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Data analytics in small and mid-size enterprises: Enablers and inhibitors for business value and firm performance

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ABSTRACT

A critical question arises as to whether data analytics (DA) can bring value and improve organizational performance. The benefit offered by DA can be achieved only when organizations are able to direct their attention on the conditioning factors that amplify business value. At the same time, organizations should cautiously resolve the issues that dampen DA business value. This study applied resource-based view (RBV) and the dual factor concept to understand such factors within the Small and Mid-size Enterprises (SMEs) context. The results revealed that information and systems qualities were the catalysts for data analytics business value, whereas lack of understanding and concerns over data security and privacy were the most salient predictors that could prevent SMEs from realizing DA business value. Our study highlights the importance of understanding both enablers and inhibitors in IT business value research. We also offer strategies to stakeholders to help SMEs realize DA business value.

1. Introduction

Competitive business environments require firms to quickly adapt to meet customers' needs and employ innovative practices. Data analytics (DA) has the potential to bring about a range of innovations by enabling firms to leverage data such as customer preferences and product sales. Leveraging on DA, firms can identify, accumulate, and utilize knowledge to address existing and future potentially challenging business environments (Wu et al., 2019a). For instance, a tremendous amount of data on social media usage, web browsing patterns, and mobile phone usage can be analyzed, allowing firms to understand consumer behavior, sentiments, and opinions (Schaupp and Belanger, 2014; Tambe, 2014). At the same time, firms' efficiency can be enhanced through analysis of existing operational data from enterprise information systems (Aral et al., 2012).

In the last decade, much has been published on the benefits of DA. In the early 2000s, large companies began to recognize that DA was vital to the development of their enterprise, which entailed the use of vast amounts of data and sophisticated information technology (IT) (Davenport and Patil, 2012). IT, however, is not a panacea. As explained in Nicholas Carr's article "IT Doesn't Matter" (Carr, 2003), DA will likely have a diminishing advantage if its use remains generic rather than strategic. Research has shown that even as optimism about the potential of DA is increasing and its adoption becoming mainstream, the number of firms having a competitive advantage due to DA has declined since 2014 (Akter et al., 2016; Bean and Davenport, 2019; Ransbotham et al., 2016). A possible explanation for this trend is that the invaluable opportunity offered by DA can be achieved only when firms can continuously orient

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their businesses around process improvement (Wu et al., 2019b). Firms must also ensure their business processes generate high-quality data; they must also avoid data silos and strive to have a data-driven culture.

Implementing DA requires substantial financial and human resources (Božič and Dimovski, 2019; Grover et al., 2018). Bean and Davenport (2019) reported that 91.6% of 65 leading Fortune 1000 companies have increased the pace of their DA investment, and that 55% of these companies' DA investment exceeded $50 M. Companies have also created a new C-level position, that of Chief Data Officer, and hired more data scientists. Due to resource availability in large enterprises, DA investment spending may not be critical. However, for small and mid-size enterprises (SMEs) with limited financial and human resources, cultural barriers, and intrinsic conservatism (Ghobakhloo and Ching, 2019), investing in DA may be problematic. While the use of DA in SMEs may pose some challenges, DA can potentially enable SMEs to digitally transform their businesses. For example, a Singapore SME that develops software for the food and beverage industry provides its customers with an online application that includes a checkout, customer engagement, shared accounting and tax services. With this application, data can then be processed seamlessly, and information visually displayed on a dashboard, allowing SMEs to track their accounting actions in real-time (Pan and Sun, 2018). Understanding how DA can benefit SMEs is, therefore, worth investigating (Coleman et al., 2016).

Our research aimed to explore the extent to which SMEs in Singapore utilized DA applications to generate business value. This study can shed light on how accountants should mobilize their DA capabilities along with other organizational resources to create distinctive resources. DA landscape in Singapore is intriguing. The Singapore government has provided several initiatives for digital transformation, such as the Smart Nation Initiative and various grants for innovation and technology implementation, but challenges remain for SMEs to implement DA. This is evident from two surveys conducted in 2017 and 2020. First, the Committee on the Future Economy (CFE) reported that about one-third of local companies had not yet realized the potential of Big Data Analytics or other technologies. In addition, about 80% had not harnessed the potential of artificial intelligence (AI) technologies. Many of these companies stated that they lacked awareness and expertise in using Data Science and AI or that they feared violating data protection regulations (The Committee on the Future Economy, 2017). Second, a study conducted by the Singapore Association of Small and Medium Enterprises (ASME) and Microsoft on digital technology adoption found that digital transformation had accelerated, with 83% of SMEs having a digital transformation strategy. COVID-19, however, delayed their plans to adopt digital technologies. Furthermore, only two out of five SMEs in that study perceived their efforts in implementing digital technologies as successful[1].

Considering the significant amount of effort in encouraging adoption and investment in DA, investigating the impact of DA on business value and firm performance is essential. While research on DA continues to proliferate, the link between DA capabilities (e.g., DA systems and information quality) as potential enablers and inhibitors, business value, and firm performance remains unexplored. Recently, researchers have taken an active interest in understanding this link (Akter et al., 2016; Božič and Dimovski, 2019; Ghasemaghaei, 2021; Grover et al., 2018; Ren et al., 2017). They have found that DA infrastructure and DA capabilities may potentially impact DA value creation and firm performance (Grover et al., 2018). To generate DA business value, challenges may come from managing the technology, data, and human assets. These three resources are crucial for successfully delivering value from DA use (Božič and Dimovski, 2019; Grover et al., 2018).

With increasing research on DA business value, it is timely to examine both enablers and inhibitors on the value and impact of DA. Some work has focused on enablers rather than inhibitors. Ren et al. (2017) studied the extent to which information and system qualities affected DA business value and firm performance, while Ghasemaghaei (2021) found that big data characteristics such as volume, velocity, variety, value, and veracity had a positive impact on firm performance. To date, little salient research has been found on the inhibitors of DA business value and firm performance. Hence, our research investigated both potential deterrents and catalysts for firms to attain business value and firm performance from DA. To guide our research, we posed the following question: *What are the enablers and inhibitors of DA business value and impact on firm performance?*

Our research contributions are four-fold. First, we build on current research using the resource-based view (RBV) theory and information technology business value (ITBV) concept (Barney, 1986; Barney, 1991; Bharadwaj, 2000). We then adapt the dual factor concept to examine the role of enablers and inhibitors by extending the investigation to their impact on DA business value and firm performance (Cenfetelli, 2004; Cenfetelli and Schwarz, 2011). Second, our study elaborates on the relevant variables for inhibitors affecting DA business value. Our DA measurement of business value includes self-reported financial and non-financial performance, which are variables used also to determine business value in the accounting information systems (AIS) domain (Elbashir et al., 2008; Koreff et al., 2021; Krieger et al., 2021; Masli et al., 2011; Rikhardsson and Yigitbasioglu, 2018). Our analysis suggests that lack of understanding and concerns over data security and privacy were the most salient predictors that could prevent SMEs from realizing DA business value. Third, our analysis indicates that DA capabilities play a moderating role in the relationship between DA business value and firm performance. This role, however, needs to be interpreted cautiously in the context of SMEs. Fourth, we offer a practical contribution. As our focus is on SMEs, currently a group of under-represented businesses in the extant literature on DA business value, our research may potentially have practical relevance to them.

In the following section, we describe RBV, ITBV and the dual factor concept which together, form our research framework. We then summarize extant research on SMEs and DA business value before explaining how our hypotheses were developed. Next, we explain our research method and sample data, followed by a discussion of the practical benefits and contributions of our work. We conclude with limitations and possible future research in the area.

[1] https://news.microsoft.com/en-sg/2020/10/22/over-80-of-singapore-smes-embrace-digital-transformation-more-than-half-report-slowdowns-due-to-covid-19-asme-microsoft-study-2020/

2. Literature review and hypotheses development

2.1. Resource-based view and IT business value

Information technology business value (ITBV) has its roots in the resource-based view (RBV) literature (Nevo and Wade, 2010; Ferguson et al., 2005; Masli et al., 2011; Wade and Hulland, 2004). RBV assumes that firms compete and sustain their businesses with organizational resources, which are valuable, rare, imperfectly imitable, and non-substitutable (Barney, 1986; Barney, 1991; Bharadwaj, 2000). Many companies can readily afford, implement, and adopt IT into their business processes. However, some companies may not readily assemble multiple resources to successfully achieve business value and firm performance with IT (Bharadwaj, 2000; Melville et al., 2004).

IT enables organizations to create "unique" resources to help improve business. Organizations must, however, be aware that creating resources requires organizational capabilities to (re)configure IT with existing resources. People, processes, and technologies can be modified and reconfigured in various ways to help organizations run their businesses optimally and sustain their business models (Grover et al., 2009; Melville et al., 2004). In the accounting domain, earlier attempts were made by Nicolau (2004) and Poston and Grabski (2000) to establish a relationship between technology and firm performance. Although these researchers did not base their investigation specifically on RBV theory, their analysis is consistent with what the theory proposes. They suggest that enterprise resource planning (ERP) helps firms create distinctive resources and capabilities. Other resources such as management and leadership must also support ERP implementation, adoption, and configuration, failing which these resources may inhibit business value generation from ERP.

Prior research applied RBV to understand the role of technology in creating business value that ultimately leads to optimized business performance (e.g., Bharadwaj, 2000; Melville et al., 2004; Grover et al., 2009; Nevo and Wade, 2010). The application of this theory has led to a research stream on IT business value (ITBV), or IT-enabled resources, in the information systems (IS) domain. Research on ITBV has been featured in primary IS journals (i.e., MISQ, ISR, and JMIS) since the turn of the 21st century (Jeyaraj and Zadeh, 2020). ITBV refers to the impact of IT on organizational performance at both the intermediary process level and the whole organization level, and includes both efficiency and competitive effects (Melville et al., 2004). In the accounting field, RBV has been used in multiple studies, for example, to support effective IT governance (Prasad and Green, 2015), to understand how IT enables organizations to improve analytical capabilities and how it is highly valued by investors (Huang et al., 2018; Muhanna and Stoel, 2010), as well as to understand how small businesses create value through social media (Schaupp and Belanger, 2014).

ITBV research can be traced to the intriguing question by scholars and practitioners about the payoffs of enormous IT investment (Brynjolfsson, 1993) and the finding that huge investments in IT do not necessarily correlate with productivity growth (Brynjolfsson and Hitt, 2000). Hence, whether firms need to spend their resources on IT becomes a critical issue for many large firms, and more so for small firms with limited resources. Initial attempts to understand the relationships between IT spending and firm performance have shown mixed results. Although IT has been shown to create value (Kohli and Grover, 2008), its impact on firm performance depends on firms' ability to strategically differentiate their IT resources, which include IT infrastructure, IT human capabilities, and IT strategy (Bharadwaj, 2000; Kohli and Devaraj, 2008; Mithas and Rust, 2016). Firm performance can also be reflected by financial, process, and perceptual measures (Kohli and Grover, 2008). For example, Mithas et al. (2012) reported that IT investment affected firms' financial measures (i.e., profitability); in this case, firm profitability increased due to the revenue growth enabled by IT rather than the cost reduction enabled by IT. On the other hand, Ghasemaghaei (2021) and Ghasemaghaei et al. (2018) studied perceptual firm performance variables affected by big data. Ghasemaghaei (2021) examined the extent to which perceived Big Data characteristics (i.e., volume, velocity, variety, and veracity) influenced perceived data value and firm performance. Volume, velocity, and variety were found to be associated with data value, while veracity and data value could affect business performance.

Following research on ITBV, scholars are now attempting to understand DA impact on firm performance. Ghasemaghaei (2021), for example, studied the link between big data characteristics and firm performance. She found that large amounts of data and the speed of generating or collecting data did not necessarily affect data value leading to firm performance. Diversity of data, however, did affect data value and firm performance. Overall, researchers seem to agree that DA can lead to firm productivity when firms use it to continually improve their existing processes (Wu et al., 2019a). Our research referenced RBV and ITBV literature to guide us on the extent to which DA can help generate value and lead to improve SMEs' performance.

Following the ITBV classification proposed by Masli et al. (2011), we consider the financial and non-financial outcomes of DA enterprise value. Financial outcomes include accounting performance outcomes (reduction in operating costs and return on financial assets) and marketing performance outcomes (improved customer relationships and services), while non-financial performance comprises supply chain management efficiency, increased employee productivity, and a faster response to change. However, due to limited access to our samples' financial data, self-reported data were collected instead.

2.2. Dual factor concept

The dual factor concept is largely applied to research on IT adoption and use. In much of research in this area, scholars tend to focus on one aspect – acceptance. Acceptance is driven by enablers such as effort expectancy, performance expectancy, information quality and service quality (DeLone and McLean, 1992; Petter et al., 2008; Venkatesh et al., 2012; Venkatesh et al., 2016). Information system (IS) adoption may be accelerated due to the presence of enablers (Lapointe and Rivard, 2005). Little is known, however, about the factors that affect firms' decision to not adopt and use technology (van Offenbeek et al., 2013). These factors include both enablers and inhibitors of IT adoption and use (Cenfetelli, 2004). However, inhibitors are not the opposite of enablers (Cenfetelli, 2004). Both enablers and inhibitors refer to perceptions; the difference is that while one set of perceptions encourages IT adoption and usage, the other set discourages (Cenfetelli, 2004).

In fact, both enablers and inhibitors can coexist in IT adoption and use (Cenfetelli, 2004; Cenfetelli and Schwarz, 2011; van Offenbeek et al., 2013). This indicates that one may hold both favorable and unfavorable perceptions about technology that affect adoption and usage, or one may also hold either of the perceptions because enablers and inhibitors have an independent effect on IT adoption and usage. This assertion is supported by the following studies. Using Delone and MacLean's IS success model (DeLone and McLean, 2003), Cenfetelli and Schwarz (2011) studied both enablers and inhibitors of IT usage at the individual and system levels. They proposed information and systems qualities as the enablers. The inhibitors, on the other hand, could derive from the unfavorable attributes of the IS, such as information overload, irrelevant requests, intrusiveness, and process uncertainty. In their study, Henderson et al. (2016) classified inhibitors of IT usage as object-based (systems problems) and behavioral-based (i.e., perceived threats), and the enablers as perceptual (perceived ease of use and perceived usefulness). King and Teo (1994, 1996) suggested five enablers of IT strategic use at the organisational level, namely, innovative needs, competitive position, environment, economies of scale, and top management guidance; they also identified three inhibiting variables, namely, lack of IT drivers, lack of economies of scale, and lack of innovative needs. Following the logic of dual factor, we extend its use to investigate enablers and inhibitors of DA business value and firm performance.

While technology adoption research has incorporated both enablers and inhibitors (Cenfetelli, 2004; Cenfetelli and Schwarz, 2011; van Offenbeek et al., 2013), we argue that this dual factor concept can also help us understand the business value of IT. Our argument is consistent with RBV theory (Barney 1986; 1991; Bharadwaj, 2000) and the ITBV or IT-enabled resources research stream (Jeyaraj and Zadeh, 2020). Following the RBV, we posit IT assets (i.e., IT resources and IT capabilities) as the enabled resources in organizations. IT resources include physical IT infrastructure components, human IT resources, and intangible IT-enabled resources such as knowledge assets. On the other hand, IT capabilities include IT design and the ability of organizations to deploy IT resources (Drnevich and Croson, 2013).

Our study focused on IT capabilities, which are the DA applications that can analyze data and generate information to facilitate organizations to leverage data and gain actionable insights, ultimately leading to better organizational performance. However, these IT capabilities need to be supported by other organizational resources such as skills and infrastructures, data management, leadership, and management support (Bharadwaj, 2000; Wade and Hulland, 2004; Willcocks et al. 2018). Otherwise, the IT capabilities would not deliver the expected business value. Drnevich and Croson (2013) stated that realizing the IT business value depends on an appropriate assemblage of IT resources and non-IT resources. Therefore, other organizational resources must complement IT capabilities to create synergistic IT-enabled resources (Nevo and Wade, 2010). When properly implemented, IT and other organizational resources will be the enablers. In contrast, organizational resources that fail to synergize with IT resources will inhibit the ITBV creation. Unfortunately, research remains limited in examining these inhibitors. Research is needed to shed light on the factors that might inhibit the realization of ITBV (Nevo and Wade, 2010). Table 1 presents our description of the dual factor concept in ITBV research.

2.3. *Data analytics in accounting*

Data analytics research in accounting broadly uses four terminologies: Business Intelligence (BI) (e.g., Elbashir et al., 2008; Peters et al., 2016; Peters et al., 2018), Business Analytics (BA) (e.g., Appelbaum et al., 2017), Business Intelligence and Analytics (BI&A) (e.g., Rikhardsson and Yigitbasioglu, 2018) and Data Analytics (DA) (Koreff et al., 2021; Krieger et al., 2021). BI systems are a subset of data analytics and reporting that support leadership positions at various levels with timely, relevant, and easy-to-use information enabling them to make better decisions (Elbashir et al., 2008). Peters et al. (2018) suggest that BI includes management support systems for data collection, storage and access to support decision making. This decision-making is essential to support management control systems and evaluate the business unit's performance (Peters et al., 2016). Appelbaum et al. (2017) adopted the BI&A definition of Davenport and Harris (2007) for the context of management accounting. They suggested that BI&A helps management accountants to use data with IT, statistical analysis, quantitative methods, and mathematical or computer-based models. BI&A includes descriptive, predictive, or prescriptive methods that facilitate organizations in generating relevant information from business

Table 1
Dual factor concept in IT research.

Dual Factor Concept in IT Adoption and Usage	
Enablers	Inhibitors
Information systems and technology (IST) that is generally well designed and functionally adept (Cenfetelli, 2004)	A poorly designed and non-functioning IST (Cenfetelli and Schwarz, 2011)
Examples of enablers can be IT capabilities such as information quality and system quality (Cenfetelli, 2004)	Examples of inhibitors can be information inhibitors and systems inhibitors (Cenfetelli and Schwarz, 2011)
Adaptation of Dual Factor Concept to ITBV Research	
Enablers	Inhibitors
IT resources and capabilities are the enablers for organizations to create business value (Drnevich and Croson, 2013; Wade and Hulland, 2004)	Inhibitors emerge when there is lack of alignment and support from other organizational resources to support IT resources (Bharadwaj, 2000; Nevo and Wade, 2010)
Examples of enablers are IT design architecture, IT features, IT skills (Drnevich and Croson, 2013; Wade and Hulland, 2004)	Examples of inhibitors are lack of IT intangible resources such as skills and knowledge (Nevo and Wade, 2010)

operations and producing actionable insights. Rikhardsson and Yigitbasioglu (2018) adopted a similar view as Appelbaum et al. (2017) by defining BI&A boradly. Recently, Krieger et al. (2021) used DA terminology to describe statistics, data mining, and visualization techniques to extract and transform data into relevant and valuable information.

Prior research in accounting also categorized DA usage into basic and advanced usage (Krieger et al., 2021), or low to high usage (Peters et al., 2018). Basic or low usage reflects the use of DA for traditional analysis such as descriptive analytics and the use of spreadsheet-based technologies. In contrast, advanced or high usage goes beyond traditional usage and includes sophisticated predictive analysis, advanced tools, and sophisticated techniques. In general, DA research in accounting seeks to link the application of analytics to core accounting topics, i.e., management, taxation, finance, information systems, and auditing (e.g., Cao et al., 2015; Cheng et al., 2021; Kogan et al., 2019; Eilifsen et al., 2020; Lassila et al., 2019; Perols et al., 2017; Rikhardsson and Yigitbasioglu, 2018; Zhang, 2019). Recently, advanced DA capabilities (i.e., machine learning) have also been integrated with artificial intelligence (AI) and robotic process automation (RPA). This integration enables the accounting industry to implement intelligent process automation (IPA) for more complex tasks involving structured and unstructured data (Zhang, 2019). Together with other technologies like Blockchain and Cloud Computing, DA and IPA enable organizations to optimally run their business processes and generate business value, which ultimately affect their overall business performance.

DA is widely used in the accounting domain. It helps accountants to understand the patterns embedded in the data and use the data for decision making. DA can also help streamline data processing and help accountants focus more on inference, prediction, and assurance (Schneider et al., 2015). DA is, therefore, beneficial for both large and small businesses (Chen, et al., 2018; Pan and Sun, 2018; Coleman, et al., 2016). While larger companies may be better at adopting and implementing DA, SMEs may face challenges to do the same. SMEs may have to make trade-offs between cost and functionality, lack in-house expertise, and face other complex issues such as data security (Liu et al., 2020a). Therefore, we argue that despite the challenges that SMEs may face with DA, harnessing DA practice with good system design intervention has strong potential to increase SMEs' growth.

Although many studies have explored and addressed data analytics issues (e.g., Ghasemaghaei, 2021; Ghasemaghaei et al., 2018), few have examined how SMEs adopt and implement DA. Our study sought to address the lack of literature on SMEs and DA. While standard ERP or accounting software have some analytics capabilities, our research investigated DA applications that are separate from that software. Specific DA applications focus on description, prediction, prescription, exploration, and visualization. Our initial observation revealed that SMEs' use of DA could be divided into basic and advanced use, as we explained earlier. In basic usage, SMEs use relational database management systems (RDBMS) to store their data and integrate spreadsheets to analyze and visualize their financial data. Other SMEs use specialized data visualizations software to further explore their accounting data. SMEs that can afford more sophisticated DA applications include predictive analytics and combined automation with analytics capabilities for document understanding, text analysis, and object identification. These capabilities can be used to streamline their accounting procedures particularly to automate document extraction. Table 2 shows the DA purpose of use, tools, and applications used by SMEs.

2.4. SMEs and data analytics value creation

Both large and small enterprises across the globe are adapting to the changing environment and fierce competition accompanying digital transformation (Brynjolfsson and McElheran, 2016; Li et al., 2018). The transformation is inevitable; the question is, which firms would be the innovators and which, the late adopters. The sudden rise of DA to leverage company data forces many firms, including SMEs, to adopt analytics technology. It is true that technology adoption alone may not guarantee the success of DA. Rather, key to achieving the potential of DA is the ability of firms to properly manage their data, use relevant techniques to reveal hidden patterns in the data, and make sense of the analytics results.

When correctly implemented, DA could also enable SMEs to generate value (Božič and Dimovski, 2019). DA application may be basic, such as understanding past sales and the most profitable products. It may then proceed to complex tasks like managing inventory and analyzing customer sentiment. When SMEs can turn the results into actionable insights, the value of DA will be realized. Take, for instance, Pendleton & Son, a local butcher in London, which installed simple sensors that allowed the firm to track the number of people walking by the shop, the number stopping to look at their displays, and the number entering the store. The analytics results may

Table 2
Data analytics purpose of use.

Data Analytics Purpose of Use	Data Analytics Tools	Types of Data	Data Analytics Techniques and Applications
Business Intelligence	Google Sheet and Microsoft Excel	Accounting and finance, human resource, and other operational data	Dashboard and visualization
Business Intelligence	MySQL, Microsoft Access, SQL Server, and PostgreSQL		
Business Intelligence	Tableau, Qlik Sense, Microsoft Power BI, and Microstrategy		
Advanced Analytics	Opinion Crawl, and Semantria	Customer feedback or opinion on social media	Audit analytics, Process automation.
Advanced Analytics	R and Python	Accounting and finance, human resource, customer feedback or opinion on social media and other operational data	
Advanced Analytics	Alteryx Designer, RapidMiner and Orange		
Advanced Analytics	SAS, KNIME, MS Azure Machine Learning Studio, and BigML		

look simple; however, the firm turned the results into actionable insights to create a promotional display that attracted their customers. Further, the firm expanded their analytics by introducing a customer loyalty application (Marr, 2016).

DA in SMEs could be impactful due to its significant contribution to economic growth. In many countries, its revenue contribution ranges from 70% to 95% of all firms (OECD, 2017). While this potential is acknowledged, challenges remain to strategically use DA in SMEs. Despite their limited financial and human resources, and environmental uncertainty (Raymond et al., 2019), SMEs tend to be nimbler than their larger counterparts. This characteristic could help them readily reconfigure their business processes with less bureaucracy (Chan et al., 2019). However, SMEs may face certain challenges, such as the lack of DA understanding and resistance to change among SME owners and employees, the lack of commitment to DA adoption, and limited financial resources (Krieger et al., 2021). The latter challenge might compel SMEs to consider a trade-off between cost and function.

Another possible challenge is determining how success of DA implementation is measured. The ITBV from DA implementation, can be manifested in many ways, such as reducing lead time, mitigating potentially fraudulent activities, increasing employee and customer satisfaction, projecting accounting measures, and achieving profitability. However, the results of IT implementation may not be immediate, as it may take years to realize its value (Kohli and Grover, 2008). This challenge prompts us to examine how DA is beneficial for SMEs. Unlike the study by Ren et al. (2017) on the enablers of DA business value using systems and information qualities, our research offers insights into both enablers and inhibitors of DA business value. We focus on the business value that relates to general accounting processes, such as process improvement in supply chain management, operating costs efficiency, improvement on return on assets, employee productivity, customer satisfaction, and facilitation of better-quality products. DA business value related to the SMEs' internal control and governance processes is beyond our research scope. Additionally, we contend that the relationship between DA business value and firm performance may be different, depending on DA technological capabilities, such as whether the firm uses business intelligence or advanced analytics. Fig. 1 presents our research model.

2.5. *Enablers of DA business value*

The quality constructs – system quality and information quality – are acknowledged to be important in IS research; for example, they have been used to evaluate IS success (DeLone and McLean, 1992; Petter et al., 2013), IS use (Cenfetelli and Schwarz, 2011), and IS trust (Vance et al., 2008). Both systems and information qualities are part of IT capabilities because they reflect IS design and architecture, which allow IS to perform tasks relevant to organizational needs (Drnevich and Croson, 2013). Thus, aligning with RBV, systems and information qualities are the IT-capabilities enablers that facilitate SMEs to derive DA business value (see, Table 3). System quality reflects one's perception about their interaction with the systems (Nelson et al., 2005), such that the more favorable one's perceptions are toward the systems, the more likely these perceptions reflect the high quality of the systems. System quality can have multiple dimensions, such as reliability, flexibility, accessibility, response time, and integration (Nelson et al., 2005).

In the context of DA, system quality can be reflected by the DA software features. For example, data visualization tools are more flexible for data exploration than spreadsheets. R and Python are more customizable with their different packages for multiple

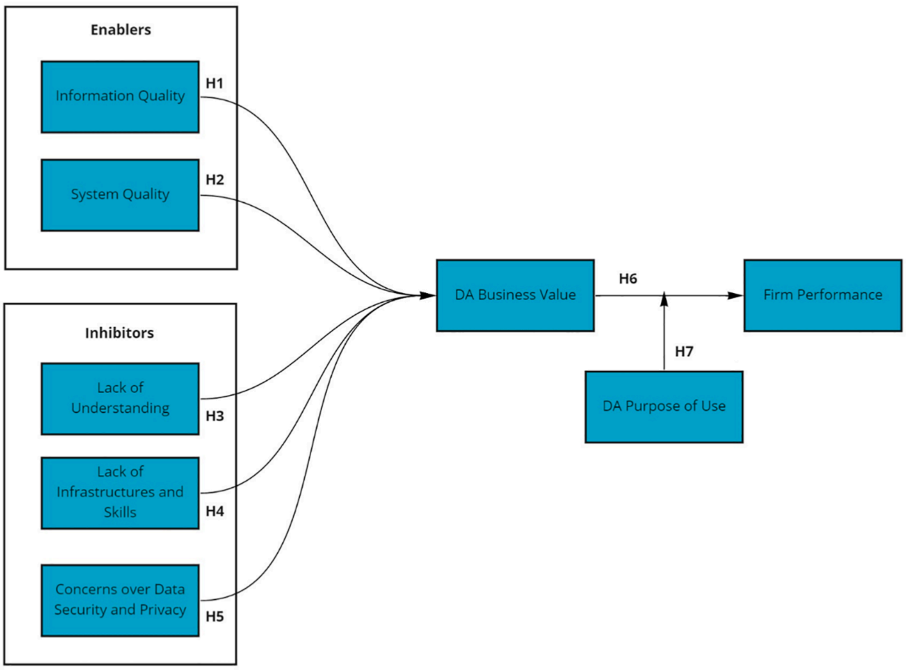

Fig. 1. Research model.

Table 3
Summary of SME characteristics and enablers and inhibitors for DA business value.

SME Characteristics	Enablers and Inhibitors of DA Business Value
• SMEs tend to be more agile than their larger counterparts (Chan et al., 2019). • They face limited financial and human resources, as well as environmental uncertainty (Raymond et al., 2019). • They lack technological understanding and exhibit resistance to change (Chau, 2001). • They are concerned about security, privacy, and confidentiality matters (Coleman et al., 2016; Liu et al., 2020a). • SMEs may have to accept trade-offs between cost and functionality (Liu et al., 2020b).	**Enablers**: Even though SMEs' financial resources are limited, and they may prioritize costs over functionalities, SMEs may be quick to adopt technology applications due to their agility (Liu et al., 2020b). For example, these cost considerations may drive SMEs to find affordable DA applications with sufficient system and information qualities, such as open-source DA applications (e.g., Python, R or Orange), as well as pay-as-you-go or Software as a Service (SaaS) models. Therefore, this financial limitation does not necessarily affect the ability of SMEs to acquire DA systems. Agility and a less bureaucratic hierarchy than that in large companies may, in fact, help SMEs select appropriate DA applications. **Inhibitors**: Limited financial resources, lack of IT capabilities and infrastructure, and privacy and data security concerns are organizational resources that must be addressed (Kannabiran and Dharmalingam, 2012; Lee et al., 2013), Otherwise, the lack of these resources will hinder the realization of the business value of DA (Bharadwaj, 2000; Nevo and Wade, 2010).

analyses. We argue that unlike large enterprises, SMEs may prioritize costs over functionalities when adopting DA applications. This cost consideration may encourage SMEs to find affordable DA applications with sufficient system quality. For example, R or Python, which have sufficiently strong system quality and require no subscription fees, could be used to develop advanced analytics. Similarly, the pay-as-you-go model, which is more affordable for sophisticated DA applications, and Software as a Service (SaaS) could be adopted to help SMEs reduce DA acquisition, development and maintenenace costs with high quality services (Liu et al., 2020a). Overall, we contend that DA system quality will likely help SMEs realize the value of the analytics results – an assertion supported by other research (Ren et al., 2017). Hence, we propose Hypothesis 1:

Hypothesis 1.. *System Quality will have a positive relationship with DA Business Value.*

Information quality refers to information that is fit for use. Research devoted to information quality, such as that by Neely and Cook (2011), generally agrees that information quality is multidimensional. Wang and Strong (1996) propose several information quality dimensions: value add, relevancy, timeliness, completeness, appropriate amount of data, interpretability, ease of understanding, representational consistency, and representational concision. Nelson et al. (2005) suggest four dimensions to measure information quality: accuracy, completeness, currency, and format. Information quality is essential in decision making because it helps users leverage data and promotes informed decisions (Chengalur-Smith et al., 1999; Neely and Cook, 2011).

Our focus is on information quality instead of data quality. To some extent, the quality of information is affected by the capabilities of DA applications, such as such as visualization, layout and interactivity. Information quality is also dependent on data quality. Poor data quality will produce poor information regardless of the technological applications. For example, poor quality data entered into an ERP module would affect other modules, ultimately affecting the information quality generated from ERP (Haug et al., 2009). High quality data, though, should be complemented with sufficient and available DA features for analytics to produce high quality information for use in operations, decision making and planning (Liu et al., 2020b). As such, data quality is totally independent of the DA applications. For example, when developing a dashboard with visualizations, the analyst must conduct data preparation and cleansing prior to performing the analysis.

When the applications of DA generate high-quality information, SMEs can then generate decision-relevant insights. We argue that limited financial resources may not be a constraint for SMEs to adopt sophisticated DA applications. For example, Python and R are freely available for SMEs to generate sophisticated and high-quality information for data-driven decision making, which will turn into business value (Ren et al., 2017). The challenge for SMEs, rather, may lie in the availability of technical skills (Willets et al., 2021) to generate good quality data. Therefore, SMEs need to ensure that the data they use for analysis is of high quality. Accordingly, we offer hypothesis 2:

Hypothesis 2.. *Information Quality will have a positive relationship with DA Business Value.*

2.6. Inhibitors of DA business value

As mentioned, little attention has been given to investigating inhibitors of IT adoption (Chau, 2001; Kannabiran and Dharmalingam, 2012; King and Teo, 1994, 1996; Lee et al., 2013). Also, inhibitors could emerge from the organizational resources that fail to support IT resources. This could result in IT capabilities becoming commodities and hindering organizations to sustain and achieve competitive advantage (Bharadwaj, 2000; Nevo and Wade, 2010) (see, Table 3). An example of an inhibitor is the lack of IT drivers, which reflects the lack of IT knowledge (King and Teo, 1994). Little understanding of IT is the most salient factor explaining the reluctance of small businesses to adopt electronic data interchange (Chau, 2001). When firms are not aware of the benefits of technology and are unable to manage the potential uncertainty that may occur when implementing technology, they would hesitate to adopt new technology (Lee et al., 2013). Similarly, unavailability of experts, lack of experience, and lack of IT infrastructure matter. Small businesses, especially, are more cautious about adopting IT due to the lack of IT support (Chau, 2001; Lee et al., 2013). The increasing use of customer data leading to concerns over security, privacy and confidentiality adds yet another layer of complexity for small businesses to leverage their data (Lee et al., 2013).

We contend, therefore, that lack of understanding, lack of infrastructure and skills, and concern over data security and privacy affect both adoption and user behavior. Lack of understanding, for example, may hinder the effective use of technology (Burton-Jones

Table 4
Measurement items.

Measurement Items	Sources
System Quality	
• SQ1: The data analytics software should operate reliably for the analytics to produce relevant information. • SQ2: The data analytics software could be flexibly adjusted to new demands or conditions during analysis. • SQ3: The data analytics software should pull together data from different departments in the organization. • SQ4: The data analytics software should allow easy access to information. • SQ5: The data analytics software should allow information to be accessible to anyone in the organization. • SQ6: The data analytics software should protect personal data.	(DeLone and McLean, 2003; Petter et al., 2008; Petter et al., 2013)
Information Quality	
• IQ1: The data analytics software should provide a complete set of information. • IQ2: The data analytics software should produce the most current information. • IQ3: The data analytics software should provide accurate information. • IQ4: The data analytics software should present information in a way that is easy to understand.	(DeLone and McLean, 2003; Petter et al., 2008; Petter et al., 2013)
Lack of Understanding	
• LU1: Data analytics use could be hindered by employees' reluctance to adapt to change. • LU2: Data analytics use could be hindered by a lack of understanding about data analytics. • LU3: Data analytics use could be hindered by uncertainty about how to measure costs and potential benefits.	(King and Teo, 1994, 1996)
Lack of Infrastructures and Skills	
• LIS1: Data analytics use could be hindered by a lack of information systems infrastructure support. • LIS2: Data analytics use could be hindered by a lack of intuitive software. • LIS3: Data analytics use could be hindered by a shortage of data analytics expertise both in-house and in the labour market. • LIS4: Data analytics use could be hindered by re-assignment of personnel trained on data analytics solutions. • LIS5: Data analytics use could be hindered by limited financial resources for data analytics investment.	(King and Teo, 1994, 1996)
Concerns over Data Security and Privacy	
• DSP1: Data analytics use could be hindered by concerns over data security. • DSP2: Data analytics use could be hindered by concerns over data protection and data privacy.	(King and Teo, 1994, 1996)
DA Business Value	
• BV1: Data analytics could save time in supply chain management. • BV2: Data analytics reduces operating costs. • BV3: Data analytics reduces the need to increase the workforce. • BV4: Data analytics increases returns on financial assets. • BV5: Data analytics enhances employee productivity. • BV6: Data analytics enables quicker responses to change. • BV7: Data analytics helps to improve customer relations. • BV8: Data analytics helps to provide better products or services to customers.	(Gregor et al., 2006; Ren et al., 2017)
Firm Performance	
• FP1: With data analytics, my organization's customer retention rate has improved. • FP2: With data analytics, my organization's sales have improved. • FP3: With data analytics, my organization's profitability has improved. • FP5: With data analytics, we introduce new products or services to the market more quickly than before. • FP6: With data analytics, our customers respond more favourably to our new products/services than before. • FP7: With data analytics, our market share has increased.	(Ren et al., 2017; Tippins and Sohi, 2003; Wang et al., 2012)

and Grange, 2013). Further, when the technology is used ineffectively, the impact of said technology to create value to the firm is delayed (Trieu, 2017). Hence, we put forward Hypotheses 3, 4 and 5:

Hypothesis 3.. *Lack of Understanding will have a negative relationship with DA Business Value.*

Hypothesis 4.. *Lack of Infrastructure and Skills will have a negative relationship with DA Business Value.*

Hypothesis 5.. *Concerns over Data Security and Privacy will have a negative relationship with DA Business Value.*

2.7. DA business value and firm performance

Regardless of the size of the company, the central relevant question for IT implementation is how it can generate value to a firm that could lead to improvement in firm performance (Kohli and Grover, 2008; Melville et al., 2004). For example, the explosion of data compounded with the availability of sophisticated data analytics tools and techniques can potentially enable SMEs to generate business value (Božič and Dimovski, 2019). Such value can be reflected by firms' ability to understand their internal processes, external environments, and customers' needs. Different types of businesses, however, may place different emphases and priorities on generating business value from their data. To illustrate, manufacturing companies may leverage data to optimize production or delivery processes, whereas retail companies may be interested in understanding their inventory management and improving sales from targeted marketing (Bianchini and Michalkova, 2019). In other words, DA business value is multidimensional. Prior research suggests that resources that can generate value will contribute to firm performance (Kozlenkova et al., 2014; Ren et al., 2017). For example, when a firm can clearly identify its customers' needs and provides products or services to satisfy existing and potential customers, it would likely be able to improve firm performance – evident through improved revenue and profitability.

While the positive relationship between DA business value and firm performance is known (Ren et al., 2017), what remains unknown is the factor that could strengthen or weaken this relationship. We contend that different uses of DA could affect the relationship between DA business value and firm value. In this context, we consider two types of DA use: business intelligence and advanced analytics (Halper and Stodder, 2014). Business intelligence permits SMEs to conduct mainly descriptive and diagnostics analytics, whereas advanced analytics enable the SMEs to perform descriptive, diagnostic, predictive and prescriptive analytics. We posit that firms which emphasize the use of advance analytics over business intelligence will likely realize a positive relationship between DA business value and firm performance. Therefore, we propose Hypotheses 6 and 7:

Hypothesis 6.. *DA Business Value will have a positive relationship with Firm Performance.*

Hypothesis 7.. *DA Purpose of Use will moderate the relationship between DA Business Value and Firm Performance.*

3. Research methodology

3.1. Measurement items development

A survey was carried out among SMEs to test the proposed hypotheses addressing our research question and determine how different variables interact to affect business value and firm performance. Our measurement item development followed the guidelines suggested by Moore and Benbasat (1991). First, the relevant constructs in the dual factor concept and ITBV literature were identified. Potential and relevant measurement items were then assessed and selected for each of the constructs. Redundant items were removed and items that shared similar themes were grouped together. Another iteration of the process was performed to ensure consistency in assessing the measurement items. At this stage, the sentences used in the measurement items were crafted for clarity and conciseness, to minimize the common method bias possibility (Podsakoff et al., 2003). When the items were finalized by the research team, the measurement items were evaluated by two professionals from industry. Their opinion was sought on the relevance of the measurement items to the associated constructs and on the clarity of the items. Their feedback was also sought on the appropriateness of the classification of the measurement items and the constructs.

Based on their feedback, our constructs and measurement items were refined. Using a 5-point Likert scale, our survey measured eight latent variables: system quality, information quality, lack of understanding, lack of infrastructure and skills, concerns over data security and privacy, DA business value, and firm performance. These variables reflected the operationalization of perceptual/behavioral concepts. Our research model was, therefore, well suited to the common factor model (Benitez et al., 2020; Müller et al., 2018; Schuberth et al., 2018). Positive Likert-scale scoring was used for enabler variables and negative Likert-scale scoring for inhibitor variables. As for DA purpose of use, survey participants were requested to select a relevant option that reflected their companies' use of DA for either business intelligence or advanced analytics (see Table 2). The measurement items were developed from

Table 5
Sample size.

Phases	Survey Administration	Number of Respondents
Phase 1	with a mid-tier accounting firm	4
Phase 2	with ISCA	24
Phase 3	with Qualtrics	146
Total Sample Size		174

prior studies, as shown in Table 4.

3.2. Sample data

This study used purposive sampling as the target participants were employees of Singapore SMEs. The survey was conducted over three phases. It was first conducted through our collaboration with a mid-tier accounting firm in Singapore, where the survey was randomly distributed to their business clients. In the second phase, the survey was distributed to members of the Institute of Singapore Chartered Accountants (ISCA). In the final phase, another set of data was obtained through Qualtrics, an online research panel, which provided randomly collected data from Singapore SME employees. Checks were performed on all the samples collected to ensure there were no repeated participants. In total, 174 completed surveys were obtained. Tables 5 and 6 present the sample data.

As presented in Table 6, the majority of respondents belonged to the Business Unit/Department Manager category, while the smallest portion were from the Executive Manager/Vice President category. By industry, most respondents were in services, followed by retail, utilities, manufacturing, finance, and information technology. More than half of the sample worked in companies with an annual turnover of *less than SGD 25 million*, and *SGD 25 million to < SGD 50 million*. The majority of respondents' companies were using DA for business intelligence rather than advanced analytics. In addition, more than half of the respondents' companies had staff strength of <150 (from <50 and *100 to < 150*).

4. Results

In the following subsections, we explain the results of our analysis. Partial least squares path modeling (PLS-PM) was used to analyze the survey data to assess our common factor model (Benitez et al., 2020; Lee et al., 2011; Sarstedt et al., 2016). Hair et al. (2014) recommended the minimum requirements for determining the sample size for PLS-PM: 'ten times the largest number of formative indicators used to measure one construct; or ten times the largest number of inner model paths directed at a particular construct in the inner model' (p.109). Our sample data, therefore, exceeded the minimum requirements. In the following sub sections, we first present our evaluation of the measurement model to ensure its reliability and validity. We then assess the structural model to determine the hypothesized links among the variables.

4.1. Measurement model

Assessment of our common factor model was based on the work of Benitez et al. (2020) and Hair et al. (2017). The standardized root mean squared residual (SRMR) suggests fit of model is attained when the result is below the threshold 0.080. To ensure the

Table 6
Sample characteristics.

Dimension	Category	Percentage %
Role	Executive Manager/Vice President	12
	Business Unit/Department Manager	43
	Middle Level Manager	29
	Assistant Manager	17
Industry	Financial	11
	Information Technology	7
	Manufacturing	11
	Retail	17
	Services	37
	Utilities	16
Years of Experience	1 to < 5 years	15
	5 to < 10 years	30
	10 to < 15 years	41
	> 15 years	14
Annual Turnover	less than SGD 25 million	40
	SGD 25 million to < SGD 50 million	30
	SGD 75 million to < SGD 100 million	10
	more than S$100 million	10
Length of DA Use	< 1 year	9
	1 to < 3 years	34
	3 to < 6 years	47
	6 to < 9 years	6
	9 to < 10 years	4
DA Purpose of Use	Business Intelligence	70
	Advanced Analytics	30
Staff Strength	<50	21
	50 to < 100	27
	100 to < 150	25
	150 to < 200	12
	>200	14

reliability and validity of our measurement items, the composite reliability (CR) and the validity criteria of the measurement items were evaluated. According to Hair et al. (2017), CR is technically more appropriate than Cronbach's Alpha measures. Our analyses found all CR for the measurement items was above 0.8, suggesting that measurement reliability was satisfied. To assess the measurement items' validity, the average variance extraction (AVE) and Heterotrait-Monotrait Ratio (HTMT) were evaluated (Benitez et al., 2020). AVE reflects the correlation between measurement items which reflect a particular construct, whereas HTMT indicates whether particular constructs are distinct from one another (Hair et al., 2017). The AVE of all the measurement items was found to be above 0.50, indicating that on average the construct explains more than half of the variance of its indicators. All HTMT ratio on the assigned construct was <0.9 compared to other constructs, indicating that each construct was sufficiently unique in recording a phenomenon. Tables 7 and 8 present the descriptive statistics of the variables assessed in this study, and Table 9 presents the summary statistics of composite reliability, AVE, and HTMT.

Note all measures from 1 to 5

To examine the potential common method bias (CMB), the variance inflation factor (VIF) for each measurement items was determined. VIF can be used to assess common method bias for both reflective and formative constructs (Kock, 2015). Consistent with established guidelines (Hair et al., 2017; Kock, 2015), the VIF figures for all measurement items was found to be 'consistent with established guidelines (Table 10). Our data was also analyzed using Harman's one-factor test. The total percentage variance extracted by one factor was 32.940% (<50% threshold) (Podsakoff et al. 2003). This study is, therefore, unlikely to be biased from common method issues. The results of the measurement model also showed that each item contributed significantly to the associated indicators. All the loads and weights were significant at $p < 0.001$ (Table 11).

4.2. Structural model

Following the measurement items' reliability and validity assessment, the structural model was evaluated using the PLS-PM algorithm and the bootstrapping technique. The path coefficients for the research model are illustrated in Fig. 2, and the summary of the hypothesis findings shown in Table 12. As presented in the table, while H1, H2, H3, H5, H6, and H7 were supported, H4 was not. All path coefficient signs for enablers were positive and for inhibitors, negative. The results also showed that both enablers and inhibitors accounted for about 70% variation of *DA Business Value*, and 45 % of *Firm Performance* variation could be accounted for *DA Business Value*. The effect size of our hypotheses ranged from weak to large (0.02 to 0.7). The larger effect size is displayed by the relationship

Table 7
Means/standard deviation for each measurement.

Measurement Items	System Quality	Information Quality	Lack of Understanding	Lack of Infrastructure and Skills	Data Security Concerns	DA Business Value	Firm Performance
1	4.051/0.775	3.890/0.813	2.120/0.853	2.925/0.587	2.425/0.560	4.068/0.724	3.844/0.722
2	3.994/0.813	3.931/0.862	2.086/0.642	3.000/0.442	2.373/0.722	4.080/0.840	3.770/0.783
3	4.086/0.757	4.086/0.829	2.080/0.805	2.919/0.530	–	4.00/0.830	3.936/0.767
4	4.350/0.633	4.086/0.836	–	2.896/0.568	–	4.080/0.715	3.908/0.729
5	4.109/0.699	–	–	2.959/0.540	–	3.977/0.703	3.896/0.781
6	4.413/0.607	–	–	–	–	4.034/0.830	3.758/0.830
7	–	–	–	–	–	3.948/0.782	–
8	–	–	–	–	–	4.091/0.721	–

Table 8
Summary statistics of variables.

Variables	Means	Standard Deviation
Enablers		
Information Quality	4.17	0.54
System Quality	4.00	0.70
Inhibitors		
Lack of Understanding	2.10*	0.62
Lack of Infrastructure and Skills	2.94*	0.76
Concerns over Data Security and Privacy	2.40*	0.55
Outcomes		
DA Business Value	4.04	0.55
Firm Performance	3.85	0.62

* reverse scoring.

Table 9
Measurement items' reliability and validity.

Variable	CR	AVE	Heterotrait-Monotrait Ratio (HTMT)						
			System Quality	Information Quality	Lack of Understanding	Lack of Infrastructure and Skills	Concerns over Data Security and Privacy	DA Business Value	Firm Performance
System Quality	0.882	0.560	–	–	–	–	–	–	–
Information Quality	0.902	0.700	0.858	–	–	–	–	–	–
Lack of Understanding	0.846	0.650	0.447	0.447	–	–	–	–	–
Lack of Infrastructure and Skills	0.866	0.620	0.394	0.394	0.538	–	–	–	–
Concerns over Data Security and Privacy	0.839	0.720	0.707	0.627	0.449	0.321	–	–	–
DA Business Value	0.892	0.510	0.786	0.829	0.510	0.376	0.854	–	–
Firm Performance	0.919	0.660	0.428	0.482	0.236	0.234	0.564	0.741	–

Table 10
Variance inflation factors.

Measurement Items	System Quality	Information Quality	Lack of Understanding	Lack of Infrastructure and Skills	Data Security Concerns	DA Business Value	Firm Performance
1	2.820	1.819	1.544	1.883	1.248	1.758	2.222
2	2.465	1.682	2.119	1.752	1.248	1.600	2.726
3	2.869	2.420	1.505	1.521	–	1.593	2.491
4	2.432	2.259	–	1.413	–	1.859	2.015
5	1.759	–	–	–	–	1.658	2.107
6	1.970	–	–	–	–	1.756	1.650
7	–	–	–	–	–	1.751	–
8	–	–	–	–	–	2.045	–

between *DA Business Value* and *Firm Performance* (0.7), followed by the relationships between *Concerns over Data Security and Privacy* and *DA Business Value* (0.178), and *Information Quality* and *DA Business Value* (0.176).

In our research model, *DA Purpose of Use* was included as the moderating variable, and *DA Business Value* as the mediating variable. It was noted that when *DA Purpose of Use* was excluded from the model, 43 % of *Firm Performance* variability could be explained from *DA Business Value*. This variance proportion was, however, 2% higher when *DA Purpose of Use* was incorporated in the model as the moderator. To assess whether DA business value fully or partially mediated the relationships between enablers, inhibitors, and *Firm Performance*, Baron and Kenny's (1986) guideline was used to evaluate this mediation effect (see Table 13 for the direct relationships analysis). Our findings showed that the direct impact between enablers and *Firm Performance* was significant for the relationship between *Information Quality* and *Firm Performance* ($\beta = 0.271$, $p < 0.05$), and not statistically significant for the relationship between *System Quality* and *Firm Performance* ($\beta = 0.070$, $p > 0.05$). As for the inhibitors, only the relationship between *Concerns over Data Security and Privacy* and *Firm Performance* was statistically significant ($\beta = -0.266$, $p < 0.05$). The other two inhibitors, *Lack of Understanding* and *Concerns over Data Security and Privacy* and *Lack of Infrastructure and Skills*, had insignificant relationship with *Firm Performance* (the path and the significance were $\beta = 0.019$, $p > 0.05$ and $\beta = -0.050$, $p > 0.05$, respectively). Our assessment, therefore, indicates that *DA Business Value* fully mediates the relationships between *System Quality*, *Concerns over Data Security and Privacy*, and *Firm Performance*, and partially mediates the relationships between *Information Quality*, *Lack of Understanding*, *Lack of Infrastructure and Skills*, and *Firm Performance*.

Also compared in the independent and joint analyses of our research model were the r^2 on DA business value. Overall, our analysis showed that the joint analysis increased the proportion of the variation of DA business value while the path coefficient direction and significance remained the same (four relationships showed $p < 0.05$ and one relationship showed $p > 0.05$). Table 14 presents the results of both joint and independent analyses of enablers and inhibitors.

Independent assessment was first performed to determine whether enablers or inhibitors affected DA business value, whereas joint analysis considered both enablers and inhibitors on DA business value. The higher r^2 on DA business value was evident from the joint analysis rather than from the independent analysis. The joint analysis revealed that enablers accounted for 57% of DA business value variability, whereas inhibitors accounted for 46% of variability. All enablers recorded a positive coefficient, and all inhibitors recorded a negative. In the independent analysis, all relationships for both enablers and inhibitors were found to be similarly significant as those in the joint analysis. The coefficient of determination showed that DA business value could be satisfactorily accounted for when both enablers and inhibitors were incorporated.

Table 11
Weight and loading for each measurement item.

Items	Weight	Load
SQ1 → System Quality	0.27	0.81
SQ2 → System Quality	0.25	0.81
SQ3 → System Quality	0.29	0.83
SQ4 → System Quality	0.19	0.73
SQ5 → System Quality	0.14	0.58
SQ6 → System Quality	0.17	0.69
IQ2 → Information Quality	0.31	0.80
IQ3 → Information Quality	0.28	0.86
IQ4 → Information Quality	0.31	0.86
LU1 → Lack of Understanding	0.22	0.67
LU2 → Lack of Understanding	0.54	0.92
LU3 → Lack of Understanding	0.43	0.81
LIS1 → Lack of Infrastructure and Skills	0.29	0.82
LIS2 → Lack of Infrastructure and Skills	0.38	0.83
LIS3 → Lack of Infrastructure and Skills	0.27	0.75
LIS4 → Lack of Infrastructure and Skills	0.33	0.75
DSP1 → Concerns over Data Security and Privacy	0.56	0.83
DSP2 → Concerns over Data Security and Privacy	0.62	0.87
BV1 → DA Business Value	0.18	0.69
BV2 → DA Business Value	0.17	0.63
BV3 → DA Business Value	0.16	0.70
BV4 → DA Business Value	0.18	0.74
BV5 → DA Business Value	0.18	0.72
BV6 → DA Business Value	0.17	0.73
BV7 → DA Business Value	0.16	0.69
BV8 → DA Business Value	0.20	0.79
FP1 → Firm Performance	0.21	0.82
FP2 → Firm Performance	0.23	0.86
FP3 → Firm Performance	0.21	0.84
FP4 → Firm Performance	0.20	0.80
FP5 → Firm Performance	0.22	0.82
FP6 → Firm Performance	0.15	0.71

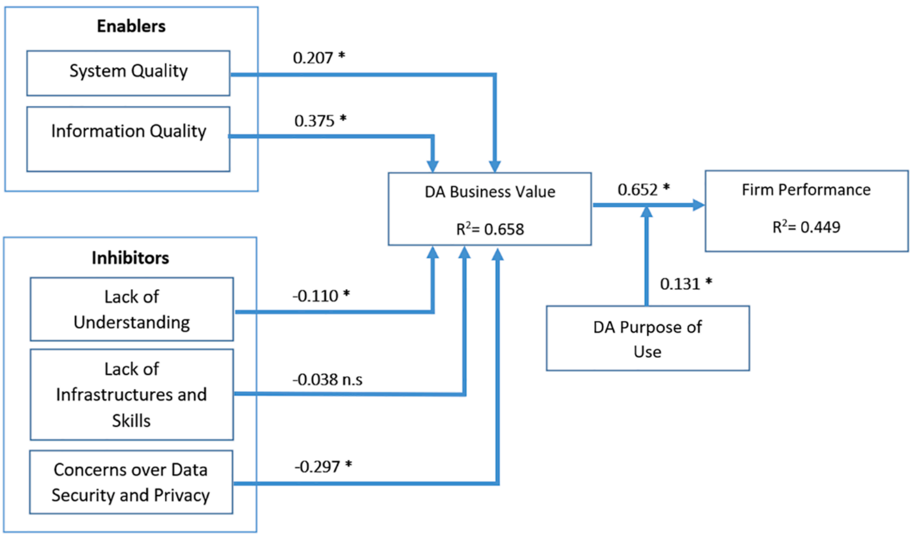

Fig. 2. Structural model and path coefficients. *p < 0.05, n.s = not supported.

5. Discussion

By investigating and integrating both enablers and inhibitors, we provide further understanding of how the dual factor concept can explain DA business value and firm performance. In the following section, we discuss our research contributions and limitations, and outline avenues for future research.

Table 12
Summary of hypotheses tests.

Hypotheses	p Values	Effect Size (f^2)	Support for hypotheses
Enablers			
H1: Information Quality → DA Business Value	0.000**	0.176	Support
H2: System Quality → DA Business Value	0.010**	0.048	Support
Inhibitors			
H3: Lack of Understanding → DA Business Value	0.031*	0.026	Support
H4: Lack of Infrastructure and Skills → DA Business Value	$0.478^{n.s}$	0.032	No Support
H5: Concerns over Data Security and Privacy → DA Business Value	0.000**	0.178	Support
Moderating Effect			
H6: DA Business Value → Firm Performance (Moderated by DA Purpose of Use)	0.036*	0.023	Support
Business Value and Firm Performance			
H7: DA Business Value → Firm Performance	0.000**	0.764	Support

*$p < 0.05$; **$p < 0.01$; n.s = not supported.

Table 13
Direct relationships between enablers, inhibitors and firm performance.

Direct Relationships	Path Coefficient	p Values
Enablers		
Information Quality → Firm Performance	0.271	0.020*
System Quality → Firm Performance	0.070	$0.524^{n.s}$
Inhibitors		
Lack of Understanding → Firm Performance	0.019	$0.811^{n.s}$
Lack of Infrastructure and Skills → Firm Performance	−0.050	$0.478^{n.s}$
Concerns over Data Security and Privacy → Firm Performance	−0.266	0.000**

*$p < 0.05$; **$p < 0.01$; n.s = not supported.

Table 14
Joint and independent analyses of enablers and inhibitors.

Relationships	Joint Analysis		Independent Analysis			
			Enablers		Inhibitors	
	Path Coefficient	p Values	Path Coefficient	p Values	Path Coefficient	p Values
Enablers						
Information Quality → DA Business Value	0.207	0.000*	0.437	0.000*		
System Quality → DA Business Value	0.375	0.010*	0.371	0.000*		
Inhibitors						
Lack of Understanding → DA Business Value	−0.110	0.031*			−0.204	0.006**
Lack of Infrastructure and Skills → DA Business Value	−0.038	$0.478^{n.s}$			−0.108	$0.133^{n.s}$
Concerns over Data Security and Privacy → DA Business Value	−0.297	0.000*			−0.530	0.000**
r^2 *DA Business Value*	**0.658**		**0.571**		**0.455**	

*$p < 0.05$; **$p < 0.01$; n.s = not supported.

5.1. Theoretical contributions

DA has been gaining momentum both in academia and practice in the last few years (Chen et al., 2018; Günther et al., 2017; Mikalef et al., 2020a; Mikalef et al., 2020b). It has also become one of the essential components to help organizations survive and thrive (Mikalef et al., 2020a). DA research in accounting information system (AIS) is also flourishing (e.g., Appelbaum et al., 2017; Elbashir et al., 2008; Rikhardsson and Yigitbasioglu, 2018; Koreff et al., 2021; Krieger et al., 2021), with studies conducted on the impact of DA on organizational performance (e.g., Appelbaum et al., 2017; Elbashir et al., 2008; Peters et al., 2016; Peters et al., 2018). At the same time, debates have arisen as to whether DA can indeed bring value to organizations. It is, therefore, critical to examine how DA can be implemented effectively and what factors direct its implementation to generate organizational business value (Mikalef et al., 2020b). With our research model for understanding the conditions that can either encourage or impede DA business value and firm performance, our study contributes to a better understanding of Elbashir et al.'s (2008) work on the relationships between DA, business processes and firm performance. By showing how SMEs' characteristics relate to enablers and inhibitors, our research demonstrates that these organizations need to manage the relevant enablers and barriers to achieve DA business value generation.

Our theoretical contribution is threefold. First, we add to the literature insights on the use of the dual factor concept (Cenfetelli, 2004; Cenfetelli and Schwarz, 2011; Wolverton and Cenfetelli, 2019). While research has used the dual factor concept on IT usage and adoption, in ITBV research, scant attention has been given to enablers and inhibitors. Drawing on RBV theory, we structured the antecedents of DA business value and firm performance using the dual factor concept (i.e., enablers and inhibitors). Our findings showed that SME employees held both favorable and unfavorable perceptions about DA business value. While they favored the system and information qualities as the catalysts for DA business value, they were concerned, at the same time, with lack of understanding, lack of infrastructure and skills, and data security and privacy that could deter DA business value generation. Both these perceptions co-existed and affected DA business value. While the literature suggests that enablers and inhibitors are independent in affecting IT use or IT business value, our results suggest that the joint effect of enablers and inhibitors can contribute to greater variability to DA business value rather than their independent effects. Our analysis also found a positive relationship between enablers and DA business value and a negative relationship between inhibitors and DA business value.

Our second contribution is in identifying three variables in the inhibitors construct, namely, lack of understanding, lack of infrastructure and skills, and concern over data security and privacy. While research has identified the inhibitors of generic IT use (Chau, 2001; King and Teo, 1994; Lee et al., 2013), little is known of the factors that could dampen DA business value. Our analysis suggests that lack of understanding is the most critical inhibitor for DA business value compared to the other two inhibitors.

Third, we show that DA purpose of use has a moderating role on the relationship between DA business value and firm performance. Our findings showed the variation of firm performance was 2% when DA purpose of use was considered. While a 2% addition is statistically significant, in the context of SMEs, the moderation role of DA purpose of use should be interpreted judiciously. Our findings further indicate that unlike large enterprises, SMEs may not use advanced analytics excessively in their business operations. This might be true considering the nature of SMEs' businesses, which is less complex than that of large firms. While our sample comprised SMEs that used DA for either business intelligence or advanced analytics, more than two thirds of them reported employing DA for business intelligence. Therefore, the use of either business intelligence or advanced analytics may not make a significant difference to SMEs' performance. For SMEs that use business intelligence, the spreadsheet normally rules the analysis involving slicing and dicing. Even if they have invested in DA, they typically use low-cost or open-source analytics tools. Analytics remain limited to structured data analysis, reporting and visualization (Halper and Stodder, 2014). Data silos often exist, and cross-functional decision processes remain unsupported. In contrast, SMEs that apply advanced analytics use structured and unstructured data in their analysis. They use sophisticated statistical techniques and machine learning algorithms for predictive modelling and decision optimization (Halper and Stodder, 2014). Further, they use DA to support cross-functional or company-wide decision processes.

5.2. Implications for practice

Although numerous studies have been conducted on ITBV, little is known about how SMEs could realize business value from DA. Compared to their large enterprise counterparts, SMEs encounter many challenges in implementing DA due to resource constraints and perceived higher risks (Bouwman et al., 2019; Li et al., 2018; Riemenschneider et al., 2003). Despite these challenges, SMEs can be more flexible and agile (Chan et al., 2019).

Our results suggest practical implications for SMEs, the government, and regulatory bodies to strategically implement DA effectively, which could result in improved business performance. As part of the AIS process, DA plays a vital role in a company's strategic positioning. In this digital transformation era, a company's ability to leverage the value of DA is essential in enhancing its performance. When designing an AIS platform, therefore, SMEs need to consider their DA capability which can deliver the intended services and information. Ultimately, this will enable them to realize the business value that leads to optimized firm performance.

Our study suggests that DA business value is the essential factor associated with firm performance. Among the enablers of DA business value, information quality has a greater effect size on firm performance than system quality does. This finding suggests that the information provided by analytics should help SMEs obtain actionable insights, as they could choose the systems that are the most relevant and affordable to them. Our sample data include SMEs that have implemented business intelligence and advanced analytics, some using proprietary tools and others using open-source tools. Almeida and Bernardino (2021) suggest that open-source tools such as R, KNIME, and Rapidminer are suitable for SMEs, as they offer fundamental and advanced analyses, thus allowing SMEs to generate relevant, high-quality information (Neely and Cook, 2011). For example, some SMEs in Singapore can generate reports and metrics from the integrated cloud accounting and inventory data and from multiple outlets to improve operational efficiency and understand profitability trends (Pan and Sun, 2018). However, SMEs should be aware that the availability of relevant and high-quality data is a necessary condition for information quality. This factor may be a challenge for some SMEs due to the insufficient amount of data to be analyzed and the lack of infrastructure for data management (Willets et al., 2021).

On the other hand, lack of understanding and concern over data security are the most critical inhibitors of DA business value. This finding aligns with results in prior studies, suggesting that the lack of DA understanding and resistance to change are barriers to SME management's adoption and implementation of technology (Chang et al., 2012; Ghobakhloo et al., 2011). To resolve this conundrum, the government, professional bodies, or the DA industry should help SMEs understand how they can leverage DA to harvest valuable information from their data. Professional accounting associations, for example, can help facilitate DA training and workshops for SMEs to familiarize themselves with DA tools. The trainings and workshops can also help SMEs formulate a useful strategy for implementing DA. Greater awareness of the value of DA will help them to effectively implement DA in their firms. At the same time, concerns over data security and privacy issues among the SMEs can also lead to the decrease of DA business value. Our effect size analysis suggests that this factor is the most salient that can dampen DA business value. As such, government and regulatory bodies should create training opportunities to help SMEs comply with the relevant personal data and protection act and legislations. Compared to larger firms that have more resources, SMEs are likely to be more prone to data breach due to their limited IT resources and skills.

The insignificant relationship between lack of infrastructure and skills and DA business value suggests that this variable may be the least critical inhibitor. While SMEs may have limited resources such as infrastructure and skills, this limitation could be resolved by outsourcing DA provision to a third party. One practical suggestion is that the government and regulatory bodies could consider providing shared analytics services for SMEs. Such shared services would be more cost efficient than for SMEs to subscribe to individual analytics services in the market. With such shared services, the government and regulatory bodies may standardize some of the analytical features for reporting and compliance while allowing SMEs to customize other analytics features according to specific industry purposes. Additionally, skills shortage may be resolved by providing consultancy and upskilling SME employees through analytics training.

Our study has shown DA can indeed facilitate SMEs to survive and thrive. Our results also suggest that improving the supply chain, reducing operating costs, increasing return on financial assets, and improving customer service are the most favorable business values of DA (see Table 7). Of these, reducing operating costs and increasing return on investment are the metrics related to accounting, while the rest are related to business process improvement. However, achieving the optimum DA business value will require management effort (e.g., to communicate the values of DA to employees, support them in the use of DA, and provide them with sound infrastructure), employee willingness (e.g., with a positive attitude towards change management to incorporate DA in their daily work), and government support (e.g., to provide technical help to SMEs and alleviate the fear of data security breach to adhere to the relevant PDPA legislation).

With COVID-19 drastically changing business processes, SMEs are forced to quickly integrate digital technology into their daily work. Even though the notion of an inflection point for technology usage or digital disruption is not new, the COVID-19 crisis is an inflection point of historic proportions (Mckinsey & Company, 2021). Our study can guide SMEs on factors that contribute to the optimization of DA use, especially during the pandemic when there are no other options but to use technology to improve business value.

5.3. Limitations and Future research

The results of our study should be interpreted in light of its five limitations. First, while we strive to elaborate on the enablers and inhibitors of DA business value, our explanations do not fully reflect all potential enablers and inhibitors. In this study, we focused on information and system qualities as enablers of DA capabilities. Future studies could consider other organizational resources, such as leadership or management support, as enablers. For example, research from other technological applications such as RPA has shown that management support is one of the keys to RPA success (Willcocks et al., 2018). Future research could also investigate whether this variable helps the organization create unique resources in pursuing DA business value. Second, our survey instrument considered only two categories of DA capabilities: business intelligence or advanced analytics. With advancement in analytics and automation, future research could explore the use of process automation as a new category alongside business intelligence and advanced analytics. Third, our sample was limited to SMEs in Singapore, which means that our findings should be interpreted cautiously. Future research could compare the use of DA in different countries, to provide a broader understanding of how SMEs in different countries realize DA enterprise value and whether DA enterprise value improves their firms' performance. Fourth, our analysis of enablers and inhibitors was based on perception-based firm performance. Therefore, the analysis could not determine the impact of DA business value on financial measures such as firm profitability. Future research could, therefore, extend the analysis to include financial measures. Fifth, our concept of DA business value was limited to general accounting value. Future research should consider the business value of DA from an accounting perspective – for example, how DA helps to enable internal audit controls, mitigate potential risks or threats, and provide early warning systems for potentially fraudulent transactions or accounting misconduct.

6. Conclusion

As stated, the primary objective of this research was to examine the extent that SMEs utilized DA applications to generate business value. To this end, we investigated both potential enablers and inhibitors of DA business value relevant to SMEs. Specifically, information quality and system quality were found to be the strong predictors of DA business value enablers, whereas lack of understanding and concerns over data security and privacy were the most salient predictors of DA business value inhibitors. Our analysis highlights the importance of understanding both enablers and inhibitors in IT business value research. We offer practical suggestions to the relevant stakeholders on formulating strategies to mitigate potential deterrents of DA business value generation in SMEs, so that SMEs can reap the benefits from DA.

CRediT authorship contribution statement

Arif Perdana: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Hwee Hoon Lee:** Conceptualization, Writing – original draft, Writing – review & editing. **SzeKee Koh:** Conceptualization, Methodology, Formal analysis, Project administration, Supervision, Investigation, Funding acquisition, Writing – review & editing, Resources. **Desi Arisandi:** Conceptualization, Investigation.

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