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The Role of Organizational Culture on Artificial Intelligence Capabilities and Organizational Performance

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Abstract. In recent years, artificial intelligence (AI) has become increasingly relevant for organizations to exploit business-related databases and remain competitive. However, even though those technologies offer a huge potential to improve organizational performance, many companies face challenges when adopting AI technologies due to missing organizational and AI capability requirements. Whereas existing research often focuses on technological requirements for the application of AI, this study focuses on those challenges by investigating the influence of organizational culture on a company's AI capability and its organizational performance. We conducted a quantitative study in Scandinavia and employed a questionnaire receiving 299 responses. The results reveal a strong positive relationship between organizational culture, AI capabilities, and organizational performance.

Keywords: Artificial intelligence capabilities · AI · Organizational culture · Organizational performance

1 Introduction

Society has been experiencing technological leaps for decades throughout the industrial revolution, computer age, internet, and social networks. Advances in technology and the abundance of data has prompted many industries to reposition themself to take advantage of the potential Artificial Intelligence (AI) technologies can provide them. This progress and change in technology lead to a change in how societies are organized, and how they are interacting with each other [1]. According to a recent survey the number of enterprises implementing AI grew 270% in the past four years [2]. And despite the impact of COVID-19, 47% of AI investments remained stable since the start of the pandemic, and 30% planned to increase their investments in AI [3].

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While there is much interest about what potential AI technologies can provide to organizations, it is reported that the organizations adopting these technologies are facing challenges that prevent them from achieving the desired performance gains. According to MIT Sloan Management Review from 2019, seven out of ten companies report minimal to no impact by AI technologies [4]. Accordingly, the organizations that struggle to generate value from AI show up as having organizational challenges rather than technological. Whereas organizations that can capture value from their AI activities exhibit a distinct set of organizational behavior. Thus, while many organizations consider AI as a technological aspect, the organizations that consider AI from an organizational perspective are more likely to derive value from their AI investments [4].

Prior studies have been primary focusing on capabilities for adopting AI and Big Data Analytics, and less on the cultural perspective. A large proportion of empirical studies assume that there is a direct relationship between AI capability and performance, however there is a lack of research that investigates organizational culture as a primary influencing factor [5, 6]. Organizational culture impacts many different aspects of an organization and is viewed as a critical factor for why new technological initiatives fail [7]. Thus, we consider organizational culture as having a large (indirect) impact on the capability of an organization to apply AI; and thereby also indirectly on the performance of organizations. Therefore, the goal of this study is to understand the importance of organizational culture in the context of AI capabilities, and its implications on firm performance, which is generated by a successful implementation of AI technologies. By conducting a questionnaire-based quantitative empirical study in Scandinavia, we address the following research questions (RQ):

RQ1: What influence does organizational culture have on an organization's ability to adopt and use AI?
RQ2: How does an organization's AI capability influence its performance?

The remainder of the paper is structured as follows. The theoretical background provides an overview of the relevant concepts and explains the constructs for our survey. The Sect. 3 introduces the conceptual research approach and presents the hypotheses to be tested. Followed by the data analysis in Sect. 4 as well as the discussion of the results in Sect. 5. The paper is finalized by the research's implications and a conclusion in Sect. 6.

2 Theoretical Background and Constructs

To answer the proposed research questions, we initially conducted an extensive literature review regarding the concepts of interest. Based on our results we were able to narrow the field of investigation and retrieved the respective dimensions and indicators for the derivation of our measurement constructs.

2.1 Organizational Culture

Organizational culture describes the working environment and how it influences an employee's way of thinking, acting and experiencing work [8]. It can have a significant influence on performance, the way people engage, and their efforts and the organization's attraction towards new talent [9]. Organizational culture can be understood as a system of shared beliefs held by the members of an organization; those shared beliefs distinguish the organization from other organizations. Organizations do have common behavior patterns that are used by employees to achieve an objective and which are taught to new members and represent the tacit and intangible level of an organization [10]. Prior research suggests that organizational culture significantly influences financial performance and is more effective than organizational strategy and structure [11].

Although organizational culture is a well-researched area, it is complex and there is no consensus on a single definition. It is often defined as *"a collection of shared assumptions, values, and beliefs that is reflected in its practices and goals and further helps its members understand the organizational functions"* [12]. Organizational culture impacts the challenges that organizations are facing while adopting new technologies. Thus, the use of AI implies radical changes to the business- and organizational culture for the firms to achieve accurate decision-making and to improve innovation and performance [13]. To gain value from AI technologies organizations must create a work culture that values collaboration, working towards collective goals, and shared resources [5]. Thus, organizational culture might have a significant impact on the adoption of AI usage in an organization and can be critical for organizations that want to adopt AI into their organization. For the investigation of the RQs, we divided the construct of organizational culture into three dimensions with two to three indicators [14] (Table 1).

Table 1. Dimensions and indicators of organizational culture [14].

Artifacts	Values	Assumptions
Appreciation of employees	Risk-taking	Openness and flexibility
Inter-functional cooperation	Competence and professionalism	Internal communication
Success		Responsibility

The dimension of *artifacts* consists of three indicators. First, appreciation of employees addresses how an organization values their employees and rewards them for their accomplishments towards the organization's goals. It is measured by how an organization recognizes and rewards their individual employees and takes time to commemorate their work achievements. Inter-functional cooperation is about coordination and teamwork within the organization. It is measured by how organizations value cooperation, coordination and sharing information among different work teams. Success is to what extent an organization strives for the highest standards of performance by encouraging employees to excel and reach for challenging goals. Success is measured by how an organization values success and performance, and that they aspire to be the best firm in their market.

The dimension of *value* is divided into two indicators. Risk-taking is about how an organization values experimenting with new ideas and challenging the status in the organization. It is measured by how an organization values willingness to experiment with new ideas and challenge the status quo. Competence and professionalism refers to how organizations value knowledge and skills among their employees. They are measured by how much the organization values the professional knowledge and skills of its employees and whether advocacy for the highest level of professionalism is valued in the organization.

Lastly, the dimension of *assumptions* is represented by three indicators. Openness and flexibility refer to how much an organization values flexible approaches to problem solving and how open and receptive it is to new concepts. It is measured by how open an organization is to new ideas, how it responds to those ideas, and whether it places a high value on being flexible in solving problems. Internal communication is about having open communication that facilitates information flows within an organization. It is measured by whether an organization values open and high-quality internal communication. Responsibility refers to how organizations value their employees being proactive, taking initiative, and being responsible for their own work.

2.2 Artificial Intelligence

Due to the long history and the ongoing increase in research, it is challenging to identify a single and holistic definition for AI [15]. On a meta-level, McCarthy [16] define AI as being "*concerned with methods of achieving goals in situations in which the information available has a certain complex character. The methods that have to be used are related to the problem presented by the situation and are similar whether the problem solver is human, a Martian, or a computer program*". Whereas this definition describes the general potential for AI application, its instantiation in an organizational context can be defined by conducting functions like machine learning, robotics, natural language processing, expert systems, or speech recognition [15, 17]. However, for a company to implement and exploit the described functions, it needs to provide the respective capabilities to conduct AI (and its functions), rather than focusing on its technological features [18]. Thus, AI capabilities is the ability of a firm to select, orchestrate, and leverage its AI-specific resources. Based on the literature review, we were able to develop the construct of AI. According to Mikalef and Gupta [5], who define AI capabilities as "*the ability of a firm to select, orchestrate and leverage its AI-specific resources*", AI capabilities constructs can be conceptualized through three dimensions: *tangible resources, human resources*, and *intangible resources*. These dimensions are interdependent and can be summarized as consisting of several indicators (Table 2).

Table 2. Dimensions and indicators of artificial intelligence [5].

Tangible resources	Human resources	Intangible resources
Data	Technical skills	Data-driven culture
Technology	Business skills	Organizational learning
Basic resources		

Tangible resources are resources that can be sold or bought in a market, like physical or financial assets. Those resources are divided into data, technology, and basic resources.

Data is a key indicator for leveraging the potential of AI [19] and is measured by the organization's access to data and how it is managing the integration of data from multiple internal and external resources. Technology is required to be able to handle all forms of data. It is about how organizations need to have some type of database management systems to adopt AI in their business. This is measured by investigating how willing they are to explore or adapt to different computing approaches, visualization tools, services, software, and databases. Basic resources are referring to time and financial resources. They are measured by the strength of the organization's concepts and basic resources when investing in AI initiatives and giving the investments sufficient time to grow.

The dimension of *human resources* addresses the human capital of an organization. It addresses the employees and managers skills, knowledge, experience, leadership qualities, vision, communication and collaboration competencies, and problem-solving capabilities [5]. This dimension is divided into technical skills and business skills. These are the skills required to deal with implementation and realization of AI algorithms [5]. Measuring technical skills will provide an overview of an organization's ability to provide and own the skills to emphasize AI. Business skills are a necessary skill for managers in order to realize business value of AI investments. To manage such large-scale changes, leaders need to have a required understanding and commitment. It is important that leaders get familiar with AI technologies and its potential [5]. This is measured by how the AI managers understand and appreciate, ability to work, coordinate, and anticipate the needs of other functional managers, suppliers, and customers.

Intangible resources are those resources that are difficult for other companies to replicate and are regarded as of high importance in an uncertain market and which are difficult to identify [5]. Intangible resources are divided into the indicators of data-driven culture and intensity of organizational learning. Data-driven culture refers to the extent to which all managers and employees within an organization base their decisions on data. This is measured by the extent of data-based versus intuition-based decisions in an organization. In order to cope with an uncertain and changing market, organizations need to make efforts to exploit their existing knowledge and explore new knowledge. Firms with a high intensity of organizational learning are likely to have higher organizational knowledge [20]. This can be assumed to create a higher level of AI capabilities. Thus, the indicator of organizational learning is measures by an organization's ability to acquire new knowledge and how they exploit their existing one.

2.3 Organizational Performance

Based on our research approach, firm performance is divided into three dimensions: social performance, market performance and competitive performance. New technology gives many opportunities for increasing social performance, and previous research concludes that technology such as AI has a positive impact on **social performance** [21, 22]. The corporate social responsibility is represented by the contributions undertaken by organizations to society through its business activities and its social investment [23]. To create awareness of this issue, organizations have started to develop and share their responsibility report [24]. This construct is included to measure the social performance awareness in European based organizations and their focus on these issues. It refers to gender equality, workers and their family's health, poverty, and level of nutritional focus. **Market performance** is related to an organization's ability to attract and retain customers, and obtain market growth [11, 25]. The questions measure an organization's ability to satisfy their clients, the firm's ability to keep current and attract new clients, and their desire to grow their market share. **Competitive performance** refers to the consequences of an organization's strategic position, and to which extent the organization performs [26]. These activities generate a strategic advantage over its competitors that ensures them a large market share [26]. Early adopters of AI-driven technologies have shown an increase in profit margins in different sectors of the economy, which shows that they are more successful than their competitors [27]. The construct's questions measure strategic advantage, market share, success, earnings before interest and taxes (EBIT), return of investment (ROI), and return on sales (ROS). In the following the relations of the retrieved concepts are defined and the respective hypotheses explained.

3 Research Design and Hypotheses

The conceptual research model is based and developed on the previously derived constructs from the literature review. By developing measurement constructs from established research, we ensure quality and recognition to the field of IS. Further, we implemented our own empirical work to increase reliability and validity of the conceptual research model (Fig. 1).

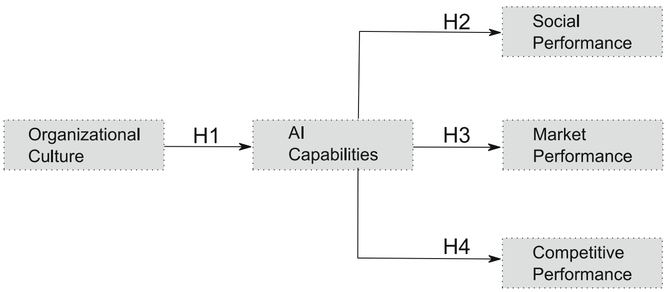

Fig. 1. Conceptual research model

Organizational culture refers to shared meanings and assumptions among the members of an organization. When incorporating AI, an organization will not be able to realize performance gains unless they change their existing way of doing business, even though all the other factors are in place [5]. To gain the best results from implementing AI, organizational culture should be carefully considered as many earlier technology acceptance studies recognize culture as an important influential factor [28]. AI implies radical changes for the organizational culture in businesses in order to achieve accurate decision-making and improved performance [13]. It uses large data sets in order to assist professionals with their tasks, is argued to facilitate better decision-making by providing a wider range of insight [29], and is seen as a crucial strategy for gaining a competitive advantage [30]. Thus, we formulated the first hypothesis:

H1: "Organizational culture has a positive effect on artificial intelligence capabilities".

Previous studies argue that AI technologies cannot provide a competitive advantage by themselves, as they are available for all firms in the market. However, an organization can achieve a competitive advantage by developing AI capabilities [5]. Furthermore, leveraging IT in order to build dynamic capabilities is a key component for gaining competitive advantage [5]. Building and seizing dynamic capabilities enables organizations to form a strategy, a business model, and organizational transformation that leads to increased performance [32]. Thus, developing AI capabilities – a combination of tangible, human and intangible resources – can result in performance gains for organizations [33]. We formulated the following hypotheses about the relation between AI capabilities and organizational performance:

H2: "AI capabilities have a positive effect on social performance"
H3: "AI capabilities have a positive effect on market performance"
H4: "AI capabilities have a positive effect on competitive performance".

4 Results

4.1 Measurements and Reliability

An online questionnaire was developed in order to answer the prosed research questions and to investigate the hypotheses. It consisted of 23 questions which used a seven-point Likert scale. Besides nine control questions, the construct of organizational culture was measured by eight indicators with 25 items, the construct of AI capabilities was measured by seven indicators with 32 items, and construct of firm performance was measured by three indicators using 14 items[1].

We primarily aimed at medium and large Scandinavian business and allowed some additions of small businesses, if they suited for the population criteria. The reason for mainly targeting medium and large businesses was the uncertainty of the population size and the challenge of identifying which organizations were actively using AI. Further, we used the social platform LinkedIn to reach out to the targeted population.

The selected population consisted of a wide range of organizations in different industries. Due to the use of the snowball method technique, the survey was initially distributed to an unknown number of organizations. We received a reply by 326 respondents, of which 299 of the questionnaires were complete.

Reliability and validity of the structural model is ensured by determining different statistical measures for the items and constructs. First, we determined Cronbach's alpha (CA) for the different constructs. All constructs exceed the recommended CA threshold of 0.7 and remain below 0.90, which is the maximum recommended value [34]. For the construct validity, the values of average variance extracted (AVE) should exceed the recommended AVE's threshold of 0.50, which is supported in our study. By using the Fornell-Larcker criterion we assured that the square root of the AVE of each construct is

[1] Due to space restrictions, we are not able to present the questionnaire in this paper. The reader is advised to contact the authors of the paper for access to the survey.

higher than any of the inter-factor correlations. Further, we identified the t-values of all formative items as a two tailed test and determined the p-values, that should be below 0.05. We also used SmartPLS to calculate the path coefficients (weights) of the latent variables. Lastly, we checked the VIF measurements to verify if they are below 10, which holds true. Thus, validity can be assumed for this model and the discriminant validity between the constructs is supported.

4.2 Hypotheses Testing

For testing the hypotheses, we calculated the weight of each single hypothesis as displayed in Table 3. The weight reveals, whether an investigated effect is negative or positive. All hypotheses show a positive effect which can be explained as an increase in the independent variable will affect the dependent variable with an increase as well. The significance of the relation is displayed as p-value. To be considered as having a significant influence, the p-value needs to be lower than 0.05.

Table 3. SEM analysis of the research model.

Hypotheses	Indep. variable	Dep. variable	Weight	T-value	P-value	Decision
H1	Org. Cul.	AI Cap.	0.619	15.601	$p < 0.001$	Supported
H2	AI Cap.	Soc. Per.	0.515	10.767	$p < 0.001$	Supported
H3	AI Cap.	Mar. Per.	0.472	9.423	$p < 0.001$	Supported
H4	AI Cap.	Comp. Per.	0.459	9.570	$p < 0.001$	Supported

Hypothesis 1 has a strong effect of 0.619. The hypothesis is supported with a T-value of 15.601, which is significantly above 99.9%, and a P-value below 0.001. The reliability and validity is acceptable, which confirms that hypothesis 1 is supported.

Hypothesis 2 has a strong effect of 0.515. The hypothesis is supported with a T-value of 10.767, which is significantly above 99.9%, and a P-value below 0.001. The reliability and validity is acceptable, which confirms that hypothesis 2 is supported.

Hypothesis 3 has a strong effect of 0.472. The hypothesis is supported with a T-value of 9.423, which is significantly above 99.9%, and a P-value below 0.001. The reliability and validity is acceptable, which confirms that hypothesis 3 is supported.

Hypothesis 4 has a strong effect of 0.459. The hypothesis is supported with a T-value of 9.570, which is significantly above 99.9%, and a P-value below 0.001. The reliability and validity is acceptable, which confirms that hypothesis 4 is supported.

5 Discussion

Our study is based on previous research and can therefore be viewed as confirmation on the measurements of AI capabilities, as well as the connection between AI capabilities and firm performance [5, 14]. Based on our literature review and our knowledge, the relationship between organizational culture and AI capabilities has not been empirically tested in the past. In addition, to our knowledge, there are no similar studies mainly focusing on Scandinavian organizations. We investigated four hypotheses to determine and evaluate the influence of organizational culture on AI capabilities and their influence on a firm's performance. Based on the questionnaires results we were able to confirm our anticipated relation between the three concepts.

First, we examined how the construct of organizational culture has an effect on the AI capability of a company; more specifically how it influences the ability of a company to introduce and use the potential of AI. Our results revealed a strong positive effect supporting the interdependence between organizational culture and AI and can be related to the challenges that organizations are facing when adopting AI in their organization. The use of AI implies radical changes to the business- and organizational culture within companies in order for them to achieve accurate decision-making to improve innovation and performance [13]. To gain value from AI technologies, organizations must create a work culture that values collaboration, working towards collective goals, and shared resources [5]. In a fast moving and rapidly changing business market due to the fast development of technology it is crucial for organizations to stay competitive. In order to achieve this goal, organizations are constantly adopting new technological tools such as AI. This finding can help organizations to understand what factors are important to utilize the value of AI, by showing that organizational culture has an important effect on AI capabilities. As it is unlikely that technical factors alone will increase performance, organizations also need to consider the organizational factors to increase their performance. Thus, organizational culture will have a significant impact on the adoption of AI usage in an organization and can therefore be regarded as critical for organizations that want to adopt AI into their organization.

As we were furthermore able to reveal the positive effect of AI capabilities on a company's performance in general, it is crucial for the organizations to deal with this competency and, thus, indirectly with their organizational culture to stay competitive. AI capabilities support organizations in keeping their clients satisfied and also in attracting new clients. Further, our findings reveal the important role of AI capabilities for market performance as well as their relevance for social performance. Additionally, in order to gain strategic advantages over competitors, this finding could help organizations to accept the important relation between AI capabilities and competitive performance.

To gain AI skills a data-driven business must ensure that business-analytics becomes a part of the organizational culture that is shared between all employees and especially between those who are responsible for the decision making. Data-driven decision-making skills cannot simply be gained through recruitment of data scientists [35]. As employees are likely to give up on using analytical systems if they do not understand how the systems work, or if it feels too time consuming [36], it requires a necessary AI orientation within the organization [38]. Thus, our results support the need for a culture of coordination, mutual understanding, and cooperation between the different departments within the organization [5, 32]. Further, our findings supports Ransbotham et al. [4], who state that organizations, that are looking at AI from an organizational perspective, rather than from a technological perspective, are more likely to derive value from AI. Our study also contributes to Pappas et al. [1], who revealed that developing a data-driven culture, fostering technical and managerial skills, and promoting organizational learning are critical factors in realizing value when going through a digital transformation.

6 Conclusions

The main goal of the study was to investigate the influence of organizational culture on AI capabilities and on firm performance. As we were able to confirm a positive influence between organizational culture and AI capabilities as well as between AI capabilities and firm performance, we were able to reveal an indirect positive effect of organizational culture on firm performance.

Previous research has often focused on the technical aspects of AI or the adoption of AI where organizational culture only is mentioned as one of several factors for successful AI implementation [15]. Less research has focused on how to achieve value from AI in the context of organizational culture. Thus, our research provides as a theoretical contribution a first attempt on addressing this research gap by providing a deeper understanding of the relations between organizational culture as an important non-technical factor and performance relevant AI capabilities. Furthermore, as practical contribution, our results can help organizations to identify critical constructs of organizational culture and AI capabilities. An example of this could be an organization that has invested in tangible resources, but still has a lack considering the organizational culture. By using the constructs, a Chief Information Officer (CIO) could identify relevant weak resources and take necessary actions. These constructs could also be used to evaluate the culture and AI capabilities of an organization, and thereby evaluate if it has an organizational culture that is ready for AI technology adoption.

As in every research project there are limitations. Although our constructs are based on previous research, our research model could be extended. To achieve even more significant values, the performance, organizational culture, and AI constructs can be refined and extended. Further, the survey contained several questions with a technical context and terms that could have been difficult for participants with limited technical knowledge. Lastly, having chosen a quantitative approach can be regarded as a limitation of the study, as we were not able to ask the participants additional questions regarding their answers and thereby did not get further insights into their motives. However, this is subject to future research, as we would like to conduct qualitative interviews based on our current findings. Additionally, we intend to apply qualitative comparative analysis (QCA) to the data set in order to reveal necessary and/or sufficient combinations of organizational culture conditions leading to successful AI capabilities [37, 38]. Thereby we will be able to compare and complement our SEM analysis results with QCA and provide further insights into the relation between organizational culture and AI capabilities.

References

1. Pappas, I.O., Mikalef, P., Giannakos, M.N., Krogstie, J., Lekakos, G.: Big data and business analytics ecosystems: paving the way towards digital transformation and sustainable societies. Inf. Syst. E-Bus. Manag. **16**(3), 479–491 (2018). https://doi.org/10.1007/s10257-018-0377-z

2. Howard, C., Rowsell-Jones, A.: 2019 CIO survey: CIOs have awoken to the importance of AI (2019)
3. Goasduff, L.: 2 Trends on the gartner hype cycle for artificial intelligence (2020). https://www.gartner.com/smarterwithgartner/2-megatrends-dominate-the-gartner-hype-cycle-for-artificial-intelligence-2020. Accessed 01 Apr 2022
4. Ransbotham, S., Khodabandeh, S., Fehling, R., LaFountain, B., Kiron, D.: Winning with AI - pioneers combine strategy, organizational behavior, and technology. MIT Sloan Management Review and Boston Consulting Group (2019)
5. Mikalef, P., Gupta, M.: Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Inf. Manage. **58**, 103434 (2021). https://doi.org/10.1016/j.im.2021.103434
6. Mikalef, P., Pappas, I.O., Krogstie, J., Giannakos, M.: Big data analytics capabilities: a systematic literature review and research agenda. Inf. Syst. E-Bus. Manag. **16**(3), 547–578 (2017). https://doi.org/10.1007/s10257-017-0362-y
7. Shamim, S., Zeng, J., Shariq, S.M., Khan, Z.: Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: a dynamic capabilities view. Inf. Manage. **56**, 103135 (2019). https://doi.org/10.1016/j.im.2018.12.003
8. Warrick, D.D., Milliman, J.F., Ferguson, J.M.: Building high performance cultures. Organ. Dyn. **45**, 64–70 (2016). https://doi.org/10.1016/j.orgdyn.2015.12.008
9. Warrick, D.D.: What leaders need to know about organizational culture. Bus. Horiz. **60**, 395–404 (2017). https://doi.org/10.1016/j.bushor.2017.01.011
10. Atrian, N., Soltani, I., Rashidpour, A., Etebarian, A.: Presenting a comprehensive model of organizational culture change on the basis of Edgar Schein approach. Int. Bus. Manag. **10**, 1330–1336 (2016)
11. Hogan, S.J., Coote, L.V.: Organizational culture, innovation, and performance: a test of Schein's model. J. Bus. Res. **67**, 1609–1621 (2014)
12. Dubey, R., et al.: Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. Int. J. Prod. Econ. **210**, 120–136 (2019). https://doi.org/10.1016/j.ijpe.2019.01.023
13. Chatterjee, S., Chaudhuri, R., Vrontis, D.: Does data-driven culture impact innovation and performance of a firm? An empirical examination. Ann. Oper. Res. (2021)
14. Schein, E.H.: Organizational Culture and Leadership. Wiley, Hoboken (2017)
15. Collins, C., Dennehy, D., Conboy, K., Mikalef, P.: Artificial intelligence in information systems research: a systematic literature review and research agenda. Int. J. Inf. Manag. **60**, 102383 (2021). https://doi.org/10.1016/j.ijinfomgt.2021.102383
16. McCarthy, J.: Mathematical logic in artificial intelligence. Daedalus **117**, 297–311 (1988)
17. Dejoux, C., Léon, E.: Métamorphose des managers...: à l'ère du numérique et de l'intelligence artificielle. Pearson (2018)
18. Davenport, T., Ronanki, R.: Artificial intelligence for the real world (2018). https://hbr.org/2018/01/artificial-intelligence-for-the-real-world
19. Ransbotham, S., Gerbert, P., Reeves, M., Kiron, D., Spira, M.: Artificial intelligence in business gets real. MIT Sloan Manag. Rev. (2018)
20. Gupta, M., George, J.F.: Toward the development of a big data analytics capability. Inf. Manage. **53**, 1049–1064 (2016). https://doi.org/10.1016/j.im.2016.07.004
21. Bag, S., Gupta, S., Kumar, S., Sivarajah, U.: Role of technological dimensions of green supply chain management practices on firm performance. J. Enterp. Inf. Manag. **34**, 1–27 (2020). https://doi.org/10.1108/JEIM-10-2019-0324
22. Hong, Z., Zhang, H., Gong, Y., Yu, Y.: Towards a multi-party interaction framework: state-of-the-art review in sustainable operations management. Int. J. Prod. Res. 1–37 (2021)
23. Pothuraju, D.V.L., Alekhya, D.P.: Impact of corporate social responsibility on organization performance. Int. J. Adv. Sci. Technol. **29**, 2256–2261 (2020)

24. Jeble, S., Dubey, R., Childe, S.J., Papadopoulos, T., Roubaud, D., Prakash, A.: Impact of big data and predictive analytics capability on supply chain sustainability. Int. J. Logist. Manag. **29**, 513–538 (2018). https://doi.org/10.1108/IJLM-05-2017-0134
25. Ahmed, E.A.: Market sensing, innovation capability and market performance: the moderating role of internal information dissemination. Int. J. Adv. Appl. Sci. **4**, 56–67 (2017). https://doi.org/10.21833/ijaas.2017.08.009
26. Sambamurthy, V., Bharadwaj, A., Grover, V.: Shaping agility through digital options: reconceptualizing the role of information technology in contemporary firms. MIS Q. **27**, 237–263 (2003)
27. Kordon, A.: Applied artificial intelligence-based systems as competitive advantage. In: Proceedings of the 10th International Conference on Intelligent Systems (IS), pp. 6–18 (2020). https://doi.org/10.1109/IS48319.2020.9200097
28. 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. Manag. **48**, 63–71 (2019). https://doi.org/10.1016/j.ijinfomgt.2019.01.021
29. Mazzone, M., Elgammal, A.: Art, creativity, and the potential of artificial intelligence. Arts. **8**, 26 (2019). https://doi.org/10.3390/arts8010026
30. Shi, G., Ma, Z., Feng, J., Zhu, F., Bai, X., Gui, B.: The impact of knowledge transfer performance on the artificial intelligence industry innovation network: an empirical study of Chinese firms. PLoS One **15**, e0232658 (2020). https://doi.org/10.1371/journal.pone.0232658
31. Mikalef, P., Pateli, A.: Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: findings from PLS-SEM and fsQCA. J. Bus. Res. **70**, 1–16 (2017). https://doi.org/10.1016/j.jbusres.2016.09.004
32. Warner, K.S.R., Wäger, M.: Building dynamic capabilities for digital transformation: an ongoing process of strategic renewal. Long Range Plann. **52**, 326–349 (2019). https://doi.org/10.1016/j.lrp.2018.12.001
33. Mishra, A.N., Pani, A.K.: Business value appropriation roadmap for artificial intelligence. VINE J. Inf. Knowl. Manag. Syst. **51**, 353–368 (2021). https://doi.org/10.1108/VJIKMS-07-2019-0107
34. Tavakol, M., Dennick, R.: Making sense of Cronbach's alpha. Int. J. Med. Educ. **2**, 53–55 (2011). https://doi.org/10.5116/ijme.4dfb.8dfd
35. Carillo, K.D.A., Galy, N., Guthrie, C., Vanhems, A.: How to turn managers into data-driven decision makers: measuring attitudes towards business analytics. Bus. Process Manag. J. **25**, 553–578 (2019). https://doi.org/10.1108/BPMJ-11-2017-0331
36. Spano, A., Bellò, B.: Business intelligence in public sector organizations: a case study. In: Mancini, D., Dameri, R.P., Bonollo, E. (eds.) Strengthening Information and Control Systems. LNISO, vol. 14, pp. 133–143. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-26488-2_10
37. Ragin, C.C.: Redesigning Social Inquiry. University of Chicago Press, Chicago (2008)
38. Vassilakopoulou, P., Haug, A., Salvesen, L. M., O. Pappas, I.: Developing human/AI interactions for chat-based customer services: lessons learned from the Norwegian government. Eur. J. Inf. Syst., 1–13 (2022, in press)
39. Pappas, I.O., Woodside, A.G.: Fuzzy-set qualitative comparative analysis (fsQCA): guidelines for research practice in information systems and marketing. Int. J. Inf. Manage. **58**, 102310 (2021)