



Evaluating the impact of big data analytics usage on the decision-making quality of organizations



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ABSTRACT

Big data initiatives are critical for transforming traditional organizational decision making into data-driven decision making. However, prior information systems research has not paid enough attention to the impact of big data analytics usage on decision-making quality. Drawing on the dynamic capability theory, this study investigated the impact of big data analytics usage on decision-making quality and tested the mediating effect of data analytics capabilities. We collected data from 240 agricultural firms in China. The empirical results showed that big data analytics usage had a positive impact on decision-making quality and that data analytics capabilities played a mediating role in the relationship between big data analytics usage and decision-making quality. Hence, firms should not only popularize big data analytics usage in their business activities but also take measures to improve their data analytics capabilities, which will improve their decision-making quality toward competitive advantages.

1. Introduction

Big data technologies are transforming the way businesses operate and reshaping how organizations make decisions, and their importance in building firm competitiveness has been widely recognized (Vial, 2019). More than 80% of firms believe that big data will change the competitive landscape and that the adoption of big data is a vital means to gain market share (Ghasemaghaei and Calic, 2020). The use of big data analytics tools can substantially revamp the level of production standardization, operation network, and service precision (Wolfert et al., 2017). In recent years, a growing number of firms have accelerated the deployment of their big data analytics initiatives with the aim of developing critical insight that can ultimately provide them with a competitive advantage (Pham and Stack, 2018). However, some studies have found that only 25% of firms claim that the use of big data analytics has significantly improved their organization's outcomes, and most firms that have invested in processing big data have yet to gain unique insights to improve their outcomes (Ghasemaghaei and Calic, 2019). One reason for the failure is that many firms still have a shallow understanding of big data analytics and do not know the necessary conditions for generating insights from data analytics (Wamba et al., 2017). Hence, understanding how to effectively use big data analytics to

improve decision-making quality is salient to firms' competitive advantage.

Existing research on big data and decision-making quality has some limitations. Previous studies have presented inconsistent conclusions regarding the impact of big data analytics usage on decision-making quality. Some scholars have shown that big data analytics usage has a positive impact on decision-making quality (Shamim et al., 2019), while others have reported contrary findings (Ghasemaghaei and Turel, 2021). There is limited knowledge of how big data initiatives can help firms cultivate their decision-making quality (Coble et al., 2018; Pham and Stack, 2018; Lioutas and Charatsari, 2020; Lin et al., 2021), and the effect and mechanism of big data analytics usage on decision-making quality are unclear. Therefore, additional in-depth studies are warranted to explain the mechanisms by which the benefits of big data analytics usage on decision-making quality can be achieved.

In the big data environment, data analytics capabilities, which refer to the ability of a firm to effectively deploy technology and talent to capture, store, and analyze data to generate insight, are an important organizational capability that can lead to competitive advantages (Rialti et al., 2019). Data analytics capabilities can improve firms' decision-making efficiency and effectiveness by capturing, storing, transmitting, sharing, searching, analyzing, and visualizing data (Gupta

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et al., 2020; Joshi et al., 2021). Accordingly, firms that develop superior data analytics capabilities by facilitating the pervasive use of big data analytics should be able to maximize decision-making quality (Akter et al., 2016). However, previous studies have mainly taken data analytics capabilities as the antecedent of firms' decisions, and have discussed the direct and indirect effects of data analytics capabilities on decision-making quality (Wamba et al., 2017; Shamim et al., 2019, 2020; Awan et al., 2021). It is yet unclear whether data analytics capabilities mediate the relationship between big data analytics usage and decision-making quality.

To fill the above-mentioned gaps and advance this line of research, this study drew on dynamic capability theory and developed a model that investigated the impact of big data analytics usage on decision-making quality and gauged the mediating role of data analytics capabilities in the linkages between them. The study makes three key contributions by: (1) expanding the previous IS research on the value of big data analytics, testing the effects of big data analytics usage on decision-making quality, and providing empirical evidence that firms can leverage big data analytics to facilitate decision-making quality; (2) revealing the mechanism through which big data analytics usage positively influences the firms' decision-making quality, identifies the mediation role of data analytics capabilities, and provides a novel lens for firms using big data analytics to gain competitive advantages; and (3) supplementing the applicability of dynamic capacity theory and finding that big data analytics usage (i.e., a low-order organizational capability) can promote data analytics capabilities (i.e., a high-order organizational capability).

2. Theoretical background

2.1. Big data analytics usage

Big data has revolutionized information processing technology and analysis methods, improved information processing capabilities, and has been widely used in many aspects of various fields (Lioutas and Charatsari, 2020). To exemplify, in agricultural industries, big data has already found many applications, such as weather forecasting, monitoring for crops' pests, and consumer preference (Lioutas et al., 2019). Big data analytics capture the real-time state of the agricultural industry chain in the form of data, helping organizations make smart decisions (Pham and Stack, 2018). Firms use big data analytics tools to process and analyze data resources, obtain supported decisions, and create a competitive advantage (Kamilaris et al., 2017; Dong and Yang, 2020). Firms can gain deep insights to make decisions by utilizing different types and quantities of data (Rodriguez et al., 2017). According to prior research, the use of big data analytics can help firms collect and analyze data and make decisions and predictions, which can provide useful guidance for further decision making (Ribarics, 2016; Lioutas et al., 2019). However, according to the IT paradox, big data analytics usage may not have a positive impact on decision-making quality (Panda and Rath, 2016; Castillo et al., 2021). Big data analytics usage requires matching big data storage technology, analytics talents, and management knowledge, which may pose a technical burden on firms, which may lack the capacity to extract valuable information from the data (Ross et al., 2013; Kamilaris et al., 2017). In this sense, we are cognizant that there is no consistent research conclusion on the relationship between big data analytics usage and firm decision-making quality, and the effects and mechanisms of big data analytics usage on firm decision-making quality are still unknown. Therefore, more research on the impact of big data analytics usage on firm decision-making quality is warranted.

2.2. Dynamic capability theory

The dynamic capability theory posits that the organizational capability of integrating, building, and reconfiguring internal and external

competencies to respond to rapidly changing environments can sustain a firm's competitive advantage (Teece et al., 1997; Mu, 2017). The theory also indicates two levels of dynamic capabilities low- and high-order organizational capabilities that create competitive advantages (Liu et al., 2013). Organizations can form rare high-order capabilities through the integration and allocation of low-order capabilities (Grant, 1996; Ayabakan et al., 2017). In the existing literature, big data analytics usage refers to the scope and frequency of using big data mining and analysis techniques within organizations (Iqbal et al., 2020). It mainly reflects the operational capability of the big data department, which is considered a low-order dynamic capability (Ghasemaghaei et al., 2017). Data analytics capabilities refer to the ability to mobilize and deploy data analytics-based resources (e.g., big data analytics usage) by combining other resources and capabilities to improve decision-making quality and bring competitive advantages. It achieves specific goals through cross-level and cross-departmental collaboration, and is considered a high-order dynamic capability. Thus, big data analytics usage is the low-order organizational capability that is critical to achieving data analytics capabilities (a higher-order organizational capability). As such, the dynamic capability theory is an appropriate lens to understand the impact of big data analytics usage on data analytics capabilities and subsequent decision-making quality.

2.3. Data analytics capabilities

Data analytics capabilities have become critical organizational capabilities to processing data due to the increase in data volume, diversification of data types, and rate of data change in business (Wolfert et al., 2017). Firms' data analytics capabilities refer to their ability to utilize and develop resources based on big data analytics to gain insight, which can lead to sustainable competitive advantages in a dynamic environment (Pham and Stack, 2018; Rialti et al., 2019; Shamim et al., 2020). Building data analytics capabilities requires the integration of strategic resources, including tangible, non-tangible, and human skills (technical and managerial skills), among which human skills stand out as the most crucial for executing and developing data analytics capabilities as dynamic capabilities (Akter et al., 2016; Gupta and George, 2016). Human skills, as uniquely dynamic resources that can be acquired but not imitated, not only help to establish big data analytics technology, but also play a vital role in achieving the maximum potential of that big data analytics technology (Gupta et al., 2020). Past research has highlighted the importance of human skills and showed that firms merely adopting big data analytics will make no difference if the adoption is not supported by the appropriate human skills (Papadopoulos et al., 2017; Helfat and Raubitschek, 2018). Specifically, technical skills refer to the know-how required to use new forms of big data analytics to extract intelligence from big data, including data extraction, data cleaning, and statistical analysis (Gupta et al., 2016). Technical skills not only execute big data analytics but also capture market sentiment, thus helping firms find market opportunities, rationally utilize organizational resources and achieve continuous organizational renewal (Akter et al., 2016). Managerial skills can be described as the ability of employees to organize and configure big data analytics to perform their daily work and make decisions, such as strategic foresight for big data deployments and application of the extracted insights (Gupta and George, 2016). Productive managerial skills help employees to be capable of making real-time decisions through big data analytics, which help firms accurately collect and evaluate market intelligence, rapidly mobilize resources to respond to changes, and achieve organizational reorganization in dynamic conditions (Wamba et al., 2017). In summary, firms can combine human skills (technical skills and managerial skills) to form the dynamic capabilities (data analytics capabilities) that help organizations sense, seize, and transform data to improve decision-making quality and gain competitive advantages (Teece, 2007; Mikalef et al., 2018). Along the same lines, this study proposes technical skills and managerial skills as two important aspects of a firm's data

analytics capabilities.

With the extensive use of big data analytics, researchers are focused on data analytics capabilities in firms. They have indicated that using big data analytics will help firms identify, share, and analyze data resources (e.g., production information, logistics information, and price information), as well as encourage them to develop matching data analytics capabilities (Kamilaris et al., 2017; Coble et al., 2018). Moreover, data analysis capabilities may fully exploit the value of data, and provide firms with insights that are helpful for optimizing allocation, product traceability, operation planning, decision making, and implementation (Horita et al., 2017). Therefore, data analytics capabilities cannot be ignored in the research of big data analytics usage.

2.4. Decision-making quality

Decision-making quality refers to the correctness and accuracy of decisions, which is evaluated by decision effectiveness and decision efficiency in the process of decision making (Aydinera et al., 2019; Ghensemaghaei, 2019). In line with Shamim et al. (2019), decision effectiveness focuses on the accuracy, precision, and reliability of decision results, whereas decision efficiency considers the time, cost, and other aspects of the resources involved. The increasingly diversified consumer demands and the occurrence of public events, such as the COVID-19, have put forward higher requirements on firms' decision-making quality (Pham and Stack, 2018; Aydinera et al., 2019). Big data is occurring at all stages of the industrial chain, which has transformed the way that firms make decisions, enabling firms to quickly identify opportunities and problems, shorten the process of decision making, and improve decision-making quality (Chae et al., 2014; Pham and Stack, 2018). For example, big data can provide agricultural firms with accurate production information (e.g., leaf greenness, temperature, seeding, and pesticide spraying rate) and improve decision-making quality through intelligent prediction functions. Moreover, the application of big data in business processes can assist agricultural firms in quickly transferring market and customer information and performing real-time analysis and insights to support decision making (Lioutas and Charatsari, 2020). According to this conception, efficient decisions can help firms control costs, ensure product quality, and improve customer satisfaction. Therefore, this study aimed to examine the mediating roles of data analytics capabilities between big data analytics usage and decision-making quality.

3. Research model and hypothesis development

3.1. Big data analytics usage and decision-making quality

Big data analytics usage can realize the value of data produced by firms and change their traditional decision-making processes. First, big data analytics usage promotes the collection of data in the industrial chain, including production, processing, and sales data, and the formation of a database (Wolfert et al., 2017; Mark, 2019). Comprehensive and sufficient data can provide hidden value for firms and help them improve decision-making quality (Pham and Stack, 2018). Second, using advanced big data analytics tools can help provide scientific analysis results for firms, thereby changing the way of experiential decision making and improving decision-making effectiveness (Delgado et al., 2019; Hughes and Ball, 2020). Third, firms use big data analytics tools to mine data, including user interest, network behavior, and emotional semantic analyses, all of which can help firms grasp changes in customer demand and improve decision-making efficiency (Jun et al., 2018). Finally, through big data model prediction, including machine learning, modeling, and simulation, firms can obtain decision support and forecasting reports to make timely decisions (Carolan, 2018). Previous studies have also found that the veracity, variety, and velocity of big data provide the guarantee of decision-making quality. Big data analytics usage plays a key role in increasing data diagnosis and improving

firm decision making (Janssen et al., 2017; Riwthong et al., 2017). Therefore, we hypothesize the following:

H1: Big data analytics usage is positively associated with decision-making quality.

3.2. Big data analytics usage and data analytics capabilities

Big data analytics usage has promoted the digitalization of firms and brought new vitality into their development (Wolfert et al., 2017). It has the potential to realize intelligent production, reorganize supply chains, and promote the digital transformation of firms (Bendre et al., 2015; Pham and Stack, 2018). However, big data also brings challenges to firms. There are various types of big data, including semi-structured, structured, and unstructured data (Ribarics, 2016). Complex data require that firms possess the corresponding data analytics capabilities to provide the firms with big data architectures to store large amounts of data and a nested computer network to analyze different types of data (Rialti et al., 2019; Kamblea et al., 2020). Data analytics capabilities can help firms capture and analyze all kinds of data quickly, thereby realizing the value of data (Suoniemi et al., 2020). Further, when firms use big data analytics, they reasonably allocate resources related to data processing, such as talents, infrastructure, management, and other resources, to drive the formation of data analytics capabilities and ensure their successful use of big data analytics tools (Wolf and Wood, 2010; Pham and Stack, 2018; Belhadi et al., 2019). Therefore, we hypothesize the following:

H2: Big data analytics usage is positively associated with data analytics capabilities.

3.3. Data analytics capabilities and decision-making quality

Data analytics capabilities are important organizational capabilities that can help firms make use of data resources (e.g., production data, market supply and demand data, and logistics data), mine hidden information in the supply chain, find opportunities and threats, and improve decision-making quality (Kamblea et al., 2020). For instance, data analytics capabilities can enhance the analysis of the environment required for product production and develop production schemes for each unit, thereby optimizing production operations (Visinescu et al., 2017; Lioutas and Charatsari, 2020). Thus, data analytics capabilities can transform raw data from various IT applications into customer insights and help firms search for hidden consumption patterns, identify consumer preferences, and design and innovate marketing strategies (Carolan, 2018; Dong and Yang, 2020). Furthermore, data analytics capabilities can also make appropriate decisions for future planning and resource allocation by gaining insights into the primary business activities of firms (Pham and Stack, 2018; Corte Real et al., 2020). In short, firms with a high level of data analytics capabilities can also take full advantage of data analytics tools to ensure decision-making quality. In particular, through the analysis and processing of big data, data analytics capabilities can gain comprehensive and farsighted insights, helping firms to improve their decision efficiency and decision effectiveness. Therefore, we hypothesize the following:

H3: Data analytics capabilities are positively associated with decision-making quality.

Drawing on dynamic capability theory, this study proposes the research model presented in Fig. 1 and demonstrates the hypothesized relationships between big data analytics usage, data analytics capabilities, and decision-making quality.

4. Methodology

4.1. Scale development

This study used questionnaires to collect data from agricultural firms. The questionnaire included fundamental information about the

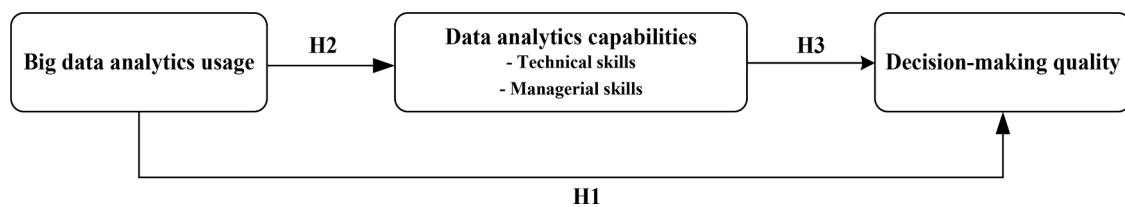


Fig. 1. Research model.

agricultural firms and the measurements of each variable in the model. All items were adapted from extant literature and modified in the context of agricultural firms to fit the needs of this study (see the Appendix). Big data analytics usage was adapted from [Yunis et al. \(2018\)](#) while data analytics capabilities were adapted from [Ghasemaghaei \(2019\)](#). Decision-making quality was measured by the items from [Ghasemaghaei et al. \(2018\)](#). We developed the questionnaire rigorously to ensure the validity of the scale. As the targeted respondents were Chinese professionals, the questionnaire was translated into Chinese by a Chinese-speaking co-author and adjusted according to Chinese culture to ensure its accuracy. Two doctoral students proficient in both Chinese and English proofread the questionnaire separately. Any inconsistency was discussed until a satisfactory agreement was reached. We then pretested the questionnaire with 20 students majoring in agricultural big data analysis. According to their feedback, the scale was modified and improved to make the content more accurate.

4.2. Data collection

The target respondents of this study were senior top or middle executives from the provincial level of agricultural firms in China because of their relatively comprehensive understanding of their firm's big data initiatives, resource allocation, and business strategies. With the assistance of China's Department of Agriculture and Rural Affairs, we obtained the contact list of 2652 provincial agricultural firms in China. A web link to the survey questionnaire was sent to the target respondents from these firms. We sent reminder emails to participants who had not yet responded two months after distributing the questionnaire. After three months, 286 questionnaires were completed and returned. Excluding 46 questionnaires with missing content, 240 valid questionnaires were collected and used for the empirical analysis. The statistical characteristics of the sample are shown in [Table 1](#). In terms of firm size, 50.8% of firms had less than 500 employees, and 49.2% had more than

Table 1
Descriptive statistics of the sample.

| Attributes | Options | Frequency | Percentage (%) |
|---|------------------------------|-----------|----------------|
| Firm size (number of employees) | <, 500 | 122 | 50.8 |
| | 500–1000 | 75 | 31.3 |
| | 1000–2000 | 25 | 10.4 |
| | > 2000 | 18 | 7.5 |
| IT department size (number of IT employees) | < 10 | 38 | 15.8 |
| | 10–20 | 56 | 23.3 |
| | 20–30 | 55 | 22.9 |
| | 30–40 | 27 | 11.3 |
| Difficulties in the use of big data analytics tools | > 40 | 64 | 26.7 |
| | Immaturity of analysis tools | 53 | 22.1 |
| | Large quantity of data | 46 | 19.2 |
| | Insufficient professionals | 108 | 45.0 |
| The age of using big data analytics tools (Year) | Low data quality | 33 | 13.7 |
| | Not usage | 0 | 0 |
| | 0–2 | 80 | 33.3 |
| | 2–5 | 111 | 46.3 |
| | >5 | 49 | 20.4 |

500 employees. Firms were noted to attach importance to IT, with 60.9% of firms having more than 20 IT employees. Insufficient professionals accounted for 45.0% of difficulties in the use of big data analytics tools. Those who had used big data analysis tools for more than 2 years were 66.7%. [Table 2](#) presents the characteristics of respondents: 46.3% were men, 53.8% were women, 97.1% were between 20 and 40 years old, and 88.7% had an undergraduate education.

5. Empirical analysis and results

5.1. Common method bias and nonresponse bias assessment

We conducted the marker variable technique proposed by [Lindell and Whitney \(2001\)](#) to address the common method bias. The marker variable was assumed to have no relationship with one or more variables, so any correlation between it and other variables can be attributed to the common method bias. In this study, we used gender, a theoretically unrelated construct, as our marker variable. The correlation between gender and other variables was denoted by the average correlations (r_M), and it was treated as an indicator of common method bias. The results ([Table 3](#)) showed that r_M was 0.014, and the differences between the basic and adjusted correlations were relatively small ($\Delta r \leq 0.010$), implying that the common method bias was not an issue in our data. The explained variances of endogenous variables in the two models were also very similar, and the path estimates of the two models were not statistically different ($\chi^2 = 9$, $p = 0.109$), which further indicated that common method bias was not a problem in this study.

This study also examined non-response bias by comparing early respondents with late respondents. First, the sample was divided into a group of 185 early respondents (those who replied before the reminder) and a group of 55 late respondents ([Karahanna et al., 1999](#); [Liu et al., 2018](#)). Then, a *t*-test was performed on the key constructs, and the results (see [Table 4](#)) revealed that there was no significant difference in the means of the constructs between the two groups. Chi-square tests comparing early and late respondents in terms of firm size ($p = 0.345$) revealed no significant response bias. Therefore, we believe that non-response bias was not an issue in our model.

5.2. Measurement model

The results of factor loading showed that three indicators were below the threshold of 0.600, including BDU4, DQ1, DQ4, and DQ8, which

Table 2
Descriptive statistics of the respondents.

| Attributes | Options | Frequency | Percentage (%) |
|------------|-----------------------|-----------|----------------|
| Gender | Male | 111 | 46.3 |
| | Female | 129 | 53.8 |
| Age | 20–30 | 139 | 57.9 |
| | 31–40 | 94 | 39.2 |
| Education | 41–50 | 6 | 2.5 |
| | > 50 | 1 | 0.4 |
| Education | High school and below | 5 | 2.1 |
| | Junior college | 22 | 9.2 |
| | Bachelor's degree | 176 | 73.3 |
| | Master and above | 37 | 15.4 |

Table 3

Estimation results of common method bias.

| | Baseline model | Adjusted model |
|------------------------------|----------------|----------------|
| Factor correlations | $r_M = 0.014$ | |
| $r(BDU, DAC)$ | 0.622** | 0.617*** |
| $r(BDU, DQ)$ | 0.477** | 0.470*** |
| $r(DAC, DQ)$ | 0.538** | 0.531*** |
| Structural paths | | |
| $\beta(BDU \rightarrow DQ)$ | 0.249*** | 0.238*** |
| $\beta(BDU \rightarrow DAC)$ | 0.636*** | 0.631*** |
| $\beta(DAC \rightarrow DQ)$ | 0.387*** | 0.378*** |
| Predictive power | | |
| SMC (DAC) | 0.404 | 0.396 |
| SMC (DQ) | 0.334 | 0.325 |

Note: BDU, big data analytics usage; DAC, analysis capabilities; DQ, decision-making quality, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 4

Estimation results of non-response bias.

| Factors | Non-response bias | | |
|-----------------------------|--------------------------------|------------------------------|------------------------|
| | Early respondents (n = 185) | Late respondents (n = 55) | Significance (p-value) |
| Big data analytics usage | 3.897 | 3.800 | 0.353 |
| Data analytics capabilities | 3.939 | 3.570 | 0.202 |
| Decision-making quality | 3.800 | 3.600 | 0.348 |

reduced the overall reliability and validity. After these indicators were excluded, all indicators were qualified. As Table 5 shows, all indicator loadings ranged from 0.616 to 0.862 and AVE scores ranged from 0.510 to 0.700, suggesting that the scale has satisfactory convergent validity. All VIF values were below 10 and between 1.212 and 1.787, suggesting that multicollinearity was not a problem in our constructs. Cronbach's α ranged from 0.774 to 0.786, above the threshold of 0.700. The composite value ranged from 0.822 to 0.875, well above the threshold of 0.700. We also used the heterotrait-monotrait ratio of correlations (HTMT) to measure discriminant validity. The HTMT should be lower than 0.850 (stricter threshold) or 0.900 (more lenient threshold) or significantly smaller than 1. The results are presented in Table 6. The HTMTs of all variables were below the recommended threshold of 0.900. Therefore, the scale had good discriminant validity.

5.3. Structural model

We used SmartPLS 3.3.2 to test the hypothesis, and this technique was selected for three reasons: (1) The PLS technique has been widely used in IS research, which can test the precise model fit and be used for

Table 5

Reliability and validity.

| Variables | Item | Loading | VIF | AVE | CR | α |
|-----------------------------|------|---------|-------|-------|-------|----------|
| Big data analytics usage | BDU1 | 0.826 | 1.571 | | | |
| | BDU2 | 0.823 | 1.626 | 0.606 | 0.822 | 0.774 |
| | BDU3 | 0.862 | 1.787 | | | |
| Data analytics capabilities | DAC1 | 0.784 | 1.385 | | | |
| | DAC2 | 0.737 | 1.212 | 0.700 | 0.875 | 0.786 |
| | DAC3 | 0.813 | 1.437 | | | |
| Decision-making quality | DQ2 | 0.743 | 1.523 | | | |
| | DQ3 | 0.711 | 1.367 | | | |
| | DQ5 | 0.748 | 1.567 | 0.510 | 0.838 | 0.758 |
| | DQ6 | 0.743 | 1.491 | | | |
| | DQ7 | 0.616 | 1.286 | | | |

Note: BDU, big data analytics usage; DAC, data analytics capabilities; DQ, decision-making quality; VIF, variance inflation factors; AVE, average variance extracted; CR, composite reliability; α , Cronbach's α .

Table 6

Heterotrait-monotrait ratio of correlations.

| Variables | 1 | 2 | 3 |
|----------------------------|-------|-------|---|
| 1.Big data analytics usage | | | |
| 2. Analysis capabilities | 0.857 | | |
| 3. Decision-making quality | 0.662 | 0.698 | |

exploratory theory building (Braojos et al., 2019; Braojos et al., 2020). We utilized this emerging research model to explore the effects of big data analytics usage on data analytics capabilities and decision-making quality. (2) PLS have advantages in model estimation of small to medium sample sizes (Yu et al., 2018). In this research, our sample size of 240 was not large, which is sufficient for the use of the PLS technique. (3) PLS does not require identical distribution of residuals (Liu et al., 2018). To examine the coefficients of skewness and kurtosis, we found that our sample data did not fully follow the normal distribution. Hence, we believe that SmartPLS was well suited for this study.

All the results are shown in Table 7. All our hypotheses were supported. Big data analytics usage had positive impacts on decision-making quality ($\beta = 0.223$, $p < 0.01$), supporting H1. It likewise had a positive impact on data analytics capabilities ($\beta = 0.623$, $p < 0.001$), supporting H2. Data analytics capabilities had positive impacts on decision-making quality ($\beta = 0.394$, $p < 0.001$), supporting H3. The variance interpretation rates of data analytics capabilities and decision-making quality were 38.9% and 32.5%, respectively. Further, we used firm size and IT department size as control variables to test their impact on decision-marking quality. We found that firm size did not affect decision-making quality ($\beta = -0.012$, n.s.), nor did the IT department size affect decision-making quality ($\beta = 0.038$, n.s.).

5.4. Mediating effect testing

We used the Sobel and bootstrap tests to examine the mediating effect of data analytics capabilities, and the results are shown in Table 8. The Sobel test results showed that data analytics capabilities had significant mediating effects on the relationships between big data analytics usage and decision-making quality. Bootstrap test results showed that under the 95% confidence interval, the confidence interval (LLCI = 0.123, ULCI = 0.329) for the impact of big data analytics usage on decision-making quality did not include 0, and the mediating effect size was 0.218. Therefore, data analytics capabilities have a partially mediating effect between big data analytics usage and decision-making quality.

5.5. Robustness test

We conducted a robustness test to verify the findings and gain additional insights. We adopted similar techniques as did past research by considering big data analytics usage, data analytics capabilities, and

Table 7

Structural model evaluation.

| Relationship | Beta coefficient |
|---|----------------------------------|
| Big data analytics usage→Decision-making quality (H1) | 0.223** (2.956) [0.548, 0.701] |
| Big data analytics usage→Data analytics capabilities (H2) | 0.623*** (16.010) [0.548, 0.701] |
| Data analytics capabilities→Decision-making quality (H3) | 0.394*** (4.601) [0.224, 0.559] |
| Firm size→Decision-making quality (CV) | -0.012 (0.644) [-0.138, 0.112] |
| IT department size→Decision-making quality (CV) | 0.038 (0.187) [-0.080, 0.153] |

Note: t-values are presented in parentheses. Confidence intervals are presented in square brackets, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (based on $n = 4999$, one-tailed test). CV, control variable.

Table 8
Results of testing for mediating effects.

| Path | Bootstrap test | | Sobel test Confidence interval (95%) | T value | Standard error | P-value | Conclusion |
|------------|----------------|----------------|---|---------|----------------|---------|------------|
| | Effect | Standard error | | | | | |
| BDU→DAC→DQ | 0.218 | 0.053 | [0.123, 0.329] | 4.44 | 0.056 | 0.00 | Supported |

Note: BDU, Big data analytics usage; DAC, Data analytics capabilities; DQ, Decision-making quality. *** $p < 0.001$ and ** $p < 0.01$.

decision-making quality as composite constructs and re-ran our model (Wei et al., 2020). As shown in the Appendix, an assessment of the measurement model revealed that all VIF values were below 1.787, suggesting that multicollinearity was not a problem. Moreover, all loadings were significant, indicating that all composite indicators should be retained. We then performed the confirmatory composite analysis to assess the goodness of fit of the saturated model. Thus, we evaluated the standardized root mean squared residual (SRMR), unweighted least squares (ULS), discrepancy (dULS), and geodesic discrepancy (dG). The results in Table 9 showed that the SRMR was lower than the threshold of 0.08; SRMR and dULS were within the 95% quantile of bootstrap discrepancies and dG was within the 99% quantile of bootstrap discrepancies. Overall, all the results showed good properties for our measures.

We also estimated the beta coefficients and significance level of the hypothetical relationships. As shown in Table 10, all the hypotheses were supported, and the results were not substantially different from the previously described main findings. We also evaluated the effect size (f^2) and R² values of the hypothetical relationships. The R² values of our endogenous variables were 0.403 and 0.381, indicating good explanatory power. F² values ranged from 0.084 to 0.675, indicating weak-to-large effect sizes in our hypothesized significant relationships. We also evaluated the goodness of model fit for the structural model. SRMR values for each model were below the threshold of 0.800, and SRMR, while dULS and dG were less than the 95% quantile of bootstrap discrepancies, indicating a good fit between the model and data. In summary, all the findings indicate that our structural model was appropriate and supported our previous results.

Moreover, we estimated one additional research model to check for the robustness of the proposed research model. In the alternative model, we assumed that data analytics capabilities positively influence big data analytics usage. The empirical results (see Table 10) showed that the values of SRMR and DULS were all unqualified. As such, the alternative model was not statistically better than the overall estimated model fit of the proposed research model, indicating again that our proposed research model was appropriate.

6. Discussion

The purpose of this study was to explore the influence of big data analytics usage on decision-making quality. From a dynamic capability view, this study examined the impact of big data analytics usage on decision-making quality through data analytics capabilities. Our results showed that big data analytics usage had positive impacts on decision-making quality, and data analytics capabilities had positive impacts on decision-making quality and a partially mediating effect on the relationship between big data analytics usage and decision-making quality. A summary of the empirical test results is shown in Table 11.

First, we found that big data analytics usage had significant impacts on decision-making quality. Big data analytics usage was significantly

Table 9
Results of the confirmatory composite analysis.

| Discrepancy | Constructs Value | HI ₉₅ | HI ₉₉ | Conclusion |
|------------------|---------------------|------------------|------------------|------------|
| SRMR | 0.034 | 0.039 | 0.042 | Supported |
| d _{ULS} | 0.137 | 0.179 | 0.216 | Supported |
| d _G | 0.070 | 0.079 | 0.092 | Supported |

Table 10
Robustness test of structural model evaluation.

| Relationship | Baseline model | Alternative model |
|---|-------------------------------------|-------------------------------------|
| Big data analytics usage→Decision-making quality (H1) | 0.296*** (3.965) [0.112, 0.494] | 0.249** (3.701) [0.078, 0.489] |
| Big data analytics usage→Data analytics capabilities (H2) | 0.635*** (16.850) [0.536, 0.732] | |
| Data analytics capabilities→Decision-making quality (H3) | 0.385*** (4.977) [0.193, 0.591] | 0.369*** (4.629) [0.155, 0.559] |
| Data analytics capabilities→Big data analytics usage | | 0.633*** (16.576) [0.532, 0.731] |
| Endogenous variable | R ² | Adjusted R ² |
| Big data analytics usage | | 0.41 |
| Data analytics capabilities | 0.403 | 0.401 |
| Decision-making quality | 0.381 | 0.376 |
| SRMR value | 0.034 | 0.050 |
| SRMR HI ₉₅ | 0.039 | 0.045 |
| d _{ULS} value | 0.137 | 0.297 |
| d _{ULS} HI ₉₅ | 0.179 | 0.237 |
| d _G value | 0.070 | 0.091 |
| d _G HI ₉₅ | 0.079 | 0.088 |
| f ² | | |
| Big data analytics usage→Decision-making quality (H1) | 0.084 | 0.043 |
| Big data analytics usage→Data analytics capabilities (H2) | 0.675 | |
| Data analytics capabilities→Decision-making quality (H3) | 0.143 | 0.141 |
| Data analytics capabilities→Big data analytics usage | | 0.630 |

Note: t-values are presented in parentheses. Confidence intervals are presented in square brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (based on $n = 4999$, one-tailed test).

Table 11
Hypothesis test results.

| Path | Path coefficient | T value | P-value | Conclusion |
|-------------|------------------|---------|-------------|------------|
| H1: BDU→DQ | 0.223 | 2.956 | $p < 0.01$ | Supported |
| H2: BDU→DAC | 0.623 | 16.010 | $p < 0.001$ | Supported |
| H3: DAC→DQ | 0.394 | 4.601 | $p < 0.001$ | Supported |

Note: BDU, Big data analytics usage; DAC, Data analytics capabilities; DQ, decision-making quality.

and positively related to decision-making quality ($\beta = 0.223$, $p < 0.01$), thereby supporting H1. This finding could be attributable to the fact that big data utilization can help firms gain the confidence that they can improve firm decisions by enhancing data diagnosis and shifting from experiential decision making (Ghasemaghaei and Calic, 2019). Big data analytics usage enables firms to make full use of big data, such as production big data, processing big data, circulation big data, and sales big data, and tap potential value to provide insights for decision-making, thus enhancing decision-making quality.

Second, we found that big data analytics usage had a significant impact on data analytics capabilities. Big data analytics usage was significantly and positively related to data analytics capabilities ($\beta = 0.623$, $p < 0.001$), supporting H2. This indicates that big data analytics usage has an important role in driving the formation of data analytics capabilities. Big data analytics utilization enables firms to process and

sense the data and converts them into knowledge for employees (Wu et al., 2020). Furthermore, the use of sophisticated data analytics tools enables firms to obtain detailed information and in-depth knowledge about their partners, competitors, and customers (Chatterjee et al., 2020). Based on the resource-based view, the use of big data analytics tools in firms can be regarded as a valuable resource (knowledge asset) that can be appropriately exploited to develop and improve data analytics capabilities in the firms (P. Mikalef et al., 2020). Therefore, the findings confirm the notion that big data analytics may be used to drive data analytics capabilities.

Third, we discovered that data analytics capabilities had significant impacts on decision-making quality. Big analytics capabilities were significantly and positively related to decision-making quality ($\beta = 0.394, p < 0.001$), thereby supporting H3. This finding is in line with the commonly held beliefs about the effects of big data, namely that data analytics competency improves the correctness and accuracy of decisions (Ghasemaghaei et al., 2018; Ghasemaghaei, 2019). This result indicates that data analytics capabilities can help firms make and implement appropriate decisions quickly, seize business opportunities in a dynamic market environment, and find ways to transform and innovate. Furthermore, this study found that the use of big data analytics affected decision-making quality by forming data analytics capabilities, revealing the important mediating effect of data analytics capabilities. This indicates that the use of big data analytics matches its own resources and capabilities (data analytics capabilities), which will bring good outcomes to firms.

6.1. Theoretical contributions

First, from a theoretical perspective, examining the impact of big data analytics usage on decision-making quality has been a critical research topic in extant IS research (Corte Real et al., 2020). Yet, there is no consensus on whether big data analytics usage improves or impedes the decision-making quality of organizations. Most prior research asserts that big data analytics usage has a positive effect on decision-making quality (Visinescu et al., 2017; Shamim et al., 2019). However, some have found the existence of a big data paradox that is, increased big data analytics usage in some firms is associated with no or reduced decision-making quality (Ghasemaghaei et al., 2018). Scholars argue that the use of big data analytics will lead to knowledge hiding, including evasive hiding and playing dumb, which negatively affects decision-making quality (Ghasemaghaei and Turel, 2021). In short, although most previous analyses find that the big data-decision relationship is generally positive across studies, they also show that big data analytics usage might reduce decision-making quality in some situations. As a result, there is still a limited understanding of big data analytics usage and how it relates to the quality of firm decisions. To address this gap, this study examined the impact of big data analytics usage on the decision-making quality of organizations. The results indicate that big data analytics usage not only had a positive effect on decision-making quality, but also positively affected data analytics capabilities and in turn improved decision-making quality. This finding enriches IS studies of big data analytics usage and decision-making quality, providing a novel lens for firms using big data analytics to improve decision-making quality.

Second, there is evidence indicating that using big data analytics to improve firms' decision-making quality is not always simple, and there may be an undiscovered mechanism that translates big data analytics usage into decision-making quality (Janssen et al., 2017; Suoniemi et al., 2020). However, its internal mechanism is still unclear. This study adds to the growing body of knowledge in the field of big data analytics by conceptualizing data analytics capabilities (technical and managerial skills) as responsible for firms' responsiveness in facing abrupt changes and market volatility. Specifically, both managerial skills and technical skills are game-changing, adding data analytical capabilities to firms. Firms can enhance their data analytics capabilities by improving the

managerial and technical skills of employees, thus allowing a firm to sustainably engage in enterprise-level sensing, seizing, and reconfiguring of internal and external processes. This view can explain one possible reason for the conflicting findings concerning the business value of big data analytics in firms (Ghasemaghaei, 2018; Awan et al., 2021). This study reveals the mechanism driving the influence of big data analytics usage on decision-making quality, and contributes to our understanding of how the presence of big data analytics usage can improve firms' decision-making quality through data analytical capabilities.

Third, this study supplements the dynamic capability theory by leveraging it to elaborate on how big data analytics usage affects data analytics capabilities and in turn decision-making quality. Although research has examined the link between data analytics capabilities and decision-making quality (Ghasemaghaei, 2018; Awan et al., 2021), there is still a limited understanding of big data analytics usage and how they relate to data analytics capabilities. Our results indicate that big data analytics usage had a positive impact on data analytics capabilities, indicating that big data analytics usage (i.e., a low-order organizational capability) can promote data analytics capabilities (i.e., a high-order organizational capability). This finding enriches management studies of big data analytics usage and data analytics capabilities by providing a better understanding of how big data can enable data analytics capabilities via enhancing big data analytics usage.

6.2. Managerial contributions

From a practical perspective, our findings indicate that to better achieve decision effectiveness and decision efficiency, firms should make full use of big data analytic tools to accelerate the transformation from traditional to data-driven decision making (Lioutas and Chatzatsari, 2020). Firms can employ big data analytic tools to integrate databases, detect market changes, identify competitive opportunities, reorganize organizational resources, and finally make high-quality decisions (Pappas et al., 2018; Kamblea et al., 2020). This has been well verified in practice, and there are many successful examples to draw on. For instance, Pagoda, a leading fruit firm in China, signed the "Pagoda big data platform project" in 2018 to build a retail data center. Pagoda then strengthened its promotion of the advantages of using big data analytics to enhance the awareness of employees, provide opportunities for employees to learn how to utilize big data analytics, and develop and improve managerial skills and technical capabilities in big data analytics. During the epidemic, Pagoda staff performed demand forecasting, quality management, inventory management, development layout, and public opinion monitoring using a variety of data analysis techniques. Sales increased by 20% year over year as a result of these meticulous decisions. Thus, firms should develop strategic plans for big data analytics usage, provide technical knowledge training, and encourage employees to use big data analytics tools for daily work, thereby promoting a digital corporate culture (Acharya et al., 2018).

Second, as data analytics capabilities have positive impacts on decision-making quality, the development of data analytics capabilities cannot be overlooked. Data analytics capabilities can help firms make informed decisions, identify opportunities and threats, and fine-tune operations (Horita et al., 2017). As the largest agricultural firm in Guangdong province (China), Wens Food Group has invested heavily in the development of data analytics capabilities, such as building a big data warehouse and training employees in business and data analysis technology. The data analytics capabilities help Wens understand and grasp the changes in market demand, market capacity, and market competition, maximizing its profits. To improve data analytics capabilities, firms should strengthen the construction of their IT infrastructure by improving platform systems, introducing advanced analysis tools, and adopting large-capacity data storage tools to guarantee big data analytics usage (Pappas et al., 2018). Similarly, firms should acquire the technical talents needed for big data analytics usage by recruiting cutting-edge IT talents and improving training for existing

technicians, thus providing a talent guarantee for the successful use of big data and response to technical crises (P. Mikalef et al., 2020).

6.3. Research limitations and future research

This study has several inevitable limitations. The variance interpretation rate of decision-making quality was 32.5%, implying that other factors may affect decision-making quality, an issue that will require further investigation in the future. Although this study was based on a static model and cross-sectional data, using big data analytics to improve firms' decision-making quality is a long-term goal. Thus, it is necessary to conduct longitudinal empirical analysis in future research. The findings suggest that future studies should consider not only the influence of big data analytics usage on decision-making quality but also possible factors that may moderate such impact. Future research could

build on our findings by examining the potential role of data analytics capabilities in mediating the influence of big data analytics use on other firm outcomes (e.g., firm resilience and firm agility).

7. Author statement

All authors have equally contributed to the paper.

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Appendix

Measurement items of the variables.

| Variables | Item | Item description | VIF | Loading | Weight | Source |
|-----------------------------|------|---|-------|----------|----------|----------------------------|
| Big data analytics usage | BDU1 | Our enterprise often uses big data analytics tools. | 1.540 | 0.756*** | 0.321** | Yunis et al. (2018) |
| | BDU2 | I consider myself a frequent user of my enterprise's big data analytics tools. | 1.221 | 0.758*** | 0.461*** | |
| | BDU3 | Our enterprise integrates big data analytics tools into work processes. | 1.445 | 0.746*** | 0.331** | |
| | BDU4 | Our enterprise uses big data analytics tools and data analytics capabilities. | 1.238 | 0.605*** | 0.266*** | |
| Data analytics capabilities | DAC1 | Our data analytics users possess a high degree of data analytics expertise. | 1.571 | 0.825*** | 0.401*** | Ghasemaghaei (2019) |
| | DAC2 | Our data analytics users are knowledgeable when it comes to utilizing such tools. | 1.627 | 0.818*** | 0.368*** | |
| | DAC3 | Our data analytics users are skilled at using data analytics tools. | 1.787 | 0.867*** | 0.425*** | |
| | DQ1 | In my enterprise, decision outcomes are often flawless. | 1.492 | 0.488*** | 0.213* | |
| Decision-making quality | DQ2 | In my enterprise, decision outcomes are often reliable. | 1.557 | 0.681*** | 0.251** | Ghasemaghaei et al. (2018) |
| | DQ3 | In my enterprise, decision outcomes are often precise. | 1.545 | 0.696*** | 0.286** | |
| | DQ4 | In my enterprise, decision outcomes are often error-free. | 1.625 | 0.280** | 0.311** | |
| | DQ5 | In my enterprise, decision outcomes are often correct. | 1.614 | 0.624*** | 0.136* | |
| | DQ6 | In my enterprise, decision outcomes are often accurate. | 1.575 | 0.736*** | 0.437*** | |
| | DQ7 | In my enterprise, the time to arrive at decisions is fast. | 1.500 | 0.588*** | 0.148 | |
| | DQ8 | In my enterprise, the speed of arriving at decisions is high. | 1.407 | 0.523*** | 0.231* | |

Note: BDU, Big data analytics usage; DAC, Data analytics capabilities; DQ, decision-making quality. The range for measures is from 1 to 5 (1 = Very much disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Very much agree).

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