PACIS 2021 Proceedings

Pacific Asia Conference on Information Systems (PACIS)

7-12-2021

Understanding the Antecedents and Consequences of Data Analytics Capabilities: A Literature Review in IS field

Prashanth Madhala
Tampere University, prashanth.madhala@tuni.fi

Hongxiu Li
Tampere University, hongxiu.li@tuni.fi

Nina Helander
Tampere University, nina.helander@tuni.fi

Understanding the Antecedents and Consequences of Data Analytics Capabilities: A Literature Review in IS field

Completed Research Paper

Prashanth Madhala
Tampere University
Korkeakoulunkatu 8
33720 Tampere, Finland
prashanth.madhala@tuni.fi

Hongxiu Li
Tampere University
Korkeakoulunkatu 8
33720 Tampere, Finland
hongxiu.li@tuni.fi

Nina Helander
Tampere University
Korkeakoulunkatu 8
33720 Tampere, Finland
nina.helander@tuni.fi

Abstract

Data analytics capabilities (DAC) create value for organisations. Prior literature has shown that organizational DAC are associated with different factors and lead to different value propositions. To provide a comprehensive understanding of both the antecedents and consequences of DAC in organizational context, this study examines the antecedents and consequences of DAC based on a literature review of the articles published at the leading information systems (IS) conferences and top IS journals. We synthesize four types of antecedents (data, business and management, technology, and organizational environment) and four consequences of DAC (innovation, business performance, strategy development, and decision making). This study also suggests the future research directions to guide IS scholars' research in the field of DAC.

Keywords: Data analytics capabilities, antecedents, consequences, literature review

Introduction

Technology development and digital transformation in organizations make big data available. Organizations collect huge amount of data from various sources such as social media, videos, business transactions, and IoT (Internet of Things) devices. To make use of big data, organizations also need to embrace, develop, and deploy data analytics to realize the value of big data, which makes data analytics capabilities (DAC) become an important organizational capability. DAC is applied in various scenarios for value creation such as competitive intelligence (Ranjan and Foropon 2021), business model renovation to help thrive in a competitive environment (Chen et al. 2017), business process performance (Aydiner et al. 2019), and product innovation (Niebel et al. 2019). These examples showcase the value of DAC and encourage organizations to consider its usage. But data only provide a new resource for value creation, and DAC is needed to capture the expected value of data in business.

In this regard, DAC is important for creating value in business. Thus, it is important for organizations to understand how to build DAC and how to achieve the value in business based on their DAC. Prior literature has examined DAC from different angles. Some scholars stated that DAC consists of tangible resources, human resources, and intangible resources, and can enhance market and operational performance as well as business innovation (Shuradze and Wagner 2016). Other researchers argued that DAC is determined by IT infrastructure, personnel expertise, and relationship structure in organizations (Gupta and George 2016). According to Mikalef et al. (2017), tangible resources (i.e. technology, data, financial), intangible resources (i.e. organizational learning, data-driven culture), and human skills (i.e. technical, managerial) make up DAC and lead to business value under certain enablers and inhibitors. Some research has focused on what defines DAC in specific context, such as in supply chain management (Arunachalam et al. 2018).

Prior studies have examined different antecedents and the value of DAC, and also highlighted that the variation in DAC might lead to difference in value realization. And it is indispensable to understand what determines the DAC and what are the consequences of DAC. Thus, a comprehensive understanding of the antecedents and consequences of DAC in various contexts is essential. To address the research gap, this study conducted a literature review based on publications at the top IS journals and two leading IS international conferences to provide a full picture of the antecedents and consequences of DAC. In doing so, the study aims to find out the antecedents and consequences of DAC and to contribute to existing literature on DAC.

The paper discusses the theoretical background of the study followed by an introduction of the research method. Then the findings of the paper are discussed including the antecedents and consequences of DAC. After the discussion of the findings, suggestions for future research are presented followed by the contribution and limitations of the study.

Theoretical Background

Capabilities

According to Amit and Schoemaker (1993), capabilities is defined as the ability of an organization to use its resources (physical, human, and technological) with other organizational factors to achieve a desired goal. A reflection of an organization's capability can be witnessed by the output it creates to ensure its existence and success (Winter 2000). Day (1994) defines capabilities as a complicated arrangement of skills and collective learning that can be exploited through organizational processes. The author classifies capabilities as inside-out, outside-in, and spanning processes. Inside-out processes are internally oriented, for example: produced due to market demand, outside-in processes are externally oriented, for instance, market responsiveness, and spanning processes integrates both the inside-out and outside-in processes, for e.g., business partnership management (Wade and Hulland 2004).

Grewal and Slotegraaf (2007) argued that capabilities are deeply embedded in the structural, cultural, and social aspects of organizations. If an organization's capabilities are refined or improved, it can lead to efficient operational performance and achieving competitive advantage through building dynamic capabilities on top of existing ordinary capabilities (Teece 2012). Competitive advantage can stem from possessing four types of capability differentials namely regulatory capability (e.g., possessing intellectual property rights), positional capability (e.g., effect of past actions), functional capability (e.g., ability to perform certain actions), and cultural capability (e.g., behavior in the form of attitudes, beliefs, habits and values) (Hall 1993) and the first two types arise from assets (possessing something) while the latter is specific to competencies (doing something). In addition to the types, there are various organizational capabilities that have been a subject of empirical research. For instance, information technology (IT) capability, which concerns with an organization's ability to organize and utilize IT-based resources has been linked with organizational performance (Bharadwaj 2000). Digital capabilities has been found to be related to managerial improvement (Levallet and Chan 2018).

Data analytics capabilities (DAC)

DAC can be defined as business capabilities enabled by IT to combine competencies from information management and analytics expertise (Ashrafi et al. 2019). The ability to assemble, combine, and use data analytics resources defines its data analytics capability (Gupta and George 2016). Seddon et al.

(2012) defines DAC as the ability to make use of data to enable sound decision making based on evidence. DAC can be also defined as a process that involves fact-based decision making enabled by technology and architecture (Presthus 2014). Shuradze and Wagner (2016) conceptualize DAC as containing infrastructure (analytical ability), personnel expertise (marketing and technical knowledge), and structure (social capital). In the literature, some scholars have used different terms to represent DAC, such as business analytics capabilities and big data analytics capabilities. Duan and Cao (2015) mention that there is no commonly accepted term for DAC but it can be defined as techniques and processes related to data analysis for the purpose of knowledge and intelligence generation, which can ultimately lead to competitive advantage.

DAC is enabled by technology tools such as data warehouses, on-line analytical processing (OLAP), statistical techniques, and data management tools (Seddon et al. 2012). Technology support for DAC is paramount. For instance, the emergence of cloud computing technology has paved way for efficiently handling big amounts of data and can provide many benefits with regards to data processing, especially in healthcare (Rajabion et al. 2019). IoT as a major source of data requires a technical IoT architecture for supporting DAC (Shin 2017). The development of artificial intelligence (AI) requires highly advanced data processing and statistical techniques that can enhance products or service efficiency, optimize business processes (both internal and external), and speed up analytical capabilities through possession of DAC (Davenport 2018). For instance, chatbots as computer programs driven by DAC can help transform the communication between citizens and government for information seeking and transaction related reasons (Androutsopoulou et al. 2019). Thus, DAC have been developed with technology development but also rely on modern technologies to create value both in private and public sectors.

Research Methodology

We conducted a literature review in this study. According to Rowley and Slack (2004), literature reviews help with identifying new research questions, topics, or in formulating new hypothesis in addition to developing insights to a theoretical concept. They condense findings, identify gaps in the research, and provide avenues for future research (Okoli 2015). An efficient review creates a strong base for advancing knowledge, supports theory development, concludes existing research, and exposes areas where research is required (Webster and Watson 2002).

The first step in literature review is article database selection, followed by article searching, keyword selections, article filtering, and final articles selection. To explore the antecedents and consequences of DAC in IS field, the articles published at the eight Basket of Journals in IS field (European Journal of Information Systems, Information Systems Journal, Information Systems Research, Journal of AIS, Journal of Information Technology, Journal of MIS, Journal of Strategic Information Systems and MIS Quarterly) and two other top IS journals (Information and Management; Decision Support System) and the two leading IS international conferences (International Conference on Information Systems (ICIS), European Conference on Information Systems (ECIS)) are selected for article search. The journals are considered as high-quality journals in the field of IS. Whereas ICIS is the most prominent conference in IS, and ECIS is the leading conference in IS in Europe.

The keywords and phrases *"analytics capabilities" OR "analytics capability" OR "analytical capabilities" OR "analytical capability"* was applied to search for the articles between the years 2010 and 2021. The articles published between 2010 and 2021(until February) have been selected since DAC has become an emerging research topic in IS field with innovative technology development and digitalization in the past years. The keywords and phrases search yielded a total of 238 articles. Based on full paper readings, 87 articles contained the discussion with regards to data analytics, big data, business intelligence (& analytics), business analytics (BA), and data analytics (and big data). The final inclusion criteria are based on whether these articles contained discussion around DAC, its antecedents, and consequences. Figure 1 presents the article searching process.

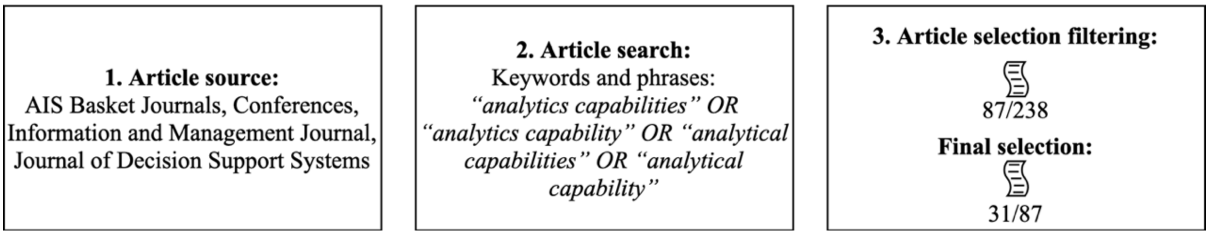

Figure 1. Article searching

As seen from the above image, 31 articles (18 journal articles and 13 conference articles) were chosen for final analysis to understand the antecedents and consequences of DAC. The distribution of articles is as follows: 10 from ICIS, 3 from ECIS, 2 from European Journal of Information Systems, 1 from Journal of Management Information Systems, 12 from Information and Management journal, and 3 from Journal of Decision Support Systems. The total number of articles corresponding to publication year is presented in Figure 2.

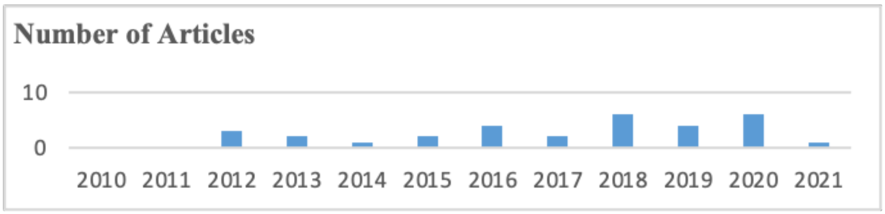

Figure 2. Number of articles and publication year

As shown in Figure 2, the selected articles for review are published between the years 2012 and 2021 with more than 50% of those published in the past 5 years, indicating the increasing research interest in the topic in recent years.

Findings

Based on reading the full articles of the selected 31 articles, we made a summary of the findings on research context, research method, theoretical base, the antecedents, and consequences of DAC identified in these articles. The details are presented in Table 1.

Findings on the antecedents of DAC

Prior studies have investigated the antecedents of DAC in organizations from different angles, and have applied different theories in their studies, such as Means-end chain (MEC), Resource-based view (RBV), Dynamic capabilities (DC), Knowledge-based view (KBV), affordance theory, socio-technical systems theory, and relationship marketing theory (Battleson et al. 2016; Dremel et al. 2020; Fay and Kazantsev 2018; Fink et al. 2017; Ghasemaghaei 2019; Gupta and George 2016; Kitchens et al. 2018; Tan et al. 2016). The antecedents of DAC fall into four major dimensions, namely data, business and management, technology, and organizational environment. First, ***Data*** is found to be an important dimension in the antecedents of DAC. The specific factors related to data dimension are high quality data (Ghasemaghaei 2019; Seddon et al. 2012); data sources (Jha et al. 2020; Krishnamoorthi and Mathew 2018a; Zhang et al. 2019), and data infrastructure (Alexander and Lyytinen 2019; Malladi and Krishnan 2013; Shanks et al. 2012). High quality data is important in determining DAC, because valuable analytics requires data that is reliable, timely, relevant, secure, accurate, and has all the appropriate details. Data sources is necessary for DAC, based on RBV and DC, Zhang et al. (2019) found that having different data sources such as meteorological data and pollutant source data is necessary to achieve predictive capability in the context of air pollution management. Data infrastructure is suggested to be an important factor in building DAC, because having a strong data

Table 1. List of Prior Research on the Antecedents and Consequences of DAC.

Article	Research context	Research method	Theory	Antecedents				Consequences			
				Data	Business and management	Technology	Organizational environment	Innovation	Business performance	Strategy development	Decision-making
Seddon et al. (2012)	General business organizations	Case study		- Data quality		-Integrated business intelligence platform	-Analytical people				Evidence-based decision making
Shanks et al. (2012)	Mining	Case study	RBV	- Data infrastructure	-Metrics and dimensions -Senior management support -Change management and governance -People with hybrid skills	-High quality technology			Reporting performance		
Yogev et al. (2012)	Innovation	Survey	RBV			-BI system	-BI team		Operational performance	Strategic goals	
Malladi & Krishnan (2013)	Innovation	Survey	Technology-Organization-Environment (TOE) framework	-Data infrastructure	-Managerial challenges -Data management challenges	-Technology readiness	-Organization size -Industry competitive intensity		Business performance		
Kurniawati et al. (2013)	Social media	case study	- Organizational motivation theory - RBV		-Organizational competences (resource collection and people skills)	-Technology assets			Business performance	Strategy improvements	
Chae (2014)	Manufacturing	Survey	RBV	-Data accuracy	-Advanced analytics				Operational performance		
Hitt et al. (2015)	Social media	Survey	Information processing theory (IPT)		-Data analytics skills						Decentralized decision making
Wu & Hitt (2015)	Innovation	Survey			-Data skills	-Enterprise systems					Decision making
Anand et al. (2016)	Organizational investment	Survey	-DC		-Investments			Organizational innovation	Organizational performance		
Battleson et al. (2016)	Cloud computing	Case study	DC			-Cloud computing	-Organizational factors (mature IS governance, employee empowerment, IT infrastructure maturity)		Service effectiveness (quality, innovativeness, satisfaction) and efficiency (time and cost).	Development of dynamic capabilities	

Tan et al. (2016)	E-commerce	Case study	DC, MEC, RBV	-Authentication data	-Domain expertise -Customer requirements -Data preprocessing	-Technological infrastructure			Identity verification	Strategy development for fraud detection	Decision optimization
Gupta & George (2016)	General business organizations	Survey	RBV		-Human skills	-Tangible resources	-Intangible resources		-Market performance -Operational performance		
Wan et al. (2017)	Innovation	Interviews and survey			-Business knowledge of IT team -Data collection ability		-Analytics maturity		Organizational performance		
Fink et al. (2017)	Agriculture and telecom industry	Interviews and survey	RBV			-BI infrastructure	-BI team			Operational and strategic capabilities	
Naseer et al. (2018)	Cyber security	Interviews	DC	-Data		-Analytics architecture			Efficiency and effectiveness of enterprise security performance	Dynamic capability development	
Fay & Kazantsev (2018)	Smart manufacturing	Secondary data	RBV	-Sufficient volumes of data -Availability of data	-Information integration -BDA skills -Data governance	-Infrastructure scalability - Data management tools and platforms	-Data-driven culture			-Production effectiveness -Cost cut -Product servitization -Product personalization -Higher customer satisfaction	
Krishna-moorthi & Mathew (2018b)	General business organizations	Survey	RBV			-Analytics technology assets			Business performance		
Kitchens et al. (2018)	E-commerce	Case study	Relationship marketing theory			-IT-supported data infrastructure.					Decision making
Wang et al. (2018)	Healthcare	Case study	Practice-based view (PBV)		-Traceability -Decision support capability -Data aggregation	-Predictive capability			Organizational performance		

					-Data analysis -Data interpretation						
Krishnamoorthi & Mathew (2018a)	General business organizations	Case study	RBV	-Data sources	-Analytics adoption -Analytics alignment with business -Analytics skill -People management	-Analytics tools, software -IT and ERP infrastructure -BI infrastructure -Reporting and visualization tools	-Analytics culture -Analytics organizational structure -Evidence-based decision making in the organization's DNA.		Business performance (ROI)		
Alexander & Lyytinen (2019)	Innovation	Survey	DC	-Data -Data infrastructure	-Skills			Business innovation	Organizational performance		
Zhang et al. (2019)	Air pollution management	Case study	RBV, DC	-Data sources -Data quality	-Data orchestration -Data specific investments						Decision making in real time
Shamim et al. (2019)	General business organizations	Survey	DC		-Leadership -Talent management	-Technology	-Organizational culture				Decision making effectiveness and efficiency
Ghasemaghaei (2019)	General business organizations	Survey	KBV	-Data quality	-Data utilization -Employee analytics capability -Knowledge sharing	-Tools sophistication					Decision making quality
Mikalef & Krogstie (2020)	Innovation	Survey	RBV	-Data	-Managerial skills -Technical skills	-Technology	-Data-driven culture -Organizational learning	Process innovation capabilities (incremental and radical)			
Mikalef et al. (2020)	General business organizations	Survey	RBV, DC		-Human skills	-Tangible resources	-Intangible resources		Competitive performance		
Mikaleft et al. (2020)	Innovation	Survey	RBV, Information governance theory		-Human skills	-Tangible resources	-Intangible resources	Incremental and radical innovation capabilities			
Dremel et al. (2020)	Automotive industry	Case study	Affordance theory, Socio-		-Alignment and funding -Collaboration	-Technology infrastructure - Data platform	-Analytics subunits			-Customer-centric marketing,	

			technical systems theory		-Interworking -Data integration	-Data collection technologies -Data lake	(marketing and R&D) -Data scientists			data-driven service development -Optimized production processes	
Suoniemi et al. (2020)	Business companies	Survey	RBV		-Analytics skills	-IT infrastructure	-Organizational big data resources		Organizational performance		
Jha et al. (2020)	Supply chain management	Interviews		-Data -Data sources	-Training -Leadership -Top management support -Central planning	-Advanced/quality software	-Analytics strategy -Data manager -Skilled employees		Competitive advantage		
Mikalef and Gupta (2021)	General business organizations	Survey	RBV		-Human skills	-Tangible resources	-Intangible resources		Organizational performance and creativity		

infrastructure can ensure easier collection and cleaning of data for extensive analytics usage (Malladi and Krishnan 2013).

Business and management were identified as another important dimension of the antecedents of DAC. Prior literature has listed some specific factors related to it, such as skills of employees, business knowledge of IT team, and business and analytics alignment in business organizations (Krishnamoorthi and Mathew 2018a; Wan et al. 2017). For instance, business knowledge is required for addressing business problems with data analytics (Krishnamoorthi and Mathew 2018a). Skills, such as analytical, managerial, technical, and hybrid skills are imperative for orchestrating data into value via data analytics (Alexander and Lyytinen 2019; Gupta and George 2016), and is needed for implementing effective data analytics in organizations. Senior management support, decision support capability, and leadership are pivotal in building DAC (Jha et al. 2020; Krishnamoorthi and Mathew 2018a; Shamim et al. 2019; Shanks et al. 2012; Wang et al. 2018). Senior management support plays an important role because their support is desired for investing in the appropriate software and tools for effective data-driven analytics (Jha et al. 2020).

Some factors related to the ***Technology*** dimension was identified as antecedents of DAC. Infrastructure is frequently mentioned in these articles as important antecedent of DAC in different research contexts, such as e-commerce, smart manufacturing, automotive, service industry, agriculture and telecom industry (Dremel et al. 2020; Fay and Kazantsev 2018; Fink et al. 2017; Kitchens et al. 2018; Krishnamoorthi and Mathew 2018a; Suoniemi et al. 2020; Tan et al. 2016). For instance, an infrastructure reflects an organization's data-driven ability (Fink et al. 2017) and having an infrastructure makes it easier for processing and analyzing huge volumes of data (Dremel et al. 2020). In addition to technology infrastructure, analytics software, analytics tools, data management tools, tools sophistication, and data collection technologies are needed for DAC irrespective of the context (Dremel et al. 2020; Fay and Kazantsev 2018; Ghasemaghaei 2019; Jha et al. 2020). For instance, analytics software is very useful for providing solutions to business problems whether it has to do with running the daily operations or when introducing strategic changes to the business (Krishnamoorthi and Mathew 2018a). With the help of sophisticated tools, deep knowledge concerning past, present, and future events can be obtained efficiently (Ghasemaghaei 2019).

Some factors related to ***Organizational environment*** are found to be the antecedents of DAC, mainly from the view of organizational culture and resources. Such as analytics culture or data-driven culture have been found to be essential for DAC (Fay and Kazantsev 2018; Krishnamoorthi and Mathew 2018; Mikalef and Krogstie 2020; Shamim et al. 2019). For instance, evidence based decision making requires a data-driven culture that supports it (Mikalef and Krogstie 2020) and culture is a reflection of the awareness of the value that data-driven analytics can provide to the organization (Krishnamoorthi and Mathew 2018a). People involved in data and data analytics in organizations, such as executives, professionals, and employees, BA/BI teams, and experts, and an organization structure for data analytics are required for data-driven activities (Dremel et al. 2020; Jha et al. 2020; Seddon et al. 2012; Yogev et al. 2012). Some studies highlighted that analytics structure in organizations (i.e. unit or subunit of data analytics) and organizational learning are other key factors identified in this dimension (Krishnamoorthi and Mathew 2018a; Mikalef and Krogstie 2020). For example, Krishnamoorthi and Mathew (2018a) found that having an organizational structure for analytics drives the analytics culture. In addition, having dedicated organizational unit for analytics attracts data scientists and analytics individuals who are a prerequisite for performing data analytics (Dremel et al. 2020).

Findings on the Consequences of DAC

Prior studies have investigated the consequences of DAC in organizations from different angles, and have applied different theories to explain how DAC lead to different consequences, such as RBV, information governance theory, DC, PBV, TOE framework, IPT, and KBV (Ghasemaghaei 2019; Hitt et al. 2015; Malladi and Krishnan 2013; Mikalef, Boura, et al. 2020; Naseer et al. 2018; Wang et al. 2018). The consequences of DAC in these studies mainly fall into four dimensions, namely business performance, innovation, strategy development, and decision making. ***Business performance*** is the most examined consequence of DAC (Alexander and Lyytinen 2019; Anand et al. 2016; Battleson et al. 2016; Chae et al. 2014; Gupta and George 2016; Jha et al. 2020; Kurniawati et al. 2013; Malladi and

Krishnan 2013; Mikalef and Gupta 2021; Shanks et al. 2012; Suoniemi et al. 2020; Tan et al. 2016; Wan et al. 2017; Wang et al. 2018; Yogev et al. 2012). Battleson et al. (2016) found that DAC leads to an increase in effectiveness (innovative product and service offerings, quality, and customer satisfaction) and efficiency (with respect to cost and time) in organizations. Kurniawati et al. (2013) made use of organizational motivation theory to understand the effect of DAC in social media context and identified benefits related to business performance which includes enhanced product and service performance, cost reduction and profit increase, and improved organizational effectiveness. Shanks et al. (2012) used RBV to investigate the benefits of applying DAC in business and reported that organizations can achieve benefits in human resources, asset management, and health & safety enabled by DAC. Naseer et al. (2018) used DAC to achieve efficient and effective security performance. Chae et al. (2014) applied RBV to study the effect of advanced analytics on improving the operational performance of manufacturers from the view of DAC. Gupta and George (2016) found a positive effect of DAC on market and operational performance. The research of Mikalef et al. (2020) has shown the effect of DAC on competitive performance from the integrated view of RBV and DC.

Decision making is another examined consequence of DAC. For instance, Kitchens et al. (2018) used relationship marketing theory to explain how advanced customer analytics helps achieve strategic business decision making in the context of e-commerce. In the context of social media, Hitt et al. (2015) applied IPT as a base for understanding the role of DAC in accomplishing decentralized decision making across all departments within an organization. From a combined view of MEC, DC, and RBV, Tan et al. (2016) found that DAC is useful for optimized decision making by providing information in real-time to take the best course of action in the context of e-commerce. Using KBV, Ghasemaghaei (2019) found that DAC can greatly improve the decision making quality in an organization. In their study, Shamim et al. (2019) assessed the effect of DAC on an organization's decision making quality especially the effectiveness and efficiency of the decisions with DC as the theoretical base. Some studies discussed about decision making without any specific theory (Seddon et al. 2012; Wu and Hitt 2015). Such as Seddon et al. (2012) studied the effect of DAC on evidence-based decision making.

Third, ***Strategy development*** is observed to be an important consequence of DAC**.** Based on DC, Naseer et al. (2018) explained the dynamic capability development in the context of cyber security where DAC contributes to the development of improved awareness, threat intelligence (for e.g., detecting threats), and dynamic risk assessment (for e.g., identifying, assessing, analyzing, and taking actions). Battleson et al. (2016) also explored dynamic capability development in the context cloud computing and found that cloud-based DACs can create competitive advantage with regards to product offerings which can act as differentiators in major market segments. Using RBV, Fay and Kazantsev (2018) and Yogev et al. (2012) investigated how DAC helps achieve strategic goals and objectives respectively. For instance, strategic goals in the form of creating new business models, products, services, etc. and strategic objectives as a result of recognition of business opportunities. Based on a combined view of socio-technical systems theory and affordance theory, Dremel et al. (2020) explained how to achieve optimization of production processes, data-driven vehicle development, setting up of data-driven services for vehicles, and customer-centric marketing via DAC.

Innovation is also one important consequence of DAC in organizations (Alexander and Lyytinen 2019; Anand et al. 2016; Mikalef, Boura, et al. 2020; Mikalef and Krogstie 2020). For instance, Alexander and Lyytinen (2019) studied the effect of DAC on business insights which can be helpful in producing business innovation as a consequence. Anand et al. (2016) used DC to study the effect of DAC on organizational innovation through the role of agency and resource allocation. Mikalef and Krogstie (2020) investigated the effect of different configurations of DAC on incremental and radical innovation capabilities using RBV. Mikalef et al. (2020) used RBV and information governance theory and found that both incremental and radical innovation capabilities are positively affected by DAC. Figure 3 presents the antecedents and the consequences of DAC in organizations, and the applied theories in these articles are also summarized.

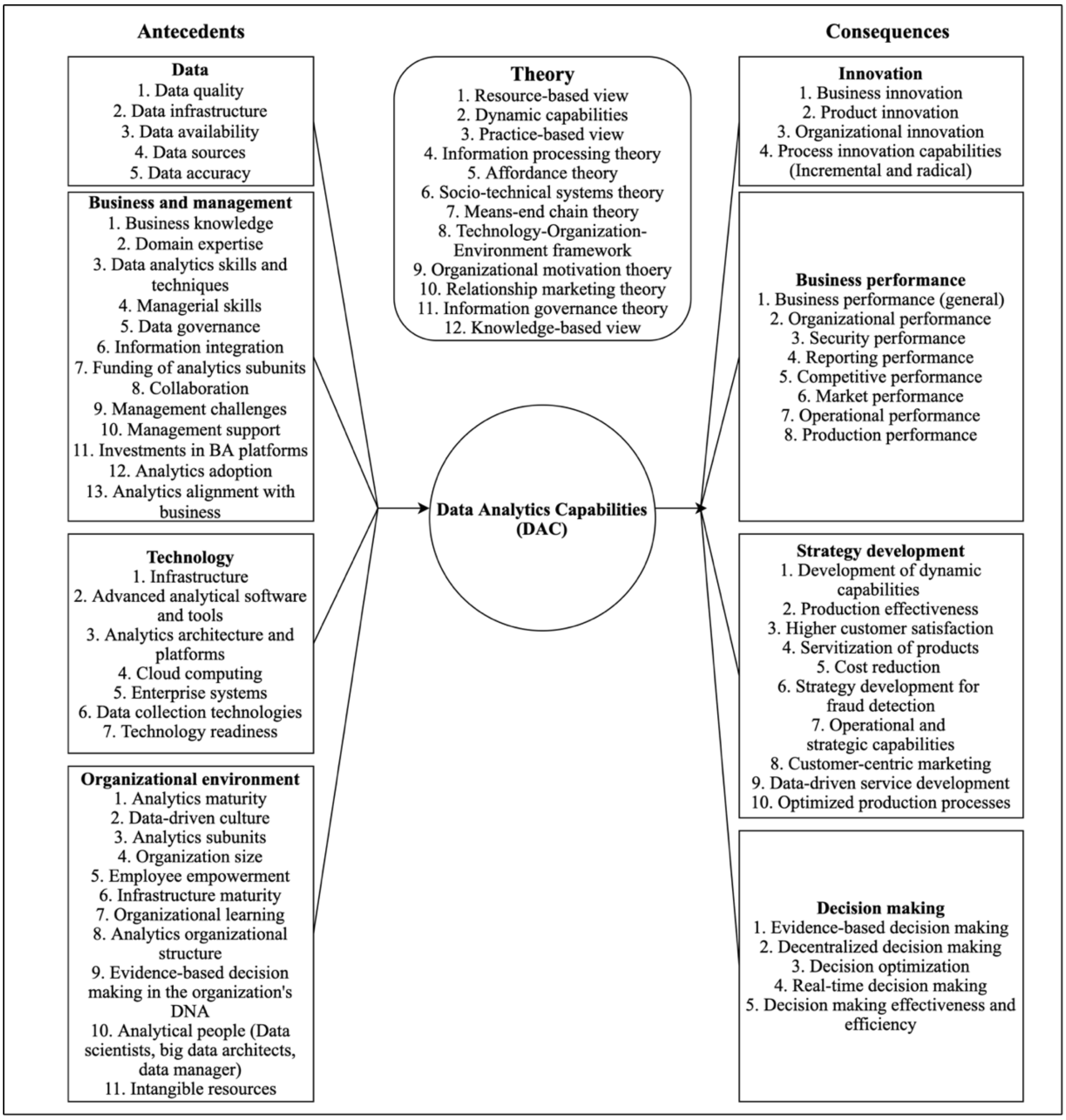

Figure 3. Antecedents and consequences of DAC

Suggestions for future research

The prior research has studied about different factors that help in building DAC and its consequences. However, there are potential areas for research missing in prior research. First, though different antecedents and consequences have been identified in the prior literature, but there is a lack of evidence on how different antecedents work jointly for different outcomes. This is an interesting and important topic for future IS scholars to work on as it will provide organizations clear knowledge on how to build DAC and for what objectives. In addition, it can help unravel the mechanisms to explain how different combination of antecedents lead to different consequences. An organization can implement mechanisms that are favorable for matching a certain antecedent to a desirable consequence.

Second, most of the prior studies have focused on investigating the positive consequences of DAC, and few studies have explored the dark side of DAC and the critical factors for failure in achieving the value of DAC in organizations. There is a call for research on these topics to provide companies with knowledge on what is needed and what is not necessary for building DAC successfully and how to capture the value via data analytics as they expected.

Third, prior studies discuss DAC in general, there is a lack of knowledge on how different antecedents impact different types of data analytics such as descriptive, predictive, and prescriptive analytics, and how to measure the maturity of DAC in organizations. Future research should work on these topics to provide knowledge to organizations on how to evaluate their DAC, and how the level of maturity of DAC will affect the value capturing in organizations. There are still other topics in DAC, such as how DAC should be embedded into an organization's business processes and how can organizations build a data-driven culture.

This research has contributed to the knowledge in the field of DAC via providing a comprehensive understanding of the antecedents and consequences of DAC in organizations and identifying the research gap with the suggested future research directions.

There are limitations to this study. First, only limited number of articles from IS field are selected in the review process. Therefore, it would be good to conduct systematic literature review on a broader scale of articles published in various journals rather than only in IS journals. Second, this paper only focuses on the antecedents and consequences of DAC, and the mechanisms of realizing the value of DAC is not explored to uncover the process from DAC to value creation. Third, the research did not consider the challenges or limitations of antecedents and consequences of DAC. Addressing these limitations could provide more knowledge about DAC and enrich the DAC literature.

References

Alexander, D., and Lyytinen. 2019. "Organizing Around Big Data: Organizational Analytic Capabilities for Improved Performance," in *ICIS 2019 Proceedings*.

Amit, R., and Schoemaker, P. J. H. 1993. "Strategic Assets and Organizational Rent," *Strategic Management Journal* (14:1), pp. 33–46.

Anand, A., Sharma, R., and Coltman, T. 2016. "Realizing Value from Business Analytics Platforms: The Effects of Managerial Search and Agility of Resource Allocation Processes," in *ICIS 2016 Proceedings*.

Androutsopoulou, A., Karacapilidis, N., Loukis, E., and Charalabidis, Y. 2019. "Transforming the Communication between Citizens and Government through AI-Guided Chatbots," *Government Information Quarterly* (36:2), pp. 358–367.

Arunachalam, D., Kumar, N., and Kawalek, J. P. 2018. "Understanding Big Data Analytics Capabilities in Supply Chain Management: Unravelling the Issues, Challenges and Implications for Practice," *Transportation Research Part E: Logistics and Transportation Review* (114), pp. 416–436.

Ashrafi, A., Zare Ravasan, A., Trkman, P., and Afshari, S. 2019. "The Role of Business Analytics Capabilities in Bolstering Firms' Agility and Performance," *International Journal of Information Management* (47), pp. 1–15.

Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S., and Delen, D. 2019. "Business Analytics and Firm Performance: The Mediating Role of Business Process Performance," *Journal of Business Research* (96), pp. 228–237.

Battleson, D. A., West, B. C., Kim, J., Ramesh, B., and Robinson, P. S. 2016. "Achieving Dynamic Capabilities with Cloud Computing: An Empirical Investigation," *European Journal of Information Systems* (25:3), pp. 209–230.

Bharadwaj, A. S. 2000. "A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation," *MIS Quarterly* (24:1), pp. 169–193.

Chae, B., Yang, C., Olson, D., and Sheu, C. 2014. "The Impact of Advanced Analytics and Data Accuracy on Operational Performance: A Contingent Resource Based Theory (RBT) Perspective," *Decision Support Systems* (59:1), pp. 119–126.

Chen, H.-M., Schutz, R., Kazman, R., and Matthes, F. 2017. "How Lufthansa Capitalized on Big Data for Business Model Renovation," *MIS Quarterly Executive* (16:1), pp. 19–34.

Davenport, T. H. 2018. "From Analytics to Artificial Intelligence," *Journal of Business Analytics* (1:2), pp. 73–80.

Day, G. S. 1994. "The Capabilities of Market-Driven Organizations," *Journal of Marketing* (58:4), pp. 37–52.

Dremel, C., Herterich, M. M., Wulf, J., and vom Brocke, J. 2020. "Actualizing Big Data Analytics Affordances: A Revelatory Case Study," *Information and Management* (57:1), p. 103121.

Duan, Y., and Cao, G. 2015. "Understanding the Impact of Business Analytics on Innovation," in *ECIS 2015 Proceedings*.

Fay, M., and Kazantsev, N. 2018. "When Smart Gets Smarter: How Big Data Analytics Creates Business Value in Smart Manufacturing," in *ICIS 2018 Proceedings*.
Fink, L., Yogev, N., and Even, A. 2017. "Business Intelligence and Organizational Learning: An Empirical Investigation of Value Creation Processes," *Information and Management* (54:1), pp. 38–56.
Ghasemaghaei, M. 2019. "Does Data Analytics Use Improve Firm Decision Making Quality? The Role of Knowledge Sharing and Data Analytics Competency," *Decision Support Systems* (120), pp. 14–24.
Grewal, R., and Slotegraaf, R. J. 2007. "Embeddedness of Organizational Capabilities," *Decision Sciences* (38:3), pp. 451–488.
Gupta, M., and George, J. F. 2016. "Toward the Development of a Big Data Analytics Capability," *Information and Management* (53:8), pp. 1049–1064.
Hall, R. 1993. "A Framework Linking Intangible Resources and Capabiliites to Sustainable Competitive Advantage," *Strategic Management Journal* (14:8), pp. 607–618.
Hitt, L., Jin, F., and Wu, L. 2015. "Data Skills and Value of Social Media: Evidence from Large-Sample Firm Value Analysis," in *ICIS 2015 Proceedings*.
Jha, A. K., Agi, M. A. N., and Ngai, E. W. T. 2020. "A Note on Big Data Analytics Capability Development in Supply Chain," *Decision Support Systems* (138), p. 113382.
Kitchens, B., Dobolyi, D., Li, J., and Abbasi, A. 2018. "Advanced Customer Analytics: Strategic Value Through Integration of Relationship-Oriented Big Data," *Journal of Management Information Systems* (35:2), pp. 540–574.
Krishnamoorthi, S., and Mathew, S. 2018a. "Business Analytics and Business Value: A Comparative Case Study," *Information and Management* (55:5), pp. 643–666.
Krishnamoorthi, S., and Mathew, S. 2018b. "An Empirical Investigation into Understanding the Business Value of Business Analytics," in *Proceedings of the 2018 Pre-ICIS SIGDSA Symposium*.
Kurniawati, Shanks, G., and Bekmamedova, N. 2013. "The Business Impact Of Social Media Analytics," in *ECIS 2013 Proceedings*.
Levallet, N., and Chan, Y. 2018. "Role of Digital Capabilities in Unleashing the Power of Managerial Improvisation," *MIS Quarterly Executive* (17:1), pp. 4–21.
Malladi, S., and Krishnan, M. 2013. "Determinants of Usage Variations of Business Intelligence & Analytics in Organizations – An Empirical Analysis," in *ICIS 2013 Proceedings*.
Mikalef, P., Boura, M., Lekakos, G., and Krogstie, J. 2020. "The Role of Information Governance in Big Data Analytics Driven Innovation," *Information and Management* (57:7), p. 103361.
Mikalef, P., Framnes, V., Danielsen, F., Krogstie, J., and Olsen, D. 2017. "Big Data Analytics Capability: Antecedents and Business Value," in *PACIS 2017 Proceedings*.
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 and Management* (58:3), p. 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.
Mikalef, P., Krogstie, J., Pappas, I. O., and Pavlou, P. 2020. "Exploring the Relationship between Big Data Analytics Capability and Competitive Performance: The Mediating Roles of Dynamic and Operational Capabilities," *Information and Management* (57:2).
Naseer, H., Ahmad, A., Maynard, S., and Shanks, G. 2018. "Cybersecurity Risk Management Using Analytics: A Dynamic Capabilities Approach," in *ICIS 2018 Proceedings*.
Niebel, T., Rasel, F., and Viete, S. 2019. "BIG Data – BIG Gains? Understanding the Link between Big Data Analytics and Innovation," *Economics of Innovation and New Technology* (28:3), pp. 296–316.
Okoli, C. 2015. "A Guide to Conducting a Standalone Systematic Literature Review," *Communications of the Association for Information Systems* (37:1), pp. 879–910.
Presthus, W. 2014. "Breakfast at Tiffany's: The Study of a Successful Business Intelligence Solution as an Information Infrastructure," in *ECIS 2014 Proceedings*.
Rajabion, L., Shaltooki, A. A., Taghikhah, M., Ghasemi, A., and Badfar, A. 2019. "Healthcare Big Data Processing Mechanisms: The Role of Cloud Computing," *International Journal of Information*

Management (49), pp. 271–289.
Ranjan, J., and Foropon, C. 2021. “Big Data Analytics in Building the Competitive Intelligence of Organizations,” *International Journal of Information Management* (56), p. 102231.
Rowley, J., and Slack, F. 2004. “Conducting a Literature Review,” *Management Research News*, pp. 31–39.
Seddon, P., Constantinidis, D., and Dod, H. 2012. “How Does Business Analytics Contribute to Business Value?,” in *ICIS 2012 Proceedings*.
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 and Management* (56:6), p. 103135.
Shanks, G., Bekmamedova, N., and Willcocks, L. 2012. “Business Analytics: Enabling Strategic Alignment and Organisational Transformation,” in *ECIS 2012 Proceedings*.
Shin, D. H. 2017. “Conceptualizing and Measuring Quality of Experience of the Internet of Things: Exploring How Quality Is Perceived by Users,” *Information and Management* (54:8), pp. 998–1011.
Shuradze, G., and Wagner, H. T. 2016. “Towards a Conceptualization of Data Analytics Capabilities,” in *Proceedings of the Annual Hawaii International Conference on System Sciences* (Vol. March), pp. 5052–5064.
Suoniemi, S., Meyer-Waarden, L., Munzel, A., Zablah, A. R., and Straub, D. 2020. “Big Data and Firm Performance: The Roles of Market-Directed Capabilities and Business Strategy,” *Information and Management* (57:7), p. 103365.
Tan, F. T. C., Guo, Z., Cahalane, M., and Cheng, D. 2016. “Developing Business Analytic Capabilities for Combating E-Commerce Identity Fraud: A Study of Trustev’s Digital Verification Solution,” *Information and Management* (53:7), pp. 878–891.
Teece, D. J. 2012. “Dynamic Capabilities: Routines versus Entrepreneurial Action,” *Journal of Management Studies*, pp. 1395–1401.
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.
Wan, X., Mao, J., Hsieh, J., and Chen, F. 2017. “The Influence of Data Analytics Capabilities on Organizational Performance: The Mediating Role of Exploitative and Exploratory Innovation,” in *ICIS 2017 Proceedings*.
Wang, Y., Kung, L. A., Wang, W. Y. C., and Cegielski, C. G. 2018. “An Integrated Big Data Analytics-Enabled Transformation Model: Application to Health Care,” *Information and Management* (55:1), pp. 64–79.
Webster, J., and Watson, R. T. 2002. “Analyzing the Past to Prepare for the Future: Writing a Literature Review,” *MIS Quarterly* (26:2), xiii–xxiii.
Winter, S. G. 2000. “The Satisficing Principle in Capability Learning,” *Strategic Management Journal* (21:10–11), pp. 981–996.
Wu, L., and Hitt, L. 2015. “How Do Data Skills Affect Firm Productivity: Evidence from Process-Driven vs. Innovation-Driven Practices,” in *ICIS 2015 Proceedings*.
Yogev, N., Fink, L., and Even, A. 2012. “How Business Intelligence Creates Value,” in *ECIS 2012 Proceedings*.
Zhang, D., Pan, S. L., Yu, J., and Liu, W. 2019. “Orchestrating Big Data Analytics Capability for Sustainability: A Study of Air Pollution Management in China,” *Information and Management*, p. 103231.