Developing data analytics capabilities: integrating the information systems success model and the resource-based view

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Abstract

Purpose – The information systems (IS) literature has indicated the importance of data analytics capabilities (DAC) in improving business performance in organizations. The literature has also highlighted the roles of organizations' data-related resources in developing their DAC and enhancing their business performance. However, little research has taken resource quality into account when studying DAC for business performance enhancement. Therefore, the purpose of this paper is to understand the impact of resource quality on DAC development for business performance enhancement.

Design/methodology/approach – We studied DAC development using the resource-based view and the IS success model based on empirical data collected via 19 semi-structured interviews.

Findings – Our findings show that data-related resource (including data, data systems, and data services) quality is vital to the development of DAC and the enhancement of organizations' business performance. The study uncovers the factors that make up each quality dimension, which is required for developing DAC for business performance enhancement.

Originality/value – Using the resource quality view, this study contributes to the literature by exploring the role of data-related resource quality in DAC development and business performance enhancement.

Keywords Data analytics capabilities, IS success model, Resources, Quality, Business performance enhancement

Paper type Research paper

1. Introduction

Data have become an important resource to create business value (Grover *et al.*, 2018). In recent years, organizations have increasingly invested in data-related resources to develop data analytics capabilities (DAC). Gupta and George (2016) defined DAC as an organization's ability to gather, unify, and deploy data-related resources. DAC have been found to increase business organizations' decision-making efficiency (Ghasemaghaei *et al.*, 2018), business performance and creativity (Mikalef and Gupta, 2021), and product efficiency and effectiveness (Raguseo *et al.*, 2021). Some scholars have also argued that DAC could enhance business organizations' sensemaking capabilities such as in understanding customer needs (Abbasi *et al.*, 2018) and service effectiveness (Battleson *et al.*, 2016).

Business organizations have increasingly developed their DAC for business performance enhancement. The retail company Walmart has built a centralized analytics hub, Data Café, which collects and combines data from multiple data sources to support real-time decision-

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making through data analytics (Marr, 2021). Consequently, Walmart has developed its DAC and achieved business value in terms of decision-making support and cost savings. The automotive manufacturer Tesla has leveraged a huge amount of sensor data from cars and used data analytics to make predictions and support decision-making in business (Yada, 2023). In this way, Tesla has developed its DAC to enhance the safety of its cars and customers, maintenance services and customer experience. These examples highlight the potential of DAC in enhancing business performance.

Data-related resources alone cannot generate value; they should be applied effectively and efficiently to business contexts in order to generate value (Amit and Schoemaker, 1993). According to Bharadwaj (2000), a lack of knowledge on how to apply data-related resources to build DAC in business may lead to business organizations' failure to realize the value of data and data analytics. Business organizations differ not only in their resources but also, more particularly, in their ability to apply their resources to create value (Amit and Schoemaker, 1993; Bharadwaj, 2000). Prior research in information systems (IS) has highlighted the importance of resources necessary to develop DAC from a resource-based perspective and has identified various resources for DAC development, such as tangible, human, and intangible resources (Gupta and George, 2016), talent capability, management capability, and technology capability (Akter *et al.*, 2016), infrastructure (Grover *et al.*, 2018), and a data-driven culture (Oesterreich *et al.*, 2022). Business value could be determined by how business organizations apply data-related resources (Bharadwaj, 2000; Iyer *et al.*, 2006).

Even though organizations have data resources and utilize these resources in business, the outcomes of the investments in data and data analytics vary across organizations. For instance, some organizations have been successful in developing DAC and realizing the value of data and data analytics, while some have failed (Amankwah-Amoah and Adomako, 2019). Differences in DAC and business performance may also be linked to the quality of resources that they operate with. Based on the foundations of resource-based view (RBV) (Barney, 1991), high-quality resources may help organizations to possess resource attributes that are valuable, rare, inimitable and non-substitutable. These resource attributes will enable organizations to achieve competitive advantages and enhance business performance. According to Fosso Wamba *et al.* (2019), both resources and the quality of resources should be considered while investigating DAC and its impact on business performance. Prior IS literature has also emphasized the importance of quality as a dominant logic in explaining system performance (Prahalad and Bettis, 1986). For instance, the quality of management practices has been suggested to be one of the key drivers of good system performance (Ravichandran and Rai, 2000). The IS success model posits that the quality of information, systems, and service resources associated with IS is crucial in achieving IS success at the organizational level (DeLone and McLean, 2003).

The quality-dominant logic provides a valuable framework for understanding DAC development by focusing on resource quality. In IS research, the concept of resource quality has been utilized to investigate IS success and its business outcome and similarly, this could be applicable to data-related resource investments and DAC development. Having data-related resources may not be enough for developing DAC and achieving success in investment in data and data analytics; rather, the quality of data resources is important (Akter *et al.*, 2023; Fosso Wamba *et al.*, 2019). Therefore, DAC development and its impact on business performance could be better justified from a resource quality perspective.

The existing literature has explored the importance of different data-related resources (e.g. tangible and intangible resources) for developing DAC and enhancing business performance. Yet, the literature has failed to explain how the quality of data-related resources may affect DAC development and organizations' business performance. By jointly investigating resources and their quality, we could better evaluate the outcomes of data-related resource investments in organizations from the view of DAC development and its impact on organizational business performance. In this regard, this study aims to address the following research question: "How is the quality of data-related resources related to the development of DAC for enhancing business performance?"

Bridging this research gap in the current study, we used RBV (Barney, 1991) and the IS success model (DeLone and McLean, 2003) to explain DAC development and its link with business performance in business organizations. The RBV can suitably explain which resources are necessary for DAC development and how these resources can be deployed to build DAC for business performance enhancement. Meanwhile, the IS success model provides a theoretical lens through which to explain how the quality of data-related resources can affect DAC development and business performance. We collected empirical data via semi-structured interviews to answer the research question in this study. We found that data quality, data system quality, and data service quality are associated with DAC development and DAC is linked with organizations' business performance enhancement.

This study contributes to the literature in two ways. First, this study explores the role of data quality, data system quality, and data service quality in DAC development and business performance enhancement from a resource quality perspective. Second, this study identifies the factors associated with the quality of these resources through a joint view of RBV and the IS success model. This study also offers practical guidelines for business organizations on how to improve data quality, data system quality, and data service quality to develop DAC and enhance business performance.

2. Theoretical background

2.1 Resource-based view

Organizations need resources in order to achieve good business performance and competitive advantages (Grant, 1991). According to the RBV, resources comprise assets, capabilities, processes, organizational attributes, information, and knowledge (Barney, 1991). Resources may include both tangible and intangible organizational capital, land, equipment, and labor skills (Mahoney and Pandian, 1992). The RBV has argued that resources have four attributes that enable organizations to establish and sustain competitive advantages: value, rarity, inimitability, and non-substitutability (Barney, 1991). Developing capabilities using resources is a complex process involving time and effort, which could make it difficult for competitors to imitate such capabilities (Bharadwaj, 2000). Accordingly, to remain competitive, organizations can gather and deploy resources to create unique capabilities that are difficult for rival organizations to imitate (Barney, 1991; Bharadwaj, 2000).

IS researchers have used the RBV to understand various IS phenomena, such as IT investment, IT consulting, IT capabilities, and information management capabilities. Bharadwaj (2000) used the RBV to empirically investigate the relationship between IT capabilities and organizational performance, finding that IT resources (infrastructure, human and IT-enabled intangibles) can help create organizational IT capabilities. Meanwhile, Ray *et al.* (2005) used the RBV to explore the role of IT in customer service, revealing that IT, when combined with shared knowledge, enhances this process. Iyer *et al.* (2006) used the RBV to explain organizational incentives for procuring IT consulting services. They discovered that the integration of IT resources, organizational structures and work processes can generate services and capabilities. Mithas *et al.* (2011) used the RBV to investigate the role of information management capabilities in organizations and found that information management capabilities, along with other capabilities (performance management, customer management and process management), improved organizational performance, including customer performance, financial performance, human resource performance and organizational effectiveness.

Recently, the RBV has been used to explore data-related phenomena, such as business analytics (BA), big data analytics (BDA) and artificial intelligence (AI) capabilities. Drawing on the RBV, Wang *et al.* (2019) explained BA's role in generating business value. Hyun *et al.* (2020) used the RBV to explain BDA's role in developing organizational agility, finding that both advanced and basic BDA—combined with an organizational culture of democratization—could lead to organizational agility. Suoniemi *et al.* (2020) used the RBV to explain the role of BDA resources in improving organizational performance. Their findings revealed a positive link between BDA and organizational performance. Lou and Wu (2021) also used the RBV to explain the role of AI capabilities in accelerating the drug development process. They found that resources, such as AI skills and domain expertise, play a vital role in AI-based innovation.

In the prior literature, researchers have argued that organizational resources include both assets (whether tangible or intangible) and capabilities (abilities, skills, or processes; Barney, 1991). According to Day (1994), capabilities are complex amalgamations of skills, learning, and resources that organizations can leverage. In this sense, DAC are unique capabilities that require the integration of data-related resources—such as data themselves, data-related technology, and data-related human resources. Therefore, in the data analytics context, organizations must deploy data-related resources to develop DAC and provide data-related services for different organizational needs. Through such an approach, business organizations' DAC would be unique and possibly difficult to imitate due to their use of intangible resources. Furthermore, intangible resources such as expertise and knowledge help develop DAC and enhance business performance. Business organizations must invest in data-related resources to develop DAC, which, in turn, could enhance business performance.

To summarize, business organizations should collect, unify, and deploy various data-related resources to develop DAC and enhance their business performance (Gupta and George, 2016). These resources must be integrated and deployed to create data services that fulfill the needs of business organizations (Bharadwaj, 2000). Accordingly, combining resources to provide data services could address business needs (Krishnamoorthi and Mathew, 2018). According to the IS success model, although different IS resources, such as information, systems, and services are essential to achieving IS success, they may not ensure IS success, and the quality of these resources could play an important role in achieving IS success (Gu and Jung, 2013). Thus, the quality of data-related resources might better explain how resources are combined to develop DAC and enhance business performance. It is necessary to take resource quality into account when studying DAC and its impact on business performance from the RBV.

2.2 Information systems success model

DeLone and McLean (1992) introduced the IS success model to explain IS success, which highlights the importance of two quality dimensions: information quality and system quality. DeLone and McLean (2003) updated the IS success model by introducing service quality as another important quality dimension, alongside information quality and system quality, to explain IS success.

The updated IS success model has been used to explain various IS phenomena. Lee and Kozar (2006) investigated website quality's effect on e-business success using the IS success model. They found that information quality, system quality, and service quality are important factors that determine website preference, which was linked to e-business success. Later, Gorla *et al.* (2010) used the IS success model to study the impacts of information quality, system quality, and service quality on organizations and found that the three quality dimensions influence organizations' internal efficiency, customers, suppliers, products, and services. Ifinedo *et al.* (2010) used the IS success model to investigate organizations' success after implementing enterprise resource planning, validating the effects of system quality, information quality, and service quality at the individual, work group, and organizational levels. For instance, the three quality dimensions were found to affect costs, overall productivity, and customer satisfaction at the organizational level. Meanwhile, Gu and Jung (2013) studied the effect of IS capabilities and IS qualities (information, system, and service) on organizational performance and found that IS capabilities indirectly influence business performance via IS qualities. Perdana *et al.* (2022) investigated the factors that inhibit and enable organizational performance using the IS success quality dimensions, such as information and system quality. They discovered positive associations between information quality, system quality and organizational performance.

In some recent studies, researchers have used the IS success model to explain how data and DAC influence organizations. For instance, Ashrafi *et al.* (2019) investigated the role of BA capabilities in supporting organizations' agility and performance. They found that information quality is positively linked to BA capabilities. To summarize, the literature includes different findings regarding the importance of quality dimensions in achieving IS success and performance. Particularly, by exploring how different qualities can impact IS success and organizational performance.

2.3 Link between the information systems success model and the resource-based view

Although the RBV focuses on employing resources to enable organizations to establish and sustain competitive advantages, and the IS success model highlights the importance of resource quality in achieving IS success and its impacts on business, Fosso Wamba *et al.* (2019) stated that RBV is consistent with the IS success model. Both theories explain how organizations use their resources to build competences and influence their business performance. Some scholars have argued that since the RBV does not provide specific elements from the resource view, scholars could consider incorporating new elements or concepts in RBV to answer the "how" questions (Priem and Butler, 2001). Thus, this study extends the RBV by incorporating the three types of resources and the quality of these resources from the IS success model to explain how resource quality affects DAC development, as well as the role of DAC in enhancing business performance through the perspective of resource quality.

Specifically, the RBV emphasizes the strategic importance of organizational resources which can be classified as tangible and intangible resources (Wernerfelt, 1984). According to the RBV, resources are considered vital for organizations in achieving and sustaining competitive advantage in business (Barney, 1991). Accordingly, we applied the general concept of resources from RBV in this study and argued that data-related resources (input) can be used to build DAC and enhance business performance (output). The IS success model posits that information, systems, and services are the resources for IS development, and the quality of these resources (information quality, system quality, and service quality) determines the success of an IS. The IS success model provides the theoretical base for the inclusion of data, data systems, and data services as specific data-related resources and how the quality of these resources (data quality, data system quality, and data service quality) affect DAC development and business performance from the perspective of resource quality.

As mentioned in Section 2.1, developing DAC involves resources such data, data-related technology, and data-related human resources (Gupta and George, 2016). First, data is considered an important resource for organizational decision-making. Data can be collected from different sources and utilized to generate valuable information and knowledge. The information and knowledge should be reliable and accurate for decision support (Ghasemaghaei and Calic, 2019). Therefore, data quality is important for DAC development. Second, data-related technologies enable organizations to use data to address business problems. The hardware and software for data use represent the technical elements of data systems and affect the quality of data systems, including speed, infrastructural capability, convenience, functionality, etc (Khayer *et al.*, 2020; Petter and McLean, 2009), which could influence the utilization of data in organizations (Fink *et al.*, 2017). Thus, data system quality is important for DAC development. Third, data-related human resources comprising skills, expertise, and knowledge are needed for steering the utilization of data and data analytics in business. The quality of these data-related human resources will determine whether an organization can use data and data analytics to provide reliable and efficient data services. Therefore, data service quality is important for DAC development (Petter and McLean, 2009).

3. Research methodology

To explore the link between data-related resources and their quality in developing DAC and enhancing business performance, this study utilized qualitative research methodology. According to Flick (2018), qualitative research focuses on interactions with research participants with the aim of understanding their perspectives about a certain phenomenon. Qualitative research could be used to answer questions related to "how" things happen at organizations (Rosaline, 2008). This study aims to answer questions about how the quality of data-related resources is related to DAC and business performance. The research question is a typical "how" question at the organizational level. Thus, the qualitative research method could be an appropriate research method for this study.

3.1 Data collection

The empirical data were collected via semi-structured interviews. Semi-structured interviews assist researchers in gathering organization-specific information from research participants by facilitating a dialogue or conversation between the interviewer and the interviewee (Cassell, 2015). The interview questions were centered around data-related resources and their quality in developing DAC and business performance enhancement. The RBV and the IS success model were used as the theoretical base for developing the interview questions. Following DeLone and McLean's (2003) IS success model, we conceptualized data, data systems, and data services as data-related resources. The participants were asked about the characteristics of data, data systems, and data services that are associated with the quality of these resources, and how the quality of these resources affects DAC development and business performance. In addition, questions concerning interviewees' professional background, work experience and responsibilities were asked at the beginning of each interview. This approach was to ensure that the interviews were appropriate for answering the interview questions and that their answers captured the subjectivity concerning the utilization of data and data analytics in business, thereby supporting the interpretive validity of this study (Maxwell, 2012).

Regarding whom to interview, the interview design considered participants whose work profile is related to the use of data and data analytics in daily work life. The rationale for selecting interviewees was based on their prior and current work experience in utilizing data and data analytics in business. The interviewees were recruited through the network of researchers in industries and through recommendations from some interviewed participants. Table 1 presents this study's interviewees, their present roles and the industry in which they worked during our data collection.

In total, 19 interviewees from different countries participated in this project, but the majority were from Finland. The interviewees' current roles ranged from technical to strategic in the field of data and data analytics in business, and the sample included a data scientist, a data analyst, a data engineer, business analysts, consultants, a data product owner, a product manager, a sales manager, a UX designer, team leaders, a marketing

Interviewee	Role	Industry
1	Data scientist	Insurance
2	CEO	Software
3	CEO	Software
4	CEO	Construction
5	Consultant	Retail
6	Data analyst	Electronics
7	Consultant	IT service
8	Data product	Insurance
9	Data engineer	IT service
10	Consultant	IT service
11	Manager - Data, analytics and application programming interface (API)	Manufacturing
12	Business analyst	Manufacturing
13	Business analyst	Manufacturing
14	Digital experience team leader	Manufacturing
15	Director of IT and digital services	Manufacturing
16	Marketing specialist	Manufacturing
17	User experience (UX) designer	Manufacturing
18	Product manager	Manufacturing
19	Sales manager	Manufacturing

Source(s): Authors' own work

Table 1. Interviewee information

specialist, a director, and CEOs. Moreover, the interviewees worked in different industries, including retail, insurance, software, IT services management, construction, electronics, and manufacturing. These participants had rich work experience in various roles and industries. The sample size was sufficient for answering the study's research question as no additional themes emerged from the interviews (Morris, 2015).

Interviews were conducted between March 2022 and July 2022. Each interview lasted around 60 min. The interviews were conducted in English, using both online communication tools (for example, Microsoft Teams and Zoom) and face-to-face communication. The interviewees were asked to consent to interview-recording before the interviews took place. The interviews were recorded and transcribed using the automatic transcription provided by Microsoft Teams. The verbatim transcription of each interview ensured the descriptive validity of this study (Maxwell, 2012).

3.2 Data analysis

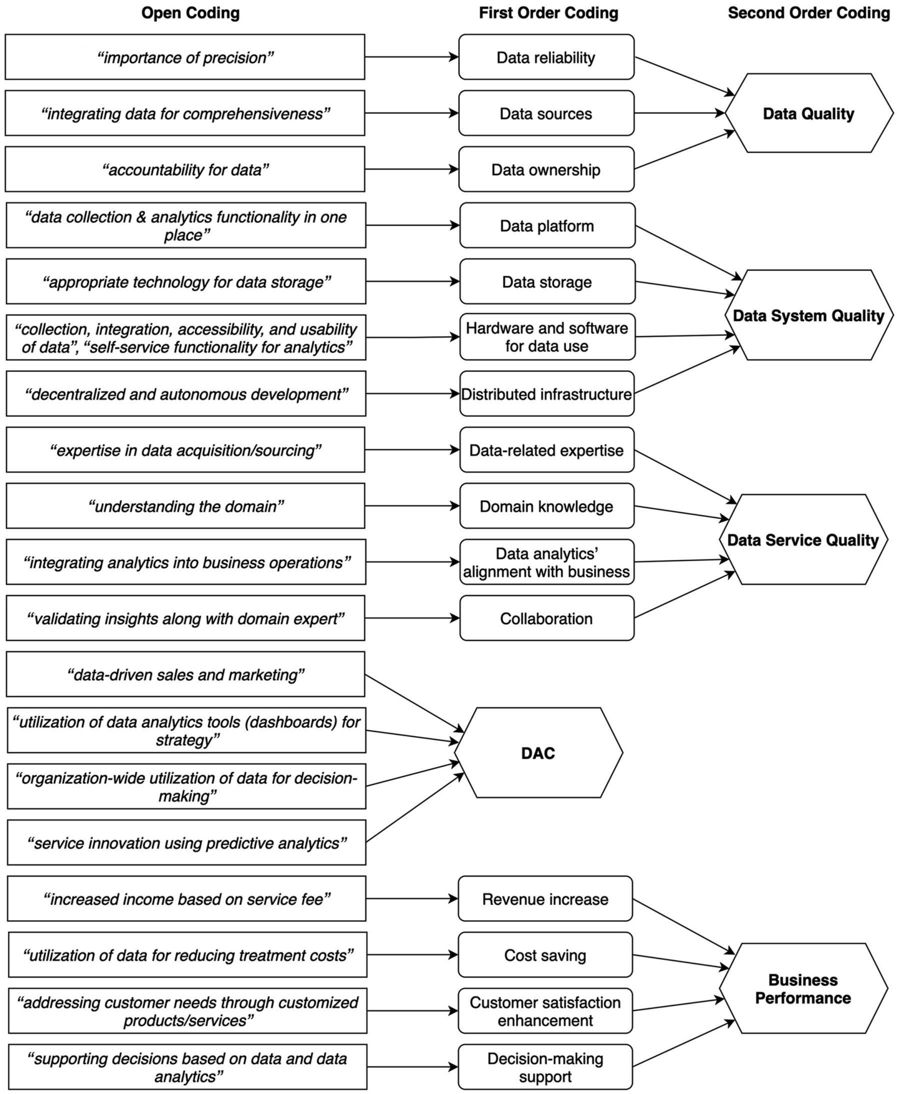
In this study, the data was analyzed thematically following thematic analysis. According to Boyatzis (1998), qualitative data can be coded using thematic analysis to help identify themes, indicators, and causal relationships. Such themes are defined as patterns that can help explain a phenomenon (Myers, 2019). According to Myers (2019), thematic analysis involves generating initial codes, identifying themes from these initial codes, and reviewing, defining, and naming themes. We applied an inductive coding approach in this study, generating themes from the interview data. This inductive coding approach focused on identifying how business organizations combined resources to develop DAC regarding data, systems, and services. The codes were mapped into appropriate data analytics-related quality dimensions, such as data quality, data system quality, and data service quality. Codes related to DAC and business performance were also generated. During the data analysis process, the researchers screened the interview transcripts carefully while listening to the interview recordings to maintain the interviews' accuracy and consistency while preserving the interviewees' meaning and intent. The data were analyzed at the organizational level.

The coding process started with open coding. In open coding, we explored each interview transcript to gain a comprehensive understanding of the perspective of the interviewees. In this stage, the data was coded descriptively without being subjected to preconceived code categories or concepts. For example, "importance of precision" was descriptively coded based on the interviewee's statements emphasizing the importance of precision in the data collection process. The second stage of the coding process is first-order coding, where the descriptive labels were mapped to the themes generated in the open coding. In the first-order coding, openly coded labels were categorized into appropriate themes related to data-related resources. For example, data reliability was identified as an important theme about data resources for organizations, based on the open coding of data attributes such as data precision and data accuracy. Subsequently, other first-order codes were also generated in this manner. Then, we mapped the themes identified in the first-order coding to data quality, data system quality, and data service quality, following the three quality dimensions proposed in the IS success model.

In this study, data reliability, data sources and data ownership were categorized as important factors determining data quality. Data reliability and data sources were mapped to data quality dimensions based on the interpretation of interviewees' statements and prior literature (Côrte-Real *et al.*, 2020; Ghasemaghaei and Calic, 2019). For instance, unreliable data can affect the quality of data and validity of insights generated via data analytics. Robust data analytics requires variety of data sources. Based on the discussions with some interviewees, data quality was not only limited to technical issues alone but also involved managerial aspects such as who owns data and who is responsible for the credibility of the data. Hence, in this study, data ownership was mapped under the data quality dimension. In addition, any factors related to data collection, storage, processing, sharing, analysis of data, and dissemination of analytical insights involving hardware and software resources were mapped under the data system quality dimension. Furthermore, any factors related to how employees use data and data analytics in business were mapped under the data service quality dimension. For example, interviewees mentioned the role of humans in developing DAC from the perspectives of having good talent, domain knowledge, the importance of aligning data analysis tasks to business objectives, and collaboration for providing better data-related services in the organization, which were coded for data service quality in the coding.

In this study, DAC coding was based on the definition of DAC – the capability to collect, unify, and deploy data, data-related technology, and data-related human resources in business. It includes the organizational capability to gather large amounts of data and various types of data for business, the capability to make business predictions based on data and data analytics, the capability of technical and managerial personnel to orchestrate the data analytics process, and to generate insights for decision-making.

The open coding for business performance focuses on the enhancement of business outcomes through the utilization of data and data analytics. The interviewees mentioned different aspects related to business performance, such as support for business decision-making in operations, reduction of marketing costs and efficient customer management. Subsequently, we derived first-order codes for business performance enhancement based on the themes identified in the initial open coding. Four primary themes were generated to measure business performance enhancement through the deployment of DAC in business: revenue increase, cost saving, customer satisfaction enhancement and decision-making support. These four themes were further coded to assess business performance enhancement. Figure 1 illustrates the code generation process in this study.



Source(s): Authors’ own work

Figure 1.
Data coding and analysis

Finally, we generated themes linking the three quality dimensions to DAC, and we also coded the association between DAC and business performance. During our data analysis, we revisited our codes for further discussion. Our data analysis process was completed when we had mutually agreed on our interpretation of the codes in relation to the studied phenomena. We conducted the data analysis using Atlas, a qualitative data analysis program. In Table 2, we present the definitions for data quality, data system quality, data service quality, DAC, and business performance, which support our coding.

Concept	Definition
Data quality	Data quality is defined by the usability, importance, accuracy, timeliness, completeness, and relevancy of data in an organization (DeLone and McLean, 2003)
Data system quality	Data system quality is defined as the degree to which the data system including its hardware, software, and technical attributes such as speed, reliability, and functionality can support the data-related needs of an organization (DeLone and McLean, 2003)
Data service quality	Data service quality is defined as the degree to which the data service in an organization provides efficient, effective, and reliable services to support the needs of different users (DeLone and McLean, 2003)
DAC	DAC refers to the ability of an organization to gather, unify, and deploy different data-related resources (including data-enabled services) in business (Gupta and George, 2016)
Business performance	Business performance is defined as the favorable business outcomes that are achieved by an organization. Such favorable business outcomes are related to quantitative (e.g. cost saving) or qualitative (e.g. customer satisfaction) benefits (Koohang *et al.*, 2023; Krishnamoorthi and Mathew, 2018)

Source(s): Authors' own work

Table 2. Definition of key concepts in this study

4. Findings

4.1 Link between data quality and data analytics capabilities

Our analysis of the data indicated an association between data quality and DAC. Data reliability, data sources, and data ownership were identified as data quality dimensions and were linked to DAC.

4.1.1 Data reliability. Organizations that work with data have concerns about data's reliability since data may contain too much noise, inhibiting organizations' ability to utilize data effectively (Abbasi *et al.*, 2016). Interviewee (Int.) 1 mentioned that the incompleteness, duplication or untimeliness of data could affect their ability to generate and validate insights based on data and data analytics. According to Int. 4, timeliness of data could affect an organization's ability to use data to manage schedules. Int. 2 suggested that, if data retrieved from various sources were incomplete and inaccurate, organizations' ability to deploy data and data analytics could be affected. Int. 16 mentioned that incomplete data affect organizations' ability to deploy reliable data for marketing operations.

> Every piece of the data needs to be of high quality so that everything that you see upstream is reliable and you can use it for making decisions or building models. . . . [If] they [organization] are to make decisions using questionable quality data, especially in an industry like healthcare, it's not going to work. . . . I would say that validity of whatever you build will get questionable. (Int. 1)

> Data should help and direct the decision-making, but if it doesn't, if it's wrong, then obviously, the direction will be wrong as well. (Int. 2)

> If we think about the customer who is in the construction phase, so they look [at] the data, and in order to be on top of the schedule management . . . so they know that once they have, for example, casted new concrete, then they can see from the data that they are on track of getting dry enough figures in the time period [desired]. So, they can forecast based on that data. It's actionable insight. So, if they say that this won't be drying fast enough, then they can put dryer heaters in place and start heating and speeding up the process. (Int. 4)

> We have these types of issues. For example, in our customer relationship management, the data is not complete. Some customers are lacking their email addresses or other type of contact information, and then we struggle with reaching those customers. (Int. 16)

4.1.2 Data sources. Poor data quality has been a major concern when gathering data from multiple sources. For example, dataset format mismatches could be avoided by gathering consistent data across all sources. This approach could lead to good data quality for analytics (Hashem *et al.*, 2015). Int. 15 discussed how predictive maintenance requires data from different sources, such as machine data and operative data. Int. 10 mentioned that to accurately forecast how much energy the solar panels could produce, the interviewee's organization need access to data from the customer's solar panels and the building's energy consumption systems. According to Int. 3 and Int. 8, organizations could make business predictions or forecasts based on data gathered from different sources.

> We get the accuracy of +90% when we predict how many people will visit tomorrow, based on the weather [data]. (Int. 3)

> By combining that data from different sources, ownership data about our customers, just in general the building data in the country, weather data, then okay, this is a good idea to do here. This is a bad idea to do here . . . the way data helps with decision is both on the monitoring side, like backwards. Also, I guess, on predictions. (Int. 8)

> Customers could, for example, get forecasts about how much energy will the solar panel produce. . . from the solar panel system and the energy consumption of the building that are different data sources. (Int. 10)

4.1.3 Data ownership. Data ownership concerns the ownership of, access to, and privacy of data, which can limit the number of data sources that a business organization can access (Günther *et al.*, 2017). In this study, data ownership was mentioned as a dimension of data quality in DAC development. Int. 7 mentioned that data ownership is key to ensuring good data quality for data analytics.

> I think that kind of comes to the ownership, that owning the data should be part of owning the business process because the business process is where it's [data quality is] defined. . . . then use that data for. . . understanding the customers better to be able to target the kind of sales campaigns. (Int. 7)

The prior literature has highlighted data quality's importance in determining DAC. For example, Ghasemaghaei and Calic (2019) found that the ability to use data in decision-making depends on data quality. Meanwhile, Côrte-Real *et al.* (2020) found that data quality (complete, accurate, and current data) is positively linked with DAC. Data sources could lead to new product success and marketing decisions via DAC (Hajli *et al.*, 2020). Moreover, data ownership has been found to be associated with data quality (Vilminko-Heikkinen and Pekkola, 2019), which is closely associated with DAC development. Consistent with the literature's previous findings, the current study's findings reveal an association between data quality and DAC. Therefore, we proposed:

> *Proposition 1.* Data quality (e.g. data reliability, data sources, and data ownership) is associated with DAC.

4.2 Link between data system quality and data analytics capabilities

Our analysis of the data indicated an association between data system quality and DAC. Technological infrastructure resources—such as data storage, data platforms, hardware and software, and distributed infrastructure—compose the data system quality dimensions. These individual factors are explained in the following subsections.

4.2.1 Data storage. Data storage is essential for handling a variety of data from multiple sources and in large volumes in order to meet business organizations' demand for efficient data retrieval (Günther *et al.*, 2017). According to Int. 1, data storage is vital because data should be stored in data warehouses/stores to be conveniently utilized for different types of data analytics applications.

> We need data storage that's high in quality, that's easy to retrieve data from . . . and we also need computational capabilities that are low-latency—low-latency meaning you need to be able to get your solutions quickly deployed. (Int. 1)

> We might have decentralized data stores. For example. . . If you have an agent [insurance] sitting in front of their computer, they're going to have some data of their clients. We are going to have different data stores. And all these data stores that are decentralized, need to be piped into a centralized data store. (Int. 1)

4.2.2 Data platforms. Data platforms help organizations generate, collect, and analyze transactional data to understand customers' purchasing behavior (Xie *et al.*, 2016). These platforms can perform complex computations to guide organizational decision-making by gathering results quickly. According to Int. 12, Int. 13, and Int. 14, data platforms can help customers understand how machines and their operators are performing by gathering data from different sources. The machines produce different types of data—for example, data related to how much wood has been cut, as well as the daily production rates of machines and machine operators. Int. 11 and Int. 17 suggested that customers can obtain analytics solutions through online digital data platforms. Data can be visualized meaningfully in relation to a specific user's requirements on a data platform. For example, the data platform displays information relating to machine behavior through data collected using machine's sensors. Such data were collected from the machines and then processed and visualized on the data platform. The insights generated on a data platform guide customers' business action. According to Int. 2, a data platform is a key resource for DAC development.

> We can easily gather the customer data and customer transaction data from different sources. . . . They [customers] can create segments out of it easily, create different rules, based on the changes [related to the data], and then implement the campaigns using our tool. (Int. 2)

According to Int. 3, data platforms allow managers to take actions based on the insights generated from data.

> We bring in [data] from different data sources. . . . The maintenance manager might see the temperatures of pools but he's not that interested about sales . . . which is the general manager stuff, so that you have different views and insights of data to what is actually in your portfolio. (Int. 3)

4.2.3 Hardware and software for data use. Data software is used in the process of collecting data, setting up data flow pipelines, data visualization and data analysis. Meanwhile, hardware devices increase computational power and help connect devices to manage data (Ives *et al.*, 2016). According to Int. 3, hardware components may affect DAC. For instance, energy consumption meters may have data delivery cut-offs, disconnected hardware may hinder data transfer, cameras might count wrongly, and connectivity issues might arise from telecom providers that could affect data's accuracy. Therefore, hardware's ability to capture data can also affect the accuracy of the insights generated through data and data analytics. Int. 4 mentioned that sensors and cloud services allow customers to collect and analyze data for multiple use cases, such as schedule management, systems monitoring, and alarm systems. Int. 6 mentioned that analytics software allows organizations to create pricing-related dashboards to monitor key performance indicators (KPIs).

> We call it, pricing health dashboard. So, not only looking at the data but, say, putting all things together and come up with a strategy for the product—all things meaning, in our language, is nine KPIs . . . you can select different product lines and then, based on these nine boxes, we can define a strategy or find issues from the operations. (Int. 6)

4.2.4 Distributed infrastructure. Data infrastructure allows business organizations to integrate data from multiple sources for analytical applications. Distributed technology infrastructure could lay a foundation for the creation of data-related microservices for different organizational units (Tilson *et al.*, 2010). A conversation with Int. 9 suggested that distributed technology infrastructure also plays a vital role in allowing individual departments to deploy their own technology infrastructures (e.g. the cloud). The provision of data-related microservices could enable data development more catered to these teams. Hence, data can be much more quickly deployed to address business needs.

> Why are we now talking about distributed development in the data? And I would say it's partly because data has become more like everyday thing. (Int. 9)

> They [teams] want to utilize data that they're working with. So, all of a sudden, the demand for the data. . . has popped up, and that has driven to the point where the centralized approach might not be in some cases, you know, scalable enough. (Int. 9)

In the prior literature, technology has been said to play a critical role in DAC development. For example, Shamim *et al.* (2019) found a positive link between data-related technology and DAC. Data storage technologies—such as data warehouses and data lakes—are important for organizations' DAC development (Lehrer *et al.*, 2018). According to Watson (2017), technology infrastructure components, such as data storage, enable DAC because they can store various kinds of data. Data analytics software and tools also play a vital role in the development of DAC. For example, data visualization may provide transparent information based on data and allow organizations to predict hidden relationships or customer behaviors based on data analytics (Chang *et al.*, 2022). In alignment with the previous findings in the literature and based on the current study's findings regarding the factors related to data system quality and DAC, we proposed:

> *Proposition 2.* Data system quality (e.g. technological infrastructure tools, such as data storage, data platforms, hardware and software for data use, and distributed infrastructure) is associated with DAC.

4.3 Link between data service quality and data analytics capabilities

The findings in this study indicate an association between data service quality and DAC. Data-related expertise, domain knowledge, data analytics' alignment with business, and collaboration compose the data service quality dimensions. The following subsections explain these individual factors.

4.3.1 Data-related expertise. DAC development requires the mobilization of experts in statistics, business, data and programming (Shao *et al.*, 2022). Our conversation with Int. 1 suggested that DAC depends on various areas of data-related expertise at an organization.

> If you are generating an insight. . . you take this to a provider. You take this to an internal clinician who knows what exactly it is. . . . If you are working on cancer, you talk to an oncologist. . . and say, "Okay, this is what I'm saying. Is this possible?" And then, that doctor will go back and look at what you're exactly trying to say, and they will validate what you're saying, or they might not validate what you're saying. (Int. 1)

Int. 6 discussed how data engineering expertise is required to set up the technological environment required for data analytics.

> They can be the middleman between me and the IT, so they can help [quickly] to get the server running. (Int. 6)

Business organizations need technical and managerial data-related expertise to fulfil specific BA needs in different business units, according to Int. 8.

> let's say motor [business function] comes to me and says that we want to change this existing delivery. Let's research this change and let's make it happen. So, the data warehouse implements this change, tests it, the business unit tests it with me, and then, okay, we kind of push the button, and it's flowing in a new way. . . . So, they act as internal clients in a way, and we act as internal implementers. (Int. 8)

4.3.2 Domain knowledge. Domain knowledge has been cited as an important factor in understanding business problems and formulating analytical solutions to address those problems (Chen *et al.*, 2012). In addition, domain knowledge is vital for translating business-specific problems into tasks for machine-learning models (Zhang *et al.*, 2020). Int. 19 mentioned that domain knowledge plays a vital role in DAC development. For example, salespeople should develop knowledge about how to talk to a customer regarding applications that involve data and data analytics in business. According to Int. 19, customers are becoming more data-aware and demanding more data-based insights to meet their business needs. Int. 3 mentioned that domain knowledge is critical for DAC.

> We know the facilities. We provide services, and. . . they [customers] want to have transparent information into their organization, and typically, . . . we consult with them . . . on what to do with this data. . . I bet we are faster; we are agile in everything, and like I said, we even know . . . some examples, new ideas, stuff like this. So, we have [or understand] the business context [of customers]. (Int. 3)

4.3.3 Data analytics' alignment with business. Günther *et al.* (2017) identified the absence of stakeholder interests, organizational structures, and data-driven business models as factors that lead to a misalignment between data analytics and business. To accomplish business goals and objectives, data analytics should fit with a business strategy. Int. 9 suggested that alignment is important for DAC development. He noted that data engineering teams at a customer organization enabled the DAC development for specific business tasks or specific units (e.g. the marketing department) in an organization. Such as data engineering teams provide data-related microservices to different business units in the form of guidelines, code templates, and different kinds of infrastructure as code to ensure DAC development and deployment. The provision of data-related microservices allowed marketing departments' experts to work on data and data analytics themselves. Meanwhile, conversations with Int. 12, Int. 13, and Int. 14 explained that a virtual team had been established to align data analytics with different business tasks and needs, such as product management and UX design. These interviewees mentioned that the alignment of data analytics and business needs made the development of, for example, data-based customer solutions easier. DAC development was much more efficient through the alignment. Int. 7 mentioned the importance of data analytics' alignment with business when developing DAC.

> They [domain experts] kind of had their like built-in, the way of working, there are these experienced people, they have been doing this a lot. So, they know, and. . . it kind of comes from the backbone that this is how we do things. So, then, we introduced the predictive models. . . So, instead of them continuing to use that gut feeling and the intuition and the expertise, they actually were offered machine learning models, [which] produced recommendations, like some propensities that this flight might be delayed this much, based on the weather and all the other factors. (Int. 7)

4.3.4 Collaboration. Collaboration between data and business is crucial. For instance, the collaboration between analytics and business teams is essential to develop analytics applications and services (Dremel *et al.*, 2020). According to Int. 5, Int. 6, and Int. 10, collaboration is a key resource when developing DAC because collaboration helps organizations to establish a shared language about a work or process, align data analytics with business needs and make data analytics services efficient.

They [business representatives] didn't even know what the analysts were doing, who the analysts were, and it really took several months of sitting side by side and, you know, having lunches and just trying out several different things before we started understanding, (a) what they were able to offer to us as business and (b) what we really could have asked from them because they didn't know what we need and we didn't know what they can provide. (Int. 5)

[When] I send the report to them. It's not the end of the report. We need continuous discussion on how do we use it better, what do we need to build on top of that, alerts or dashboards? Do we want to visualize that in a better way? (Int. 6)

A typical problem is that the analytical expertise is quite scattered, and also the data tends to be quite business-unit–specific. So, then, you have to pay a lot of attention coordinating how to do things in a systematic way so that people are not just doing everything their own way, then, because in that case, the kind of IT landscape becomes very difficult to manage. You may have five different analytics tools, you have to talk with different vendors, and the data is very scattered. Everybody is preparing data for their own purposes, and people may not have similar ideas about what different pieces of data mean. (Int. 10)

Data-related expertise plays a critical role in DAC development. Organizations need data analytics skills to understand data's value and fully leverage this value. Suoniemi *et al.* (2020) revealed that data analytics skills are an important factor in DAC development because they are essential in building predictive models. Domain knowledge is needed to validate algorithms and review analytics results contextually (Tan *et al.*, 2016). Moreover, alignment (intellectual, social, and operational) with data analytics is essential for developing DAC and achieving business objectives (Dremel *et al.*, 2020). Collaboration has been found to be key in deploying data analytics resources and developing business organizations' DAC (Jha *et al.*, 2020). Therefore, in accordance with previous studies and based on our findings, we proposed:

Proposition 3. Data service quality (e.g. data-related expertise, domain knowledge, data analytics' alignment with business, and collaboration) is associated with DAC.

4.4 Link between data analytics capabilities and business performance

This study's interviewees discussed the link between DAC and business performance when business organizations develop their DAC. Our findings indicate that DAC could enhance business organizations' performance. The interviewees discussed business performance from different angles, for example, revenue increase, cost saving, customer satisfaction enhancement, and decision-making support. Int. 15, Int. 3, and Int. 2 mentioned that business organizations with strong DAC can enable new business models (via digital service development), increase their customers (via changing clients' service portfolios), and improve sales conversions, thereby increasing revenues.

The value comes from increased sales, increased sales conversion. So, if you are, let's say, communicating to customer, if you communicate more targeted and more personalized, that usually always increases the conversion. (Int. 2)

Int. 1, Int. 2, Int. 3, and Int. 4 discussed business organizations' DAC leading to cost saving. According to Int. 1, DAC helps cut customer management costs. Int. 2 and Int. 3 explained that they had reduced advertising costs via efficient segmentation and target marketing. Meanwhile, Int. 4 stressed the importance of real-time data for schedule management, which helps avoid project delays and excessive costs.

For instance, [on] Tuesday, 11:00 . . . we can [recommend the customer] to . . . make some swimming teaching lessons to bring more people in, and then advertise those [lessons]. So, you know when to advertise, you know what to advertise, and to whom you want to advertise. You can also cut the costs on those advertisements. (Int. 3)

Int. 11 and Int. 13 mentioned that business organizations' DAC leads to the enhancement of customer satisfaction. They revealed that DAC enables customers to better visualize machine usage and forestry results and allows them to have good control of their daily machine and business operations. Customers can also know the production rates of their machines' operators. These DAC-based customer services make customers feel satisfied with the products and services that a company provides.

They [customers] know how their business is doing, and... they visualize, ... for example, ... how much it [machine] is producing this day and, on this day. (Int 13)

DAC have been shown to improve business organizations' decision-making. Int. 7 mentioned that DAC could help operators at a control centre to automate calculations and assist with decision-making. Int. 8 discussed enhanced decision-making support based on DAC.

Also, really in-the-moment decisions—should we, for example, sell insurance to this person with this [social security number], who, for example... has only that salary or has bad credit rating, but he owns three properties and five cars?... Should we really sell insurance to him? Does he have a risk of... defaulting? So, that is also part of the decisions that we use data for. (Int. 8)

The prior literature has identified DAC's importance in achieving business performance. For instance, DAC have been found to positively influence competitive performance and decision-making performance (Ghasemaghaei *et al.*, 2018; Mikalef *et al.*, 2020). Through a meta-analysis, Oesterreich *et al.* (2022) found that DAC has influenced organizations' business performance. DAC could allow organizations to respond to customer needs and, thereby, enhance their business performance (Zhou *et al.*, 2018). In addition to such findings from the prior literature, the current study also supports the association between DAC and business performance. Accordingly, we proposed:

Proposition 4. DAC are linked to organizations' business performance (e.g. revenue increase, cost saving, customer satisfaction enhancement, and decision-making support).

5. Discussion

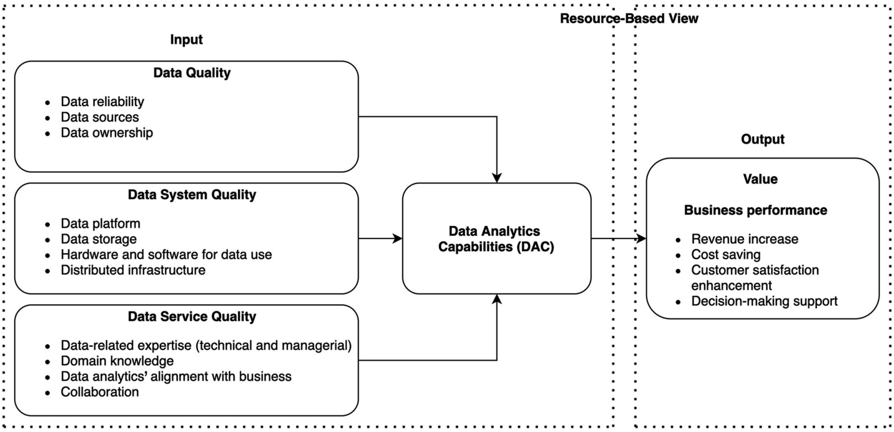
In this study, we examined how the quality of data-related resources is related to DAC and enhanced business performance by gathering interview data from employees working in various industries. We identified three quality dimensions that explain DAC development: data quality, data system quality, and data service quality. Moreover, we found DAC to be linked with organizational business performance. In this study, we also explored the factors that explain each of the three quality dimensions and business performance.

First, we found evidence that data quality is associated with business organizations' DAC development. The major factors that ensure data quality, we argued, are data reliability, data sources, and data ownership. Insights generated from data can only be reliable if their corresponding data are reliable (Chae *et al.*, 2014). Additionally, business organizations should have sufficient data sources to ensure data quality. For instance, problem-solving using data analytics may involve both internal and external data sources. To understand customers and meet their needs, business organizations may need to use multiple data sources to gather good-quality data for their analytics. In addition, data ownership may hamper access to data, which is needed for accessing data for data analytics. Good data reliability, broad data sources, and owning or accessing data are important for ensuring high-quality data, which is crucial for developing business organizations' DAC.

Second, we found data system quality to be associated with DAC. Organizations need data systems to ensure that data is collected, stored securely, and retrieved and used efficiently. Such systems' hardware is important to data collection and storage, ensuring an efficient data flow for business organizations. Data systems' software is also essential for business organizations to integrate different systems or technologies, create and run algorithms, visualize data, and scale their computing needs (Cascavilla *et al.*, 2018). Additionally, distributed infrastructure is essential to setting up a data pipeline, supporting data analytics, and scaling data analytics' development. Distribution of technology infrastructure could enable data-driven problem-solving at various organizational levels and provide good data system quality for DAC development. By maintaining high levels of data system quality, business organizations can effectively manage data storage, computation, analytics, and visualization, which would lead to high DAC.

Third, in this study, we found that data service quality is associated with DAC. Data-related expertise, domain knowledge, data analytics' alignment with business, and collaboration constitute data service quality. Technical expertise is vital for orchestrating data and technology to obtain insights (Shao *et al.*, 2022), such as in creating prediction models for developing services. Managerial or domain expertise is needed to communicate data service requirements to the rest of an organization and create domain-specific analytics solutions. On the other hand, business organizations should know how and where to apply data analytics, which requires domain knowledge in business. Domain knowledge allows business organizations to efficiently deploy data, technology, and human expertise in order to solve domain-specific problems (Kettinger *et al.*, 2021; Krishnamoorthi and Mathew, 2018). Additionally, the data services provided to different business units should be aligned with the business objectives to ensure that data analytics address specific business problems and achieve certain business goals. Furthermore, collaboration in data analytics increases synergy across business domains by establishing a common language and shared understanding of business problems between data analytics and business teams. Collaboration can also ensure an efficient data analytics process and the application of insights generated via data analytics efficiently. Thus, data-related expertise, domain knowledge, data analytics' alignment with business, and collaboration will help develop good data services that will, in turn, develop business organizations' DAC.

Fourth, in this study, we revealed the association between DAC and business performance. Our findings support the previous literature linking DAC with business performance (Ghasemaghaei *et al.*, 2018). Our findings show that DAC benefits business organizations. These benefits vary across organizations and industries. By deploying DAC, business organizations can not only create new services, but also new revenue streams or new data-driven business models based on these services. DAC allow business organizations to derive data-enabled insights and knowledge that can optimize business processes, operations, and management, thereby reducing costs. Furthermore, customer satisfaction is one metric by which business organizations can evaluate their business performance. For instance, business organizations can enhance their understanding of customer preferences and provide tailored products and services based on customers' needs via DAC. Additionally, DAC help with business organizations' decision-making. Organizations have regarded data and data analytics as important resources in supporting business decision-making. Business organizations' DAC could provide data-enabled insights and actions to support different business decisions efficiently. Thus, organizations' DAC should lead to enhanced business performance via revenue increase, cost saving, improved customer satisfaction, and data-driven decision-making support. Figure 2 depicts the resource quality model for DAC development and business performance enhancement.



Source(s): Authors' own work

Figure 2. The resource quality model for the development of data analytics capabilities and business performance enhancement

6. Contributions

6.1 Theoretical implications

This study offers several contributions to the literature. First, it explains business organizations' DAC development from the resource quality perspective, based on the RBV and the IS success model. The prior literature has used the RBV to explain what resources are needed to develop business organizations' DAC. This study enriches the RBV literature by examining the role of data-related resource quality in DAC development and extends the understanding of how resources could be applied to develop DAC within organizations from the resource quality view. In addition, this study extends the application of the IS success model to the DAC field by borrowing the three quality dimensions (information quality, system quality, and service quality) of the IS success model and developing three quality dimensions of data-related resources (data quality, data system quality, and data service quality) for DAC development.

Second, this study explores how the quality of data-related resources (data quality, data system quality, and data service quality) influences DAC development and enhances business performance by identifying the specific factors that are associated with the quality of these resources. Factors such as data reliability, data sources, and data ownership are identified as being related to data quality. Data platform, data storage, hardware, and software for data use, as well as distributed infrastructure, are important factors linked to data system quality. Data service quality depends on business organizations' data-related expertise, domain knowledge, data analytics' alignment with business, and collaboration. These findings provide a deep understanding of the factors associated with data-related resource quality and their association with DAC development and business performance from a quality perspective.

Third, this study contributes to the literature by providing a comprehensive explanation for data service quality's role in DAC development. The prior literature has highlighted the importance of data and data systems in this development. The findings in this study on data service quality's importance in developing DAC indicate that this development involves the orchestration of data, technology, and human resources. This process helps generate DAC to enhance business performance from a social-technical perspective.

6.2 Practical implications

This study's findings also provide some practical guidelines for business organizations to use DAC development to enhance business performance from a perspective of data-related resource quality.

First, our findings on the importance of data-related resource quality in DAC development provide practical guidelines for business organizations' DAC development from a combined view of resources and quality. Business organizations should not only invest in data-related resources but also improve the quality of data-related resources to develop their DAC. Specifically, they should not only invest in data, data systems, and data services but also adopt strategies that maintain the quality of their data, data systems, and data services when developing DAC. These strategies can further enhance their business performance.

Second, we identified different factors related to data quality, data system quality, and data service quality in DAC development and business performance enhancement. These findings provide practical guidelines for business organizations' maintenance of good quality of data, data systems, and data services for DAC development and business performance enhancement. Specifically, business organizations should consider using reliable data as well as having broad data sources and data ownership to ensure data quality when developing DAC. Additionally, business organizations should invest in the hardware and software for data use, build distributed infrastructure to establish their data systems, establish data platforms in collaboration with other stakeholders, and increase their data storage capability to improve their data systems quality and develop their DAC. Moreover, business organizations should understand the importance of data-related expertise, domain knowledge, data analytics' alignment with business, and collaboration in establishing data service quality in developing DAC. Our findings also indicate that business organizations should consider DAC development from a socio-technical perspective. For instance, business organizations should understand the importance of not only data and technologies (e.g. data and data systems) but also the role of humans (e.g. data services) in developing DAC to enhance business performance.

Third, this study provides evidence of DAC's role in enhancing business organizations' performance. Thus, business organizations should understand the different value propositions of DAC development from different views regarding business performance and take action to improve their DAC for business performance enhancement. Specifically, in this study, DAC were found to be related to revenue increase, cost saving, decision-making support, and customer satisfaction enhancement. The findings indicate that business organizations should implement holistic strategies focused on data-related resources and their quality to develop DAC and consequently, enhance business performance. For example, business organizations could leverage data and data analytics to develop their DAC and create innovative data-driven business models to boost their revenues. To achieve cost saving, business organizations could utilize data and data analytics to optimize their cost management strategies. To enhance customer satisfaction, business organizations should better understand customer needs based on data and data analytics and refine their products/services. Additionally, if business organizations want to support their decision-making through data and data analytics, they should embed data and data analytics at different organizational levels and improve their DAC.

7. Limitations and future research directions

This study faced limitations that should be acknowledged. First, we examined DAC development and business performance from a perspective that integrated the RBV and the IS success model, but we did not consider some other factors related to DAC development, such as digitalization, leadership, or organizational culture. Future research could explore the role of these factors in DAC development and business performance enhancement through other theoretical lenses, such as socio-technical systems theory and dynamic capabilities.

Second, in this study, we collected empirical data across industries, such as manufacturing, insurance, software services, construction, retail, electronics, and IT service management. With this approach, we sought to present a general perspective. Future research could explore the role of resource quality in DAC development and business performance enhancement in specific industries. Such a specific focus might help identify differences in value propositions for business performance across industries.

Finally, the current study used semi-structured interviews for empirical data collection. This approach could introduce biases in the interpretation of statements, which may differ across researchers. However, other research methods—such as surveys, participant observation, and action research—could also yield insights into DAC research. Future research could apply such methods or combine qualitative and quantitative approaches to further examine DAC phenomena.

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