Search strings.

#	Search string
1	(“Artificial Intelligence” OR “Machine Learning” OR “Deep Learning”) AND (Challenges OR “Success Factors” OR Difficulties OR Issues OR Problems OR Framework OR Adoption)
2	(“Digital Strategy” OR “Digital Business Strategy” OR “IT Strategy” OR “IT-Strategy”) AND (Characteristics OR Framework OR Process OR Development)
3	(“Artificial Intelligence” OR “Machine Learning” OR “Deep Learning”) AND Maturity
4	(“Artificial Intelligence” OR “Machine Learning” OR “Deep Learning”) AND Readiness

Following the suggestion by Webster and Watson [9], the search was focused on leading journals that are most likely to contain the major contributions in a field. For this paper, “leading” was defined relatively broadly, orientated by the VHB-JOURQUAL rankings for business informatics (information systems), as well as strategic management, that include more than 100 international journals and conference proceedings. The search was executed on the websites of the journals. Papers from 2010 to present were included. From 1,483 results in the initial search, 249 had to be neglected due to missing accessibility of the full texts. The remaining papers were manually evaluated based on their title and abstract, leaving 138 papers for a full-text detailed review. 57 relevant papers were included in the final analysis (55 papers in English, 2 papers in German). As suggested by Kitchenham [10], data extraction forms were used to accurately record the information from the literature.

4.2 Development of Conceptual Framework

To develop the conceptual framework, open coding and the codes-to-theory model by Saldaña [11] has been used, which is a specific approach for grounded analysis [12] of qualitative data [36]. It represents an inductive procedure to consolidate codes and categories in order to transcend the qualitative data toward a conceptual or theoretical level [11]. In this study, the lowest level of coding (level 3) is represented by the factors recorded in the data extraction forms. Subsequently, these factors have been further aggregated to categories (level 2) based on their similarity. As a final aggregation step, the categories were grouped to themes (level 1). Finally, to develop the conceptual framework, the relationship between the different themes (level 1) was highlighted by visualizing them in a particular order and indicating influences with arrows. The categories (level 2) were also included in the final framework.

5 Results

5.1 Factors and Framework for AI Strategy

In the open coding procedure, 57 factors that should be considered in an AI strategy were identified in the literature. The individual factors, as well as their consolidation to the higher-level categories and themes, are shown in Table 2. In the analysis, 17 categories and 7 themes resulted and were included in the final framework.

The framework sorts the themes of the AI strategy by three main parts, as shown in Fig. 1. In the center of the framework, the main strategic themes can be seen, that are actively shaped in the formulation of the AI strategy. These include the necessary infrastructure and data to realize use cases in AI applications, but also capabilities and organizational considerations. These core elements of the AI strategy are embedded in both, an internal and external context. The internal context consists of managerial processes that are required for a recurring strategy development and thus constitute the dynamic part of the framework. On the other hand, external constraints in the form of ethical and legal considerations are imposed on the core themes of the AI strategy.

5.2 Strategic AI Themes

As **data** have become an asset [45] and are seen as the fuel for AI [44], they play a key role in the AI strategy framework. Use cases are directly dependent on the quality and availability of suitable data [25]. With regard to data, three aspects need to be considered: data storage, data management and data governance. Data storage mainly deals with the physical storage and administration of data for which a solid infrastructure is needed. The main task of data management is to verify quality and consistency of data throughout the data life cycle from its initial collection to its eventual deletion. A proactive view on data collection is needed to provide data instantly for upcoming use cases [25]. As data security is a major concern in AI [24, 53], data governance is another important category. It represents overarching processes for data security, data access and data usage in general [34, 80].

Storage and management of data is supported by the necessary **infrastructure**. An important aspect is the make or buy decision (sourcing) [52]. Depending on this decision, the technical architecture is built in-house or with an external partner. In general, a flexible infrastructure that supports fast deployment and changing use cases is needed [71, 75]. Within the domain of infrastructure, the technology that will be used, i.e. which specific tools and frameworks will be deployed, is another important domain. The deployed technologies mainly depend on the make or buy decision and the capabilities of the

Table 2. Factors and coding procedure.

Factor/Code	Source	Category	Theme
Single source of truth	[37]	Data storage	Data
Lack of standardization	[38–41]		
Data platform	[42, 43]		
Data availability	[24, 25, 29, 32–35, 37, 40–55]	Data management	
Data quality	[25, 35]		
Data collection	[34, 48]		
Data sources	[40, 47]		
Data management	[33, 56]		
Data culture	[33]	Data governance	
Data security	[24, 28, 33, 37, 48, 49, 53]		
Culture	[30, 33, 37, 43, 44, 55, 57–59]	Corporate culture	Organization
Mindset	[27, 30, 40, 44, 51, 60–62]		
User resistance	[24, 28, 63]		
High expectations	[29]		
Trust in technology	[25, 41, 53, 64]		
Top management support	[24, 26, 34, 35, 37, 40, 46, 51, 53, 57, 61, 65–68]	Leadership	
Top-down Guidance	[37, 65]		
Leadership skills	[40, 53, 61, 65, 69]		
Communication	[37, 57, 65, 70, 71]	Communication	
Integrate stakeholders	[62, 72]		
Visualization of strategy	[70]		
Understanding of strategy	[70]		
Business to IT communication	[33]		
Change Management	[51]		
Collaboration	[47, 65, 69, 73]		
Integration of C level	[35, 58]	Organizational structure	
Central analytics team	[24, 34, 35, 71]		
Organizational structure	[65]		

(*continued*)

Table 2. (*continued*)

Factor/Code	Source	Category	Theme
Appoint CDO	[58, 74]		
Clear responsibilities	[66]		
Mainstream vendors	[65]	Technology	Infrastructure
Compatibility	[34, 46]		
Implementation process	[40, 66]		
Understandable technology	[35]		
IT resources	[27, 30]	Technical architecture	
Deploy in existing systems	[32]		
Silo-oriented systems	[39, 54]		
Flexible infrastructure	[25, 32, 33, 44, 54, 71, 73, 75]		
Complexity	[34, 46]	Sourcing	
Make or buy	[52]		
IT capabilities	[28, 44]	Organizational capabilities	Capabilities
IT not a core competency	[71]		
Training	[34, 43, 53, 58, 63, 67]	Human resources	
HR strategy	[52, 62]		
Lack of employees with AI skills	[24, 29, 34, 44, 67, 71, 76, 77]		
Lack of understanding	[56, 59, 67]		
Individual skills	[27, 30, 31, 33, 37, 40, 46, 51, 52, 55, 71, 78, 79]		
AI knowledge	[26]		
Ethical conditions	[26, 49]	Ethical conditions	Constraints
Legal conditions	[26, 30, 34]	Legal conditions	
Identify use cases	[24, 29, 34, 59]	Use Cases	Use Cases
Business as driver of use cases	[32, 34, 35, 37, 40, 53, 65]		
Financial justification	[28]		
Repetitive tasks	[38]		
Decision process for AI-technologies	[35]	Decision processes	Managerial processes
Selection process for use cases	[32, 59, 77]		
Alignment of strategies	[37, 40, 55, 67, 71, 72]	Strategic alignment	

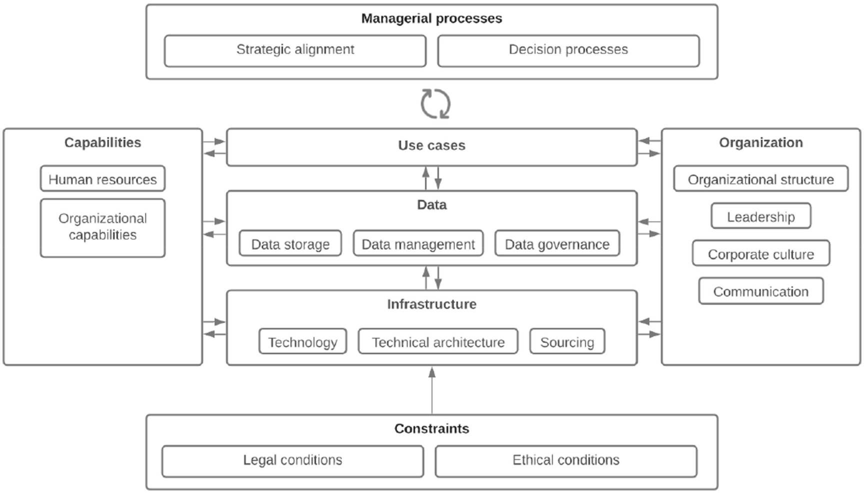

Fig. 1. Framework for corporate AI strategy (Source: Own Illustration).

organization. If no previous skills are available, easy to use technologies are favorable [35].

Managerial processes are guiding and control mechanisms in an AI context. As AI is a complex topic, predetermined process can help to guide strategic AI activities. The literature mainly indicates the importance of decision and alignment processes. For example, given limited resources, use case selection processes can act as a funnel to optimally allocate resources to maximize the outcome for the company [32, 77]. If processes are managed and executed centrally, synergetic effects can be leveraged as resources are distributed optimally [52, 71]. Processes can include technological selections, strategic alignment or change management. It is important that these processes are carried out regularly in order to achieve their full potential.

To use AI effectively, specific and high-quality **use cases** have to be developed and documented [37]. A use case specifies the intended use and outcome of an AI activity. When defining use cases, it is recommended to identify prerequisites at an early stage [37]. The literature shows, that many companies struggle to identify suitable use cases [59]. This is closely linked to the level of understanding of AI technologies [24, 25, 29, 34]. This lack of understanding leads to employees being unable to connect current problems with AI solutions. This is further exacerbated by low levels of acceptance [24]. Furthermore, AI use cases have special properties that need to be considered. Thus, regarding the evaluation of identified use cases, classic KPIs can only be used to a limited extent as metrics for an AI project [34].

A company's structure and culture as well as internal communication and leadership is bundled in the theme of **organization**. Within the organization, corporate culture creates values which in turn substantiate decisions and behavior [81]. The AI strategy should facilitate an innovative culture [34, 59] which is is data-driven and relies on fact-based decisions instead of gut feeling [30, 33, 37, 55]. The organizational structure determines roles and responsibilities and should describe how AI teams are implemented in the organization to provide optimal support for AI activities. The literature presents different structures, such as decentralized or centralized, that can be used in an AI context [34, 35, 65, 71]. As managers are confronted with the adoption and implementation of AI, leadership capabilities are needed to ensure a seamless integration. One of the most important factors is that the top management has to be fully committed to the AI initiatives [35, 40, 46, 51, 61, 66–68]. Highly committed managers increase trust in new technologies and facilitate necessary cultural and behavioral changes that are needed for AI adoption [61]. A major reason for the failure of strategic initiatives, such as an AI strategy, is lack of communication and the resulting lack of understanding among the employees [70]. Therefore, an AI strategy needs to consider how internal communication channels are used for communication. As AI induces far-reaching changes, this includes initiatives for knowledge sharing and change management as well as communication strategy for the adoption of AI [51, 71].

With regard to **capabilities**, it can be distinguished between two levels. The individual level is summarized in the category human resources. This contains all activities regarding employee management. Depending on decisions made in the technical architecture, companies need to deploy a strategy to attract and retain highly skilled employees as these are scarce [24, 34, 37, 56, 67]. Companies often rely on personal initiative of employees while forgetting the lack of skills to implement AI productively [24, 67]. As one interviewee in Pumplun et al. [34] states: “Especially with machine learning and artificial intelligence. […] You need the experts.”. The second level are organizational capabilities that are needed to support AI adoption. These are not directly linked to individual skills but describe the way of working in the company [30]. Therefore, these capabilities are dependent on the other described concepts.

The use of AI is subject to different **constraints** that need to be evaluated prior to adoption. First and foremost, compliance to the General Data Protection Regulation (GDPR) or similar laws must be assured to secure the company’s image and trustworthiness [30, 34]. Therefore, every use case needs to be analyzed regarding the usage of personal data. Secondly, ethical issues should be regarded to avoid unethical behaviour by the AI. This is due to the fact that AI applications can induce bias from past data that they have been trained with [26]. Accordingly, all use cases must be examined to preclude any form of discrimination against employees or customers.

6 Conclusion, Limitations, and Future Research Opportunities

This research shows that companies should consider diverse aspects when formulating an AI strategy. Besides technologies and their application in use cases, organizational and managerial aspects have to be considered to ensure success in gaining competitive advantage by adopting AI. Furthermore, an alignment of the AI strategy with the overall business strategy is crucial, as well as paying attention to legal and ethical constraints.

The authors hope that this framework will be a useful aid for practitioners when developing an AI strategy, or struggling with the general question, how to approach the field of AI. The wide range of aspects that were unveiled in this research highlights the necessity for interdisciplinary collaboration, covering tasks and responsibilities from business departments, as well as, IT departments. Additionally, the results imply that different organizational levels, ranging from top management to operational staff, need to combine their skills and knowledge to formulate a successful strategy.

Finally, a number of potential limitations of this study need to be considered. First, this study's analysis relies on prior studies that were conducted based on different methodologies and contexts. This might be a source of bias if the findings from previous studies are not transferable to other settings. Second, as the focus of this research was to provide a holistic overview of the topic, it does not cover detailed advice regarding the individual themes, for instance, the technological infrastructure for AI.

It is therefore recommended that further research should be undertaken in the following areas: First, additional studies should be conducted to corroborate and refine the framework. Possible research designs could be based on interviews with experts that can share practical experiences regarding AI strategies, as well as case-based or action-oriented methods to apply the framework in a specific industry setting. Second, specific recommendations, guidance or strategies should be elaborated for each of the themes in the framework.

References

1. Russell, S., Norvig, P.: Artificial Intelligence: A Modern Approach. 3rd edition. Pearson, Upper Saddle River (2009)
2. Haenlein, M., Kaplan, A.: A brief history of artificial intelligence: on the past, present, and future of artificial intelligence. Calif. Manage. Rev. **61**(4), 5–14 (2019)
3. Bean, R.: How Big Data and AI Are Driving Business Innovation in 2018. https://sloanreview.mit.edu/article/how-big-data-and-ai-are-driving-business-innovation-in-2018/
4. Miller, S.M.: AI: augmentation, more so than automation. Asian Manage. Insights **5**(1), 1–20 (2018)
5. McKinsey Analytics: Global survey: The state of AI in 2020. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/global-survey-the-state-of-ai-in-2020
6. Buxmann, P., Schmidt, H. (eds.): Künstliche Intelligenz: Mit Algorithmen zum wirtschaftlichen Erfolg. Springer, Heidelberg (2019). https://doi.org/10.1007/978-3-662-57568-0
7. Panetta, K.: Gartner Top 10 Strategic Technology Trends for 2018. https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2018/
8. vom Brocke, J., et al.: Reconstructing the giant: on the importance of rigour in documenting the literature search process. In: 17th European Conference on Information Systems (ECIS), Verona, Italy, pp. 2206–2217 (2009)
9. Webster, J., Watson, R.T.: Analyzing the past to prepare for the future: writing a literature review. MIS Q. **26**(2), 13–23 (2002)
10. Kitchenham, B.: Guidelines for performing Systematic Literature Reviews in Software Engineering. Keele University and Durham University Joint Report (2007)
11. Saldaña, J.: The Coding Manual for Qualitative Researchers. Sage, Los Angeles (2009)
12. Glaser, B.G., Strauss, A.L.: The Discovery of Grounded Theory: Strategies for Qualitative Research. Aldine de Gruyter (1967)
13. Girasa, R.: Artificial Intelligence as a Disruptive Technology. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-35975-1
14. Ertel, W.: Grundkurs Künstliche Intelligenz: Eine praxisorientierte Einführung. Springer, Wiesbaden (2016). https://doi.org/10.1007/978-3-658-13549-2

15. Ashri, R.: The AI-Powered Workplace. How Artificial Intelligence, Data, and Messaging Platforms Are Defining the Future of Work. Apress, Berkeley (2020)
16. Kaplan, A., Haenlein, M.: Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Bus. Horiz. **62**(1), 15–25 (2019)
17. Pennachin, C., Goertzel, B.: Contemporary approaches to artificial general intelligence. In: Goertzel, B., Pennachin, C. (eds.), Artificial General Intelligence. Cognitive Technologies, pp. 1–30. Springer, Heidelberg (2007). https://doi.org/10.1007/978-3-540-68677-4_1
18. Müller, V.C., Bostrom, N.: Future progress in artificial intelligence: a survey of expert opinion. In: Müller, V.C. (ed.) Fundamental Issues of Artificial Intelligence. SL, vol. 376, pp. 555–572. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-26485-1_33
19. Henderson, B.D.: The Origin of Strategy. Harvard Business Review, pp. 139–143. (November–December 1989)
20. Camphausen, B.: Strategisches Management. De Gruyter (2013)
21. Mangiapane, M., Büchler, R.P.: Modernes IT-Management: Methodische Kombination von IT-Strategie und IT-Reifegradmodell. Springer, Wiesbaden (2014). https://doi.org/10.1007/978-3-658-03493-1
22. Gerow, J., Grover, V., Thatcher, J., Roth, P.: Looking toward the future of IT-business strategic alignment through the past: a meta-analysis. MIS Q. **38**(4), 1159–1185 (2014)
23. Alsheibani, S., Cheung, Y., Messom, C.: Factors inhibiting the adoption of artificial intelligence at organizational-level: a preliminary investigation. In: AMCIS 2019 Proceedings, pp. 1–10 (2019)
24. Bauer, M., van Dinther, C., Kiefer, D.: Machine learning in SME: an empirical study on enablers and success factors. In: AMCIS 2020 Proceedings, pp. 1–10 (2020)
25. Baier, L., Jöhren, F., Seebacher, S.: Challenges in the deployment and operation of machine learning in practice. In: 27th European Conference on Information Systems (ECIS), Stockholm & Uppsala, Sweden (2019)
26. Duan, Y., Edwards, J.S., Dwivedi, Y.K.: Artificial intelligence for decision making in the era of big data – evolution, challenges and research agenda. Int. J. Inf. Manage. **48**(1), 63–71 (2019)
27. Chen, P.-T., Lin, C.-L., Wu, W.-N.: Big data management in healthcare: adoption challenges and implications. Int. J. Inf. Manage. **53**(1), 1–11 (2020)
28. Nam, K., Dutt, C., Chathoth, P., Daghfous, A., Khan, M.S.: The adoption of artificial intelligence and robotics in the hotel industry: prospects and challenges. Electron. Mark. **31**, 553–574 (2020)
29. Kessler, R., Gómez, J.: Implikationen von machine learning auf das datenmanagement in unternehmen. HMD Praxis der Wirtschaftsinformatik **57**(1), 89–105 (2020). https://doi.org/10.1365/s40702-020-00585-z
30. Klievink, B., Romijn, B.-J., Cunningham, S., de Bruijn, H.: Big data in the public sector: uncertainties and readiness. Inf. Syst. Front. **19**(2), 267–283 (2016). https://doi.org/10.1007/s10796-016-9686-2
31. Rader, D.J.: Digital maturity: the new competitive goal. Strategy Leadersh. **47**(5), 28–35 (2019)
32. Grossman, R.L.: A framework for evaluating the analytic maturity of an organization. Int. J. Inf. Manage. **38**(1), 45–51 (2018)
33. Ramakrishnan, T., Khuntia, J., Kathuria, A., Saldanha, T.: An integrated model of business intelligence & analytics capabilities and organizational performance. Commun. Assoc. Inf. Syst. **46**(1), 722–750 (2020)
34. Pumplun, L., Tauchert, C., Heidt, M.: A new organizational chassis for artificial intelligence-exploring organizational readiness factors. In: 27th European Conference on Information Systems (ECIS), Stockholm & Uppsala, Sweden, pp. 1–15 (2019)

35. Lismont, J., Vanthienen, J., Baesens, B., Lemahieu, W.: Defining analytics maturity indicators: a survey approach. Int. J. Inf. Manage. **37**(3), 114–124 (2017)
36. Easterby-Smith, M., Thorpe, R., Jackson, P.R.: Management and Business Research. SAGE Publications, London (2015)
37. Watson, H.J.: Tutorial: big data analytics: concepts, technologies, and applications. Commun. Assoc. Inf. Syst. **34**, 1247–1268 (2014)
38. Maedche, A.: Interview with Joerg Mimmel on digitalization of purchasing at Bosch. Bus. Inf. Syst. Eng. **61**(6), 755–758 (2019). https://doi.org/10.1007/s12599-019-00616-0
39. Bygstad, B., Øvrelid, E., Lie, T., Bergquist, M.: Developing and organizing an analytics capability for patient flow in a general hospital. Inf. Syst. Front. **22**(2), 353–364 (2019)
40. Phillips-Wren, G., Hoskisson, A.: An analytical journey towards big data. J. Decis. Syst. **24**(1), 87–102 (2015)
41. Thiebes, S., Lins, S., Sunyaev, A.: Trustworthy artificial intelligence. Electron. Mark. **31**(2), 447–464 (2020). https://doi.org/10.1007/s12525-020-00441-4
42. Leavy, B.: Marco Iansiti and Karim Lakhani: strategies for the new breed of "AI first" organizations. Strategy Leadersh. **48**(3), 11–18 (2020)
43. Butner, K.: Six strategies that define digital winners. Strategy Leadersh. **47**(5), 10–27 (2019)
44. Wamba-Taguimdje, S.-L., Wamba, S.F., Kamdjoug, J.R.K., Wanko, C.E.T.: Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. Bus. Process. Manag. J. **26**(7), 1893–1924 (2020)
45. Ylijoki, O., Porras, J.: A recipe for big data value creation. Bus. Process. Manage. J. **25**(5), 1085–1100 (2019)
46. Verma, S., Bhattacharyya, S.S.: Perceived strategic value-based adoption of big data analytics in emerging economy. J. Enterp. Inf. Manage. **30**(3), 354–382 (2017)
47. Benfeldt, O., Persson, J.S., Madsen, S.: Data governance as a collective action problem. Inf. Syst. Front. **22**(2), 299–313 (2019). https://doi.org/10.1007/s10796-019-09923-z
48. Heavin, C., Power, D.J.: Challenges for digital transformation – towards a conceptual decision support guide for managers. J. Decis. Syst. **27**(sup1), 38–45 (2018)
49. Coombs, C., Hislop, D., Taneva, S.K., Barnard, S.: The strategic impacts of intelligent automation for knowledge and service work: an interdisciplinary review. J. Strateg. Inf. Syst. **29**(4), 1–30 (2020)
50. Cegielski, C., Bourrie, D., Hazen, B.: Evaluating adoption of emerging IT for corporate IT strategy: developing a model using a qualitative method. Inf. Syst. Manage. **30**, 235–249 (2013)
51. Holotiuk, F., Beimborn, D. (eds.): Critical Success Factors of Digital Business Strategy (2017)
52. Wagner, D.: Strategically managing the artificially intelligent firm. Strategy Leadersh. **48**, 19–25 (2020)
53. Akter, S., Wamba, S.F.: Big data analytics in E-commerce: a systematic review and agenda for future research. Electron. Mark. **26**(2), 173–194 (2016). https://doi.org/10.1007/s12525-016-0219-0
54. Gimpel, G.: Dark data: the invisible resource that can drive performance now. J. Bus. Strategy **42**(4), 223–232 (2020)
55. Foshay, N., Yeoh, G., Boo, Y.-L., Ong, K.-L., Mattie, D.: A comprehensive diagnostic framework for evaluating business intelligence and analytics effectiveness. Australas. J. Inf. Syst. **19**(1), 37–54 (2015)
56. Carillo, K.D.A.: Let's stop trying to be sexy – preparing managers for the (big) data-driven business era. Bus. Process. Manage. J. **23**(3), 598–622 (2017)
57. Jonathan, G.M., Rusu, L., Perjons, E. (eds.): Business-IT alignment in the era of digital transformation: Quo Vadis? (2020)
58. Plastino, E., Purdy, M.: Game changing value from artificial intelligence: eight strategies. Strategy Leadersh. **46**(1), 16–22 (2018)

59. Hofmann, P., Jöhnk, J., Protschky, D., Urbach, N. (eds.): Developing Purposeful AI Use Cases - A Structured Method and Its Application in Project Management (2020)
60. Borges, A.F.S., Laurindo, F.J.B., Spínola, M.M., Gonçalves, R.F., Mattos, C.A.: The strategic use of artificial intelligence in the digital era: systematic literature review and future research directions. Int. J. Inf. Manage. **57**, 1–16 (2021)
61. Ali, M., Zhou, L., Miller, L., Ieromonachou, P.: User resistance in IT: a literature review. Int. J. Inf. Manage. **36**(1), 35–43 (2016)
62. Kolbjørnsrud, V., Amico, R., Thomas, R.: Partnering with AI: how organizations can win over skeptical managers. Strategy Leadersh. **45**(1), 37–43 (2017)
63. Zeng, L., Li, L., Duan, L.: Business intelligence in enterprise computing environment. Inf. Technol. Manage. **13**(4), 297–310 (2012)
64. Schmidt, P., Biessmann, F., Teubner, T.: Transparency and trust in artificial intelligence systems. J. Decis. Syst. **29**(4), 260–278 (2020)
65. Kohli, R., Johnson, S.: Digital transformation in latecomer industries: CIO and CEO leadership lessons from Encana Oil & Gas (USA) Inc. MIS Q. Executive **10**, 141–156 (2011)
66. Matt, C., Hess, T., Benlian, A.: Digital transformation strategies. Bus. Inf. Syst. Eng. **57**(5), 339–343 (2015). https://doi.org/10.1007/s12599-015-0401-5
67. Nalchigar, S., Yu, E.: Business-driven data analytics: a conceptual modeling framework. Data Knowl. Eng. **117**(1), 359–372 (2018)
68. Anand, A., Sharma, R., Coltman, T.: Four steps to realizing business value from digital data streams. MIS Q. Executive **15**(4), 259–277 (2016)
69. Yeh, C.-H., Lee, G.-G., Pai, J.-C.: How information system capability affects e-business information technology strategy implementation. Bus. Process. Manage. J. **18**(2), 197–218 (2012)
70. de Salas, K., Huxley, C.: Enhancing visualisation to communicate and execute strategy. J. Strateg. Manage. **7**(2), 109–126 (2014)
71. Chanias, S., Myers, M.D., Hess, T.: Digital transformation strategy making in pre-digital organizations: the case of a financial services provider. J. Strateg. Inf. Syst. **28**(1), 17–33 (2019)
72. Dang, D., Vartiainen, T.: Digital strategy patterns in information systems research. In: Twenty-Third Pacific Asia Conference on Information Systems (PACIS) (2019)
73. Jacks, T., Palvia, P., Schilhavy, R., Wang, L.: A framework for the impact of IT on organizational performance. Bus. Process. Manage. J. **17**(5), 846–870 (2011)
74. Berman, S., Baird, C., Eagan, K., Marshall, A.: What makes a Chief Digital Officer successful? Strategy & Leadership **48**, 32–38 (2020)
75. Bharadwaj, A., Sawy, O.A., Pavlou, P.A., Venkatraman, N.: Digital business strategy: toward a next generation of insights. Manage. Inf. Syst. Q. **37**(2), 471–482 (2013)
76. Watson, H.J.: Update tutorial: big data analytics: concepts, technology, and applications. Commun. Assoc. Inf. Syst. **44**, 364–379 (2019)
77. Nilles, M., Senger, E.: Nachhaltiges IT-Management im Konzern — von den Unternehmenszielen zur Leistungserbringung in der IT. HMD Praxis der Wirtschaftsinformatik **49**(2), 86–96 (2012)
78. Adya, M., Niederman, F.: IT workforce planning: a modular design science approach. In: Proceedings of the 49th SIGMIS Annual Conference on Computer Personnel Research, pp. 42–48 (2011)
79. Power, D.J.: Data science: supporting decision-making. J. Decis. Syst. **25**(4), 345–356 (2016)
80. Balakrishnan, R., Das, S., Chattopadhyay, M.: Implementing data strategy: design considerations and reference architecture for data-enabled value creation. Australas. J. Inf. Syst. **24**(1), 1–27 (2020)
81. Flamholtz, E.: Corporate culture and the bottom line. Eur. Manag. J. **19**(3), 268–275 (2001)