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IT-business alignment, big data analytics capability, and strategic decision-making: Moderating roles of event criticality and disruption of COVID-19

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ABSTRACT

Prior research has confirmed the importance of IT-business alignment (ITBA) and big data analytics capability (BDAC) in supporting firms' strategic decision-making under normal circumstances. However, the global outbreak of COVID-19 has significantly changed firms' strategic decision-making landscapes and raised questions regarding the effects of ITBA and BDAC on strategic decision-making as conditioned by COVID-19 characteristics. In this study, we contextualize two important event impact factors (i.e., event criticality and event disruption) in the context of COVID-19 and examine their contingent roles in the effects of ITBA and BDAC on strategic decision-making. Our analyses, based on two-round, multi-respondents matched survey data collected from 175 Chinese firms to elucidate the differential moderating roles of event criticality and disruption of COVID-19 in the impact of ITBA and BDAC on strategic decision speed and quality. The results indicate the event criticality of COVID-19 strengthens the effects of ITBA on decision speed and quality but weakens the influence of BDAC on decision quality. Meanwhile, the event disruption of COVID-19 weakens the influence of ITBA on decision speed and quality but strengthens the effect of BDAC on decision speed and quality. These findings have important theoretical and practical implications, which we discuss in the conclusion.

1. Introduction

The rapid spread of the COVID-19 pandemic is becoming a significant "black swan" event for businesses and economies [53]. As a global crisis, it has pushed firms to seek more reliable market information through the application of digital technologies [22]. Given this, many firms' top priorities have been the integration of digital technologies into existing business practices and the application of big data analytics (BDA) for strategic decision-making [20]. For instance, more than half of the firms participating in a recent McKinsey survey indicated the pandemic caused them to refocus all of their business strategies around digital technologies. Meanwhile, it has been reported that about 84% of industry-leading firms in the United States and worldwide are investing in BDA [55]. Although crisis decision-making has attracted scholars' attention [46], this shift to digital technologies "is fast-paced, dramatic and not well understood" [22,p. 2].

The literature indicates that decision-making during a crisis requires the acquisition of rich information as well as its effective use [45]. In emergency responses, both digital technologies and human agents become deeply entangled as coevolving forces [22]. In reality, firms integrate digital technologies into their business to access and collect information from various business processes, which in turn can be leveraged to support data-driven decision-making [32,52]. In the literature, IT-business alignment (ITBA) reflects the extent to which IT applications are appropriately integrated with existing business processes and routines [50]. It has been identified as an important way for firms to access and collect information [57]. Scholars have suggested that ITBA enables firms to acquire rich information about business opportunities and threats and this information can support strategic decision-making [58]. Yet, as businesses become more data-driven via the high-volume, high-velocity, and/or high-variety information assets of big data [1], acquiring information through IT is not enough for adequate

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decision-making [32]. Firms thus increasingly require qualified BDA staff to help process big data and create useful market insights [20]. Accordingly, big data analytics capability (BDAC), which reflects a firm's human skills in integrating and deploying big data-specific resources [23], is becoming increasingly important for decision-making. In other words, BDAC equips firms with qualified BDA staff to process big data and generate insights for decision-making [21]. However, neither ITBA nor BDAC is alone sufficient for improving decision-making. In particular, sole focus on ITBA without BDA human skills will not yield good decisions. Alternatively, having BDA staff without ITBA does not enable firms to make decisions efficiently [52]. In this view, effective business decisions rely on ITBA and BDAC capabilities simultaneously.

Furthermore, the COVID-19 pandemic has triggered unparalleled shock to businesses with consequences that are difficult to predict [22]. It is been suggested that "there is a need for better understanding of analytics techniques to help organizational leaders and managers better identify looming challenges and make sense of their environments and make data-driven quality decisions" [53,p. 8]. According to this perspective, the global outbreak of COVID-19 has created a new context wherein the roles of ITBA and BDAC in strategic decision-making require reexamination. For most firms, responding to the unexpected business disruptions caused by COVID-19 has become a top priority [42]. It has resulted in both opportunities and challenges to leverage ITBA and BDAC for the strategic goal of creating value and developing competitive advantages. On one hand, decision-makers should actively monitor potentially disruptive events because "discrepant events, or surprises, trigger a need for explanation" [35, p. 241]. In this way, COVID-19 can act as a trigger for active applications of ITBA and BDAC in strategic decision-making. On the other hand, firms' strategic decision-making landscapes have shifted due to unexpected economic and market changes caused by the event [5]. These shifts and disruptions pose new challenges for firms making strategic decisions based on ITBA and BDAC. However, our current understandings are still limited regarding the effects of ITBA and BDAC on strategic decision-making amid the COVD-19 pandemic, thereby prompting a need for more research. Accordingly, we attempt to arrive at recommendations for effective business decisions in the context of COVID-19 pandemic by answering our research question: How does the event impact of COVID-19 amplify or mitigate the impact of ITBA and BDAC on firm business decision speed and quality?

The current study addresses this research gap by applying the dynamic capabilities view (DCV) to analyze the direct effects of ITBA and BDAC on strategic decision-making (speed and quality). In addition, we explore the potential moderating effects of the COVID-19 event impact on the direct effects. As it involves complicated information processing that can be affected by the event impact of COVID-19, the current study deepens extant understandings of the roles ITBA and BDAC play in strategic decision-making during global outbreaks [42]. As such, we contextualize the concepts of event criticality and event disruption [42] in the context of COVID-19 and examine their contingent roles according to the effects of ITBA and BDAC on strategic decision-making.

To test our conceptual model, we applied two rounds of multi-respondent matched survey data from 175 Chinese firms. The empirical results reveal the confluence of ITBA, BDAC, and the event impact of COVID-19 on strategic decision speed and quality. Specifically, we elucidate the differential influences of ITBA and BDAC on strategic decision-making (i.e., speed and quality) that are contingent on the event impact of COVID-19 (i.e., criticality and disruption).

2. Theoretical background and literature review

Crisis decision-making literature has explained that strategic decision-making can potentially avert negative organizational outcomes during crises [6]. Although the COVID-19 pandemic has caused continuous global crises, its impact on business—especially strategic decision-making—remains unclear [66]. Such crises require firms to make rapid and quality strategic decisions under considerable pressures and time constraints [43]. However, doing so is difficult because it requires firms to obtain real-time and rich information [52]. Emerging scholarship in crisis decision-making literature argues that digital technologies provide novel opportunities for strategic decision-making in times of crisis [1]. These researchers posit that the application of digital technologies empowers firms to produce and process large amounts of data for the generation of valuable insights for strategic decision-making in response to crises [16]. For example, Gkeredakis, Lifshitz-Assaf and Barrett [22] proposed the opportunity, disruption, and exposure perspectives of crisis to indicate the significance of digital technologies (e.g., BDA) in strategic decision-making during the COVID-19 pandemic. Despite conceptual work on the role of digital technologies in crisis decision-making and the empirical work on the separate effect of ITBA and BDAC in decision-making, few empirical studies have explored the influence of ITBA and BDAC in influencing strategic decision-making during COVID-19.

Given its focus on how firms sustain competitive advantages in highly dynamic and uncertain environments [60], the DCV has been applied to explain strategic decision-making [51]. According to the DCV, dynamic capabilities emphasize the integration, formation, and reconfiguration of internal and external competencies to respond to changing environments [60,62]. These capabilities are often embedded in organizational routines that involve repeated responses [44]. As developing dynamic capabilities often demands internal routines rather than acquisitions from the market, they are viewed as the most unique and difficult-to-imitate assets for securing competitive advantages [30,59]. In fast-paced, volatile market circumstances, dynamic capabilities enable firms to identify unexpected market and technological trends [65] as well as sense opportunities and threats before they become apparent [61]. The existing literature has thus recognized the importance of dynamic capabilities in strategic decision-making for effective competition in dynamic and uncertain environments [14], such as that of the COVID-19 pandemic.

In this study, we draw on the DCV to propose ITBA and BDAC as critical dynamic capabilities that enable firms to achieve a competitive advantage in decision-making. ITBA reflects the extent of the fit between IT applications and organizational business activities [50], and "heightens managers' awareness and use of information systems, and it enables a firm to better use IS to help realize its goals and objectives or obtain a competitive advantage" [27, p. 88]. Specifically, ITBA involves information, communication, and connectivity technologies that facilitate existing key business processes in terms of supplier relations (inbound logistics), production and operations, product and service enhancement, sales and marketing support, and customer relations (outbound logistics) [23]. Penetrating IT in business processes empowers firms to access and collect information regardless of the size, structure, and growth speed of the data [32]. For example, ITBA enables firms to acquire and collect internal and external information in terms of daily internal operations, supplier transactions, customer transactions, web clickstreams, e-commerce, and social media communities. Accordingly, ITBA can offer firms important capabilities for acquiring massive amounts of information from various organizational business processes that, in turn, can be leveraged to support data-driven decision-making [32,52].

BDAC, on the other hand, reflects a firm's BDA staff's skills in integrating and deploying big data-specific resources [23]. Working with big data often demands new types of technical and managerial skills, such as statistical analysis, machine learning, programming, and coordinating big data activities [23]. Such skills empower firms to not only use analytical techniques to extract insights but also understand how and where to apply these insights [24]. Therefore, BDAC involves the technical skills necessary to deploy analytical techniques in the extraction of insights from big data [15], as well as a BDA staff's understanding of customers' and businesses' current and future needs [24]. As business becomes more data-driven and big data becomes a key information asset

[23], the technical and managerial skills of BDA staff have been recognized as core strategic capital in the "war for talent" era [9]. These skills assist firms in utilizing big data-specific resources and in transforming these resources into dynamic capabilities [23]. As such, BDAC extracts insights in various business areas (e.g., marketing, R&D, accounting, and customer relationships) while simultaneously facilitating firms' comprehension of how and where to apply these extracted insights [56]. Researchers have thus conceptualized BDAC as a critical dynamic capability through which firms can innovate and create temporary competitive advantages [24]. Following the existing literature, both ITBA and BDAC can be seen as dynamic capabilities for identifying opportunities and threats that support optimal decision-making.

What's more, the global outbreak of COVID-19 represents a major crisis event that has disrupted businesses in many ways and required firms to quickly adjust their business practices [48]. Crisis events are external to entities (e.g., firms or managers) and involve various characteristics that shape cognitive feelings and subsequent attitudinal and decision-making outcomes [42]. In this study, we contextualize event criticality and event disruption in the context of COVID-19 and incorporate them into the relationship between dynamic capabilities (i.e., ITBA and BDAC) and strategic decision-making (i.e., speed and quality). *Event criticality* reflects "the degree to which an event is important, essential, or a priority" to an entity [41]. Critical events tend to command attention and resource allocation [19], and are often a central focus until resolved [42]. Following this notion, we define the event criticality of COVID-19 as *the extent to which a firm believes responding to the COVID-19 pandemic is a priority*. *Event disruption* reflects the perceived threats experienced with major disruptions [41] and the degree of change in usual activities [28]. Disruptive events can block or transform ongoing routines and require entities (e.g., companies) to adjust and adapt [68]. As "things do not continue the way they did prior to the event," firms cannot rely on their conventional modes of analysis and response and are thus forced to change [42, p. 251]. Given this, we define the event disruption of COVID-19 as *the extent to which the COVID-19 pandemic undermines a firm's ability to conduct business as it did before the pandemic*.

3. Hypotheses development

Event criticality and event disruption offer valuable information regarding different aspects of event impact [42]. As mentioned above, ITBA and BDAC represent two different types of dynamic capabilities that affect strategic decision-making. Given their conceptual differences, we expect their effects on strategic decision-making (i.e., speed and quality) will be moderated differently by event criticality and disruption in the context of COVID-19 as Fig. 1 shows.

3.1. The moderating effect of event criticality of COVID-19

Event criticality of COVID-19 is expected to strengthen the positive effects of ITBA and BDAC on decision speed and quality. In particular, event criticality points to the necessity of prioritizing response to an event [19]. When managers perceive responding to the threat of COVID-19 to be critical, they tend to pay more attention to leveraging dynamic capabilities in support of strategic decision-making.

We expect ITBA will play a more salient role in supporting strategic decision-making when the event criticality of COVID-19 is high. ITBA represents the integration of IT with the firm's businesses and can help bridge the traditional gaps between business and IT functions [57] to enhance organizational knowledge for strategic decisions that are both efficient and effective. This view suggests that, when managers perceive the high event criticality of COVID-19, they will more actively rely on ITBA to improve strategic decision-making. This is because such an alignment enables firms to conduct effective internal department connections and external linkages with customers and suppliers [38], which is especially important for responding to the threats of COVID-19. For example, the event criticality of COVID-19 would push firms to use ITBA to quickly obtain high-quality information about the real-time status of intra- and inter-department business processes because firms embed IT applications into production and operations [57]. By acquiring real-time information, firms can continuously update managers on business situations during COVID-19 [50], which is key for firms in making quick, high-quality strategic decisions. Further, the event criticality of COVID-19 would motive the firm to use ITBA to develop an integrated information flow with channel partners through an integrated technological platform [34]. This integrated information flow enables firms to achieve reliable, real-time information across the supply chain. Such real-time inter-organizational information access in turn allows firms to make quick, high-quality decisions [45]. Accordingly, we propose the following hypothesis.

H1. . The event criticality of COVID-19 positively moderates the relationship of ITBA with (a) decision speed and (b) decision quality, such that this relationship is more significant when the event criticality of COVID-19 is high than when it is low.

In a similar vein, the event criticality of COVID-19 is expected to strengthen the positive effect of BDAC on decision speed and quality. BDAC holds that a firm's BDA staff has the ability to utilize the appropriate tools, techniques, and processes to analyze big data [54]. Qualified BDA staff further help obtain comprehensive business understandings and improve forecast accuracy [15] for enhancing decision-making. Under this condition, managers who perceive the high event criticality of COVID-19 would be more likely to use BDAC to improve strategic decision-making. In particular, if BDA staff have training in programming, database skills, and system analysis and

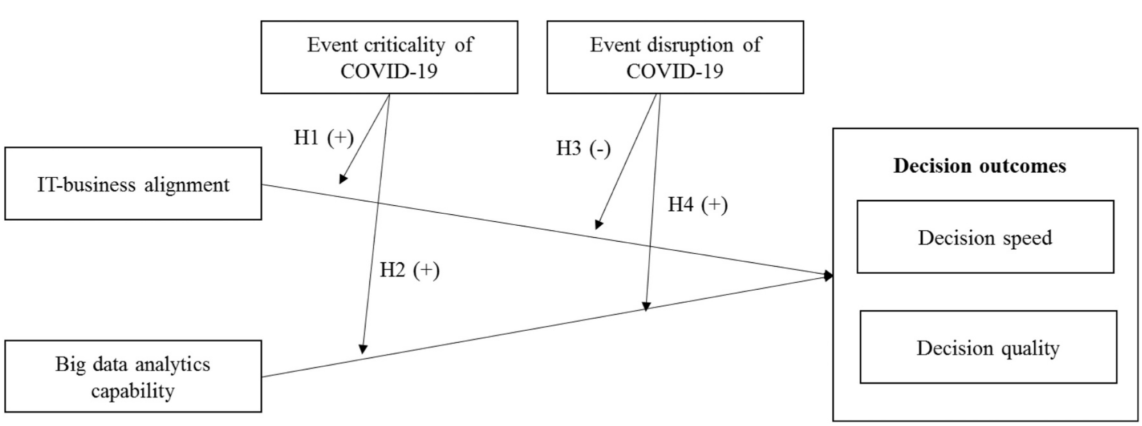

Fig. 1. Research model.

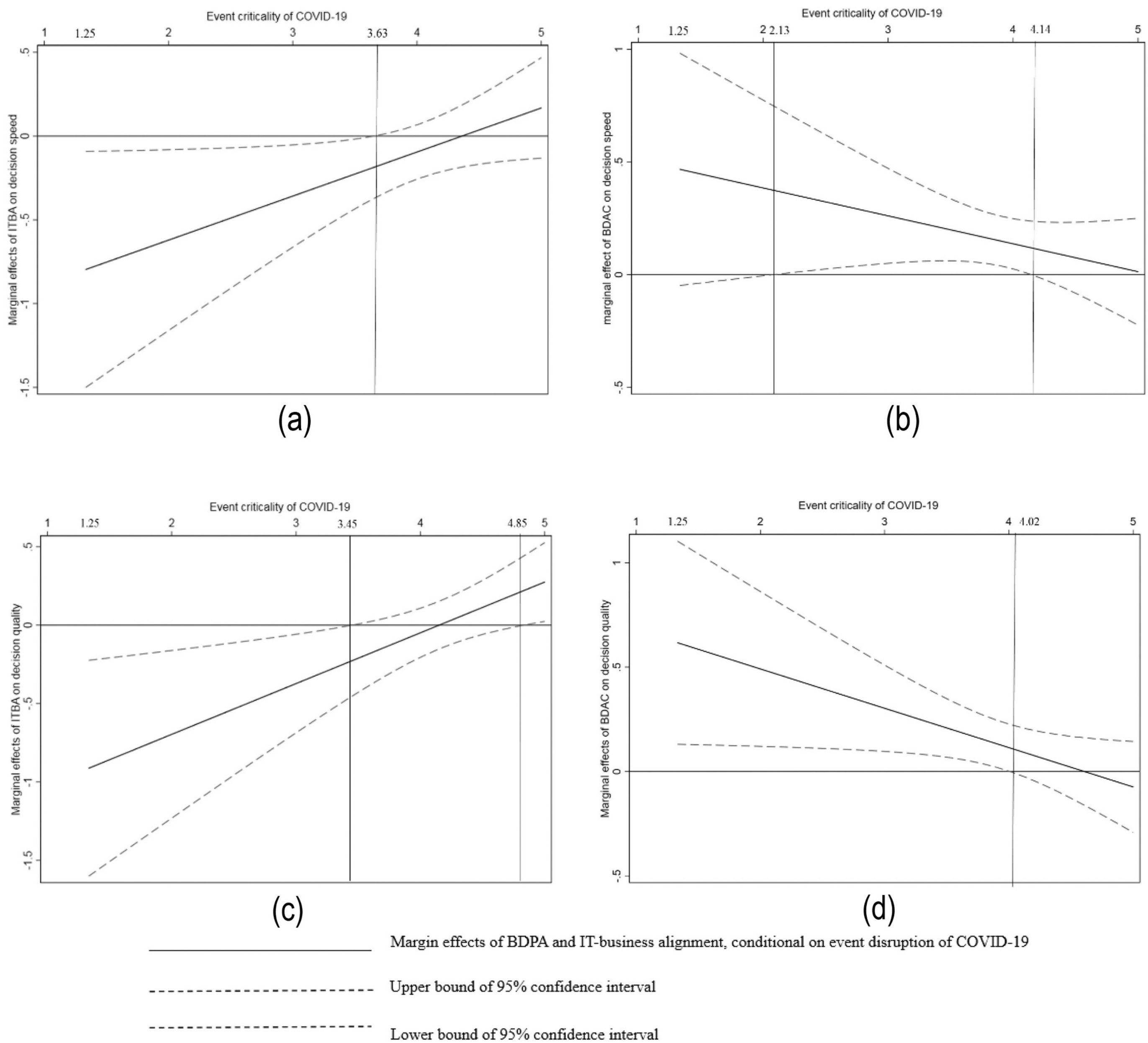

Fig. 2. The moderating role of even criticality of COVID-19.

design, they can play a more positive role in efficiently processing rich, real-time data and information [64] when firms perceive the high event criticality of COVID-19. Moreover, the event criticality of COVID-19 would motivate firms to rely on BDA staff to actively break organizational silos and enable the firm to transfer and recombine big data activities across functional units [23]. This enables other functional managers, suppliers, and customers to achieve BDA support [21], meaning they can quickly exchange and process decision-related data and make high-quality decisions efficiently. Given this, we propose the following hypothesis.

H2. . The event criticality of COVID-19 positively moderates the relationship between BDAC and (a) decision speed and (b) decision quality, such that this relationship is more significant when event criticality of COVID-19 is high than when it is low.

3.2. *The moderating effect of event disruption of COVID-19*

Unlike event criticality, the event disruption of COVID-19 is expected to weaken the effect of ITBA but strengthen the positive effect of BDAC on decision speed and quality. Specifically, the effect of ITBA on decision speed and quality will likely be negatively moderated by the event disruption of COVID-19. As mentioned above, ITBA represents an IT-related capability based on established business routines [58] that are likely to be disrupted by the COVID-19 pandemic. In particular, ITBA enables firms to acquire high-quality information within and across the firm because ITBA helps formalize and standardize intra- and inter-organizational processes with IT applications [70]. ITBA, for example, allows firms to acquire and share information across departments based on the standardized processes enabled by enterprise systems [34]. Meanwhile, ITBA supports firms in acquiring information from suppliers and customers with the standardized processes enabled by supply chain management systems and customer relationship management systems [57]. Yet, the higher the disruption, the less likely firms will be able to rely on established, standardized routines to conduct business [42]. In particular, emerging evidence shows COVID-19 has greatly disrupted business operations and work routines [66]. Therefore, the integration of a firm's IT with its established business routines is no longer an advantage and instead results in rigidity that can prevent top managers from making effective decisions efficiently. Accordingly, ITBA may play a limited role in improving decision-making when the event disruption of COVID-19 is high. We thus propose the following hypothesis.

H3. . The event disruption of COVID-19 negatively moderates the relationship of ITBA with (a) decision speed and (b) decision quality, such that the relationship is positive when event disruption of COVID-19 is low and negative when it is high.

However, BDAC is expected to play a more salient role in supporting strategic decision-making for firms experiencing a high level of event disruption of COVID-19. First, a BDA staff's technical skills in programming and databases help their firm consolidate and visualize data flow within and across the firm [20]. This consolidation enables decision-makers to quickly build a clear, insightful understanding of information concerning products, orders, and inventory within and across the firm when managers perceived the high event disruption of COVID-19. Second, a BDA staff's managerial skills help their firm span organizational boundaries and make big data activities readily available within and across the firm [11]. Managers' perception of high event disruption of COVID-19, empowers firms' departments and business partners to achieve more BDA support, which enables them to make efficient, high-quality decisions.

Finally, BDAC prompts the rapid application of new BDA applications [36]. Such skills allow firms to continuously receive more advanced BDA support for strategic decision-making when managers perceive high event disruption of COVID-19, thereby ensuring the decisions' speed and quality. In sum, as COVID-19 disrupts firms' business routines, BDAC equips firms with the resources they need to efficiently process data for scanning, searching, and exploring current and future business opportunities [23]. By doing so, firms can adapt to event disruptions with quick, high-quality decisions. BDAC thus plays a more salient role in promoting strategic decision-making in terms of both speed and quality when the event criticality of COVID-19 is perceived to be high. Accordingly, we propose the following hypothesis.

H4. . The event disruption of COVID-19 positively moderates the relationship of BDAC with (a) decision speed and (b) decision quality, such that the relationship is more significant when the event disruption of COVID-19 is high than when it is low.

4. Research method

We conducted a multi-respondent two-round survey and employed hierarchical regression to test our hypotheses. Data was collected from firms in the Yangtze River Delta area, one of the most active economies in China. China was an ideal setting for this research for several reasons. First, the Chinese government has encouraged firms—especially small and medium ones—to employ advanced digital technologies, such as enterprise systems and BDA, to achieve competitive advantages.[1] For example, some local governments have collaborated with IT organizations to offer low-price public cloud computing services for local firms to analyze big data.[2] Second, Chinese firms now face fierce competition from domestic and international rivals, which has forced managers to frequently engage in strategic decision-making activities. Third, China was the first place hit by COVID-19, which resulted in the prohibition of social events, lockdowns, and shutdowns across the country. The unexpected spread of COVID-19 has plunged Chinese firms into a state of emergency that forces firms to fight for survival. As a result, Chinese firms are actively applying ITBA and BDAC in strategic decision-making to deal with this crisis.

4.1. Sample and data collection

Our online survey was conducted in collaboration with a local administrative agency responsible for evaluating industrial development and informationalization. The agency aims to understand the status of firms' business operations and provide references for government policymaking. The agency provided us contact information and descriptive information (e.g., firm size, firm age, and industry) for a sample of 1700 firms. With strong governmental support, these firms have actively employed advanced digital technologies in their business processes. Moreover, the sample pool varied in terms of firm age and size and covered firms from a broad range of industries, such as consumer products, petroleum and chemical, machinery, and electronics. Overall, the sample allowed us to increase the external generalizability of this research.

An online survey was conducted in two rounds and targeted three senior managers of each firm (i.e, executive manager, marketing manager, and CEO). The survey's first round was conducted from April to May 2018 to examine firms' ITBA and BDAC. Executive and marketing managers from each firm were invited to voluntarily engage in the survey. Marketing managers filled out the questionnaire related to ITBA and two control variables (i.e., market turbulence and technological turbulence). As they were in charge of daily operations, executive managers were invited to finish the questionnaire by examining BDAC. After merging these surveys, a sample of 705 firms was obtained, with an effective response rate of 41.47%.

The second round of the survey was conducted from August to October 2020. During this period, China had the spread of COVID-19 under control, and Chinese firms had resumed work and production according to local health mandates. Given this, we were able to examine firms' perception of the event impact of COVID-19 and their strategic decision-making in response. Firms that engaged in the first round of the survey were contacted and invited to participate in a follow-up survey. As we focused on firms' perceptions of the event impact of COVID-19 and their corresponding strategic decisions, firm CEOs were invited to answer questions related to the speed and quality of top management team's decision-making. The study's purpose was explained in the cover letter of the online questionnaire and follow-up notifications were sent to encourage CEOs to fill it out. Of the 705 firms that engaged in the first round of the survey, 175 CEOs participated in in the second round of the survey. Hence, the final sample consisted of 175 firms, with a response rate of 24.82%. Table 1 provides the demographic information of the 175 sample firms and the 525 (175×3) respondents.

Two methods were used to assess potential non-response bias. First, we examined the difference between the response group ($N = 175$) and the non-response group of the sample pool ($N = 1525$) for firm age, firm size, and industry type. The results showed insignificant differences between the two groups in terms of firm age (t-test: $p = 0.13$), firm size (t-test: $p = 0.50$), and industry type ($\chi^2(4) = 6.37$, $p = 0.417$). Second, following Armstrong and Overton [2], we compared the early 25% with the late 25% of the response group. The results revealed insignificant differences between the two groups in terms of BDAC (t-test: $p = 0.098$), ITBA (t-test: $p = 0.091$), decision speed (t-test: $p = 0.855$), decision quality (t-test: $p = 0.770$), event disruption of COVID-19 (t-test: $p = 0.053$), event criticality of COVID-19 (t-test: $p = 0.720$), technological turbulence (t-test: $p = 0.828$), and market turbulence (t-test: $p = 0.236$).

4.2. Measures

Our survey was developed based on widely used measures in existing studies. As the research was conducted in China, a questionnaire was developed in Chinese. We then employed the back-translation method to ensure the equivalence of the questionnaire between the English and Chinese versions. In addition, four academic experts examined the questionnaire and provided feedback on the flow of questions and the appropriateness of measures. The questionnaire was subsequently

[1] http://www.gov.cn/zhengce/content/2016-05/20/content_5075099.htm
[2] http://ah.anhuinews.com/system/2017/01/11/007543391.shtml

Table 1
Profile of the sample firms and respondents.

Industry type	Obs (%)	Employee number	Obs (%)
Firm characteristics			
Consumer products	28(16.00%)	≤100	71(40.57%)
Petroleum and chemical	40 (22.86%)	101–200	56(32.00%)
Machinery	51 (29.14%)	201–300	17(9.71%)
Electronics	38 (21.71%)	301–400	12(6.86%)
Others	18 (10.29%)	>400	19(10.86%)
Firm age (years)			
≤10	56(32.00%)		
11–15	61(34.86%)		
16–20	43(24.57%)		
>20	15(8.57%)		
Respondents characteristics			
	Executive manager (1st round) Obs (%)	Marketing manager (1st round) Obs (%)	CEO (2nd round) Obs (%)
Education level			
High school and below	21 (12.00%)	32 (18.29%)	12 (6.86%)
College and bachelor	144 (82.29%)	128 (73.14%)	129 (73.71%)
Master	10 (5.71%)	15 (8.57%)	34 (19.43%)
Age (years)			
≤30	15 (8.57%)	7 (4.00%)	3 (1.71%)
31–40	63 (36.00%)	76 (43.43%)	17 (9.71%)
41–50	60 (34.29%)	75 (42.86%)	65 (37.14%)
>50	37 (21.14%)	17 (9.71%)	90 (51.43%)
Gender			
Male	122 (69.71%)	154 (88.00%)	170 (97.14%)
Female	53 (30.29%)	21 (12.00%)	5 (2.86%)

revised and a pilot study was conducted with 30 MBA students. Minor modifications were made to incorporate their advice. These processes were then applied to the second round of the survey. The Appendix presents the measurement items.

ITBA was measured with a five-item scale adapted from Tallon and Pinsonneault [58]. The scales reflected the degree of IT utilization in supporting the firm's business processes, such as customer relationship management, product/service development, and manufacturing operations. To assess *BDAC*, six items were adapted from Gupta, George and Management [23]; and Gupta, Drave, Dwivedi, Baabdullah and Ismagilova [24]. These items captured the degree to which big data staff have BDAC-specific technical and managerial skills. *Event criticality of COVID-19* was measured with a three-item scale adapted from Morgeson and Derue [41]. The scales captured the extent to which the COVID-19 event was important, essential, or a priority to the firm. *Event disruption of COVID-19* was measured using a four-item scale adapted from Morgeson and Frederick [40]. The scales assessed the impact of COVID-19 on a firm's business ability, ways of doing business and work, and ways of responding to the crisis.

As the assessment of decision speed can vary in different industry contexts, existing literature suggests that relative measures should be incorporated to supplement the limitation of purely absolute measures [12]. Hence, we followed Clark and Maggitti [12] and measure the absolute speed of decision, speed relative to rivals, and speed relative to the change rates in the competitive environment. Specifically, *decision speed* was measured with four items adapted from Clark and Maggitti [13] to evaluate the speed of decision-making relative to rivals. *Decision quality* was measured with a three-item scale adapted from Olson, Parayitam, and Bao [45]. These items reflected the overall effects of a firm's decision relative to rivals.

Five variables (i.e., *firm size*, *firm age*, *market turbulence*, *technological turbulence*, and *industry type*) were controlled that were likely to influence a firm's strategic decision-making. *Firm size* was measured by the logarithm of employee numbers. *Firm age* was measured by the logarithm of operating years. With other industries as the baseline, we also controlled industry type with four dummy variables: consumer products, petroleum and chemical, machinery, electronics, and equipment. Firm size, firm age, and industry type were calculated by the objective data. *Market turbulence* referred to the speed and degree of change in customer segments and preferences, while *technological turbulence* referred to the degree of change in production and process technologies [67]. Both market and technological turbulence reflected the firm's operating environment, which can affect decision-making [49]. Market turbulence and technological turbulence were measured by four items adapted from Wilden and Gudergan [67].

5. Analysis and results

We first tested the validity and reliability of the measures and common method bias. A hierarchical regression method was then used to analyze the moderating role of event criticality and disruption of COVID-19.

5.1. Measure validation

Construct reliability and validity were analyzed prior to regression analyses. The analysis showed acceptable reliability and validity of our measures. As shown in Table 2, the values of Cronbach's α and composite reliability (CR) were greater than 0.70, indicating good reliability. In addition, the factor loading of all items was above 0.60 (see Appendix) and the values of average variance extracted (AVE) were higher than 0.50, confirming good convergent validity of the measures [26]. Furthermore, the square root of the AVE of each construct was greater than the values of the correlation coefficient between the constructs [17], indicating good discriminant validity. In considering the threat of multicollinearity, a variance inflation factor (VIF) test was conducted. The VIF variable values ranged from 1.05 to 1.93, which was well below the recommended value of 10 [37]. This finding revealed multicollinearity was not a serious issue in our study.

Both procedural remedies and statistic tests were used to address potential common method bias. Three procedural steps in research design were followed to mitigate common method bias [47]. First, we adapted previously validated scales and carefully constructed items to keep the questions simple, specific, and concise. Second, we separated the measurement items of conceptual adjacent constructs on different pages. Third, the independent and dependent variables were answered by three informants in each firm and were conducted in two rounds.

For statistic tests, Harman's one-factor test was conducted to examine the survey procedure's effectiveness in alleviating potential common method bias. The result showed the first factor accounted for 16.00% of the variance, which was lower than the rule-of-thumb level (i.e., 50%) [47]. Moreover, followed Lindell and Whitney [33], a method variance (MV) marker variable (i.e., charitable engagement) was used to test common method bias. Charitable engagement is a single-item variable (i.e., "Our company integrates charitable contributions into its business activities") adopted from Homburg, Stierl and Bornemann [29]. We chose the second smallest positive correlation (r = 0.09) between the MV marker and other variables to adjust correlations and calculated t-values of the adjusted correlations. The significance of significant correlations remained largely unchanged after adjustment, indicating common method bias was not a serious problem. Moreover, the significance of the moderation effects suggested common method bias may not have inflated the results because it was difficult for respondents to theorize moderation effects [31]. As seven of the eight moderation effects were supported, common method bias was unlikely to be a significant concern. Common method bias was therefore not a serious problem in our study.

Table 2
Correlation matrix, descriptive statistics, reliability, and validity.

Variables	1	2	3	4	5	6	7	8	9	10	11
1. Decision speed	**0.90**	0.62***	0.02	0.17***	0.09*	0.28 ***	0.02	0.07	0.08 *	0.09 *	0.02
2. Decision quality	0.65***	**0.92**	0.03	0.16***	−0.02	0.29***	0.00	0.11**	−0.03	0.03	0.11*
3. ITBA	0.12	0.12	**0.91**	0.46***	−0.15***	0.07	0.07	0.05	0.37***	0.28***	0.28***
4. BDAC	0.25***	0.24***	0.51*	**0.89**	−0.05	0.09*	−0.07	−0.05	0.22***	0.24***	0.26***
5. Event disruption of COVID-19	0.18**	0.08	−0.04	0.04	**0.80**	0.15***	−0.24***	−0.29***	−0.01	0.00	−0.14***
6. Event criticality of COVID-19	0.35***	0.35***	0.16*	0.17**	0.23*	**0.86**	−0.04	0.07	−0.02	−0.02	0.07
7. Firm age	0.11	0.09	0.14*	0.03	−0.12	0.06	n.a.	0.09*	−0.07	0.02	−0.04
8. Firm size	0.15**	0.20***	0.14*	0.05	−0.17*	0.16*	0.18*	n.a.	−0.11**	−0.22***	0.00
9. Market turbulence	0.17**	0.07	0.43***	0.29***	0.08	0.07	0.03	−0.01	**0.74**	0.54***	0.14***
10. Technological turbulence	0.17**	0.12	0.35***	0.31***	0.10	0.08	0.11	−0.11	0.58*	**0.80**	0.05
11. Marker (Charity activity)	0.11	0.20***	0.35***	0.33***	−0.03	0.16*	0.06	0.09	0.22*	0.14	n.a.
Mean	4.27	4.27	4.21	3.88	3.30	3.96	2.61	4.92	3.64	3.67	4.09
S.D.	0.53	0.50	0.52	0.65	0.73	0.64	0.38	0.84	0.57	0.64	0.70
Cronbach's α	0.92	0.92	0.95	0.94	0.79	0.82	n.a.	n.a.	0.71	0.80	n.a.
CR	0.95	0.95	0.96	0.96	0.87	0.89	n.a.	n.a.	0.82	0.88	n.a.
AVE	0.81	0.86	0.84	0.78	0.63	0.74	n.a.	n.a.	0.54	0.64	n.a.

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The diagonal elements are the square roots of AVEs. n.a. refers to not applicable. Adjusted correlations for the potential common method bias are above the diagonal.5.2. Common method bias.

5.2. Hypothesis testing

We employed hierarchical linear regression [25] to test our hypotheses. In the first step, we assessed the direct effect of ITBA and BDAC on decision outcomes. In the second step, we assessed the effects of ITBA and BDAC on decision outcomes, given the effects of event criticality and disruption of COVID-19. To test the moderating effect, the third step assessed the effects of two-way interactions between ITBA (BDAC) and event criticality and disruption of COVID-19. Table 3 presents the regression results. Specifically, Model 1a and 1b indicated ITBA was insignificantly related to decision speed ($\beta = -0.11$, $p > 0.10$) and decision quality ($\beta = -0.05$, $p > 0.10$), while BDAC was positively associated with decision speed ($\beta = 0.18$, $p < 0.01$) and decision quality ($\beta = 0.16$, $p < 0.05$).

H3a and H3b predicted negative moderating effects of event disruption of COVID-19 on the relationship between ITBA and (3a) decision speed and (3b) decision quality. The negative interaction term of ITBA and event disruption of COVID-19 ($\beta = -0.44$, $p < 0.001$) in Model 3a indicates that event disruption of COVID-19 negatively moderates the relationship between ITBA and decision speed. Thus, H3a was supported. Model 3b also shows that event disruption of COVID-19 negatively moderates the relationship between ITBA and decision quality ($\beta = -0.48$, $p < 0.001$), supporting H3b. Furthermore, Models 3a and 3b show the effects of the interactions between BDAC and event disruption of COVID-19 on decision speed ($\beta = 0.30$, $p < 0.01$) and decision quality ($\beta = 0.26$, $p < 0.01$) are significant and positive, thereby supporting H4a and 4b.

The marginal effects of ITBA and BDAC on decision speed and decision quality were further plotted for different levels of event disruption of COVID-19 in Fig. 3. ITBA has significantly positive effects over the range of event disruption of COVID-19 from 1.33 to 2.51 but has negative effects over the range of event disruption of COVID-19 from 3.44 to 5 on decision speed. Meanwhile, ITBA has significantly positive effects over the range of event disruption of COVID-19 from 1.33 to 2.78 but has negative effects over the range of event disruption of COVID-19 from 3.50 to 5.00 on decision quality. In contrast, BDAC has significantly negative effects over the range of event disruption of COVID-19 from 1.33 to 1.80 but has significantly positive effects over the range of event disruption of COVID-19 from 3.24 to 5 on decision speed. Meanwhile, BDAC has significantly negative effects over the range of event disruption of COVID-19 from 1.33 to 1.64 but has significantly positive effects over the range of event disruption of COVID-19 from 3.27 to 5.00 on decision quality.

Notes: The y-axis denotes the marginal effects of ITBA or BDAC on decision outcomes (i.e., decision speed or decision quality), while the x-axis represents the level of event disruption of COVID-19. The dotted lines show the confidence band (95% level, two-tailed). If the confidence interval is entirely on one side of the horizontal zero line, the marginal effect of ITBA or BDAC on decision outcomes is significant at the given value of event disruption of COVID-19.

5.3. Robustness check

To check the robustness of our results, the hypotheses were further examined with a seemingly unrelated regression (SUR) [69]. As decision speed and decision quality are theoretically and empirically correlated, their equation error terms are likely to be correlated, which may influence the efficiency of estimation. However, SUR allows for the simultaneous evaluation of equations and can account for contemporaneous cross-equation error correlations [3]. SUR also helps alleviate endogeneity concerns and facilitates consistent estimates of parameters because it accounts for possible correlations between error terms [3,4]. Furthermore, SUR has been suggested as an effective method for estimating regressions with interaction effects [4]. Hence, we employed SUR to examine the robustness of the results. As shown in Table 4, the SUR analysis provided largely consistent results with our main analysis, which provided further support for our findings.

6. Conclusion

The current study sheds light on the role of digital technologies in strategic decision-making in the context of the COVID-19 crisis. It builds on DCV and event management literature to propose that event criticality and event disruption of COVID-19 could leverage the role of ITBA and BDAC as a form of dynamic capability in affecting firms' decision quality and speed. Overall, our findings provide notable insights concerning the role of digital technologies on decision-making in global crisis management.

6.1. Findings and theoretical implications

How digital technologies affect strategic decision-making remains unclear due to a lack of research investigating how an exogenous shock (i.e., COVID-19) affects the realization of benefits from IT-based capabilities [22]. This study takes the initial attempt to enrich research on this subject through an empirical investigation of how ITBA and BDAC differentially affect strategic decision-making and how their influences are contingent upon the event impact of COVID-19.

First, although existing researchers have recognized the importance of digital technologies in strategic decision-making [8], few have

Table 3
Regression results.

	Decision speed			Decision quality		
	Model 1a	Model 2a	Model 3a	Model 1b	Model 2b	Model 3b
ITBA	−0.11	−0.12	0.31	−0.05	−0.07	0.22
	[0.09]	[0.08]	[0.53]	[0.09]	[0.08]	[0.57]
BDAC	0.18**	0.15*	−0.36	0.16*	0.14*	0.02
	[0.06]	[0.07]	[0.51]	[0.06]	[0.07]	[0.53]
Event criticality of COVID-19 (EC)		0.19**	−0.44		0.21***	−0.42
		[0.06]	[0.52]		[0.06]	[0.51]
Event disruption of COVID-19 (ED)		0.09+	0.78+		0.02	1.02*
		[0.05]	[0.43]		[0.05]	[0.40]
ITBA×EC			0.26*			0.32**
			[0.13]			[0.12]
BDAC×EC			−0.12			−0.19*
			[0.10]			[0.09]
ITBA×ED			−0.44***			−0.48***
			[0.11]			[0.10]
BDAC×ED			0.30**			0.26**
			[0.09]			[0.09]
Firm age	0.13	0.13	0.09	0.07	0.06	−0.00
	[0.10]	[0.09]	[0.10]	[0.10]	[0.09]	[0.09]
Firm size	0.08+	0.08+	0.09+	0.11*	0.09*	0.10*
	[0.05]	[0.05]	[0.05]	[0.04]	[0.04]	[0.04]
Market turbulence	0.07	0.07	−0.02	−0.05	−0.04	−0.13+
	[0.09]	[0.09]	[0.09]	[0.08]	[0.07]	[0.08]
Technological turbulence	0.09	0.07	0.12	0.09	0.08	0.13+
	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]
Consumer products	0.08	0.08	0.15	0.14	0.11	0.20
	[0.15]	[0.14]	[0.13]	[0.14]	[0.13]	[0.12]
Petroleum and chemical	−0.28+	−0.21	−0.19	−0.12	−0.05	−0.02
	[0.14]	[0.14]	[0.14]	[0.12]	[0.11]	[0.11]
Machinery	−0.21+	−0.17	−0.15	−0.13	−0.09	−0.07
	[0.12]	[0.12]	[0.13]	[0.12]	[0.11]	[0.11]
Electronics	−0.23	−0.20	−0.18	−0.16	−0.15	−0.14
	[0.14]	[0.13]	[0.13]	[0.12]	[0.10]	[0.11]
Constant	2.89***	2.03***	2.39	3.06***	2.42***	1.85
	[0.42]	[0.45]	[1.93]	[0.41]	[0.42]	[2.07]
N	175	175	175	175	175	175
R^2	0.171	0.247	0.308	0.143	0.214	0.290
F value	0.494	0.473	0.459	0.477	0.459	0.442

Notes: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in bracket.
Model 3a and 3b present the results of the moderating effects of event criticality and disruption of COVID-19. H1a and 1b suggested event criticality of COVID-19 positively moderates the effect of ITBA on decision speed and quality, respectively. The significant and positive coefficients of the interaction term of ITBA and event criticality of COVID-19 on decision speed ($\beta = 0.26$, $p < 0.05$) and decision quality ($\beta = 0.32$, $p < 0.01$) provide support for H1a and H1b. Further, H2a and 2b suggested event criticality of COVID-19 would positively moderate the effect of BDAC on decision speed and quality, respectively. However, the coefficient of the interaction term between BDAC and event criticality of COVID-19 on decision speed is insignificant ($\beta = -0.12$, $p > 0.1$), rejecting H2a. The coefficient of the interaction term between BDAC and event criticality of COVID-19 on decision quality ($\beta = -0.19$, $p < 0.05$) is significant and negative, rejecting H2b.
Based on regression results from Models 3a and 3b in Table 3, the marginal effects of ITBA and BDAC were further plotted on decision speed and decision quality along with the 95% confidence bands for different levels of event criticality of COVID-19 [7]. As shown in Fig. 2, ITBA has significantly negative effects on decision speed over the range of event criticality of COVID-19 from 1.25 to 3.63. Meanwhile, ITBA has significantly negative effects over the range of event criticality of COVID-19 from 1.25 to 3.45 but has significantly positive effects over the range of event criticality of COVID-19 from 4.85 to 5 on decision quality. In contrast, BDAC has significantly positive effects on decision speed over the range of event criticality of COVID-19 from 2.13 to 4.14. Meanwhile, BDPA has significantly positive effects on decision quality over the range of event criticality of COVID-19 from 1.25 to 4.02.
Notes: The y-axis denotes the marginal effects of ITBA or BDAC on decision outcomes (i.e., decision speed or decision quality), while the x-axis represents the level of event criticality of COVID-19. The dotted lines show the confidence band (95% level, two-tailed). If the confidence interval is entirely on one side of the horizontal zero line, the marginal effect of ITBA or BDAC on decision outcomes is significant at the given value of even criticality of COVID-19.

distinguished the influence of ITBA and BDAC via empirical evidence. This study thus builds on DCV to clarify the different mechanisms through which BDAC and ITBA affect decision quality and speed. In particular, this study reinforces the findings that a greater degree of BDAC leads to better decision speed and quality. This finding is consistent with that of previous research on BDA and decision-making [21]. The most novel finding is that increasing ITBA does not lead to better decision quality and speed. A plausible explanation for the insignificant relationship is that the prevalent IT in business has made ITBA become the standardized operation routines and thus limited the importance of ITBA in improving strategic decision making. Future research should verify the validity of these explanations. This unexpected finding further challenges the prevailing perspective of IT business value in that it suggests different types of IT-based capabilities have various influences on strategic decision-making. Consistent with recent inquiries [51], our findings caution against treating the relationship between IT-based capability and decision-making as a simple relationship. Making distinctions between ITBA and BDAC can make research more precise and help avoid vague inferences regarding the effect of IT-based capability on strategic decision-making.

Second, our findings bridge the gap between information system (IS) and crisis management literature by confirming the significance of research on the contingent effect of event impact of COVID-19. COVID-19 is an unexpected event that continues to shape managers' cognitive feelings and attitudes in strategic decision-making [22]. Specifically, the finding of event criticality of COVID-19 supports our premise that the event criticality of COVID-19 can strengthen the influence of ITBA on decision-making (in terms of both decision speed and quality). Yet, the

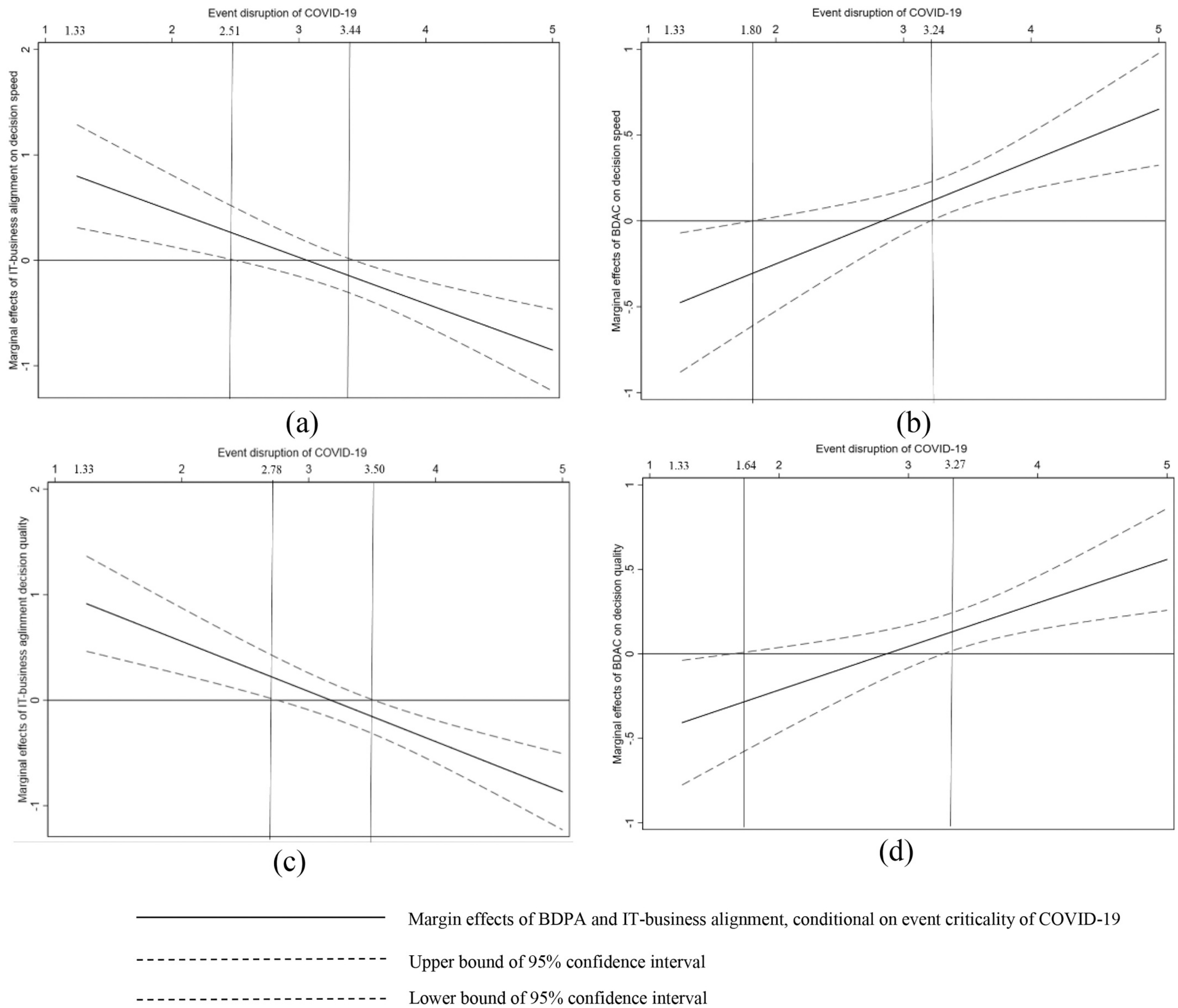

Fig. 3. The moderating role of event disruption of COVID-19.

findings indicate that the event criticality of COVID-19 does not strengthen the influence of BDAC on decision speed but rather weakens the relationship between BDAC and decision quality. These findings support the logic that the event criticality of COVID-19, with emphasis on putting extra attention and resources toward responding to the event, does not necessarily result in the need to change the company's established business routines or usual activities. This perception could provide a conducive climate for relying on IT diffusion in business and thus facilitate better decisions for a firm via ITBA. Conversely, the focus on the event criticality of COVID-19 impeded firms from making fast and high-quality decisions. This is likely attributable to the exploratory/emerging nature of BDAC. When firms perceive responding to COVID-19 as a priority, they tend to rely more on exploiting their established capability (i.e., ITBA) to support decision-making. In such cases, they can be more conservative (and even reluctant) to leverage emerging (and often less mature) capabilities to support decision-making. Meanwhile, the findings also show event disruption can strengthen the relationship between BDAC and decision-making (i.e., decision quality and speed) but weaken the relationship between ITBA and decision-making outcomes. This is consistent with the logic that the event disruption of COVID-19, with emphasis on the different ways of conducting business after the event, can block or transform ongoing routines and require entities (e.g., companies) to adjust and adapt [68].

In summary, the above findings of the moderating effect of the event impact of COVID-19 extend existing IS and crisis management literature on how the influence of digital technologies on decision-making is contingent on the event impact of COVID-19. Our findings help address the “fast-paced, dramatic and not well understood” issues related to how digital technologies cope with crisis [22,p. 2]. Prior literature has mainly investigated the influence of IT capability on decision-making under normal circumstances [39]. However, exogenous shocks, such as the COVID-19 pandemic, disrupt social and economic systems and change firms' strategic decision landscapes via extremely high degrees of uncertainty [5]. As IT-based capabilities do not operate in a vacuum, investigating how their influencing processes on decision-making are affected by environmental and contextual factors in general and COVID-19 event impact, in particular, is imperative. In particular, although examining the direct effects of ITBA and BDAC can enhance our understandings of their roles in decision-making, such research offers limited explanations for the differential contexts of the exogenous shocks of COVID-19. As our findings suggest, aside from their direct effects, ITBA and BDAC interact with the event impact of COVID-19 and

Table 4
Seemingly unrelated regression results.

	Decision speed			Decision quality		
	Model 1a	Model 2a	Model 3a	Model 1b	Model 2b	Model 3b
ITBA	−0.11	−0.05	−0.12	−0.07	0.31	0.22
	[0.09]	[0.09]	[0.08]	[0.08]	[0.60]	[0.57]
BDAC	0.18**	0.16*	0.15*	0.14*	−0.36	0.02
	[0.07]	[0.06]	[0.06]	[0.06]	[0.54]	[0.52]
Event criticality of COVID-19 (EC)			0.19**	0.21***	−0.44	−0.42
			[0.06]	[0.06]	[0.51]	[0.49]
Event disruption of COVID-19 (ED)			0.09+	0.02	0.78+	1.02*
			[0.05]	[0.05]	[0.46]	[0.44]
ITBA×EC					0.26+	0.32*
					[0.14]	[0.13]
BDAC×EC					−0.12	−0.19+
					[0.11]	[0.11]
ITBA×ED					−0.44***	−0.48***
					[0.13]	[0.12]
BDAC×ED					0.30**	0.26**
					[0.10]	[0.09]
Firm age	0.13	0.07	0.13	0.06	0.09	−0.00
	[0.10]	[0.10]	[0.10]	[0.09]	[0.10]	[0.09]
Firm size	0.08+	0.11*	0.08+	0.09*	0.09*	0.10*
	[0.05]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
Market turbulence	0.07	−0.05	0.07	−0.04	−0.02	−0.13+
	[0.08]	[0.08]	[0.08]	[0.08]	[0.08]	[0.08]
Technological turbulence	0.09	0.09	0.07	0.08	0.12+	0.13+
	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]
Consumer products	0.08	0.14	0.08	0.11	0.15	0.20
	[0.15]	[0.14]	[0.14]	[0.14]	[0.14]	[0.13]
Petroleum and chemical	−0.28*	−0.12	−0.21	−0.05	−0.19	−0.02
	[0.14]	[0.13]	[0.13]	[0.13]	[0.13]	[0.13]
Machinery	−0.21	−0.13	−0.17	−0.09	−0.15	−0.07
	[0.13]	[0.13]	[0.13]	[0.12]	[0.12]	[0.12]
Electronics	−0.23	−0.16	−0.20	−0.15	−0.18	−0.14
	[0.14]	[0.13]	[0.13]	[0.13]	[0.13]	[0.12]
Constant	2.89***	3.06***	2.03***	2.42***	2.39	1.85
	[0.44]	[0.42]	[0.47]	[0.46]	[1.87]	[1.80]
N	175	175	175	175	175	175
R^2	0.171	0.143	0.247	0.214	0.308	0.290
RMSE	0.478	0.462	0.437	0.462	0.442	0.420

Note: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

have interactive effects on strategic decision-making. Existing understandings of how to leverage IT for strategic decisions under exogenous shock is still limited. As such, this study extends this stream of literature through empirical examination of the role of digital technologies in strategic decision-making in the context of the COVID-19 pandemic. These findings further may provide some implications for the emerging studies on the influence of COVID-19 on digital transformation [18]. Since COVID-19 has disrupted normal business routines, firms are increasingly relying on digital technologies, such as BDA, blockchain, artificial intelligence, to transform into new digital business models [63]. However, our findings reveal that the effect of digital technologies, such as BDA, on organizational outcomes largely depends on managers' perceptions of the COVID-19 impact. Hence, our research provides nuanced insights regarding the influence of COVID-19 on digital transformation.

6.2. Managerial implications

In addition to the above insights, the current study also has important managerial implications. First, the findings suggest managers invest in realizing the different roles of ITBA and BDAC in improving decision speed and quality. Compared to deploying ITBA, training BDA staff would be more useful for improving decision-making. Skillful BDA staff have appropriate analytic competencies for generating insights that are helpful for decision speed and quality. Firms should thus pay more attention to BDAC and more actively deploy qualified BDA staff when managers make strategic decisions.

Second, when faced with emergency events like COVID-19, firms should carefully assess event disruption and criticality and leverage different IT capabilities for decision-making. On one hand, managers who perceive the event as disruptive should rely on insights generated from BDAC for strategic decision-making rather than those derived from ITBA. As highly disruptive events can change organizational routines, managers should also recognize that the alignment between IT and business may turn into organizational rigidity that hurts strategic decision-making. In contrast, BDAC enables firms to collect instantaneous and high-quality data from external business environments and provides firms with insights for making real-time decisions. When the level of perceived event disruption is low, managers should recognize the promotional role of IT-business alignment in supporting strategic decision-making. On the other hand, when managers perceive an event as highly important and a priority, they should take into account that neither BDAC nor ITBA is a viable option for strategic decision-making. However, when an event is less critical to the firm, managers should depend on the insights provided by BDAC and avoid leveraging said insights from IT-business alignment for strategic decision-making.

6.3. Limitations and future directions

Although this study contributes to existing understandings of the confluence of ITBA, BDAC, and COVID-19 on firms' strategic decision-making, it has some limitations that offer fruitful opportunities for future research. First, while China is a key context for examining strategic decision-making during the crisis, our research question regarding the event impact of COVID-19 on Chinese firms may differ from those in other countries and territories. China has adopted comprehensive, stringent, and thorough control measures for managing the spread of COVID-19.[3] As most of the world struggles to cope, Chinese firms have been advancing the resumption of work and production in accordance with local safety mandates. Future researchers might therefore reexamine our research in other geographic locations to provide more insights into the research model.

Second, even though we include a series of the firm and industry traits in the model to control their influence on strategic decision-making, we cannot totally rule out potential bias caused by unobservable/unmeasurable confounding. There may be other organizational factors, such as learning capability, organizational culture, and strategic orientation, that influence strategic decision-making. Future research should consider how these organizational factors influence decision-making in the context of COVID-19.

Third, our conceptualization of BDAC focuses on the human resources aspect of BDA capability. This is appropriate as this aspect of BDAC plays a critical role in dealing with uncertain and competitive environments. Yet, previous researchers have proposed that BDA capability may include other types of capabilities, such as tangible and intangible resources [23]. As such, future studies can explore how these types of BDA capabilities influence strategic decision-making.

Fourth, we conducted the survey in two waves, with the 1st wave helps to measure ITBA and BDAC while the 2nd wave for event impact and decision making. Although the literature has proposed that most firms' capability is relatively stable which is not changed greatly in short term [10], a firm's ITBA and BDAC may be developed in the second wave. Further study thus could consider the potential time effect when investigated the role of ITBA and BDAC on decision outcome.

Finally, our study measures strategic decision speed and quality based on top managers' perceptions because they are the key people making such decisions. Yet, our measures may imply certain levels of subjectivity. Given this, future studies should collect secondary data to operationalize strategic decisions.

Acknowledgements

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Appendix A

A.1. Measurement

Measures	Factor loading
Decision speed	
To what extent do you agree with the following statements. *(5-point scale: 1 "strongly disagree", 5 "strongly agree")*	
1. The top management team (TMT) routinely makes important decisions in under three months.	0.90
2. Relative to rivals, the TMT makes important decisions in a shorter time.	0.90
3. Given our competitive environment, this TMT moves quickly to make key strategic decisions.	0.93
4. Speed when planning or thinking about strategies is fast.	0.89
Decision quality	
To what extent do you agree with the following statements. *(1 "very bad", 5 "very good")*	
1. The effect that that decision has had on the company is...	0.91
2. Relative to what we expected, the results of the decision have been...	0.92
3. Overall, the TMT members feel that the decision was...	0.94
Big data analytics capability	
To what extent do you agree with the following statements. *(5-point scale: 1 "strongly disagree", 5 "strongly agree")*	
1. Our big data analytics staff holds suitable work experience to accomplish their jobs successfully	0.90
2. Our big data analytics staff is well trained.	0.90
3. We provide big data analytics training to our own staff.	0.84
4. Our big data analytics staff understand and appreciate the business needs of other functional managers, suppliers, and customers.	0.89
5. Our big data analytics staff are able to coordinate big data−related activities in ways that support other functional managers, suppliers, and customers.	0.90
6. Our big data analytics staff have a good sense of where to apply big data.	0.88
IT − business alignment	
To what extent do you agree with the following statements. *(5-point scale: 1 "strongly disagree", 5 "strongly agree")*	
1. The use of IT forges closer links with suppliers, monitors product and service quality, monitors delivery times, gains leverage over suppliers, negotiates pricing and service terms	0.90
2. The use of IT improves production throughput, boosts labor productivity, improves flexibility and equipment utilization, and streamlines operations.	0.94
3. Our firm embeds IT in products and use IT to increase pace of development / R&D, monitor design cost, improve quality, and support innovation.	0.90
4. Our firm uses IT to spot market trends, anticipate customer needs, build market share, improve forecast accuracy, and evaluate pricing options.	0.90
5. Our firm uses IT to respond to customer needs, provide after-sales service and support, improve distribution, create customer loyalty	0.94
Event disruption of COVID-19	
To what extent do you agree with the following statements. *(5-point scale: 1 "strongly disagree", 5 "strongly agree")*	
1. The COVID-19 disrupts our ability to get our business done.	0.68
2. The COVID-19 causes us to stop and think about how to respond	0.67
3. The COVID-19 alters our normal way of doing business	0.91
4. The COVID-19 requires us to change the way we do our work	0.89
Event criticality of COVID-19	
To what extent do you agree with the following statements. *(5-point scale: 1 "strongly disagree", 5 "strongly agree")*	
1. Effectively responding to the COVID-19 is critical for the long-term success of our company.	0.85
2. Responding to COVID-19 is a priority for our company.	0.86

(*continued on next page*)

[3] http://covid-19.chinadaily.com.cn/a/202004/21/WS5e9e2c62a3105d50a3d17880.html

(*continued*)

Measures	Factor loading
3. Responding to COVID-19 is a major event for our company.	0.87
Market turbulence	
To what extent do you agree with the following statements. *(5-point scale: 1 "strongly disagree", 5 "strongly agree")*	
1. In our kind of business, customers' product preferences change quite a bit over time.	0.75
2. We are witnessing demand for our products and services from customers who have never bought them before.	0.68
3. We cater to many of the same customers that we used to in the past.	0.79
4. It is very difficult to predict any changes in this marketplace.	0.72
Technological turbulence	
To what extent do you agree with the following statements. *(5-point scale: 1 "strongly disagree", 5 "strongly agree")*	
1. The technology in our industry is changing rapidly.	0.82
2. It is very difficult to forecast where the technology in our industry will be in the next two to three years.	0.69
3. A large number of new product ideas have been made possible through technological breakthroughs in our industry.	0.84
4. The technological changes in this industry are frequent.	0.85

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