ACIS 2022 Proceedings | Australasian (ACIS)

12-7-2022

Conceptualizing a Cognitive Analytics Capability

Siddharth Majhi
Indian Institute of Management Amritsar, siddharth.g.majhi@gmail.com

Arindam Mukherjee
Indian Institute of Management Ranchi, arindam.m@iimranchi.ac.in

Conceptualizing a Cognitive Analytics Capability

Full research paper

Siddharth Gaurav Majhi
IT and Computational Systems Area
Indian Institute of Management Amritsar
Amritsar, India
Email: siddharth.g.majhi@gmail.com

Arindam Mukherjee
Information Systems and Business Analytics Area
Indian Institute of Management Ranchi
Ranchi, India
Email: arindam.m@iimranchi.ac.in

Abstract

Gaining value from new, emerging technologies is a major concern for information systems researchers and practitioners. Prior research is unanimous in its argument that organizations need to develop capabilities around such novel technologies in order to leverage them effectively. In this short paper, we focus on the cognitive analytics technology. While it has attracted significant hype, the returns on investment in this technology have not been very impressive. This paper uses the resource-based view as a theoretical lens, interviews with domain experts, and a review of the academic literature on cognitive analytics to conceptualize a cognitive analytics capability. We identify the tangible, human, and intangible resources that underpin an organization's cognitive analytics capability. This research can potentially contribute to the academic literature on business value of information technology. It can also help organizations extract maximum benefits from their investments in cognitive analytics technology. Future avenues of research are also discussed.

Keywords cognitive analytics, resource-based view, organizational capability, qualitative

1 Introduction

Business value of information technology (BVIT) is an integral part of the intellectual core of the information systems (IS) field (Kim et al. 2011). One of the critical issues addressed by this research stream is called the IT productivity paradox (Brynjolfsson et al. 2021). This paradox refers to the lack of positive relationship between firm investments in IT and productivity outcomes for the firm. Researchers have examined this paradox since the early 1990s, using several theoretical perspectives to refute the paradox by demonstrating how IT investments can have beneficial effects on firm performance. Among various such perspectives, the resource-based view (RBV) (Barney 1991) has emerged as the most popular (Wade and Hulland 2004). IT and complementary resources (tangible, human, and intangible) are essential for realizing appropriate returns on IT investments (Bharadwaj 2000).

Recent research has begun exploring the *big data productivity paradox* (Gupta and George 2016). With big data analytics (BDA) capabilities considered to be essential for realizing optimal benefits from big data, interest in this topic has exploded (Wamba et al. 2017). Some recent work has linked cognitive computing technology to big data, arguing that cognitive analytics is a promising technological avenue that can help leverage benefits from the big data possessed by firms (Gupta et al. 2018). However, cognitive analytics involves sizable investments of financial and other scarce resources. Despite the rising hype around cognitive analytics since 2011 and promising results in domains like healthcare (Behera et al. 2019), the overall scenario around returns on cognitive investments is not very encouraging. Present thought on cognitive analytics, derived mostly from industry reports and technology consultant viewpoints, regards this emerging technology as a promising opportunity while warning that the adoption and usage of cognitive analytics is a challenge.

We understand from extant research that merely investing in IT (cognitive analytics in this case) is not likely to generate any competitive advantage for firms (Shamim et al. 2019). Rather, with the objective of obtaining and sustaining competitive advantage using IT, firms need to develop capabilities around the IT. These capabilities are developed by developing, deploying, and combining various firm-level assets and resources. Drawing on the RBV, such firm-level resources can be classified as tangible, human, and intangible. The research question that drives this paper is:

- *What are the resources that combine to form a cognitive analytics capability?*

In this paper, we identify the resources that are essential for developing a cognitive analytics capability in firms, drawing from a review of the academic literature and in-depth interviews with domain experts. The identified resources are classified into tangible, human, and intangible using the RBV as the theoretical lens. This is based on recent research that has utilized the tenets of the RBV to conceptualize big data analytics capability (Gupta and George 2016) and artificial intelligence (AI) capability (Mikalef and Gupta 2021), among others. Also, prior research has advised scholars to utilize theoretical frameworks such as the RBV while examining business analytics capabilities and related maturity frameworks (Cosic et al. 2015).

2 Theoretical Background

2.1 Resource-based View (RBV)

The resource-based view (RBV) contends that firms can obtain a sustained competitive advantage by selecting (picking) and controlling resources that possess four characteristics – value, rarity, inimitability, and non-substitutability (Barney 1991). Beginning with Mata et al. (1995), IS researchers have widely used the RBV to examine the different kinds of IT resources that can help firms leverage maximum benefits from their IT investments in organizational settings (Melville et al. 2004). Despite many criticisms (Kraaijenbrink et al. 2010; Priem and Butler 2001), the RBV can be considered to be an influential and well-established theoretical perspective which can be used to examine how a variety of organizational resources can, in combination, ensure superior performance for firms. We adopt RBV as the theoretical lens for this paper following similar prior studies (Gupta and George 2016).

The RBV provides a useful theoretical basis for meeting the objectives of this study, which is to isolate the resources that in combination can form a cognitive analytics capability. The key concern of the RBV is resource-selection and it has been used effectively in prior studies to identify the resources which are underpinning a particular organizational capability. RBV can help researchers and practitioners focus on a specific set of resources that are critical for developing a capability, and this can prove to be useful for managerial activities such as resource- and asset-orchestration (Sirmon et al. 2011). Specifically, in the examination of how to leverage business value from IT investments, the RBV can be used either as a standalone theoretical lens or in combination with other theoretical perspectives such as knowledge-based view, dynamic capabilities perspective, etc. (Mikalef et al. 2019).

Table 1 gives an overview of prior research using RBV to examine analytics related issues.

Paper	Overview
Gupta and George (2016)	Conceptualize a big data analytics capability comprising various resources
Ghasemaghaei (2017)	Big data analytics usage and its impact on distinctive value creation for firms
Jeble et al. (2018)	How big data and predictive analytics capability impacts supply chain sustainability
Ghasemaghaei (2019)	Role of structural and psychological readiness in firms gaining value from big data analytics
Akter et al. (2020)	Develop and operationalize a service system analytics capability
Mikalef and Krogstie (2020)	Resource-based conceptualization of big data analytics and their interplay with contextual factors to impact process innovation capabilities of firms
Hossain et al. (2020)	Resource-based conceptualization of customer analytics capability comprising six dimensions and twelve sub-dimensions
Kristoffersen et al. (2021)	Identify the business analytics related resources that must be developed and orchestrated by firms to create a business analytics capability for the circular economy
Chatterjee et al. (2021)	Impact of business analytics on organizational performance and business value
Mikalef and Gupta (2021)	Conceptualize an AI (artificial intelligence) capability by identifying and categorizing the underlying resources

Table 1. Use of RBV to examine analytics related issues

2.2 Cognitive computing-enabled analytics

Cognitive analytics "draws upon the cognitive computing environment to generate actionable insights by analysing diverse heterogeneous data sources using cognitive models that the human brain employs" (Gudivada et al. 2016: 169-170). Thus, to understand what cognitive analytics is, we need to first focus on understanding the essence of cognitive computing.

The concept of cognitive computing (CC) is inspired by human cognitive capabilities and CC systems attempt to mimic human cognitive abilities (Schuetz and Venkatesh 2020). Through the coherent combination of various functionalities offered by multiple computing platforms (Modha et al. 2011), CC offers solutions to complex problems through the large-scale processing of structured, unstructured, and semi-structured data (Williams 2016). What makes CC systems distinct from previous technological advancements (which focused on making the systems more powerful) is its focus on making machines more human (Schuetz and Venkatesh 2020). The rising popularity of CC systems is evidenced by the variety of CC services offered by leading technology firms (such as IBM's Watson, Google's DeepMind, Microsoft's Azure-based cognitive services, Amazon's Rekognition, and Facebook's AI Research) as well as other firms operating at the cutting-edge of technology (such as Clarifai, Cognitec, Kairos, and MetaMind).

While CC has no universally accepted definition, Roeglinger et al. (2018: 421) synthesize various definitions to define CC as "an umbrella term for new problem-solving models that strive for mimicking the cognitive capabilities of the human mind by autonomously reasoning and learning on incomplete structured and unstructured contextual data, and through natural interactions with humans and machines". Similarly, Chen et al. (2018: 19774) define CC as "an interdisciplinary research and application field which uses methods from psychology, biology, signal processing, physics, information theory, mathematics, and statistics in an attempt to construct machines that will have reasoning abilities analogous to a human brain".

CC systems represent the fourth stage of the evolution of machine capabilities to match or even better human capabilities, with the first three stages being (a) decision support systems (DSS), (b) expert systems (ES), and (c) intelligent agents (IA) (Schuetz and Venkatesh 2020). The most critical advantage offered by CC systems in comparison to DSS, ES, and IA is their ability to process and take advantage of unstructured data. The processing of unstructured data such as text, audio, and visual inputs was traditionally understood to be an exclusively human capability, and the capabilities of CC systems related to memory, reasoning, action, and perception represent a paradigmatic shift in computing (Laird et al. 1987). Cognitive analytics has been utilized in various domains (Majhi, Mukherjee and Anand, 2021) such as asset performance management, smart service systems, e-government, contract renewals, emergency management, healthcare, procurement, and customer lifetime value.

3 Research Methodology

We adopt a qualitative inquiry approach centred around in-depth personal interviews to address the key research objective of this study, i.e., to identify the resources that need to be combined to form a cognitive analytics capability. In this section, we describe the procedures followed in conducting the qualitative inquiry in terms of sampling, data collection, and data analysis.

To collect qualitative data for this study, we conducted 44 in-depth interviews with industry professionals who are conversant with cognitive analytics and its applications. Theoretical sampling (Eisenhardt 1989) was used to identify the participants. They were selected based on their experience with cognitive analytics technologies and the depth of their knowledge about this technology and its applications in various contexts. The participants belonged to six organizations based in India.

Data were collected using a combination of face-to-face and in-depth telephonic interviews. The interviews lasted for nearly an hour on average, while ranging from 30 to 75 minutes. The initial interviews were unstructured, and we questioned the participants on a broad range of topics about cognitive analytics, including but not limited to their experiences with the implementation of cognitive applications, the challenges associated with the use of cognitive technologies, and the applications of cognitive analytics in various organizational contexts.

We adopted thematic analysis (Braun and Clarke 2006) as the method to analyse the collected data. Thematic analysis broadly comprises six phases – (a) familiarization with the data, (b) generation of initial codes, (c) search for themes, (d) review of the themes, (e) definition and naming of the themes, and (f) production of the research report (Braun and Clarke 2006; Nowell et al. 2017). We familiarized ourselves with the collected data through repeated readings and looked for patterns and meanings that were explicit in the data. Then, we generated initial codes from the collected data and organized the codes into meaningful groups based on the convergence in their meanings. In the next step, we referred to relevant prior literature and the tenets of the RBV to identify themes based on the combination of various initial codes. At the end of this step, we arrived at a set of themes and sub-themes, which were named per similar concepts in prior literature. However, in cases where we could not find a match between an identified theme and a similar concept in existing literature, we named that particular theme in a manner that best reflected its meaning. Finally, we mapped the final set of themes and sub-themes with the corresponding data extracts of participant responses.

Firm and size	#Participants	Firm description
A, > 10000	10	IT consulting services firm, with a cognitive analytics division
B, > 10000	12	IT consulting services firm, with a cognitive analytics division
C, < 100	2	Entrepreneurial venture, working with cognitive technologies such as computer vision and NLP
D, < 100	3	Entrepreneurial venture, working with cognitive technologies such as computer vision and NLP
E, > 10000	9	Large telecommunications firm, utilizes cognitive analytics for its operations
F, > 10000	8	Large oil and gas firm, utilizes cognitive analytics for its operations

Table 2. Details of interview participants

4 Findings

The findings indicate that there are four types of tangible resources (data acquisition, data storage, computational technology, and basic resources), three types of human resources (technical, managerial, and business analysis and consulting skills), and three types of intangible resources (the relationship between technology and business teams, organizational culture, and trust in cognitive analytics) which combine to form an organizational cognitive analytics capability.

Tangible resources can be easily bought and sold in the market, and thus are not sources of competitive advantage on their own. However, they play a crucial role in the development of capabilities. Continuous acquisition of large volumes of data (big data) is essential for facilitating effective knowledge discovery that is needed for improving the intelligence of the CC system. The full potential of cognitive analytics technology can be realized only if the organization possesses good-quality big data. Mere acquisition of data, however, is not enough. Pre-processing and data engineering are critical activities which help organize the data in the right form and format. However, once the data is acquired, the organization needs to be cognizant of the appropriate storage and management of the data. Most participants believed that, on the one hand, cognitive analytics technology is expensive and, on the other, organizations are uncertain about the time duration in which they will be able to see returns from their investments in cognitive analytics. A key side-effect of the prohibitive financial investments needed for cognitive analytics implementations is that firms face a major issue in selling cognitive analytics solutions to clients (from the point of view of IT implementation firms).

We found three types of skills to be important in the context of cognitive analytics: technical skills, managerial skills, and business analysis skills. Since cognitive solutions incorporate a large number of technologies (such as AI, machine learning, computer vision, IoT, cloud, etc.), technical skills become very critical for the development of a cognitive analytics capability. Since technical skills are imitable and substitutable to a large extent, it is the managerial skills which may confer a competitive advantage to certain organizations. Also, managerial skills are essential in getting the technical human resources to deliver to their full potential. There is often a gap between the domain understanding of the technical and the managerial human resources. Thus, the bridging role of business analyst becomes extremely important in the context of a cognitive analytics capability.

Although intangible resources cannot be included in the financial statements of organizations, these resources play the most critical role in the achievement and sustenance of competitive advantage. Most intangible resources are not tradable in the market and hence can act as sources of superior firm performance. Due to a lag between implementation and visible outcomes, business leaders may often question the financial viability of cutting-edge technologies such as cognitive analytics. Thus, a strong relationship between technology leadership and the business leadership of the organization becomes critical in the case of cognitive analytics. New technologies such as cognitive analytics often represent a significant break from *business-as-usual*. Decision-making based on managerial experience and intuition gets replaced by data-driven and evidence-based decision-making. We use the term *trust in cognitive analytics* to refer to the trust placed by the decision-maker(s) in a firm on the insights generated by the cognitive analytics technology solution.

Tables 3a-3c reports the key themes that emerged from our analysis of the collected data. We have also included some exemplar quotes corresponding to each theme and sub-theme. We used the RBV as the reference theoretical framework while conducting the data analysis, and specifically used the framework suggested by Grant (1991) to arrive at the final list of themes.

Table 3a reports the various types of tangible resources and cites exemplar participant quotes corresponding to each identified tangible resource. Similarly, Tables 3b and 3c report the same for human resources and intangible resources.

Exemplar participant quote	Sub-theme	Theme
"Since we know that more the amount of good quality data I can push into my cognitive system, the better results it can come up with … we are always on the lookout to capture more and more relevant data. There are firms which are acquiring other firms just to get hold of their proprietary data"	Data acquisition	Tangible resources
"My organization has been focused on cognitive technology right from the outset. However, recently we realized that something is missing. Focusing on cognitive was good but incomplete. We underestimated the importance of the cloud. Data being key for cognitive, it is essential to have data from beyond the on-premise firewall. While we still believe that cognitive is the next big thing, we are now equally focused on cloud"	Data storage	
"This business intelligence and analytics has been there for a long period of time … you can say 10 to 15 years … what has happened with the advent of big data in the last 5 to 10 years … the processing capability of Spark and Hadoop has come in … all these facilitate cognitive analytics and advanced analytics in general … you can do a more heavy level of data processing and come out with better predictions and insights"	Computational technology	
"Significant financial investments are needed in cognitive projects" "In most projects there is a lag between the systems being set up and us observing any value addition in terms of KPIs"	Basic resources (finance, time)	

Table 3a. Themes, sub-themes, and exemplar participant quotes – Tangible resources

Exemplar participant quote	Sub-theme	Theme
"The staffing of cognitive projects will be a combination of some people already working in the organization who need to be re-trained and re-skilled, and new campus hires who need to be trained from scratch. We have a large budget set aside for such trainings every year. However, because the technology is evolving so rapidly, there are situations where the required skills are so paradigmatically different that I cannot reskill experienced folks for the same … they will be a roadblock … Here, I follow a strategy of hiring freshly minted grad students who do not come with any preconceived notions or knowledge structures … I have found that this strategy is very effective"	Technical skills	Human resources
"From my personal experience and the experiences of my colleagues, I can say that a typical cognitive implementation is not linear in flow … rather it is extremely iterative in nature … so we use the Agile methodology to manage our projects … Iterations, experiments and changing the course if needed are essential steps on the way"	Managerial skills	
"A good business analyst can be the difference between a successful implementation project and an unsuccessful implementation project. My tech resources may not understand what the end-user or the business user wants … analysts can bridge that gap". "Cognitive and AI needs a lot of thought to even structure the problem properly and think of the best approach for solving the problem. Here, things often cannot be put into business rules easily"	Business analysis skills	
"This is a new technology, and it is also very expensive. One needs to be innovative while selling this technology. Clients may not know the full extent of the capabilities that it provides. Hence, a good consultant is critical … more so in the case of cognitive analytics than in the case of any other technology solution"	Consulting skills	

Table 3b. Themes, sub-themes, and exemplar participant quotes – Human resources

Exemplar participant quote	Sub-theme	Theme
"Billing is a big concern for me as far as the cognitive team is concerned because the KPIs [key performance indicators] and KRAs [key result areas] for the cognitive analytics service line have been kept the same as other service lines ... It is difficult to bill the cognitive team members to one single project for a longer duration, and they are likely to be on the bench for extended periods of time ... if my team members stay on the bench for long periods of time, the senior management begins to ask tough and uncomfortable questions"	Business-technology relationship	Intangible resources
"My firm traditionally plays safe ... so they were reluctant to go for this [cognitive analytics] for the longest time ... while my leadership allowed me to go for this technology, they have not updated the metrics and other parameters that they use to evaluate project status and success ... so there is a lot of undue pressure on me and my team"	Organizational culture	
"Things will change because a machine is making decisions on your behalf. Also, you do not really know how exactly the output is getting generated. Initially it will be difficult to change one's way of working, but because there is so much hype about how analytics is the next big thing and it is so great, people may be willing to accept it"	Trust in cognitive analytics	

Table 3c. Themes, sub-themes, and exemplar participant quotes – Intangible resources

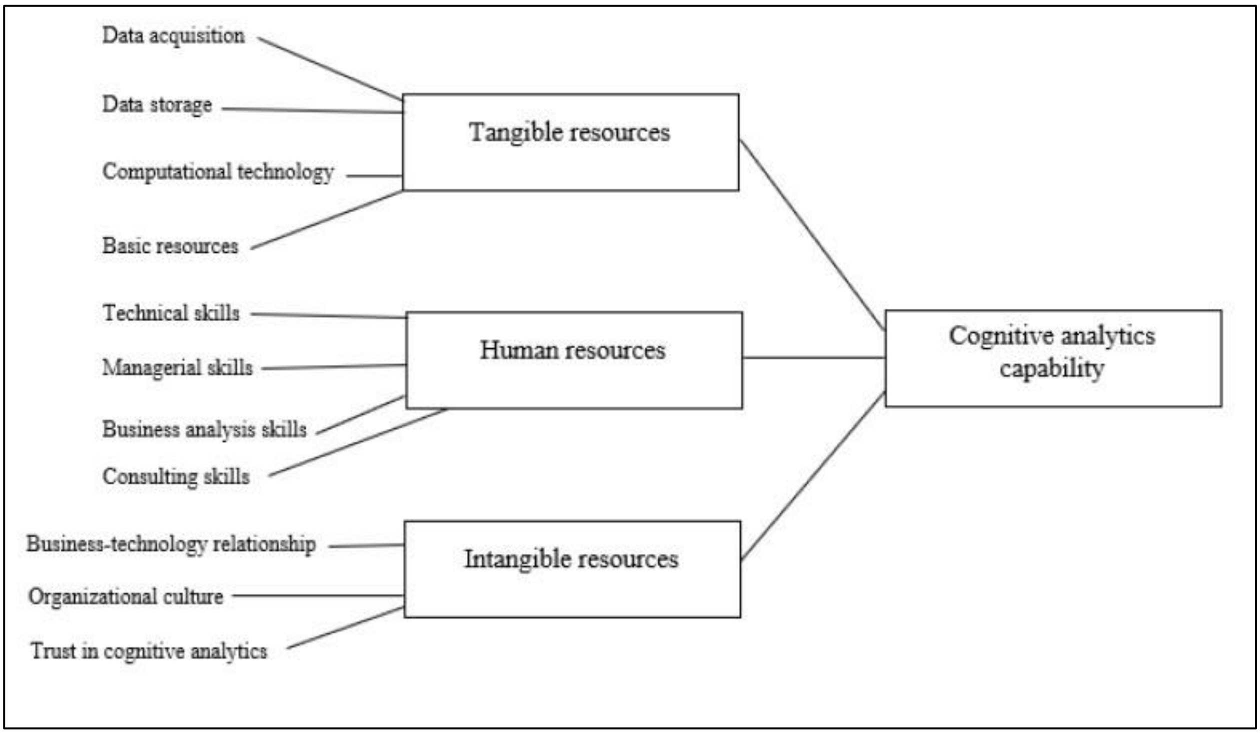

Figure 1: Conceptual framework

5 Discussion and Conclusion

In the last decade, there has been tremendous hype around big data and cognitive analytics. Firms have striven to look for value-creating opportunities using these emerging technologies but results thus far have not been very encouraging. Thus, there is a research opportunity to provide theoretically- and empirically grounded mechanisms through which firms can leverage the full potential of cognitive analytics and big data.

In this regard, the objective of this paper was to identify the resources that form an organizational cognitive analytics capability. To address this objective, this paper draws on a qualitative inquiry using RBV as the theoretical lens to conceptualize a cognitive analytics capability by identifying its underlying resources using the framework of Grant (1991). The findings indicate that there are four types of tangible resources (data acquisition, data storage, computational technology, and basic resources), three types of human resources (technical, managerial, and business analysis and consulting skills), and three types of intangible resources (the relationship between technology and business teams, organizational culture, and trust in cognitive analytics) which combine to form an organizational cognitive analytics capability.

Going beyond the mere identification and categorizing the resources underlying the conceptualized cognitive analytics, our analysis of the findings also revealed the various nuances and dynamics surrounding these resources and their use in organizations to extract or leverage maximum value from the investments in the emerging cognitive analytics technology. While prior studies have used the same framework (Grant 1991) to categorize the resources underlying a big data analytics capability (Gupta and George 2016) or an artificial intelligence capability (Mikalef and Gupta 2021), the contribution of this paper lies in unravelling certain nuances and dynamics specific to the cognitive analytics technology context.

This paper engages with a research stream that has been important for over four decades – *business value of IT*. This paper engages with the big data productivity paradox, which is a specific instance of the IT productivity paradox, which has been an enduring stream of information systems research for over three decades. Considering cognitive analytics to be an emerging approach to the leveraging of big data for organizational benefits, this paper uses the theoretical perspective of resource-based view to show how organizations can benefit from cognitive analytics and big data. Thus, it makes a novel and strong attempt to address and refute the big data productivity paradox, extending recent academic thought that cognitive analytics technology can provide a useful avenue to leverage maximum value from big data. In doing so, the findings of this paper add to the literature on the business value of information technology, specifically in this case, the business value of cognitive analytics.

This paper also has important implications for managerial practice. By identifying complementary organizational resources such as human resources and intangible resources, this paper encourages managers to move beyond merely investing in cognitive analytics technology. Thus, it helps highlight the important fact that non-technical resources play an important complementary role while organizations and managers attempt to leverage value from a particular information and communication technology. By creating an organizational capability around the technology, managers can help their organizations achieve and sustain a competitive advantage over their competitors. It supports the proposition that cognitive analytics capability is not limited to the technology or the data (Gupta and George 2016; Ross et al. 2013).

This paper is not free from its limitations. The first major limitation is the relatively smaller size of the participant sample. While we strove to obtain theoretical saturation, the relatively smaller sample size is also due to the objective and context of the research project. Since cognitive analytics is a niche domain characterized by several failures as far as industry implementations are concerned, many potential interviewees refused to participate in the research endeavor. Also, a lack of access to more organizations implementing cognitive analytics could have influenced the findings obtained from this paper.

Since cognitive analytics is an emerging technology domain, the experience of the participants with this technology is likely to be limited. Thus, there might have been potential gaps in their articulation and description of the domain and its related issues. To address this issue, future research can think of participant observation as a research method. This would allow the researchers to capture potentially richer data.

6 References

Akter, S., Gunasekaran, A., Wamba, S. F., Babu, M. M., and Hani, U. 2020. "Reshaping Competitive Advantages with Analytics Capabilities in Service Systems," *Technological Forecasting and Social Change* (159), p. 120180. (https://doi.org/10.1016/j.techfore.2020.120180).

Barney, J. 1991. "Firm Resources and Sustained Competitive Advantage," *Journal of Management* (17:1), pp. 99–120.

Behera, R. K., Bala, P. K., and Dhir, A. 2019. "The Emerging Role of Cognitive Computing in Healthcare: A Systematic Literature Review," *International Journal of Medical Informatics* (129), pp. 154–166. (https://doi.org/10.1016/j.ijmedinf.2019.04.024).

Bharadwaj, A. S. 2000. “A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation,” *MIS Quarterly* (24:1), pp. 169–196.

Braun, V., and Clarke, V. 2006. “Using Thematic Analysis in Psychology,” *Qualitative Research in Psychology* (3:2), pp. 77–101.

Brynjolfsson, E., Rock, D., and Syverson, C. 2021. “The Productivity J-Curve: How Intangibles Complement General Purpose Technologies,” *American Economic Journal: Macroeconomics* (13:1), pp. 333–372. (https://doi.org/10.1257/mac.20180386).

Chatterjee, S., Rana, N. P., and Dwivedi, Y. K. 2021. “How Does Business Analytics Contribute to Organisational Performance and Business Value? A Resource-Based View,” *Information Technology & People*. (https://doi.org/10.1108/ITP-08-2020-0603).

Chen, M., Herrera, F., and Hwang, K. 2018. “Cognitive Computing: Architecture, Technologies and Intelligent Applications,” *IEEE Access* (6), pp. 19774–19783. (https://doi.org/10.1109/ACCESS.2018.2791469).

Cosic, R., Shanks, G., and Maynard, S. 2015. “A Business Analytics Capability Framework,” *Australasian Journal of Information Systems* (19), pp. S5–S19.

Eisenhardt, K. M. 1989. “Building Theories from Case Study Research.,” *Academy of Management Review* (14:4), pp. 532–550. (https://doi.org/10.5465/AMR.1989.4308385).

Ghasemaghaei, M. 2017. “The Effects of Operational and Cognitive Compatibilities on the Big Data Analytics Usage: Firm Distinctive Value Creation,” in *Americas Conference on Information Systems: A Tradition of Innovation, AMCIS 2017*, Boston: Americas Conference on Information Systems.

Ghasemaghaei, M. 2019. “Are Firms Ready to Use Big Data Analytics to Create Value? The Role of Structural and Psychological Readiness,” *Enterprise Information Systems* (13:5), pp. 650–674. (https://doi.org/10.1080/17517575.2019.1576228).

Grant, R. M. 1991. “A Resource Based Theory of Competitive Advantage: Implications for Strategy Formulation,” *California Management Review* (33:33), pp. 144-. (https://doi.org/10.2307/41166664).

Gudivada, V. N., Irfan, M. T., Fathi, E., and Rao, D. L. 2016. “Cognitive Analytics: Going beyond Big Data Analytics and Machine Learning,” in *Handbook of Statistics Vol. 35*, V. N. Gudivada, V. V. Raghavan, V. Govindaraju, and C. R. Rao (eds.), Elsevier B.V., pp. 169–205. (https://doi.org/10.1016/bs.host.2016.07.010).

Gupta, M., and George, J. F. 2016. “Toward the Development of a Big Data Analytics Capability,” *Information & Management* (53:8), pp. 1049–1064. (https://doi.org/10.1016/j.im.2016.07.004).

Gupta, S., Kar, A. K., Baabdullah, A., and Al-Khowaiter, W. A. A. 2018. “Big Data with Cognitive Computing: A Review for the Future,” *International Journal of Information Management* (42), pp. 78–89. (https://doi.org/10.1016/j.ijinfomgt.2018.06.005).

Hossain, M. A., Akter, S., and Yanamandram, V. 2020. “Revisiting Customer Analytics Capability for Data-Driven Retailing,” *Journal of Retailing and Consumer Services* (56), p. 102187. (https://doi.org/10.1016/j.jretconser.2020.102187).

Jeble, S., Dubey, R., Childe, S. J., Papadopoulos, T., Roubaud, D., and Prakash, A. 2018. “Impact of Big Data and Predictive Analytics Capability on Supply Chain Sustainability,” *The International Journal of Logistics Management* (29:2), pp. 513–538. (https://doi.org/10.1108/IJLM-05-2017-0134).

Kim, G., Shin, B., Kim, K. K., and Lee, H. G. 2011. “IT Capabilities, Process-Oriented Dynamic Capabilities, and Firm Financial Performance,” *Journal of the Association for Information Systems* (12:7), pp. 487–517.

Kraaijenbrink, J., Spender, J. C., and Groen, A. J. 2010. “The Resource-Based View: A Review and Assessment of Its Critiques,” *Journal of Management* (36:1), pp. 349–372. (https://doi.org/10.1177/0149206309350775).

Kristoffersen, E., Mikalef, P., Blomsma, F., and Li, J. 2021. “Towards a Business Analytics Capability for the Circular Economy,” *Technological Forecasting and Social Change* (171), p. 120957. (https://doi.org/10.1016/j.techfore.2021.120957).

Laird, J. E., Newell, A., and Rosenbloom, P. S. 1987. "SOAR: An Architecture for General Intelligence," *Artificial Intelligence* (33:1), pp. 1–64. (https://doi.org/10.1016/0004-3702(87)90050-6).

Mata, F. J., Fuerst, W. L., and Barney, J. B. 1995. "Information Technology and Sustained Competitive Advantage'," *MIS Quarterly, December* (19:4), pp. 487–505. (https://doi.org/10.2307/249630).

Melville, N., Kraemer, K., and Gurbaxani, V. 2004. "Review: Information Technology and Organizational Performance: An Integrative Model of IT Business Value," *MIS Quarterly* (28:2), pp. 283–322. (https://www.jstor.org/stable/25148636).

Mikalef, P., Fjørtoft, S. O., and Torvatn, H. Y. 2019. "Developing an Artificial Intelligence Capability: A Theoretical Framework for Business Value," in *4th Workshop on Big Data and Business Analytics Ecosystems (IDEATE 2019)*, Seville, Spain.

Mikalef, P., and Gupta, M. 2021. "Artificial Intelligence Capability: Conceptualization, Measurement Calibration, and Empirical Study on Its Impact on Organizational Creativity and Firm Performance," *Information & Management* (58:3), p. 103434. (https://doi.org/10.1016/j.im.2021.103434).

Mikalef, P., and 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), pp. 260–287. (https://doi.org/10.1080/0960085X.2020.1740618).

Modha, D. S., Ananthanarayanan, R., Esser, S. K., Ndirango, A., Sherbondy, A. J., and Singh, R. 2011. "Cognitive Computing," *Communications of the ACM* (54:8), p. 62. (https://doi.org/10.1145/1978542.1978559).

Nowell, L. S., Norris, J. M., White, D. E., and Moules, N. J. 2017. "Thematic Analysis: Striving to Meet the Trustworthiness Criteria," *International Journal of Qualitative Methods* (16:1), p. 160940691773384. (https://doi.org/10.1177/1609406917733847).

Priem, R. L., and Butler, J. E. 2001. "Is the Resource-Based " View " a Useful Perspective for Strategic Management Research?," *The Academy of Management Review* (26:1), pp. 22–40. (https://doi.org/10.1355/ae26-lc).

Roeglinger, M., Seyfried, J., Stelzl, S., and Muehlen, M. zur. 2018. "Cognitive Computing: What's in for Business Process Management? An Exploration of Use Case Ideas," in *Business Process Management Workshops. BPM 2017. Lecture Notes in Business Information Processing*, E. Teniente and M. Weidlich (eds.), Springer, pp. 419–428. (https://doi.org/10.1007/978-3-319-74030-0_32).

Ross, J. W., Beath, C. M., and Quaadgras, A. 2013. "You May Not Need Big Data after All," *Harvard Business Review* (91), pp. 90–98.

Schuetz, S., and Venkatesh, V. 2020. "Research Perspectives: The Rise of Human Machines: How Cognitive Computing Systems Challenge Assumptions of User-System Interaction," *Journal of the Association for Information Systems2* (21:2), pp. 460–482. (https://doi.org/10.17705/1jais.00608).

Shamim, S., Zeng, J., Shariq, S. M., and Khan, Z. 2019. "Role of Big Data Management in Enhancing Big Data Decision-Making Capability and Quality among Chinese Firms: A Dynamic Capabilities View," *Information & Management* (56:6), p. 103135. (https://doi.org/10.1016/j.im.2018.12.003).

Sirmon, D. G., Hitt, M. A., Ireland, R. D., and Gilbert, B. A. 2011. "Resource Orchestration to Create Competitive Advantage," *Journal of Management* (37:5), (J. B. Barney, D. J. Ketchen, and M. Wright, eds.), pp. 1390–1412. (https://doi.org/10.1177/0149206310385695).

Wade, M., and Hulland, J. 2004. "The Resource-Based View and Information Systems Research: Review, Extension, and Suggestions for Future Research," *MIS Quarterly* (28:1), pp. 107–142.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., and Childe, S. J. 2017. "Big Data Analytics and Firm Performance: Effects of Dynamic Capabilities," *Journal of Business Research* (70), pp. 356–365. (https://doi.org/10.1016/j.jbusres.2016.08.009).

Williams, S. 2016. "Outthink Cognitive Hype: Creating a Business-Driven Cognitive Strategy," *Business Intelligence Journal* (21:4).