Exploring the effects of data-driven hospital operations on operational performance from the resource orchestration theory perspective

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Abstract

In the big data era, managing data-driven hospital operations has become one of the most important tasks for healthcare executives, increasing responsiveness to exceptional disruptions such as those caused by the COVID-19 pandemic. However, they are still facing the challenges of how best to orchestrate the digital medical resources for improving operational performance such as cost, delivery, and quality. Therefore, drawing upon resource orchestration theory, this study investigates how hospitals orchestrate data-driven culture (DDC) and digital technology orientation (DTO) to develop big data analytics capability (BDAC) for operational performance improvement. Survey data were collected from 105 hospitals in China and analysed using structural equation modelling and ordinary least square regression. The results show that DDC has a significant positive impact on DTO. More interestingly, there is no significant interaction effect between DDC and DTO, indicating that DDC and DTO affect BDAC independently, and not synergistically. The results further reveal that BDAC fully mediates the DTO–operational performance relationship. The findings offer useful and timely guidance on how healthcare executives can manage data-driven hospital operations to improve operational performance during and post the COVID-19 pandemic.

Keywords: Digital technology orientation; Data-driven culture; Big data analytics capability; Hospital operations; Resource orchestration theory; COVID-19 pandemic

Managerial relevance statement

This study provides valuable guidance for hospital executives on resource orchestration for a creation of BDAC, which informs hospitals how they can target their efforts and limited resources (DDC vs. DTO) to build BDAC during the COVID-19 pandemic and other crises, and under normative resource-challenged conditions. The healthcare resource orchestration model addresses an important insight for hospital executives: delivering high quality, reliable, and affordable care to patients by structuring the hospital's cultural and technological resource portfolio, and bundling and leveraging these resources to create BDAC. BDAC is one of the most important dynamics that enables hospitals to achieve a high level of competitiveness throughout the healthcare delivery.

1. Introduction

Digitisation is fundamentally changing how healthcare can be delivered as a result of rapid technology and medical innovations (KC et al., 2020). The adoption of digital technologies in the healthcare industry – including big data analytics (BDA), artificial intelligence (AI), internet of things (IoT), and blockchain (Soltanisehat et al., 2020; Ting et al., 2020) – is expected to have a significant influence on the development of big data analytics capability (BDAC), which refers to healthcare organizations' ability to gather, analyse, and process large amounts of medical data, thereby extracting valuable business insights that facilitate the data-driven decision-making process (Wang et al., 2018a, 2019; Yu et al., 2021). In the big data era, managing data-driven hospital operations has become one of the most important tasks for healthcare executives, especially at the current juncture to effectively cope with the unprecedented uncertainties created by the COVID-19 pandemic (Soltanisehat et al., 2020; Whitelaw et al., 2020). However, they are still facing the challenges in determining the best way to orchestrate medical resources (such as data-driven culture, technology, and data resources) for creating BDAC and improving operational performance in terms of cost, quality, and delivery (Chen et al., 2013; Kiron and Shockley, 2011; Wang et al., 2019). On the other hand, the healthcare and operations management literature has shown that implementing BDA for value-based healthcare delivery is a relatively under-researched area, and researchers have recently called for greater empirical research on this area (KC et al., 2020; Wang et al., 2018a).

Resource orchestration theory (ROT) suggests that when firm resources are effectively bundled and deployed by a firm, this empowers organizational capability and thus delivers a competitive advantage (Chadwick et al., 2015; Sirmon et al., 2011). Grounded in ROT, this study develops and empirically tests a resource–capability–performance model: structuring the resource portfolio of data-driven culture (cf. Gupta and George, 2016; Kiron and Shockley, 2011) and digital technology orientation (cf. Khin and Ho, 2019; Zhou et al., 2005); bundling and integrating the resources to form BDAC (Wang et al., 2018a; Yu et al., 2021); and leveraging this capability to improve operational performance (Chen et al., 2013; Slack et al., 2016). Therefore, this study addresses the following main research question: *how can hospitals manage and bundle their cultural and technological resources to create big data analytics capability that generates superior operational performance?* By answering the critical research question, this research contributes to both theory and practice in several important ways.

ROT suggests that resources may not produce value on their own, rather they need to be operationalized in bundles to create organizational capability and generate competitive advantage (Sirmon et al., 2007, 2008). However, it is not clear for either researchers or practitioners how healthcare organizations, as complex public-private entities, can create BDAC through structuring and bundling organizational data-driven culture and digital technology resources, which have been considered as critical resources required for conventional private-sector firms to reap the benefits of big data (Gupta and George, 2016; Srinivasan and Swink, 2018). Digital technology orientation (DTO) can be defined as "a firm's commitment toward application of digital technology to deliver innovative products, services, and solutions" (Khin and Ho, 2019, p.181). The IT literature argues that implementing technologies alone does not guarantee the creation of business value for technology-oriented firms (Wu et al., 2006; Yu, 2015). Although hospitals continue to invest heavily in digital transformation in the hope of achieving smart healthcare operations, they are struggling to gain the full benefits derived from practical applications on the ground, in real clinical contexts (Wang et al., 2018a, 2019). The latest big data literature, on the other hand, also suggests that data-driven culture (DDC) is a critical organizational asset to gain potential benefits of big data and develop BDAC (Dubey et al., 2019; Gupta and George, 2016; Kiron et al., 2013). DDC is defined as "the extent to which organizational members (including top-level executives, middle managers, and lower-level employees) make decisions based on the insights extracted from data" (Gupta and George, 2016, p.1053).

DTO and DDC are two important but under-researched types of strategic resources, and theoretical and empirical research on how they are managed and bundled to create BDAC remains scarce. Accordingly, drawing upon ROT, this research explores the effect of DDC on DTO, the interactive effect of DDC and DTO on BDAC, and the mediating effect of BDAC on the DTO–operational performance relationship. By exploring the direct, interaction, and mediation effects, this study refines and extends the understanding of resource orchestration (Carnes et al., 2017; Sirmon et al., 2011), especially in the healthcare context. From a practical perspective, the empirical findings of this study provide useful and timely guidance for hospital executives on managing data-driven hospital operations through effective healthcare resource orchestration, and further explains why some digital technology-oriented hospitals obtain business benefits while others do not, especially in the current COVID-19 pandemic.

This study empirically tests the resource–capability–performance model using survey data gathered from 105 hospitals in China from December 2019 to February 2020, which provides a strong and unique empirical test of the resource orchestration model in the healthcare context. During the COVID-19 outbreak, China integrated digital health technologies (such as BDA, facial recognition, thermal imaging, and AI-based triage systems) into government-coordinated containment and mitigation processes for pandemic preparedness planning, contact tracing, testing, and patient-centred care delivery (Ting et al., 2020; Whitelaw et al., 2020). Implementing BDA initiatives has become a national priority in China's healthcare industry, and many hospitals have adopted digital health tools, telehealth, and app-based ecosystems to manage data-driven healthcare operations (Zhang et al., 2018; Yu et al., 2021). Through the adoption of digital technologies (e.g., AI and deep learning systems and blockchain), healthcare organizations in China could ensure timely delivery of medications with accurate tracking, thereby providing high quality, flexible, and innovative care for patients (Ting et al., 2020).

However, because resources are limited, when building BDAC for pandemic response, healthcare providers must make choices for allocating their scarce resources, and assess the extent to which they will emphasise certain strategic resources over others (i.e., DDC vs. DTO) (Hortinha et al., 2011). This study explains how hospitals bundle and deploy their cultural and technological resources during the COVID-19 pandemic to create BDAC, thus achieving superior operational performance (using the parameters of cost, quality, and timely delivery). The empirical findings provide timely insights into healthcare resource orchestration for the creation of BDAC, informing how hospital executives can better allocate their limited resources to different strategic resources to build capabilities, and better cope with COVID-19 disruptions.

The rest of the paper is structured as follows. Section 2 presents a review of related literature on DDC, DTO, and BDAC. Section 3 discusses the theoretical framework and research hypotheses developed in this study. Section 4 presents the research methods used in this study, followed by Section 5, which reports the results of data analysis and hypothesis testing. Section 6 outlines the theoretical and managerial implications, and Section 7 draws conclusions, along with identification of limitations and future research directions.

2. Theoretical constructs and literature review

2.1. Data-driven culture (DDC)

Kiron and Shockley (2011, p.60) suggest that organizations need to create a strong DDC that supports and guides the adoption of BDA, referring to "a pattern of behaviours and practices by a group of people (in a department, line of business or enterprise) who share a belief that having, understanding and using certain kinds of data play a critical role in the success of their business". To achieve large-scale benefits derived from the application of BDA technologies, organizations need to develop a DDC, which helps top management make data-driven decisions on a dynamic, reliable, and participatory basis rather than experience-based decision-making (Dubey et al., 2019; Gupta and George, 2016; McAfee and Brynjolfsson, 2012). Previous research has viewed DDC as an important organizational asset that enables organizations to transform data into actionable insights that can inform the data-driven decision-making process (Gupta and George, 2016; Ross et al., 2013). In this study DDC in the healthcare industry is defined as the extent to which healthcare delivery providers (e.g., managers and middle-level executives, physicians, nurses, and hospital staff) make data-driven business decisions based on actionable insights extracted from data, rather than on their professional instincts and past experiences (Gupta and George, 2016; Kiron and Shockley, 2011). Developing DDC allows healthcare providers to make data-driven managerial and clinical decisions based on the insights derived from BDA, thereby using analytical insights to guide strategy, making timely and reliable treatment decisions, and predicting future patient needs (Kiron et al., 2013; Wang et al., 2018a, 2019).

2.2. Digital technology orientation (DTO)

Digital technology-oriented organizations are those that are proactive in adopting advanced digital technologies ahead of their competitors, seeking to create values for customers and achieve long-term business success by means of using the latest advanced technology to produce innovative products and services, solutions, and processes (Gatignon and Xuereb, 1997; Khin and Ho, 2019). By incorporating a firm's decision-making process, DTO focuses on employing state-of-the art technologies in new product/service development; it also promotes openness to ideas that adopt advanced technologies (Chen et al., 2014; Zhou et al., 2005). DTO in the healthcare context can be defined as a hospital's commitment toward the adoption of advanced digital technologies for developing digital health solutions and providing innovative treatments and healthcare services to patients (Gatignon and Xuereb, 1997; Khin and Ho, 2019). In the healthcare industry, a digital technology-oriented hospital advocates a commitment to the development of new treatments, the acquisition of new digital technologies (e.g., AI, machine learning, and BDA), and the application of these latest advanced technologies (Gatignon and Xuereb 1997; Hortinha et al., 2011; Wang et al., 2019a), which directs managerial attention toward technological advancement, and building a strong capability of developing and delivering effective and innovative healthcare services to patients (Bhakoo and Choi, 2013; Das et al., 2011; Kwon et al., 2016).

2.3. Big data analytics capability (BDAC)

Hospitals are now facing numerous challenges in analysing and processing a variety of structured data (e.g., electronic health and medical records) and unstructured data (such as medical notes, prescriptions, X-ray films, audio and video files, and clinical images) to deliver flexible, accessible and innovative care to patients (Raghupathi and Raghupathi, 2014; Wang and Hajli, 2017). Previous research has suggested the importance of BDA in enabling hospitals to meet the growing health care needs of patients, and thus improve the quality of care delivery and business performance (Wang et al., 2018a, 2019; Yu et al., 2021). Following the work of Wang et al. (2018a, p.6), BDAC is defined as "the ability to acquire, store, process and analyse large amount of health data in various forms, and deliver meaningful information to users that allows them to discover business values and insights in a timely fashion". Building BDAC helps hospitals facilitate the visibility of stock medication and medical supplies (Srinivasan and Swink, 2018), and anticipate and meet the challenging dynamic of patient needs (Wang et al., 2018a; Yu et al., 2021). BDAC enables healthcare professionals (such as physicians, nurses, and other medical staff) to promote data-driven decision-making (Roski et al., 2014), thereby providing high quality healthcare services and innovative treatments for patients, during crises such as the COVID-19 pandemic and in normative organizational service delivery.

3. Theoretical model and research hypotheses

3.1. Resource orchestration theory (ROT)

The resource-based view (RBV) suggests that sources of competitive advantages can be explained through possessing heterogeneous and immobile resources (Barney, 1991, 2001). While necessary, the mere possession of the distinctive resources that are valuable, rare, inimitable, and non-substitutable is insufficient in itself to enable firms to achieve superior firm performance in highly dynamic environments (Eisenhardt and Martin, 2000; Sirmon et al., 2007). Scholars have expanded upon RBV and proposed resource orchestration theory (ROT), which stresses how different types of business resources can be managed properly to optimise value creation and gain competitive advantages (Ketchen et al., 2014; Sirmon et al., 2011). Resource orchestration is "the combination of resources, capabilities, and managerial acumen that ultimately results in superior firm performance" (Chadwick et al., 2015, p.360).

Resource orchestration practices incorporate the comprehensive processes of *structuring* resource portfolio through acquiring, accumulating, and divesting resources, *bundling* the resources in a unique way to create organizational capabilities, and *leveraging* the capabilities in the marketplace through mobilizing, coordinating, and deploying resources, which enable firms to exploit business opportunities and achieve competitive advantage (Sirmon et al., 2007).

ROT provides a promising theoretical lens for this research to explore the relationships among DDC, DTO, BDAC, and operational performance in the healthcare industry. Therefore, drawing upon ROT, this study develops the resource–capability–competitive advantage model (see Figure 1) that involves a set of strategic actions taken by hospitals to respond to the significant uncertainties such as those caused by the COVID-19 pandemic, including structuring and bundling resources (i.e., DTO and DDC) to create organizational capabilities (i.e., BDAC), and leveraging these capabilities to achieve competitive advantage and create value (i.e., operational performance) (Chadwick et al., 2015; Sirmon et al., 2007). As shown in Figure 1, a digital technology-oriented hospital focuses on developing smart healthcare, which requires the hospital to structure its resource portfolio (e.g., by adopting digital technologies and developing a data-driven culture). When the technological and organizational (data) culture resources have been structured in an appropriate way, they are essential to be effectively managed and bundled to form BDAC, which consequently leads to superior operational performance (Sirmon et al., 2011).

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3.2. Resource orchestration: structuring the resource portfolio

According to ROT, hospitals need to acquire, accumulate, and divest cultural, technological, and data resources (in this case DDC and DTO) to form their resource portfolio (Sirmon et al., 2011). This study argues that DDC facilitates DTO; hospitals possessing a DDC are more likely to adopt advanced digital technologies (such as IoT, AI, and BDA) to provide a patient-led healthcare service.

Previous research has demonstrated that many big data projects fail because of the lack of data-driven decision-making culture rather than the lack of data or technology investment (Kiron et al., 2013; LaValle et al., 2011; Ross et al., 2013). Organizational culture has been considered as one of the critical intangible resources that can facilitate the successful application of innovative information technology (e.g., Liu et al., 2010; Leidner and Kayworth, 2006). For instance, Leidner and Kayworth (2006) state that firms are more likely to successfully implement innovative information systems if business values created through the systems fit their organizational culture. Liu et al. (2010) also view organizational culture as one of the key drivers for a firm's intention to implement the internet-enabled supply chain management systems. Hospitals that create a strong data-driven decision-making culture, whereby healthcare providers (e.g., managers and middle-level executives, physicians, nurses, and medical staff) perform decision-making based on data rather than on their instincts (Dubey et al., 2019; Gupta and George, 2016; McAfee and Brynjolfsson, 2012), are more inclined to implement new and advanced digital technologies. Healthcare organizations possessing a DDC prefer to invest in sophisticated digital technologies to differentiate themselves from competitors. Thus, this study argues that creating a strong DDC facilitates DTO, and proposes the following hypothesis.

H1: DDC has a significant positive impact on DTO.

3.3. Resource orchestration: bundling the resources to create capabilities

According to ROT, after the portfolio of resources has been established, firms need to integrate resources to form organizational capability (Sirmon et al., 2011). In the healthcare context, building BDAC requires a bundle of specific firm resources such as culture, technology, and data resources developed by the healthcare organization. Consistent with ROT, in the following sections three research hypotheses are developed, regarding how hospitals build BDAC through bundling DDC and DTO.

3.3.1. Effect of DDC on BDAC

According to ROT, developing organizational capabilities (i.e., BDAC) requires the integration of specific resources acquired and developed by the organization (Sirmon et al., 2007). DDC is a required intangible resource for hospitals that seeks to take advantage of their big data and then build organizational capability (Gupta and George, 2016). Previous research has suggested that fostering an organizational culture of evidence-based decision making is important for firms to gain potential benefits of BDA and develop BDAC (Dubey et al., 2019; McAfee and Brynjolfsson, 2012; Ross et al., 2013). Hospitals that establish a DDC ensure that all healthcare providers have structured and unstructured medical data at their fingertips every day, and analyse and process the data to perform smart clinical decision-making (Wang et al., 2019). Hospitals fostering a DDC always recognise BDA as a strategic resource that enables the hospitals to process extremely large amounts of medical data to generate actionable insights and deliver real benefits for patients (Kiron and Shockley, 2011; Wang et al., 2018a). Hospitals can benefit from the adoption of BDA only when their senior-level executives and hospital professionals make managerial and clinical decisions based on actual data and analytics rather than their gut feelings or experiences (Kiron et al., 2013; Ross et al., 2013). To build BDAC, hospitals need to create a strong DDC whereby healthcare providers (such as executives, doctors, nurses, and other medical staff) make smarter data-driven decisions, which in turn enables the hospitals to develop BDAC. Thus, the following hypothesis is proposed.

H2: DDC has a significant positive effect on BDAC.

3.3.2. Effect of DTO on BDAC

According to ROT, when a technology-oriented firm effectively manages its digital technology resources, BDAC can be created (Sirmon et al., 2007). With advanced and state-of-the-art technologies, digital technology-oriented organizations are more likely to prioritise research and development by allocating substantial resources, active application of new technologies, and collect and store information (Chen et al., 2014; Zhou et al., 2005), all of which enable firms to build BDAC (Gupta and George, 2016; Srinivasan and Swink, 2018). In the healthcare industry, DTO reflects on hospitals’ commitment to the adoption of new advanced digital technologies and responsiveness toward technological advancement (Gatignon and Xuereb, 1997; Khin and Ho, 2019). Highly technology-oriented hospitals focus more on the creation of innovative ideas and technological knowledge or the adoption of new methods and cutting-edge technologies (Chen et al., 2014; Das et al., 2011; Hortinha et al., 2011; Zhou et al., 2005), which in turn enhances collecting, analysing and processing vast quantities of health-related data for harvesting actionable insights on a timely basis (Soltanisehat et al., 2020; Wang et al., 2018a). A digital technology-oriented hospital is more likely to generate innovative digital solutions to obtain a better understanding of emerging treatment options for patients and technological changes in the market, thereby effectively gathering and analysing the medical data derived from patients and the market for the development of BDAC (Ho et al., 2016; Kwon et al., 2016; Wang et al., 2018a). Therefore, based on ROT, this study posits a significant positive impact of DTO on the BDAC development.

H3: DTO has a significant positive effect on BDAC.

3.3.3. Interactive effect of DDC and DTO on BDAC

In addition to the hypothesized relationships between DDC and BDAC (i.e., H2) and between DTO and BDAC (i.e., H3), according to ROT, DDC and DTO may interact to influence BDAC. ROT posits that a hospital needs to bundle and deploy cultural and technological resources to create BDAC (Chirico et al., 2011; Sirmon et al., 2011). The IT literature suggests that DTO reflects hospitals' intention to apply advanced digital technologies into their operations and decision-making processes, which is essential to gather, analyse, and process medical data to develop BDAC (Wang et al., 2018a, 2019). The big data literature, on the other hand, considers DDC as a valuable intangible asset that enables hospitals to capitalise on big data and build BDAC (Gupta and George, 2016). It is essential for hospitals to establish proactive use of an information environment where decision-making is performed based on rationality rather than intuitive thinking or individual experience (Popovič et al., 2012). A deeply rooted data-driven decision-making culture in hospitals' key business processes facilitates the measurement, testing, and evaluation of quantitative evidence, leading to more effective use of information and successful adoption of data analytics technologies (Kiron et al., 2013).

Consistent with ROT, DTO itself is a critical resource for hospitals to develop BDAC, but it might be insufficient if hospitals are not able to transform data into knowledge, for making data-informed decisions (McAfee and Brynjolfsson, 2012). Leveraging DDC may enable hospitals to take full advantage of DTO, resulting in a higher level of BDAC. DTO should be aligned with DDC to turn data into actionable insights, enabling hospitals to take full advantage of data analytics and make smarter data-driven decisions in diagnoses and treatments (Wang et al., 2018a, 2018b; 2019), which in turn results in BDAC. Drawing upon ROT, the following hypothesis is proposed.

H4: The interaction of DDC and DTO is positively related to BDAC.

3.4. Resource orchestration: leveraging BDAC to improve performance

According to ROT, when BDAC is created, firms need to conduct the leveraging process that exploits the firm's capabilities to identify market opportunities and to gain sustainable competitive advantages (Chirico et al., 2011; Sirmon et al., 2007, 2011). The main priority of leveraging is to build organizational capabilities for generating a variety of values for firms and external stakeholders (Sirmon et al., 2007). BDAC enables hospitals to deal with large volumes of data, manipulate data in a timely fashion, and capture medical data in both unstructured and structured formats (e.g., clinical images and physicians' written notes and prescriptions) (Groves et al., 2013), which improve quality of care and service productivity for service users. For instance, the adoption of BDA technologies enables hospitals to more accurately and efficiently identify dynamic patients' readmission patterns to alleviate preventable readmissions and obtain a better trade-off between capacity and cost (Bardhan et al., 2014; Wang et al., 2018a).

BDAC helps hospitals unravel the complex structure of clinical costs and identify best clinical practices accordingly (such as eliminating unnecessary extra diagnostic tests and treatments), which in turn leads to efficiency improvement and cost reduction (Bates et al., 2014). BDA in hospitals can be applied to identify latent treatment patterns and reveal associations from vast amounts of medical information, which allows hospitals to develop more thorough and insightful diagnosis and treatments for patients, leading to higher quality of care at a lower cost (Raghupathi and Raghupathi, 2014; Wang et al., 2019). Developing BDAC in hospitals is of imperative significance in the meaningful use of electronic health records and supporting the implementation of data-driven medicine practices, thus leading to enhanced quality of patient care (Wang et al., 2018b, 2019), including streamlining "virtual workflows and the management of health information and to improve patient safety, reduce physician burnout and increase physician job satisfaction" (Guo et al., 2017, p.140). Therefore, based on ROT, the following hypothesis that BDAC has a significant effect on operational performance is proposed.

H5: BDAC is positively associated with operational performance.

3.5. Mediating effect of BDAC

From the RBV perspective, DTO can be considered as an essential asset that enables hospitals to be better positioned to obtain service differentiation and cost advantages by acquiring and incorporating advanced digital technologies in their operational processes (Barney, 2001; Mandal, 2017). Hospitals that are keen to embrace new digital technologies are better able to build their capability to generate innovative and digital solutions, thereby providing the highest possible quality and excellent patient experience (Khin and Ho, 2019; Wang et al., 2018a). The adoption of cutting-edge digital technologies (such as IoT, BDA, and AI) enables timely, adequate, and accurate information to be shared among doctors, nurses, and hospital workers (Kwon et al., 2016), which is essential for the hospital to achieve desirable patient outcomes in healthcare delivery corresponding to quickly reacting to patients' requests, improving the quality of care, and reducing healthcare costs (Dobrzykowski and Tarafdar, 2015; Glover et al., 2017). Highly technology-oriented hospitals are better positioned to reduce operating costs by increasing the utilization of logistics assets, to improve service levels by alleviating stock-out, and to use less time to meet patients' diverse requirements by quickly obtaining adequate medical supplies (Chen et al., 2013; Kwon et al., 2016; Mandal and Jha, 2018).

However, the successful implementation of new technologies is a complex process, and how to extract full value from technology application is often less explicitly understood (Balasubramanian et al., 2000; Yu, 2015), especially in increasingly uncertain and volatile contexts such as the disruptions caused by the COVID-19 pandemic. While hospitals continue to increase investments in digital tools, telehealth, and app-based ecosystems in the hope of digital transformation of health services, they still struggle to extract actionable, valuable insights from associated applications (Wang et al., 2018a, 2019). Investment in technology is substantial and risky, and there has been much debate about whether IT has a direct positive impact on organizational performance (Balasubramanian et al., 2000; Shah and Shin, 2007; Yu, 2015). According to ROT, this study argues that implementing digital technologies alone in hospitals' operational processes does not produce sustainable performance advantages, but that some hospitals could gain competitive advantages by using technologies to leverage organizational capabilities (i.e., BDAC).

Resource orchestration is the comprehensive process of structuring the hospital's resource portfolio (i.e., DDC and DTO), bundling the cultural, technological and data resources to create organizational capabilities (in this case BDAC), and leveraging BDAC to create and sustain long-term value for hospitals (such as operational performance) (Sirmon et al., 2007, 2011). Given the resource–capability–performance model (see Figure 1), it can be argued that BDAC mediates the DTO–operational performance relationship. Therefore, drawing upon ROT, the following hypothesis is proposed.

H6: BDAC mediates the relationships between DTO and operational performance.

4. Methodology

4.1. Survey data collection

To test the hypothesised relationships among DDC, DTO, BDAC and operational performance (see Figure 1), survey data were obtained from hospital executives in China from December 2019 to February 2020, the peak period of the COVID-19 outbreak in China. To improve the response rate, the data collection was conducted with the assistance of Provincial Hospital Associations in different provinces and regions in China. Due to the COVID-19 outbreak, an online survey was used, and the survey invitations were sent via

WeChat to senior executives of 1000 randomly chosen hospitals. The outbreak of COVID-19 has significantly influenced the survey response rate. Non-respondents were reminded to complete the questionnaires in mid-February 2020, but most of them declined due to busy schedules to respond to the COVID-19 crisis. A total of 105 usable questionnaires were finally considered to have been correctly completed, which indicates an overall 10.5% response rate.

Determining appropriate sample size required for conducting structural equation modelling (SEM) is one of the most common issues faced by researchers (Westland, 2010; Wolf et al., 2013). While some statistics scholars have suggested a minimum sample size of 100 for conducting SEM (Boomsma, 1985; Hair et al., 2017), others have recommended various rules-of-thumb mainly using the ratio of observations (participants) to estimated parameters in the model (such as a ratio of 20:1, 10:1, or 5:1) (Bentler and Chou, 1987; Bollen, 1989; Kline, 2005; Nunnally, 1967). The review of the prior literature suggests that there has been a lack of consensus on sample size requirements for conducting SEM. (Westland, 2010; Wolf et al., 2013). Therefore, in this study two tests were carried out rather than purely relying on sample size rules-of-thumb. First, a test was conducted following the equation developed by Westland (2010), i.e., $n \geq 50r^2 - 450r + 1100$, where r is the ratio of indicators to latent variables. In this study, the ratio of indicators to latent variables is 4 ($r = 24/6$), which requires a minimum sample size of 100 for adequate SEM analysis. Second, another test was performed by employing an online calculator developed by Soper (2021). The results suggest a minimum sample size of 100 required given the structural complexity of the model, and a minimum sample of 95 needed to detect the specified effect. The results of these two tests provide strong evidence that the sample size used in this study (n = 105) meets the minimum sample size requirements and is a practically acceptable size for conducting SEM (Westland, 2010). In addition, in this study the average variance extracted (AVE) for each theoretical construct is higher than 0.50, each construct has more than three items (observed variables), and there are no missing data (Hair et al., 2017, 2018). The sample size is also comparable to prior survey-based research on hospital operations and supply chain management (e.g., Chen et al., 2013, n = 117). Thus, based on these results above, it can be concluded that the sample size of 105 is sufficient to perform SEM in this study.

Table 1 illustrates the wide variety of characteristics and backgrounds represented by the responding hospitals. It can be seen that the respondents held senior-level positions, such as directors, vice directors, and departmental directors (e.g., information technology manager, operations manager, medical director, and finance director), and the majority of them (about

80%) have held their current positions for more than 10 years. Hence, the respondents were expected to have relevant knowledge to fill out the questionnaire.

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4.2. Bias

As a cross-sectional survey was conducted, both non-response bias and common method bias (CMB) were evaluated in this research. Non-response bias was assessed by comparing early and late waves on number of employees and number of years since incorporation (Hair et al., 2018). The t-test found that there is no statistically significant difference at a significance level of 0.05 between the category means for the demographic characteristics, providing evidence for absence of significant non-response bias.

Following previous survey-based research, the ex-ante (questionnaire development) and ex-post (preliminary statistical analyses) approaches were used to estimate and minimise CMB. When developing the questionnaire, the measurement items were made as simple and intuitive as possible in order to obtain truthful and accurate responses from the respondents; different instructions were also used for different scales, and the theoretical constructs were put in different substantive sections of the questionnaire. The respondents were promised anonymity in the questionnaire cover letter (Yu et al., 2019; Zhao et al., 2011). When conducing preliminary data analysis, confirmatory factor analysis (CFA) was applied to Harman's single-factor model to evaluate CMB (Podsakoff et al., 2012). The CFA yields an unacceptable model fit of χ^2/df (1140.433/189) = 6.034, CFI = 0.631, IFI = 0.634, TLI = 0.590, RMSEA = 0.220, and SRMR = 0.112 (Hair et al., 2018; Hu and Bentler, 1999). Therefore, it can be safely concluded that CMB is unlikely to affect the results.

4.3. Measures

Appropriate measurement scales were adapted from the healthcare, big data, and operations management literature to design the survey instrument. The measurement items are reported in Table 2. To evaluate content validity, a pilot test was conducted through obtaining comments and suggestions from academics and senior hospital executives. All items were measured using a 7-point Likert format with response anchors at 1 "strongly disagree" and 7 "strongly agree".

The measures for DTO were adapted from Khin and Ho (2019) and Zhou et al. (2005), which include the items that assessed a hospital's proactivity in adopting advanced digital technologies in hospital operations. The measures for BDAC were adapted from Srinivasan and Swink (2018), which include the items that reflect the ability of a hospital to take advantages of data visualization techniques, apply healthcare dashboards to improve decision-making process, obtain and integrate information from a wide range of data sources, and capitalise on the gathered information to conduct root cause analysis. The measures for DDC were adapted from Gupta and George (2016), including the items such as viewing data as a valuable tangible asset, performing decision-making relying on data rather than on instinct, and overriding intuition when data contradict viewpoints. The measures for operational performance were adapted from Slack et al. (2016), which include the items that evaluated quality (such as offering the most suitable treatment to patients, treatment for patient is applied in a proper way, and patients are consulted and stay informed), low cost (such as distribution, facility, technology, and inventory costs), and delivery performance of a hospital (such as minimal waiting times for treatment, minimum turnaround time for test results, test results returned as promised, and proportion of appointments cancelled kept to a minimum). In this study operational performance of hospitals was assessed as a second-order construct with three distinct first-order dimensions, which help to capture the broad scope of this theoretical construct (Chen et al., 2013).

Three variables were controlled in the conceptual model, including hospital size, age, and ownership (see Table 1). Bigger and older hospitals might possess more cultural, technological, and data resources for building BDAC than smaller and younger hospitals. Number of employees was selected as the indicator of hospital size, and number of years since incorporation was used to measure hospital age. Compared with private hospitals, state-owned hospitals in China receive significant funding from central and local governments to invest in medical technologies and health information systems (Ting et al., 2020; Xie et al., 2019). Therefore, hospitals with different types of ownership might develop different levels of BDAC for improving operational performance.

------------------------------ Insert Table 2 -------------------------------

5. Analysis of results

5.1. Assessments of unidimensionality, reliability, and validity

A set of relevant analyses were carried out to evaluate construct reliability and validity and reported the results in Table 2. The CFA results indicate a good model fit: χ^2 / df = 1.760, CFI = 0.949, IFI = 0.949, TLI = 0.938, RMSEA = 0.085, and SRMR = 0.047, which suggests that unidimensionality is confirmed (Hair et al., 2018; Hu and Bentler, 1999). As indicated in Table 2, the Cronbach alpha and composite reliability (CR) values of all theoretical constructs are above the commonly accepted cut-off of 0.70, suggesting the construct reliability (Hair et al., 2018).

Table 2 indicates that all measurement items have factor loadings that are well above the recommended value of 0.70 (Hair et al., 2018) and the AVE values for all theoretical constructs are higher than the suggested threshold of 0.50 (Fornell and Larcker, 1981). Therefore, convergent validity is ensured. Table 3 indicates the means, standard deviations, square root of AVE (given at the diagonal), and the intercorrelations between the constructs. As illustrated in Table 3, the square root of each construct's AVE is greater than any correlation among any pair of latent constructs, suggesting that discriminant validity is achieved (Fornell and Larcker, 1981).

------------------------------ Insert Table 3 -------------------------------

5.2. Multicollinearity

Multicollinearity was assessed in this study as the independent variables are highly correlated (Hair et al., 2018; Yoo et al., 2014). Previous research suggests several most practical multicollinearity diagnostics, including (1) correlation coefficient between independent variables, which is the simplest and most obvious means of identifying collinearity; (2) tolerance, which is a direct measure of multicollinearity; and (3) variance inflation factor (VIF), which is another practical approach to detect multicollinearity (Hair et al., 2018). Lack of high correlations does not ensure that there is no problem of multicollinearity (Hair et al., 2018). Thus, all three approaches were employed in this study to assess multicollinearity rather than relying on an examination of the correlation matrix of independent variables. The correlation coefficients were computed. As shown in Table 3, none of the correlation coefficients between the independent variables is greater than the typical cut-off point of 0.90 (Hair et al., 2018; Lu et al., 2017; Singh et al., 2011), which indicates that multicollinearity is not a major concern for this study. To further assess multicollinearity, tolerance and VIF values were calculate for each independent variable (i.e., DDC, DTO, and BDAC). As a rule of thumb, VIF values greater than 10 or tolerance values less than 0.10 might indicate a potential problem of multicollinearity (Hair et al., 2018). The results show that the tolerance values are greater than 0.10 (0.175 for BDAC, 0.235 for DTO, and 0.447 for DDC) and the VIF values are less than 10 (5.702 for BDAC, 4.253 for DTO, and 2.240 for DDC). Thus, based on these analysis results, it can be concluded that there does not appear to be a problem with multicollinearity in this study.

5.3. Hypothesis testing (direct, mediation, and interaction effects)

The bootstrapping technique in SEM was used to test the hypothesised relationships (Malhotra et al., 2014; Rungtusanatham et al., 2014), and reported the results in Table 4. As noted above, operational performance in terms of cost, quality, and delivery was used as a second-order construct. As shown in Table 4, the model fit is deemed acceptable: χ^2/df = 1.858, CFI = 0.923, IFI = 0.924, TLI = 0.911, RMSEA = 0.091, and SRMR = 0.075. Although three controls were included in the structural model, there is no significant impact of hospital size, age, and ownership on operational performance. As shown in Table 4, the structural model reveals a significant positive impact of DDC on DTO (β = 0.692, $p < 0.001$). Hence, H1 is supported. The results also provide strong supports for H2 and H3 that both DDC (β = 0.269, $p < 0.001$) and DTO (β = 0.711, $p < 0.001$) are significantly and positively associated with BDAC. In addition, the results also indicate that BDAC has a significant positive impact on operational performance (β = 0.583, $p < 0.01$). Thus, H5 is supported.

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To further clarify how DTO helps hospitals improve operational performance, the possible mediating role of BDAC was tested using bias-corrected bootstrapping approach in SEM (with n = 10,000 bootstrap resamples) (Zhao et al., 2010). The bootstrapping results reported in Table 5 show that DTO has no significant direct effect on operational performance (β = 0.235, *n.s.*), while DTO has a statistically significant indirect effects on operational performance via BDAC (β = 0.414, $p < 0.05$) and the confidence interval (CI) does not include zero [0.146, 0.797]. In addition, this study also conducted the Sobel test, which provides additional support for testing the significance of the mediation effect. Table 5 indicates that both the bootstrap test and Sobel test (z = 2.843, $p < 0.01$) lend strong support to H6, suggesting the DTO–operational performance relationship is fully mediated by BDAC.

------------------------------- Insert Table 5 --------------------------------

SEM could not be used to test the interaction hypothesis due to the small sample size. As such, ordinary least square (OLS) regression was used to examine the interactive effect of DDC and DTO on BDAC (Hair et al., 2018). The mixed methods combining SEM and regression analysis have been used in prior survey-based research on operations management (e.g., Yu et al., 2020; Zhao et al., 2011). The results are reported in Table 6. The VIF values for all models are well below the recommended cut-off of 10, indicating that multicollinearity does not appear to be an issue in the analysis (Hair et al., 2018). Table 6 also indicates that there is no statistically significant interaction between DDC and DTO (β = -0.060, *n.s.*), suggesting that DDC and DTO affect BDAC independently rather than interactively. Thus, H4 is rejected.

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5.4. Robustness tests

As noted above, multiple approaches were used in this study to alleviate concerns about non-response bias, common method bias, and multicollinearity, which help to ensure robustness of the findings. In addition, the following two methods were further employed to assess the robustness of the measures and estimates that could reflect on the reliability and validity of the findings. First, ridge regression was used to provide further evidence of model robustness (Lu et al., 2017; Mahajan et al., 1977). As shown in Table 7, a ridge regression model was performed to test the proposed relationships between DDC, DTO, and BDAC. The results indicate that DDC (β = 0.338, p < 0.001) and DTO (β = 0.561, p < 0.001) are significantly and positively related to BDAC. The results concur with the primary results generated from SEM (see Table 4). Additional ridge regression models were also performed to investigate the relationships between DTO, BDAC, and the three dimensions of operational performance (i.e., cost, quality, and delivery), more specifically, the mediating effect of BDAC on the DTO–operational performance relationship. The ridge regression results suggest that BDAC fully mediates the relationships between DTO and quality and between DTO and delivery, and partially mediates the relationship between DTO and cost. The results support the main conclusions from SEM. Second, structural models were performed with selected samples that only include the Chinese hospitals using bootstrapping technique in SEM, which aimed to determine if the proposed model works with different hospital ownerships (Chinese vs. foreign hospitals). The results indicate that DDC (β = 0.273, p < 0.001) and DTO (β = 0.710, p < 0.001) are significantly and positively related to BDAC, and that BDAC has a significant positive effect on operational performance (β = 0.622, p < 0.01). In addition, the results also indicate that BDAC fully mediates the relationship between DTO and operational performance. The findings are almost identical to the primary results (see Tables 4 and 5). Therefore, it can be concluded that the models and findings are robust.

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6. Discussion of the findings

6.1. Contributions to theory

This study develops and empirically tests a resource orchestration model (Chirico et al., 2011; Sirmon et al., 2011) for the healthcare industry. It functions by structuring the resource portfolio of culture, digital technology, and big data resources; and bundling and integrating the resources (DDC and DTO) to build organizational capability (BDAC), while leveraging the capability to provide high-quality and reliable care at much lower costs for patients (operational performance). By providing empirical evidence for the resource–capability–performance model, this study contributes to ROT and the extant literature on healthcare, big data, and operations management.

First, this study provides insights into the relative roles of DDC and DTO in today's data-driven environment. When building BDAC, hospitals need to make choices in their allocation and prioritization of limited resources. This relates to chronic structural problems in health systems worldwide; for instance, it is estimated that there will be a worldwide shortfall of 15 million skilled healthcare professionals by 2030 (Liu et al., 2017), and existing strains and under-capacity have already been exposed in most countries during the COVID-19 pandemic. The results reveal that hospitals need to acquire, accumulate, and divest relevant resources to form the firm's resource portfolio of cultural and technological resources (Sirmon et al., 2011). To respond more effectively and successfully to the massive uncertainties such as those caused by the COVID-19 pandemic, many hospitals in China have made great efforts to create a data-oriented culture and adopt new and advanced digital technologies (e.g., IoT, AI, and advanced robotics) to boost their smart healthcare operations (Ting et al., 2020; Zhang et al., 2018). Creating a strong DDC has become more crucial than ever during the COVID-19 pandemic, with hospital professionals (such as executives, doctors, nurses, and other medical staff) making smarter decisions based on the insights derived from data rather than their past experiences (Gupta and George, 2016; Kiron and Shockley, 2011). In adopting advanced, state-of-the-art technology in the operational processes, a technology-oriented hospital is inundated with data that enables new ways of analysing and processing medical data and better understanding patient needs (Khin and Ho, 2019; Wang et al., 2019). The finding is consistent with ROT: structuring the resource portfolio enables hospitals to obtain cultural, technological, and big data resources that hospitals can use for bundling and leveraging purposes (Chirico et al., 2011; Sirmon et al., 2007, 2011). Hence, the findings provide empirical evidence of the significant role of structuring the resource portfolio in the healthcare context.

Second, after a hospital builds its resource portfolio, it must effectively manage and bundle different sets of resources to create organizational capabilities (Sirmon et al., 2007, 2011). The findings provide empirical evidence that cultural (DDC) and technological (DTO) resources serve as important antecedents to the creation of BDAC. This finding is consistent with ROT, which suggests building BDAC requires medical resources acquired and developed by the hospital (Carnes et al., 2017; Sirmon et al., 2007). Surprisingly, the results reveal that there is no interaction effect of DDC and DTO on BDAC, but a significant impact of DDC on DTO. This is an important finding, since it extends ROT to the healthcare context by demonstrating the relationship between DDC and DTO: hospitals that develop a strong DDC are more likely to adopt advanced digital technologies. Highly technology-oriented hospitals with a strong DDC have a predominant focus on adopting advanced, state-of-the-art technology (Lin and Kunnathur, 2019), and creating new ideas and methods or providing innovative care and treatment for patients (Khin and Ho, 2019; Zhou et al., 2005). In today's data-rich but highly uncertain environments, a hospital's BDAC derives from the creation of data-driven culture that facilitates the application of digital technologies into the hospital's operational process. This is one of the first empirical studies investigating the importance of bundling of culture and technology in creating BDAC in the healthcare industry.

Third, according to ROT, after BDAC is formed, hospitals can conduct the leveraging process that leverages the capability to gain competitive advantage, and ultimately superior operational performance (Chirico et al., 2011; Sirmon et al., 2007, 2011). The purpose of leveraging is to use capabilities to create value for firms (Sirmon et al., 2007). The finding of the significant effect of BDAC on operational performance reinforces the importance of the role of BDAC in enabling firms to achieve competitive advantages in the healthcare industry. Previous studies have demonstrated that BDAC is an important determinant of firm performance (Dubey et al., 2019; Srinivasan and Swink, 2018; Wang et al., 2018b, 2019). This is an important finding, since this study offers empirical evidence on the importance of BDAC in enabling hospitals to deliver high quality, reliable, and affordable care to patients during the COVID-19 pandemic. Healthcare organizations in China face intense pressure to improve operational efficiency and reduce operating costs (Gao and Gurd, 2019). The need for hospitals to improve their operational performance has become more important than ever during the current COVID-19 outbreak.

Fourth, another significant theoretical contribution of this study lies in extending the literature to empirically test the resource–capability–performance model that investigates BDAC as a mediating mechanism for digital technology-oriented hospitals to improve operational performance. This study empirically confirms that DTO indirectly influences operational performance through the development of BDAC. The findings also support the tenets of ROT, which asserts that possessing technological resources alone does not guarantee superior firm performance; instead, firms need to orchestrate their resources to build specific organizational capabilities (Eisenhardt and Martin, 2000; Sirmon et al., 2008). During the COVID-19 pandemic, many Chinese hospitals have invested heavily in adopting new and advanced digital technologies (e.g., BDA, AI, and blockchain) in order to boost smart operations. Technology-oriented hospitals naturally focus on adopting advanced technologies, but this is no guarantee of success in today's constantly changing environment (Hortinha et al., 2011). According to ROT, possessing valuable resources is necessary but insufficient condition for value creation; organizations need to effectively manage, bundle, and deploy these resources in order to create capabilities for performance improvement (Sirmon et al., 2007, 2011). This logic suggests that technology-oriented hospitals need to focus on analysing and processing large amounts of medical data to build BDAC, which directly improve operational performance. Thus, to tackle the long-term effects of COVID-19 and boost smart hospital operations, developing BDAC should be one of the key focus areas of technology-oriented hospitals.

6.2. Implications for hospital executives

The empirical findings offer several important implications for hospital executives. First, due to the global spread of COVID-19, hospitals across the globe have been challenged to improve operational efficiency and provide high-quality, safe, and timely care for patients. The needs for hospitals to adopt digital technologies and implement data-driven operations practices have become more crucial than ever for tackling COVID-19: improving the effectiveness of testing, tracing, isolation, and quarantine; understanding healthcare trends; and enhancing the detection and diagnosis of COVID-19. The healthcare resource orchestration model developed in this study addresses an important insight for hospital executives: delivering high quality, reliable, and affordable care to patients by structuring the hospital's cultural and technological resource portfolio, and bundling and leveraging these resources to create BDAC.

Second, the findings also provide useful guidance for healthcare managers to decide how to manage and allocate their limited resources (DDC vs. DTO) for the development of BDAC. In today's increasingly dynamic environment, hospitals face challenges in allocating their limited resources to the ever-increasing health demands of a vast and ageing global population. This study indicates that hospital executives should set priorities for their resource portfolio efforts relative to their resource constraints. Hospitals creating a strong data-driven culture and adopting digital technologies will be rewarded with greater BDAC. Both cultural and technological resources should be accorded equal priority, because of their significant impacts on the creation of BDAC. More importantly, hospitals should cultivate a strong data-driven decision-making culture, which enables them to facilitate the applications of advanced digital technologies.

Third, the findings reveal that building BDAC should be one of the major focuses of hospitals to succeed in today's rapidly changing environment, especially during the current COVID-19 pandemic. BDAC is one of the most important dynamics that enables hospitals to achieve a high level of competitiveness throughout the healthcare delivery. Even in hospitals with a strong technology orientation, success is not certain. This study informs hospital leaders that DTO alone does not provide an assurance of long-term success; rather, a hospital must have the ability to develop BDAC. With the rapid diffusion of new and sophisticated technologies, many hospitals have invested heavily in advanced digital technologies. However, adopting advanced digital technologies is expensive and requires significant investments, and IT investments involve costs and risks. Controlling technological resources is necessary, but this is insufficient in itself in today's highly dynamic market. These resources – particularly large amounts of medical data and information generated from technological applications – must be recombined, bundled, and effectively wielded to develop BDAC.

7. Conclusions, limitations, and future research directions

By developing and empirically testing the resource–innovation–performance model, this study contributes theoretically to the healthcare, big data, and operations management literature. The major contribution of this study is providing initial empirical evidence concerning how culture, technology, and data resources are effectively managed and bundled to create BDAC, and ultimately superior operational performance in the healthcare industry. To the authors' knowledge, this study represents the first attempt to empirically test the resource orchestration model in the healthcare industry. From a practical perspective, the empirical findings provide timely and useful guidance for hospital executives on resource orchestration for a creation of BDAC, which informs hospitals how they can target their efforts and limited resources to build BDAC during the COVID-19 pandemic and other crises, and under normative resource-challenged conditions.

Although this study makes a number of important findings with significant managerial implications, it has several limitations that may provide research directions for future research. This study examines two critical organizational resources (i.e., DDC and DTO) and their impacts on BDAC. Previous research has suggested that developing BDAC requires a distinctive set of firm resources, such as human capital and organizational learning (Gupta and George, 2016). Future research could examine how these additional organizational resources improve hospitals' capacity to analyse and process data. This survey-based research collected data at a single point in time, and the findings gained from this study are limited by its cross-sectional design. A longitudinal study (e.g., during and after the COVID-19 pandemic, or its initial phase) would provide additional insights into the resource orchestration model tested in this study. Some independent variables in this study (DTO and BDAC) have relatively high correlations. Although some practical multicollinearity diagnostics (such as correlation matrix, tolerance, and VIF) were used to address this issue, it is important to note that multicollinearity may exist.

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Table 1: Sample characteristics

	Percent (%)		Percent (%)
Respondent location (geographical regions)		**Job titles**	
Pearl River Delta	4.8	Director of the hospital	21.0
Yangtze River Delta	3.8	Vice director of the hospital	14.3
Bohai Sea Economic Area	14.3	Director of purchasing	2.9
Northeast China	21.0	Director of operations/general	11.4
Central China	19.0	Director of information technology	1.0
Southwest China	16.2	Director of doctor-patient relationship	2.9
Northwest China	21.0	Director of equipment department	1.9
Hospital age (years)		Other senior executive	44.8
≤10	2.9	**Number of employees**	
11 – 20	8.6	1 – 100	12.4
21 – 30	9.5	101 – 200	12.4
> 30	79.0	201 – 500	21.9
Years in current position		501 – 1000	19.0
≤ 5	9.5	1001 – 3000	21.0
6-10	10.5	> 3000	13.3
> 10	80.0		
Hospital ownerships			
State-owned hospital	89.5		
Private Chinese hospital	9.5		
Wholly foreign-owned hospital	1.0		

Table 2: Results of CFA

Measurement Items	Factor loadings	α	CR	AVE
1. Big data analytics capability		0.947	0.950	0.826
We easily combine and integrate information from many data sources for use in our decision making	0.849			
We routinely use data visualization techniques (e.g., healthcare dashboards) to assist users or decision-maker in understanding complex information	0.960			
Our dashboards give us the ability to decompose information to help root cause analysis and continuous improvement	0.976			
We deploy healthcare dashboard applications/information to our directors' communication devices (e.g., smart phones, computers)	0.843			
2. Data-driven culture		0.890	0.893	0.736
We consider data a tangible asset	0.817			
We base our decisions on data rather than on instinct	0.924			
We are willing to override our own intuition when data contradict our viewpoints	0.828			
3. Digital technology orientation		0.963	0.965	0.901
Compared to other hospitals, our digital technologies adopted for supply chain and operations are more advanced	0.946			
We are always the first to use sophisticated digital technologies in our industry	0.949			
We are regarded as a digital technology leader in our industry	0.952			
4. Quality		0.938	0.940	0.839
We provide the most appropriate treatment for patients	0.947			
Our treatment for patients is always carried out in the correct manner	0.966			
We ensure patients are consulted and kept informed	0.829			
5. Delivery		0.939	0.941	0.801
The time between requiring treatment and receiving treatment kept to a minimum	0.919			
The time for test results, X-rays, etc. to be returned kept to a minimum	0.952			
Proportion of appointment which are cancelled kept to a minimum	0.898			
Test results, X-rays, etc. returned as promised	0.805			
6. Cost		0.915	0.919	0.739
Distribution costs (e.g., transportation and handling costs)	0.860			
Facility costs (e.g., beds, operating theatres and laboratories)	0.864			
Technology costs (e.g., robotic surgical devices)	0.846			
Inventory costs (e.g., inventory investment and obsolescence)	0.868			
Model fit statistics: χ^2 = 306.241; df = 174; χ^2 / df = 1.760; CFI = 0.949; IFI = 0.949; TLI = 0.938; RMSEA = 0.085; SRMR = 0.047				

Table 3: Correlation matrix

	Mean	SD	HA	HS	SOH	BDAC	DDC	DTO	Q	D	C
Hospital age (HA)	3.648	0.759									
Hospital size (HS)	3.638	1.570	0.432**								
State-owned hospital (SOH)	0.895	0.308	0.005	0.180							
Big data analytics capability (BDAC)	4.667	1.657	-0.004	0.294**	-0.112	0.909[a]					
Data-driven culture (DDC)	5.083	1.456	0.067	0.229*	0.062	0.743**	0.858[a]				
Digital technology orientation (DTO)	4.175	1.797	-0.058	0.362**	-0.065	0.874**	0.632**	0.949[a]			
Quality (Q)	5.937	1.127	0.086	0.188	-0.093	0.657**	0.651**	0.556**	0.916[a]		
Delivery (D)	5.726	1.205	-0.017	0.158	-0.124	0.628**	0.592**	0.597**	0.737**	0.895[a]	
Cost (C)	5.041	1.302	-0.090	0.134	0.017	0.570**	0.526**	0.612**	0.553**	0.672**	0.860[a]

Notes: [a] The diagonal elements are the square root of AVE; ** Correlation is significant at the 0.01 level (2-tailed); * Correlation is significant at the 0.05 level (2-tailed).

Table 4: Results of hypothesis testing

Structural paths	**Standardised coefficient**	**t-values**
Data-driven culture → Digital technology orientation	0.692***	7.326
Data-driven culture → Big data analytics capability	0.269***	3.650
Digital technology orientation → Big data analytics capability	0.711***	8.623
Digital technology orientation → Operational performance	0.235	1.254
Big data analytics capability → Operational performance	0.583**	3.012
Control variables		
Hospital age → Operational performance	0.077	0.953
Hospital size → Operational performance	-0.102	-1.224
State-owned hospital → Operational performance	-0.015	-0.202
Variance explained (R^2)		
Digital technology orientation	0.479	
Big data analytics capability	0.843	
Operational performance	0.623	
Model fit statistics: χ^2 = 442.217; df = 238; χ^2/df = 1.858; CFI = 0.923; IFI = 0.924; TLI = 0.911; RMSEA = 0.091; SRMR = 0.075		

Note: The bootstrapping technique in SEM was performed with n = 10,000 bootstrap resamples.
*** $p < 0.001$; ** $p < 0.01$.

Table 5: Results of mediation bootstrapping

Structural paths	Direct effect	Indirect effect	SE of indirect effect	90% CI for indirect effect	Sobel test	Result
DTO→BDAC→OP	0.235	0.414*	0.409	0.146–0.797	z = 2.843**	Full mediation

Note: DTO = digital technology orientation; BDAC = big data analytics capability; OP = operational performance; SE = bootstrap standard error; CI = bootstrap confidence interval; Standardized effects; 10,000 bootstrap samples.
** $p < 0.01$; * $p < 0.05$.

Table 6: Moderated regression results: interaction of digital technology orientation and data-driven culture

	Model 1	Model 2	Model 3
Control variables			
Hospital age	-0.178 (-1.736)†	0.020 (0.404)	0.019 (0.400)
Hospital size	0.404 (3.872)***	-0.016 (-0.308)	-0.016 (-0.297)
State-owned hospital	-0.183 (-1.947)†	-0.086 (-1.991)*	-0.070 (-1.584)
Independent variables			
Digital technology orientation (DTO)		0.668 (11.216)***	0.670 (11.311)***
Data-driven culture (DDC)		0.329 (6.044)***	0.326 (6.023)***
Interaction effect			
DTO × DDC			-0.060 (-1.427)
R^2	0.140	0.833	0.836
Adjust R^2	0.115	0.824	0.826
F-value	5.485**	98.580***	83.349***
Max VIF	1.280	2.098	2.100

Note: Standardized coefficients and t-values are reported; Dependent variable is big data analytics capability.
*** $p < 0.001$; ** $p < 0.01$; † $p < 0.10$.

Table 7: Ridge regression results

	Dependent variable: BDAC			Dependent variable: Quality			Dependent variable: Delivery			Dependent variable: Cost		
	β	Std. Err.	t-value	β	Std. Err.	t-value	β	Std. Err.	t-value	β	Std. Err.	t-value
Control variables												
Hospital age	-0.005	0.085	-0.139	0.095	0.102	1.378	0.019	0.132	0.233	-0.035	0.129	-0.460
Hospital size	0.028	0.043	0.683	-0.032	0.052	-0.447	-0.048	0.069	-0.533	-0.065	0.066	-0.817
State-owned hospital	**-0.088**	0.200	-2.366	-0.023	0.243	-0.348	-0.052	0.300	-0.677	0.071	0.302	0.992
Independent variables												
DDC	**0.338**	0.047	8.236									
DTO	**0.561**	0.039	13.317	0.142	0.048	1.856	0.251	0.086	1.969	**0.393**	0.065	4.373
BDAC				**0.466**	0.516	6.140	**0.401**	0.090	3.237	**0.226**	0.070	2.550
Ridge k value	0.15			0.16			0.04			0.12		
Max VIF	0.999			1.009			2.734			1.311		
F-value	**92.962**			**14.901**			**13.716**			**12.701**		

Note: Significant coefficients ($p < 0.05$) and F-value ($p < 0.001$) are set in bold.

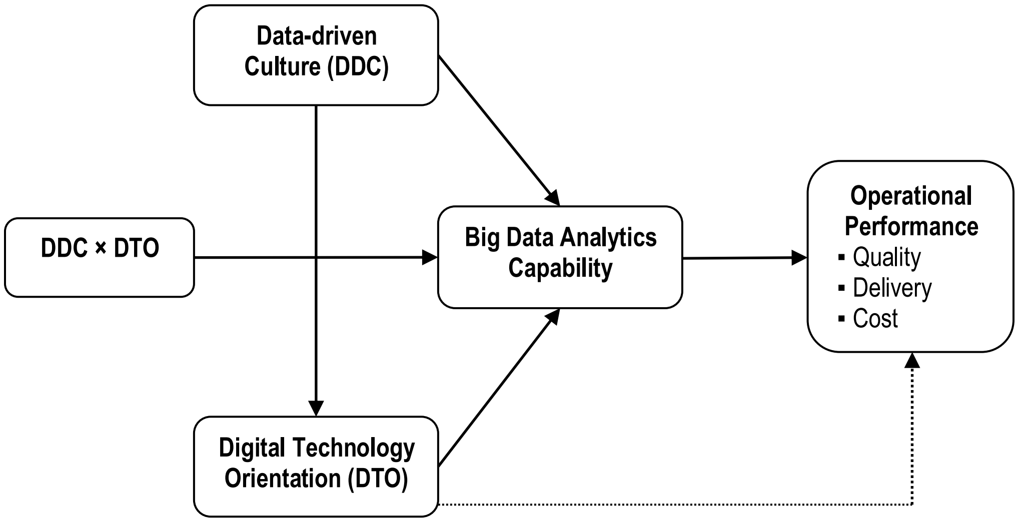

Figure 1: Proposed theoretical model