Big data management capabilities in the hospitality sector: Service innovation and customer generated online quality ratings

Abstract:

Despite the wide usage of big data in tourism and the hospitality sector, little research has been done to understand the role of organizations' capability of managing big data in value creation. This study bridges this gap by investigating how big data management capabilities lead to service innovation and high online quality ratings. Instead of treating big data management as a whole, we access big data management capabilities at the strategic and operational level. Using a sample of 202 hotels in Pakistan, we collected the primary data for big data capabilities, knowledge creation and service innovation; the secondary data about quality rating were collected from Booking.com. Structural equation modelling through SmartPLS was used for data analysis. The results indicated that big data management capabilities lead to high online quality ratings through the mediation of knowledge creation and service innovation. We contribute to the current literature by empirically testing how strategic level big data capabilities enable the firm to add value in innovativeness and positive online quality ratings through acquiring, contextualizing, experimenting and applying big data.

Keywords. Big data management; dynamic capabilities; service innovation; knowledge creation; customer generated online quality rating; hospitality.

1. Introduction

Big data applications are among the modern cutting-edge technologies enhancing consumer experience and assisting their buying decisions (Gavilan, Avello, & Martinez-Navarro, 2018). When it comes to value creation through big data, the hospitality and tourism sector is among the active users (Hashem et al., 2015). Big data, together with artificial intelligence (AI), enables the firms to explore the unanticipated patterns about clients, businesses and marketplaces (Xie, Wu, Xiao, & Hu, 2016); they also enhance organizations' knowledge about their customers' behaviour (Talon-Ballestero et al., 2018), which is one of the prerequisites of service innovation in the hospitality sector (Kim & Lee, 2013). Whilst customers rely on big data to assist their buying decisions (Gavilan, Avello, & Martinez-Navarro, 2018), hotels also rely on online quality ratings to attract customers. With the application of technologies such as AI, augmented reality, robotics and machine-learning in tourism through big data becomes a rising interest of studying the impact of these forward-looking technologies on customers' behaviour (Li et al., 2018). Some of these studies show that big data analytics are a powerful source to predict the level of customer satisfaction and the quality of products (Xiang, Schwartz, Gerdes Jr, & Uysal, 2015), which enhance online quality rating.

The emphasis of current studies on big data value creation is mainly on big data analytics and overall performance as outcome, such as Wamba et al. (2017), Dubey et al. (2019), Akhtar et al. (2019). Shamim et al. (2019a) examined value creation as an outcome of big data management capabilities (BDMCs), but their study considered value creation as a general variable and did not specify the kind of value creation. However, studies on big data-driven knowledge creation, innovativeness and how it is connected to customer generated quality rating, are still scarce, particularly in the hospitality sector. This study aims to help bridge this gap in the research.

Big data refers to data characterized by huge volume; velocity; variety; and value (Ghasemaghaei & Calic, 2020). With the advanced mobile and Web 2.0 technology available, tourism industries generate big data through devices and operations (Li et al., 2018). Big data can be user/customer generated by using the platforms of tourist firms, such as hotels and restaurants, and by third-party agents such as customer reviews on Expedia, Skyscanner and Booking.com (Xiang et al., 2015). Big data can also be collected through social media like Facebook, Twitter and Linkedin (Chua, Servillo, Marcheggiani, & Moere, 2016) as well as review sites such as TripAdvisor and Yelp (Viglia, Minazzi, & Buhalis, 2016). These data are accessible to all tourism and hospitality firms, but the ability of firms at managing big data varies. While some organizations do little about these data, others make full use of big data to assist them with their product design and understanding of customer behaviour.

In the field of tourism and hospitality, user-generated data through machine learning have been widely used to gain insights about issues in the field, such as tourism demand and tourism marketing strategy (E Silva et al., 2018). However, creating value from big data for innovative outcomes is not a simple process. Big data on platforms such as Booking.com, Expedia, TripAdvisor and Yelp are complex and vary from platform to platform. Such dynamic big data comes with challenges like different linguistic characteristics, semantic features, and different usability (Xiang et al., 2017). To create innovative outcomes from such data, organizations need certain capabilities. Consistent with the resource-based view of Barney (1991), we argue that management capabilities are crucial to create value from big data. Having access to a strategic resource such as big data is not enough, organizations need to create management capabilities to create value from strategic resources. It makes it imperative to know what the key management capabilities to harness big data are. Literature suggests strategic level capabilities to harness big data, however in order to harness strategic resources, organizations need to develop capabilities at all levels. Therefore, there is also a need to investigate big data management capabilities at the operational level (Teece, 2007). Despite the highly recognized importance of big data, however, limited empirical studies have carried out tests to understand the association between big data management capabilities (BDMCs) and value creation. Most of the existing studies are discussing big data analytics capabilities, but the management capabilities required for enabling the organization to analyse big data need specialized research.

Management capabilities can be divided into different levels: strategic, and operational capabilities (Teece, 2007). Most of the studies discussed the two capabilities separately in relation to big data management (Mcafee et al., 2012; Zeng & Glaister, 2018), but theoretically these two capabilities are interrelated as strategic level objectives can be facilitated by enhancing operational effectiveness (Witcher & Chau, 2014). Big data are a unique strategic resource and big data management requires dynamic capabilities (Shamim, Zeng, Shariq & Khan, 2019) to manage resources, generate more value and achieve a competitive advantage (Gutierrez-Gutierrez et al., 2018). The emphasis of dynamic capabilities view is on the ability of the firm to assimilate, shape and reconfigure internal and external competences to respond to constant changing environment (Teece et al., 1997;

Teece, 2007). Value co-creation through big data achieved through understanding the pattern of data supports the knowledge-creation activity. Hence, we assume operational level BDMCs mediate the relationship of strategic level BDMCs and knowledge creation.

Using the new knowledge gained through big data analysis, organizations are able to adjust or radically change their current service to meet the demands of the external market (Buhalis & Sinarta, 2019; Buhalis & Foerste, 2015). This value creation practice relies on the organizations' dynamic capability of applying the knowledge extracted from big data to improve service outcomes and co-create tourism experiences (Nieves, Quintana, & Osorio, 2016). This study investigates the influence of BDMCs (i.e. strategic and operational level) on knowledge creation, and investigates the influence of knowledge creation on hotel service innovation and customer quality ratings on www.booking.com, one of the most commonly used infomediaries for hotel bookings. This study also examines how strategic level capabilities indirectly influence knowledge creation through the mediation of operational level BDMCs. Furthermore, the influence of knowledge creation through big data on a hotel's service innovation and customer quality ratings on infomediaries (i.e. www.booking.com) is also investigated. Sources of external knowledge can stimulate innovation (Khan, Lew, & Marinova, 2019). By investigating these issues, this study aims to answer the research question of how BDMCs enhance KBDCs i.e. service innovativeness which leads to better online quality ratings?

Big data is an effective source of knowledge creation and this kind of knowledge source is extremely important for emerging and developing economies such as Pakistan, due to the issue of institutional voids caused by limited support by government bodies (Khan et al., 2019). Therefore, in the situation of institutional voids, organizations need to rely more on external sources of knowledge for innovations. Firms in developing economies such as Pakistan are in the initial stages of digital transformations, and their capabilities to create value from these technologies such as big data, differ than those of firms in developed economies. Firms in developed economies still rely on industrialized economies to import digital technologies. Despite of a reported lack of competencies, literature suggests that firms in Pakistan are creating value from big data in several ways i.e. for urban planning (Ahmed, 2018), to improve the production and service (Imran, 2018). Furthermore, new policies of the country related to digitization are also aiming at promoting digital transformations which supports the use of big data (Ministry of commerce, 2019). Therefore, it is important to discuss big data related capabilities in Pakistani organizations, enabling them to create value from big data. We therefore collected data from Pakistan, where this type of study will benefit tourist firms to understand big data and how to use big data for innovation and improve customer service.

2. Literature review and hypotheses

2.1. Knowledge-based dynamic capabilities view

DCs focus on the contribution of human actions in a turbulent business environment and have an explanatory power on business performance (Teece, 2007). This view advocates that without effective management practices, strategic resources alone are not sufficient to ensure a sustainable competitive edge (Teece, 2007; Zheng et al., 2011). Combined with other theories, the DCs view can be applied to explain competitive advantages in various industries (Wamba et al., 2017). Considering that this study focuses on the importance of knowledge creation, we combine DC with a knowledge-based view (KBV) to underpin our theoretical model. KBV considers knowledge as the key strategic resource for organizations to achieve a competitive advantage (Grant, 1996; Shamim, Cang, & Yu, 2017) and treats organizations as knowledge-bearing units with the purpose of using knowledge to create commercial value (Donate & de Pablo, Jess D Sanchez, 2015; Grant, 1996).

Combining KBV and DC together, knowledge-based dynamic capability (KBDCs) are defined as capabilities to obtain, create and pool knowledge to sense, explore, and address the environmental dynamism (Mikalef et al., 2018; Zheng et al., 2011). The fundamental phenomenon of KBDCs embraces the concept that managers can create new value through integrating the existing knowledge (Zheng et al., 2011). Organizations with dynamic capabilities are ambidextrous, they can function in both a dynamic and a stable business environment. Knowledge acquirement, knowledge generation, and integration capabilities are the sub-capabilities, representing the dimensions of KBDCs (Zheng et al., 2011). We discuss BDMCs at the strategic and operational level as heterogeneous capabilities, proposing that these two capabilities can enable organizations' knowledge creation through big data and contribute to service innovation and online quality ratings.

With the application of big data in business practice such as decision-making, marketing and production, BDMCs plays a crucial role at ensuring big data is integrated in the business process (Kim et al., 2011). We argue that innovativeness is KBDC as it heavily relies on knowledge and it positively influences the quality in the given context. BDMCs enable the firms to process and analyse big data which leads to knowledge creation. Literature supports the argument that analyses of data and understanding the pattern of data lead to knowledge creation (Uriarte, 2008). Existing studies have also used the KBDC framework to justify the relationship of strategic level capabilities, knowledge, and innovation (Zia, 2020). Based on these arguments and theoretical grounds we propose and test the conceptual model shown in figure 1.

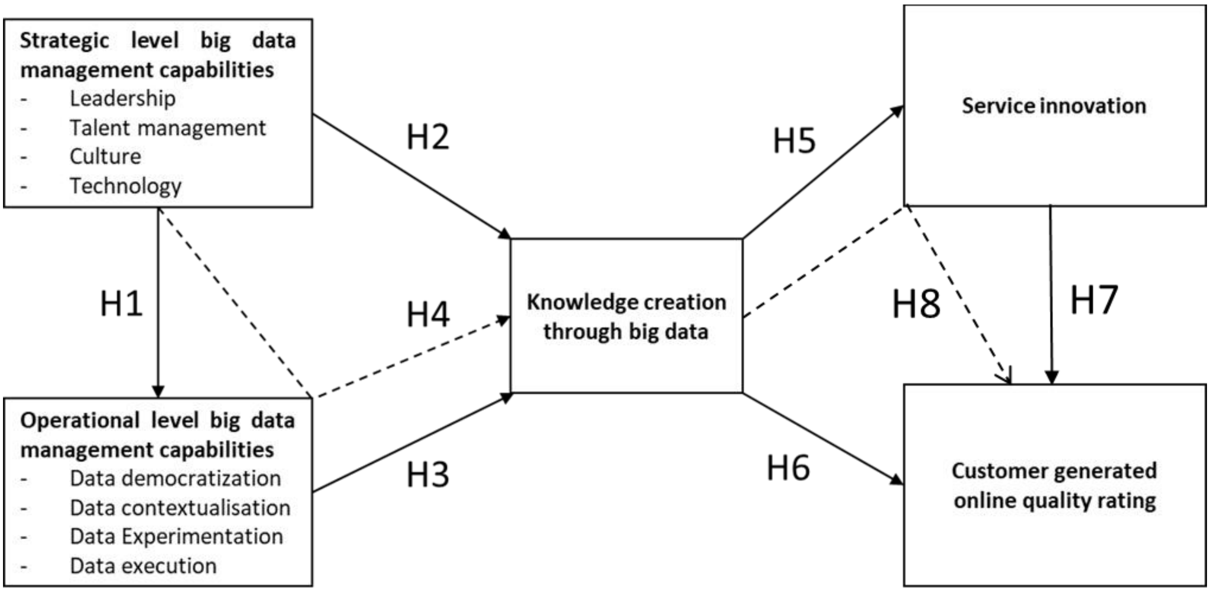

Figure 1. Conceptual model

2.2. Big data in tourism and the hospitality sector

The advancement of IT provided a foundation for big data to become widely used in the tourism industry (Hashem et al., 2015). Big data is usually generated from three sources, i.e. users/customers, devices, and operations (Li et al., 2018). The internet has also made social media a big platform for user-generated big data, e.g. photos, texts and videos (Xiang, Du, Ma, & Fan, 2017). Enhancements in the Internet of Things (IoTs) lead to the development of sensor devices which are employed to track tourist data, such as the global positioning system (GPS), Bluetooth data and Mobile Network operation data (Shoval & Ahas, 2016). The complex system of tourism covers several operational activities, such as web surfing, online booking and buying. Such activities produce transaction data, such as website visiting data, online booking data and web search data, which ultimately help to understand tourists' behaviour and to improve business strategies. If organizations are equipped with the relevant

IT capabilities, big data can be applied to understand and predict the patterns of customer behaviour and tourism markets (Li et al., 2018).

Strategic decision-making can benefit from big data in tourism and hospitality. For example, big data analytics provide information without sample bias, which helps practitioners understand tourism behaviour (Li, X., Pan, Law, & Huang, 2017). Xiang et al. (2015) posited that big data assists hotels at understanding the factors contributing to customers' satisfaction through big data text analysis of customer reviews on Expedia.com and other similar websites. Additionally, big data analytics appears to be a useful tool for knowledge generation regarding tourism destinations (Fuchs, Höpken, & Lexhagen, 2014). For example, E-Silva et al. (2018) used big data to analyse the spatiotemporal patterns of tourism in Europe. Measuring tourism destinations via using mobile tracking data is another example of big data application in the tourism sector (Raun, Ahas, & Tiru, 2016). The effect of the Booking.com rating system, bringing the hotel class into the picture, is well-known among tourism and hospitality studies (Mariani & Borghi, 2018). Geo-tagged photos of travellers are also used by researchers to explore inbound tourists' behaviour (Vu, Li, & Law, 2015).

Existing studies show that big data increasingly gains substantive attention in tourism and hospitality studies. Most of these studies focus on capturing value creation from big data through big data analytics, such as big data text analytics, using online reviews and social media to understand customers' behaviour (Xiang et al., 2015; Xiang et al., 2017). However, there is a lack of research on what types of BDMCs are required to create value out of big data.

2.3. Big data management capabilities

BDMCs are the dynamic capabilities (Shaimm et al., 2019a), enabling organizations to sense and seize opportunities to create value from big data. Dynamic capabilities can exist at all levels in the organization such as individual, organizational, strategic, and operational levels (Teece et al., 1997; Teece, 2007). Existing literature on big data mainly emphasises big data analytics capability (Wamba et al., 2017), and studies investigating BDMCs are rare. Among these few studies, Shamim et al. (2019a) pointed out that leadership, talent management, technology and culture are important BDMCs to create value from big data, and these capabilities are more strategic in nature. Zeng and Glaister (2018) and Shamim et al. (2019b) examined the impact of operational level capabilities, i.e. data democratization, data contextualization, experimentation, and execution on value creation. Most of the studies on big data capabilities investigate organizational performance as an outcome (e.g. Dubey et al., 2019; Wamba et al., 2017; Xiang et al., 2015), however less attention is paid to understanding how big data can be applied to enhancement, such as service innovation and quality ratings.

Table 1.

Literature highlights on big data management capabilities

Author	Big data capabilities	Theoretical lens	Outcomes/Value creation
Wamba et al. (2017)	Big data analytics capability	Dynamic capabilities view	Firm performance
Gunasekran et al. (2017)	Big data predictive analytics	Resource based view	Organizational performance and supply chain performance
Xiang et al. (2015)	Big data text analytics	-	Customer knowledge
Shamim et al. (2019a)	Big data management capabilities (strategic level), and big data decision making capability	Dynamic capabilities view	Decision-making quality
Shamim et al. (2019b)	Big data management capabilities (operational level)	Knowledge based dynamic capabilities view	Value creation and employee ambidexterity
Zeng and Glaister (2018)	Big data democratization, contextualization, experimentation, and execution	Resource based views, dynamic capabilities view	Value creation through big data
Akter et al. (2016)	Big data analytics capability	Resource based view	Firm performance
Akhtar et al. (2019)	Big data savvy teams' skills	Resource based view	Business performance
Angrave et al. (2016)	Big data analytics (in HR context)		Performance
Ghasemaghaei and Calic (2020)	Big data characteristics i.e. variety, volume, velocity	Organizational learning theory	Firm performance
Yasmin et al. (2020)	Big data analytics capabilities	Resource based views, and dynamic capabilities view	Firm performance
Ghasemaghaei and Calic (2019)	Big data characteristics, i.e. variety, volume, velocity	Gestalt insight learning theory	Innovation competency
Merendino et al. (2018)	Directors' capabilities for dealing with big data	Knowledge based view	Board level decision-making
Erevelles et al. (2016)	Big data consumer analytics	Resource based view, and dynamic capability view	Marketing transformation, and sustainable competitive advantage
Xu et al. (2016)	Big data analytics	Knowledge fusion taxonomy	New product success
Dubey et al. (2019)	Big data predictive analytics	Resource based view and	Cost performance and operational performance

		institutional theory	
Mikalef et al. (2018)	Big data capabilities (i.e. Planning, Sourcing, Deployment and Management	Dynamic capabilities view	Innovation; Agility; Firm performance

The most recent studies on big data value creation are shown in Table 1. The inclusion criteria for studies in Table 1 is the relevance with big data related capabilities published in last five years. Most of these studies discussed big data analytics capability and very limited studies paid attention to the management of big data, and most studies focused on theoretical framework by using resource-based view (e.g. Dubey et al., 2019; Yasmin et al., 2020) and dynamic capabilities (Erevelles et al., 2016). Shamim et al. (2019b) posited that dynamic capabilities coming from big data are actually KBDCs because big data leads to new knowledge, which in turn enables dynamic capabilities such as innovation. Firm performance as an outcome of big data capabilities is the major focus of existing literature, whilst service innovation and quality are the seldom discussed. Though Several studies on big data analytics highlight the importance of management capabilities, but big data value creation is mainly discussed in terms of performance; some exceptions are Ghasemaghaei and Calic's (2019) study about innovation and decision-making as value creation from big data (Shamim et al., 2019a), thus it indicates that service quality is a comparatively ignored area in big data value creation literature. Consistent with Shamim et al. (2019a) and Mcafee et al. (2012), this study investigates leadership, talent management, technology management, and culture development as BDMCs at the strategic level of organization. Furthermore, following Zeng and Glaister (2018) and Shamim et al. (2019b), data democratization, contextualization, experimentation, and execution are examined as operational level BDMCS. These BDMCs are explained in more detail below.

2.3.1 Strategic level big data management capabilities

Organizations need to integrate their business plan and investment with their IT technology to create an inflexible infrastructure for innovation (Chen et al., 2017; Queiroz et al., 2018). Strategic level capabilities provide directions to organizations and their members through aligning the overall contents of organizational strategy such as mission, vision, goals, strategy implementation and evaluation (Witcher & Chau, 2014). Strategic level capabilities facilitate the provision of resources and nurture a suitable culture and environment. Based on previous research (e.g. McAfee et al., 2012; Gupta & George, 2016), this study is to focus on four aspects of BDMCs at strategic level, namely leadership, talent management, technological resources and organizational cultures.

Leadership: In the context of big data, leadership capability is considered to be the organizational leaders' capabilities of integrating big data in organizational routines. Facing the unprecedented speed of change in the market, Leaders play a crucial role in identifying the need for change and reconfiguring organizational skills to accommodate new routines (Spencer, Buhalis, & Moital, 2012). Leaders with IT management capabilities are willing to invest in the latest technologies to improve organizational performance and explore innovation (Baharuden, Isaac & Ameen, 2019). Leaders are one of the core factors of developing organizations' dynamic capabilities (Koyak et al., 2015) because it requires leaders to identify and invest resources to manage people and develop strategic insight into the market evolvement (Lopez-Cabrales, Bornay-Barrachina & Diaz-Fernandez, 2017). Many organizations use big data, but it is leaders who set the organizations apart from being competitive or incompetent (Spencer et al., 2012). Marshall et al. (2015) using IBM data showed that leaders promoting data quality and making data accessible in organizations can stimulate the creation of new ideas and products. Hence, leadership is one of the determinants of big data adaption and big data analytics (Baharuden & Ameen, 2019). Companies are effective, not only due to their access to extra and healthier data, but primarily because their leadership teams have a clear vision to use big data to set and achieve visionary goals (McAfee et al., 2012).

Talent management: Talent management refers to planning and anticipation of human capital to meet organizational needs (Carpenter, Bauer, Erdogan, & Short, 2013). The purpose is to ensure the availability of the right people in the organization to achieve the desired outcomes and align the human resources with the overall organizational goals and strategies. In the context of this study, talent management refers to the fulfilment of intellectual and human capital needs of the organization for applying big data. The IT capability view posits that the IT staff's capabilities at utilizing IT knowledge at solving business problems will be more likely to succeed at meeting market changes (Kim et al., 2011).

Whilst data become more affordable and accessible for most organizations nowadays, data scientists become more valuable in the job market, where many organizations look for candidates with skills in analysing big data and transferring statistic jargon into a language that managers can understand (McAfee et al., 2012). However, it has been a challenge for many organizations to recruit people with the appropriate IT knowledge, skills and experience to adopt big data (Sivarajah et al., 2016). Maintaining the talent and continuously updating the skills of data analysts becomes critical for many organizations (De Mauro, Greco, Grimaldi, & Ritala, 2018). Due to the increasing value of big data experts, it is becoming increasingly challenging for organizations to retain talented employees with big data analytic skills (Tambe, 2014). Additionally, fostering the IT workforce takes time (Kim et al., 2011). Hence, organizations should maintain their key talents internally (Angrave et al., 2015). People are considered to be a rare and non-substitutable resource; they give organizations a competitive edge over competitors (Bharadwaj, 2000). Maintaining talented people also creates an internal pool for future leaders with IT-orientation (De Mauro et al., 2018).

Technology management: Big data is born with technology advancement. Without the IT infrastructure, it would be challenging to store large volumes of data and to interpret data in a meaningful way. Technology management here is defined as organizational management utilising technologies for value creation through big data. Technological capability is central to enabling the big data usage for data analysis (Chen & Zhang, 2014). Recently there have been prodigious enhancements in the tools, including open source software, needed to handle the dimensions of big data. Hadoop is one of the most common tools that combines open source software with the hardware (McAfee et al., 2012). Big data can be collected by many technological resources - e.g. ubiquitous information-sensing devices, software log identification readers, and sensor technologies and many more. The worldwide technological requirement for the volume of information storage upsurges almost one hundred percent every three years (Chen & Zhang, 2014). Big data has transformed dramatically how firms handle data, as they need superior storage and advanced technologies to collect, store and contact data (Chen & Zhang, 2014). Value creation through big data needs the application of the most front-line technologies to gather, store, examine and envisage data (McAfee et al., 2012).

Data-driven culture: Organizational culture comprises prevailing values, norms and shapes of behaviours that describe the core personality of the firm (Denison, 1984). Culture influences leadership styles, management processes, working climates, organisational behaviours and strategy formulations (Laforet, 2017). Data-driven organizations tend to develop a culture of knowledge-based decision-making instead of relying on hunches and intuitions (McAfee et al., 2012). Some organizations' decisions seem to be data-driven, but actually their decision is based on gut feeling. Such decisions can be too abstract for employees to comprehend, so leaders will have difficulty convincing others. Gupta and

George (2016) stated that data-driven culture affects data-driven decision-making at all levels in organizations. It is crucial for decision-makers to actively engage in big data events and apply big data methodologies in their daily business practice. The present literature on organizational culture in the perspective of DC theory argues that culture can potentially influence organizations' dynamic capabilities (Dubey et al., 2019). These arguments highlight the importance of management towards big data in the development of dynamic capabilities.

2.3.2 Operational level big data management capabilities

Strategic level BDMCs provide visions and resources (e.g. investment on IT infrastructures and appropriate IT-oriented staff and data-driven decision-making) for operational level big data management, but operational level big data management translate the strategic business ideas into reality. Literature on operational level BDMCs is rather limited. Among the very few studies on BDMCs, the framework proposed by Zeng and Glaister (2018) addresses operational level BDMCs. According to the initial exploration of Zeng and Glaister (2018), BDMCs include big data democratization, con-textualization, experimentation, and execution capabilities.

Big data democratization: Big data democratization capability means the firms' ability to transfer big data into more accessible language for employees in need of problem solving. Firms' capability at democratizing data enables an extensive range of data applications, resulting in an improvement in value creation (Zeng & Glaister, 2018). Big data democratization requires data experts and non-data experts to collaborate at data integration across departments. Agile firms make big data accessible and understandable by every relevant person in the organization. Talented staff with data analytical skills in such organizations can assist colleagues in other departments at applying and understanding data. Without such coordination between data experts and non-data experts, it is not easy to create real business values out of big data (Zeng & Glaister, 2018). Strategies intended to access new data and recurrent communications among individuals enable the firm to address the emerging needs for customers (Ajayi, Odusanya, & Morton, 2017).

Big data contextualization: The ability to contextualize data is about the capability of assigning meanings to the data. Contextualize findings provided by big data to gain a complete view can positively contribute to firms' ability at harnessing data for value creation

(Zeng & Glaister, 2018). With a large volume of data, organizations need to have a specific and clear understanding of the context, so that options generated by business analysts can be applied appropriated toward decision-making (Merendino et al., 2018). In order to contextualize the data, organizations not only need human talent at designing algorithms, but also need human intelligence at categorizing the context in which data will have an impact (Günther et al., 2017). Organizations good at harnessing big data collect customer data from multiple channels and magnify the context of their customer needs. Failing to integrate big data results into business practices means that organizations could fail to benefit tremendously from data reports (Zeng & Glaister, 2018).

Big data experimentation: Big data experimentation refers to allow employees to carry out experiments with data and build scenarios. Due to the four characteristics of big data (i.e. volume, velocity, variety and value), it is challenging for employees to gain insights from the data. Zeng and Glaister's study (2018) suggests that a greater tendency to cultivate a culture of learning and experimentation usually has a better conversation rate from the data. The trial and error approach, coupled with greater data accessibility, enhances the chances of value creation through big data (Zeng & Glaister, 2018). Excellent organizations such as 3M, Toyota and Hewlett-Packard have a common characteristic: they allow employees to experiment with new ideas and make mistakes so that innovation can be born from the lessons learnt from failures (Peters & Waterman, 2004). In the digitalization era, big data provides a more predictable pattern, which allows employees to make incremental changes to observe the effect of new ideas on customers.

Big data execution: This refers to the capability to convert data-generated understanding into activities. This operational action can result in the identification of openings for value creation (Zeng & Glaister, 2018). To create great value out of big data, organizations should empower operational employees to act and take decisions based on data insights. Organizations observing the abnormalities evolving from the data can react to the situation responsively. Taking such actions is dependent on the firm's ability to execute data insight (Zeng & Glaister, 2018).

Strategic management literature suggests that strategic level capabilities facilitate the delivery of strategic objectives in daily operations (Witcher & Chau, 2014). This relationship is also evident in the literature about big data and IT capabilities, which we discussed in the above section. Big data demonstration; contextualization, experimentation and execution require leaders to value the contribution of technology on business performance (Bharadwaj et al., 2000) and create a data-driven culture in organizations through positing big data in the heart of their decision-making (McAfee et al., 2012). Decision-making is context-based so that data-driven organizations need to have talented experts, as they can provide multiple options in accordance with different contexts of issues in organizations (Merendino et al., 2018).

With the overwhelming volume of data, it is important for organizations to have leaders and an organizational culture which encourages employees to consider learning through errors. These arguments suggest that strategic level BDMCs can influence operational level BDMCs. This argument is consistent with strategic management literature (Witcher & Chau, 2014). Wamba et al. (2017) argued that in the big data context, technology management and talent, which are strategic level capabilities, could enhance big data analytical capabilities, and process-oriented capabilities, which are operational in nature. Akter et al. (2016) also emphasized that it is a prerequisite for organizations to have technology management and talent management to gain insights from big data. Akter et al. (2016) further argued that without the alignment of capabilities at different levels, organizations cannot reap the benefit of big data. Zeng and Glaister (2018) also acknowledge the key role of leaders in benefiting data democratization, contextualization, experimentation, and execution. Shamim et al. (2019a) is also suggested that leadership, talent management, technology, and culture is associated with operational level BDMCs. There is evidence in literature which suggests that strategic level capabilities such as setting mission and value propositions influence operational level capabilities in the given context, especially if these are KBDCs (Cepeda & Vera, 2007). Based on these arguments, this hypothesis follows:

H_1: Strategic level BDMCs are positively associated with operational level BDMCs.

2.4 Knowledge creation and Big Data Management capabilities

Knowledge creation increasingly becomes a priority in organizations as it contributes to improving organizations' performance and generate new knowledge (Sujatha & Krishnaveni, 2017). Knowledge creation refers to the generation, development, implementation, and exploitation of novel ideas (Sujatha & Krishnaveni, 2017). According to the knowledge-based view, an organization's value comes from its knowledge base (Grant, 1996). Knowledge is also needed to reconfigure the resources to maintain a competitive advantage through innovation. Hence, knowledge is essential for the development of dynamic capabilities (Fuchs et al., 2014) and the most unique strategic assets are knowledge based (Grant, 1996; Donate & De Pablo, 2015). This phenomenon is well integrated in the KBDCs view of the firm, suggesting that dynamic capabilities mainly rely on knowledge resources (Zheng et al., 2011).

Big data is crucial for IT-supported knowledge creation through data analysis. It allows effective decision-making and advances business performance (Acharya, Singh, Pereira, & Singh, 2018). In the tourism and hospitality sector, big data enables hotels to create knowledge about customer preferences and generalize factors influencing loyalty and satisfaction (Xiang et al., 2015). Aggregating real time, contextual information is also critical for the management of customer experience (Buhalis & Sinarta, 2019). Management capabilities as a strategic resource are crucial to create value out of knowledge (Teece, Pisano, & Shuen, 1997; Teece, 2007). This is echoed with many other researchers' findings which posit the importance of leadership (Nonaka, Toyama, & Konno, 2000), talent monument (Jones, 2010) organisational culture (Wang, Su, & Yang, 2011) and technologic management (Acharya et al. 2018). Shamim et al. (2019a) suggest that in order to maximise value, there is a need for BDMCs at strategic level, namely: leadership focus, talent and technology management, and data driven culture. Cepeda and Vera (2007) also argued that strategic level capabilities enhance KBDCs and enable the firm to acquire the required knowledge. These arguments are consistent with the resource-based view and dynamic capabilities view of the firm that value creation from strategic resources requires management capabilities (Teece, 2007; Barney, 1991). Big data is an important strategic resource and based on these arguments, organizations need strategic level management capabilities to create value from big data i.e. knowledge creation. These arguments suggest the following hypothesis:

H_2: Strategic level BDMCs are positively associated with knowledge creation through big data.

Zeng and Glaister (2018) pointed out the importance of operational level BDMCs on knowledge creation based on big data. Democratising, contextualizing, experimenting and executing data can extract meaning from the data, which leads to knowledge creation (Shamim, Cang, & Yu, 2016). Strategic level capabilities are facilitated by operational level capabilities to achieve the desired outcomes such as knowledge creation by aligning the strategic objectives with management and operations (Witcher & Chau, 2014). To achieve the desired organizational outcomes, it is important to align strategic level capabilities with operational competencies. Existing literature argues that most of the companies are good at developing strategies, but they fail to execute the strategies, mainly because of lack of operational alignment and capabilities at strategic level (Neilson et al., 2008).

There is evidence in existing literature that strategic level capabilities can influence operational level capabilities such as management style, and entrepreneurial skill. These operational capabilities mediate the relationship of strategic level capabilities and performance in the given context (Lerner & Almor, 2002). In the context of knowledge creation through big data as the desired outcome, operational level BDMCs can facilitate the relationship between strategic level BDMCs and knowledge creation through big data. Zeng and Glaister (2018) also argued that operational level BDMCs are crucial for knowledge creation through big data. Based on these arguments and logical beliefs we argue that operational level BDMCs can support strategic level BDMCs and knowledge creation. Strategic level BDMCs can create operational level BDMCs, which enhances the process of knowledge creation through big data by accessing, contextualizing, experimenting and applying the big data insights. The democratization of big data enables the firm to access more data, contextualization can add meaning to acquired big data, experimentation and application will enable the firm to understand different patterns in data, and understanding the pattern in data leads to knowledge creation (Shamim et al., 2016). These leads to the following hypotheses:

H_3: Operational level BDMCs are positively associated with knowledge creation through big data.

H_4: Operational level BDMCs mediates the association of strategic level BDMCs and knowledge creation through big data

2.5 Service innovation

The role of service innovations in wellbeing and economic growth is well acknowledged (Den Hertog, Van der Aa, & De Jong, 2010). Innovations refer to the introduction and implementation of new concepts such as product, service and process. In the context of tourism and hospitality, innovations are often developed by new technologies that enhance tourist experiences, new hotel services, new attractions in a destination and improvement of the tours using new technologies to enhance the tourist experience (Carlisle, Kunc, Jones, & Tiffin, 2013; Buhalis & Sinarta, 2019).

Tourism and hospitality organizations face challenges, such as: changing customer demographics, tourist lifestyle, and relatively low barriers to imitation (Presenza, Petruzzelli, & Sheehan, 2019). These challenges make innovation crucial for tourism and hospitality firms to gain a sustainable competitive advantage. Most innovations in tourism and hospitality sector are service oriented. However, service innovations are under-researched in spite of the acknowledgement of the importance of service innovation in developed and developing economies (Luu, 2019).

There is evidence of the positive effect of knowledge on innovativeness (Kim & Lee, 2013), particularly in the hospitality sector. Knowledge through the use of information technology facilitates innovations (Garcia, 2015). Kim and Lee (2013) suggested that knowledge positively affects the service innovativeness in the hospitality sector. Hu et al. (2009) also suggest a positive association of knowledge and service innovation in the hospitality sector. In hospitality operations, knowledge refers to knowledge of customers, competitors, products and services, operational procedures, and job associates (Yang & Wan, 2004). Big data enables the firms to explore unanticipated patterns shown by customers, businesses and marketplaces (Xie, Wu, Xiao, & Hu, 2016), which are crucial for their service innovativeness (Kim & Lee, 2013). Learning from the customer, generated big data refers to co-learning, which is a source of innovation (Jiménez et al., 2015). This suggests that big data-driven knowledge creation can lead to service innovations. In the context of this study, big data plays a vital role in knowledge generation to understand customer preferences. Based on the improved understanding of customers' preferences, hotels use big data to adjust their service to meet customers' needs. Furthermore, innovativeness in an established KBDC, and it heavily relies on knowledge (Donate & de Pablo, 2015). These arguments suggest the following hypothesis:

H_5: Knowledge creation through big data is positively associated with service innovations

2.6 Customer generated online quality ratings

Online ratings can influence organisations' revenue (Nieto-Garcia, Resce, Ishizaka, Occhiocupo, & Viglia, 2019; Viglia, Minazzi, & Buhalis, 2016) and customer bookings in hospitality sector (Gavilan, Avello, & Martinez-Navarro, 2018). In the era of internet, hotels and their customers have access to unlimited information helping them to know each other (Sheng et al., 2019; Rhee & Yang, 2015). Hotels can use online reviews and quality ratings to advertise and improve their services, whilst customers can gain knowledge about hotels through other customers' reviews and comments on websites such as Booking.com, Expedia, TripAdvisor etc. (Rhee & Yang, 2015). Existing studies of online customer ratings either focus on why customers' ratings are important, and what the business outcomes of online ratings are (Gavilan et al., 2018; Nieto-Garcia et al., 2019; Filieri, Raguseo, & Vitari, 2018) or discuss customer-related variables as predictors of online rating consideration, such as customer sentiments (Geetha, Singha, & Sinha, 2017). However, little is known about what capabilities are needed, and how big data-based knowledge creation and innovation can enhance customer-generated online ratings.

Customer sentiments, whether positive, negative or neutral, lead to satisfaction or dissatisfaction on the online quality ratings in the tourism and hospitality industry (Geetha et al., 2017). Big data is a resource to help with the understanding of customer sentiments. For example, online reviews enhance hotel managers' understanding of customer preferences, emotions and their potential future buying behaviour (Xiang et al., 2015). The aggregated online quality rating involves several dimensions, including value for money, staff attitude and behaviour, location, service, cleanliness, facilities, and customer services (Nieto-Garcia et al., 2019). Hotels can improve their online ratings if they know their customers' preferences based on big data analysis.

The KBDCs view argues that knowledge is essential when creating capabilities needed to gain a sustainable competitive advantage (Zheng et al., 2011). It is rational to assume that knowledge generated through customer generated data is one of the most important factors ensuring hotels' competitiveness. This can result in a better customer experience, which should encourage better customer online quality ratings. The role of innovativeness is important in this interaction. Existing literature shows that knowledge creation is one of the most prominent antecedents of innovation (Donate & De Pablo, 2015). Service innovation positively affects customer satisfaction, which leads to good quality ratings (Kiumarsi et al., 2020). The real value of knowledge lies in its application, such as when it leads to innovation. In the context of this study, knowledge creation can improve online ratings if it leads to service innovativeness, hence it can be argued that service innovation mediates the relationship of knowledge creation through big data and online quality rating. This therefore leads to the following hypotheses:

H_6: Knowledge creation through big data is positively associated with customer-generated online quality ratings.

H_7: Service innovation is positively associated with customer-generated online quality ratings.

H_8: Service innovation mediates the association of knowledge creation through big data and customer-generated online quality ratings.

3 Methodology

Following the deductive approach, this study uses quantitative methodology by collecting primary and secondary data. Existing research on big data capabilities has so far paid little attention to understanding the application of big data in underdeveloped and low-tech economies, like Pakistan. This is the first attempt to see the empirical implication of BDMCs in tourism and hospitality research in a developing economy. Quantitative data through structured questionnaires were collected from hotels using Booking.com in Pakistan. It is important to discuss big data capabilities in developing and underdeveloped countries such as Pakistan, where there is a lack of support from home institutions for knowledge creation and innovation.

3.1. Sample and data collection

There are local and foreign chains of hotels operating in Pakistan, such as Marriot, Carlton, Movenpick, Ramada Plaza, Avari, Holiday Inn, and Pearl Continental Hotel etc. The hotel industry in Pakistan is one of the driving forces for the economy, generating a large proportion of the country's revenues (Memon, 2010). Hotels in Pakistan listed on www.booking.com make up the population of this study. Contact details of hotels were gathered through their official websites and through www.booking.com. Contacts were established with senior managers through phone calls, and in some cases personal visits were made.

Questionnaires were distributed by post and via personal visits and emails to the hotels which gave consent to participation in the research at the time of initial contact. We managed to establish contact with senior managers of 364 hotels, out of which 287 hotels agreed to participate in the survey. We collected data from hotels in all major cities of Pakistan. The condition for participating hotels was that the hotel should be registered on www.booking.com. Data was collected for hotels of all sizes enlisted in www.booking.com. Questionnaires were distributed to these 287 hotels and 202 usable questionnaires were returned, with a response rate of 70%. We ensured a high response rate through regular follow upemails and phone calls. Our method of data collection is consistent with similar studies such as Shamim et al. (2017). Senior managers, including general managers and directors representing their hotels, filled in the questionnaires. Authors contacted the hotels several times i.e. to distribute and explain the questionnaires, and to collect the questionnaires. During this time, the authors maintained contact with participants through phone calls and emails. The whole process of data collection took around one year.

In order to mitigate the common method bias mentioned in Podsakoff et al. (2003), we took multiple steps in the design of the questionnaire and post-hoc tests. In the survey design, we kept respondents anonymous, rotated the survey questions randomly and arranged key constructs separately. Furthermore, data were collected into two waves. For post-hoc tests, we carried out Harmon's one-factor test (Podsakoff & Organ, 1986). This only explains 38% of total variance, which indicates that the data common method bias was not significant and unlikely to contaminate the results (Yang et al., 2017).

3.2. Measures

Items measuring strategic level BDMCs were adapted from Shamim et al. (2019a). There were six items to measure leadership, four items to measure talent management, five items to measure technology, and five items to measure data-driven culture. In order to make sure the structure was meaningful and valid, we first used factor analysis to test the reliability and validity of each individual structure before aggregating the items into a single factor.

Operational level BDMCs were measured by items from Shamim et al. (2019b). We also tested reliability and validity before aggregating the items into a single factor. We used seven items to measure big data democratization capability, five items to measure big data contextualization capability, six items to measure data experimentation capability and seven items to measure execution capability. The authors developed five items to measure knowledge creation through big data. A seven-point Likert scale was used to measure all the items, with a scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Service innovation was measured by adapting five items from Donate and De Pablo (2015), assessing the hotels' service innovation performance. Apart from subjective items such as company results and performance, this measure also contained relative items such as comparison of results with competitors. Relative measures are crucial, as innovation effectiveness is explained on the basis of such comparisons (e.g., competitors' performance; firms' own previous years' results) (Zahra & Das, 1993). For service innovation, items ranged from 1 (very low) to 7 (very high). Secondary data on www.booking.com was used for customer-generated online quality ratings. We noted the online quality rating on the questionnaire before forwarding it to each hotel. Online quality ratings were collected from Booking.com for each hotel in the sample. Details of measures for all the variables can be seen in Appendix 1.

3.3 Data analysis

Structural equation modelling was used through Smartpls following partial least square approach for data analysis. PLS is a variance-based approach and it enacts lesser limitations on distribution and sample size (Chin et al., 2003). It is also an effective means to resolve multicollinearity issues (Chin et al., 2003). Reliability of measures was estimated through Cronbach's alpha. Convergent and discriminant validity was calculated by following Fornel and Lardker's (1981) approach which suggests that the factor loadings for all the items in the construct have to be higher than 0.7, however literature suggests that factor loadings higher than 0.65 are also acceptable (Matzler, Renzl & Muller, 2008); the average variance extracted (AVE) of all variables should be greater than 0.50; the AVE should be less than composite reliability (CR) and for discriminant validity, the squared correlation of constructs needs to be less than the squared correlation among constructs.

4 Results

4.1 Reliability and validity

Cronbach's alpha was used to measure the reliability of the constructs. To establish internal consistency and reliability, Cronbach's alpha should be greater than 0.7 (Nunnally &

Bernstein, 1994). Results indicate that Cronbach's alpha value for all the variables was higher than the required value of 0.7. Table 2 results show that the factor loadings for all the construct were higher than the required value of 6.5 and the AVE of all the constructs was higher than 0.50. Table 2 also indicates that the CR of all the constructs exceeded the AVE value. Hence, the convergent validity of all the variables was established. Discriminant validity was established when the squared correlation among the constructs was less than the AVE of each construct (Fornell & Larker, 1981). Table 3 shows that all the constructs met this requirement. The Chi-square value is 421.52, R-square value for outcome variable is 3.4, and the SRMR value is also less than 0.9, which reflected a good model fit. Values of skewness and kurtosis in table 2 indicate that data is normally distributed. Furthermore, the values of VIF in Table 3 suggested that multicollinearity is not a concern in this study.

Table 2. Convergent validity

Variable	Items	Factor loadings	AVE	C.R	Cronbach alpha
Leadership	Lship1	.83	.56	.83	.74
	Lship2	.69			
	Lhip3	.79			
	Lship4	.68			
Talent management	TM1	.70	.61	.85	.78
	TM2	.86			
	TM3	.85			
	TM4	.68			
Culture	Cul1	.76	.71	.90	.87
	Cul3	.78			
	Cul4	.91			
	Cul5	.90			
Technology	Tech1	.72	.61	.86	.79
	Tech2	.73			
	Tech3	.91			
	Tech4	.75			
Data democratization	Dem1	.70	.69	.93	.90
	Dem2	.85			
	Dem3	.87			
	Dem4	.90			
	Dem5	.85			
	Dem6	.79			
Data Contextualization	Con1	.83	.71	.92	.89
	Con2	.85			
	Con3	.88			
	Con4	.89			
	Con5	.75			
Data experimentation	Exp1	.73	.61	.90	.87
	Exp2	.81			
	Exp3	.80			
	Exp4	.79			
	Exp5	.79			
	Exp6	.75			

Data execution	Exe1	.75			
	Exe2	.79			
	Exe3	.84	.65	.90	.86
	Exe4	.87			
	Exe5	.76			
Strategic level BDMCs	Leadership	.65			
	Talent management	.74	.50	.80	.70
	Culture	.76			
	Technology	.68			
Operational level BDMCs	Data democratization	.85			
	Data contextualization	.70	.66	.89	.83
	Data experimentation	.87			
	Data execution	.83			
Knowledge creation through big data	KC1	.73			
	KC2	.86			
	KC3	.88	.70	.92	.89
	KC4	.82			
	KC5	.86			
Service innovation	SI1	.81			
	SI2	.82			
	SI3	.69	.53	.85	.79
	SI4	.66			
	SI5	.68			

Table 3. Discriminant validity

Factors	Mean	SD	Skewness/Kurtosis	VIF	1	2	3	4	5
1- Knowledge creation through big data	3.96	1.93	0.001/-1.57	2.10	**0.7**				
2- Online quality rating	4.29	1.83	-0.04/-1.21	1.06	0.04	**1**			
3- Operational level BDMCs	4.08	1.45	-0.10/-1.31	2.58	0.51	0.05	**0.66**		
4- Service innovation	3.97	1.49	0.06/-1.25	1.50	0.33	0.13	0.28	**0.53**	
5- Strategic level BDMCs	4.21	1.23	-0.01/-0.65	1.44	0.16	0.01	0.35	0.12	**0.5**

Note: AVE of each construct is at diagonal

Another criterion to evaluate the discriminant validity is through the heterotrait-monotrait (HTMT) ratio. The criterion suggests that in order to establish convergent validity, the HTMT ratio for each construct should be less than 0.85. Table 4 shows that all the constructs are meeting the criteria, therefore discriminant validity is established.

Table 4. Heterotrait-Monotrait Ratio (HTMT)

Factors	1	2	3	4
1- Service innovativeness				
2- Knowledge creation through big data	0.662			
3- Operational level BDMCs	0.61	0.835		
4- Stratetic level BDMCs	0.424	0.501	0.756	
5- Online quality ratings	0.413	0.234	0.245	0.245

4.2 Structural model and hypotheses testing

PLS was used to test the hypotheses. Firstly, the direct association of strategic level BDMCs with operational level BDMCs was examined. Then, the direct association of strategic and operational level BDMCs with knowledge creation through big data was tested. After testing these direct associations, the mediating effect of operational level BDMCs in the relationship of strategic level BDMCs and knowledge creation was tested. Finally, the association of knowledge creation through big data with service innovation and online quality rating was examined.

The results in Table 5 indicate that there was a direct and significant association between strategic and operational level BDMCs ($\beta = 0.59$, $p < 0.001$), hence H1 was accepted. The direct association of knowledge creation through big data at strategic ($\beta = 0.40$, $p < 0.001$) and operational level BDMCs ($\beta = 0.75$, $p < 0.001$) was also significant. These findings support H2 and H3. Results also indicated that operational level BDMCs mediate the relationship of strategic level BDMCs and knowledge creation through big data ($\beta = 0.45$, $p < 0.001$).

Our results suggest that after entering the mediator in the model, the direct effect of strategic level management capabilities on knowledge creation became insignificant ($\beta = -0.05$, $p > 0.05$), which indicated full mediation; this led to the acceptance of H4. Results also supported the positive association of knowledge creation through big data with service innovation ($\beta = 0.658$, $p < 0.001$) and online customer rating ($\beta = 0.22$, $p < 0.001$). These findings supported H5 and H6. Service innovation was also positively associated with the online quality rating ($\beta = 0.36$ $p < 0.001$); furthermore, it also mediated the relationship of knowledge creation through big data and the online quality rating ($\beta = 0.21$, $p < 0.001$). After entering service innovation as the mediator into the model, the direct association of knowledge creation and online quality rating became insignificant ($\beta = 0.01$, $p > 0.05$); this showed that there was a full mediation of service innovation in this relationship. These findings support H7 and H8.

Table 5. Path analysis

Path	Direct effects β/t-value	Indirect effects β/t-value	Total effects β/t-value	Hypotheses	Result
Strategic level BDMC → Operational level BDMC	.59***/15.70			H1	Accepted
Strategic level BDMC → Knowledge creation through big data	.40***/6.48			H2	Accepted
Operational level BDMC → Knowledge creation through big data	.75***/14.58	.		H3	Accepted
Strategic level BDMC → Operational level BDMC → Knowledge creation through big data	-.050/.70	45***/9.69	.40***/6.83	H4	Accepted
Knowledge creation through big data → Service innovation	.58***/13.86			H5	Accepted
Knowledge creation through big data → Online quality rating	.22***/3.73			H6	Accepted
Service innovation → Online quality rating	.36***/3.95			H7	Accepted
Knowledge creation through big data → Service innovation → Online quality rating	.01/.11	.21***/3.88	.22***/3.77	H8	Accepted

5. Discussion

Results are consistent with Teece (2007), which suggests that dynamic capabilities exist at all levels in organizations. Teece (2007) suggested that dynamic capabilities empower the firms to create and organise intangible assets such as knowledge, then knowledge creation leads to better business outcomes. The grounds for dynamic capabilities are the distinctive skills, processes, procedures, organizational arrangements, decision-making mechanisms and disciplines (Teece, 2007). Our findings suggest that strategic and operational level capabilities are positively related with knowledge creation, and operational level capabilities fully mediate the relationship of strategic level capabilities and knowledge creation. Having BDMCs at the strategic level is not sufficient. Organizations, i.e. hotels in the context of this study, need to work on improving operational level capabilities in order to align strategic level capabilities with the desired outcomes. Different from many research studies looking at BDMC as a whole (Wamba et al., 2017), or solely focusing on either level of BCMC (strategic level or operational level) such as (Zeng & Glaister, 2018), this study shows that hotels that want to generate service innovation need to have leaders who are good at identifying and nurturing talented people who excel at data analysis, and have organizational cultures encouraging data-informed decision-making. With the awareness of value creation through big data at the strategic level, hotels will be able to integrate the results of data gained from operational levels, such as social information exchanges, market interactions and customer calls to service innovation.

Findings are also consistent with strategic management literature suggesting that the operational level capabilities of organizations can be influenced by strategic level capabilities (Witcher & Chau, 2014). Strategic level capabilities are broader in nature and can facilitate the implementation of strategies at operational level. Strategic level capabilities ensure the delivery of strategic objectives in daily management, and operational level capabilities facilitate the alignment of strategic proclivities with the desired goals (Witcher & Chau, 2014). This study argues that BDMCs are crucial for value creation out of big data. These capabilities play a particularly crucial role in enhancing knowledge creation, and knowledge creation contributes to service innovation and better online quality ratings. This study provides empirical evidence for the theoretical framework proposed by Zeng and Glaister (2018) about the positive impact of management capabilities on value creation through big data. Hence, the strategic capability is the precursor to data management capabilities; it determines how the data is democratized and contextualized and also has an influence on employees' willingness to apply big data to their decision-making (Zeng & Glaister, 2018).

Online quality ratings reflect the overall customer experience and influences customers when making future bookings. Our findings suggest that the hotel's BDMCs are important in this context, because BDMCs enhance service innovation through the mediation of knowledge creation through big data. According to the results, hotels with a high level of service innovation receive a higher online quality rating by customers. Big data enables hotels to understand their customers through knowledge creation and that knowledge assists the hotels to enhance their service innovation, which ultimately results in higher online customer ratings. BDMCs play a key role in this process of value creation through big data. Results of data analysis support these arguments. This shows that online customer ratings, service innovation and knowledge creation through big data are related in a recycling relationship. Existing research mainly focuses on the advantage of using online customer reviews as a resource for information to enhance an organizations' knowledge and create service innovation through analysing big data gathered through customers' reviews (Xiang et al., 2015). However, this study suggests that customer ratings can a result in recycling influence via service innovation.

5.1. Theoretical Contribution

The contributions of the study are threefold. First, this study empirically tested Teece's (2007) theoretical suggestion on dynamic capabilities at the strategic and operation level and found that the two levels of capabilities are positively related. The results also extend the current understanding of the inextricably interwoven relationship between these two levels of capability (e.g. Chen et al. 2012). We established that organizations need BDMCs at both strategic and operational levels for value creation from big data, as neither of them alone is not sufficient. In the context of big data, it is important to distinguish the two capabilities, but it is equally important to emphasize the inseparable relationship of the two capabilities.

Second, the study contributes to the understanding of the role of operational level capability in knowledge creation. Zeng and Glaister (2018) analysed how organizations transform big data internally and externally to create knowledge and other values. This study extends' Zeng and Glaister's (2018) study by pointing out that this direct relationship requires strategic level capabilities as a prerequisite. In other words, organizations without appropriate strategic capabilities (e.g. leaders with IT management capability, talented staff and a data-driven culture) will face difficulties with creating operational level capabilities to create value from big data.

Third, this study empirically tested the role of knowledge creation through big data on service innovation and customer-generated online quality ratings in the hospitality industry. Existing studies on big data in the hospitality industry mainly focus on illustrating the importance of predicting customers' behaviour through data mining (see a literature review carried out by Mariani et al., 2018). Instead of focusing on techniques of analysing big data like many previous studies, this is one of the rare studies examining service innovation as value creation through big data by showing that knowledge creation through big data can enhance dynamic capability, such as service innovation in the hospitality sector.

5.2. Implications for practice

Success in contemporary businesses depends on how quickly the businesses respond to changes in the market. This research, as with McAfee et al.'s (2012), suggests the leaders in data-driven organizations should foster an organizational culture to make decisions based on data analysis and should have leaders with IT capabilities to facilitate the operational level of data analysis. With the application of artificial intelligence and robotic technology, many jobs in the service industry are replaced by machines. However, in practice, the data generated by these technologies requires people to translate statistics into more accessible language for managers. Therefore, organizations should invest in fostering talent in analytical skills in big data.

The results also imply that practitioners can apply big data analysis in organizational business practice to facilitate service innovation. With increasing assessable data in the service industry, it is easy for people in organizations to be overwhelmed by big data's volume, velocity and variety. Access to big data does not guarantee the success of the company; it requires business analysts to transfer the complex data into meaningful knowledge. Lack of awareness of value creation through big data can cause devastating consequences, such as the collapse of the UK iconic travel company, Thomas Cook (Verdict, 2019).

In the hospitality sector, big data can be used for value creation such as improved customer satisfaction, loyalty, understanding the patterns of customer behaviour (Xiang et al., 2015), helpfulness, and ratings (Xiang et al., 2017). Based on the knowledge created through big data, hospitality firms can improve their service innovativeness. The findings of this study also suggest that hotels should now limit the value of big data to knowledge creation, but they must translate that knowledge into service innovation. Only then, big data capabilities and knowledge created through big data, leads to better online quality ratings. Without service innovation, the link is missing. However, achieving these outcomes using big data is not simple. ~~Xiang et al. (2017) argues that there are huge inconsistencies and complexities in terms of big data on platforms like Expedia, Tripadvisor and Yelp. Big data can vary a lot on different platforms. For example, in the case of textual big data there are challenges associated with linguistic characteristics, semantic features, ratings, sentiments, and usefulness (Xiang et al., 2017).~~

In order to overcome these challenges and create value out of dynamic big data, hotels need to develop dynamic capabilities at the strategic and operational level. This study also shows that the operational level of BDMCs is a mediator of the relationship between strategic level BDMCs and knowledge creation through big data. This result empirically informs the managers that the results of big data analysis should be made accessible to operational level employees. Often in industry it is the case that managers do not rely on the data to make informed decisions; instead, they cherry-pick data to back up their intuition-based decisions (Mcafee et al., 2012). This can underutilise big data and prevent organizations from exploring opportunities in service/product innovation. Big data becomes valuable for organizations only if organizations use the data and respond to it in a timely manner (Zeng & Glaister, 2018). Many organizations have already given autonomy to employees, who react to the data regularly at the operational level without spending months waiting for an order from senior managers.

Our findings suggest managers that they should not solely rely on strategic level BDMCs, because strategic managers alone are not likely to implement the strategies designed for big data value creation. Most of the firms can design a very good strategy but the loose the major portion of strategy in the implementation phase. It is mainly because of lack of alignment of strategy and relevant capabilities at all levels in the organizations. This is one of the main key take away of this study for managers that along with focusing on BDMCs at strategic level; they should also focus of creating and enhancing BDMCs at operational level in the organization. Only then, they can achieve the desired result for BDMCs.

At strategic level, leaders should provide a clear vision regarding digital transformations, set clear goals, encourage big data driven decision-making, show great interest in big data, and be active in managing big data. Talent managers should hire employees who understand big data. They should also provide trainings to enhance big data skills of staff, and take steps to retain the existing big data expert in organization. Managers should ensure the availability of suitable technologies to manage big data. They should plan to enhance the technological competency to use variety of technological tools to manage big data. Furthermore, mangers should create a data driven culture, and make big data decision-making a part of organizational routine.

At operational level, managers should ensure that employees have the ability to access, understand, interpret, and contextualize big data. Mangers should encourage employees to do experiments with big data to monitor changes and come up with new things to test big data. "Trial and error" with the data should be a routine matter. Mangers should ensure that employees are able to transform big data insights into action. Employees should be able to respond to the data in a timely manner, by observing the abnormalities emerging from data and monitoring market trends and customer activities.

5.3. Limitations and Future Studies

This study has some limitations. Firstly, data collection is limited to the hospitality sector.

Secondly, cross-sectional research design is subject to common method bias. However, appropriate measures were taken to reduce this possibility. Harmon's one-factor test explains 38% of total variance, which indicates that common method bias is not significant and is unlikely to contaminate the results (Yang et al., 2018). Another limitation of this study is the low value of R-square i.e. 3.4 which indicates a low explanatory power of the model, so a large part of the variability is still unexplained by the model. This could be due to some factors not being included in the model. For instance, big data analytics capability (Wamba et al., 2017). Thus, future research is needed in order to better the understanding of big data value creation in relation to BDMCs.

In order to maintain the model parsimony, this study does not examine the mediating role of knowledge creation through big data in the relationship of strategic and operational level BDMCs with service innovation and online quality ratings. Future research should expand research findings in other sectors and contexts. This would be an interesting research area for the future to examine the mediating role of knowledge creation through big data in the given model. Furthermore, future research can categorize innovation as radical, incremental and ambidextrous in relation with BDMCs. With respect to BDMCs, big data governance capabilities can also create value for business, so future research can also examine the issue related to big data governance such as relational governance and contractual governance.

5.4. Conclusion

This study concludes that strategic level BDMCs (leadership, talent management, technology, culture) and operational level BDMCs (data democratization, contextualization, experimentation, and execution) are interrelated. Organizations looking to create value from big data will need both strategic and operational level BDMCs. without either level of the BDMCs will not be sufficient for organizations to create knowledge from big data. The results of this study indicate strategic and operational level BDMCs enable the hospitality firms to create new knowledge through big data and enhance innovativeness and online quality ratings. Knowledge creation through big data can boost the online quality ratings through the mediation of service innovation in the hospitality sector.

References

Acharya, A., Singh, S. K., Pereira, V., & Singh, P. (2018). Big data, knowledge co-creation and decision making in fashion industry. *International Journal of Information Management*, *42*, 90-101.

Ahmed, N. (2018). Big data and urban planning in Pakistan: A case study of the urban unit. https://yorkspace.library.yorku.ca/xmlui/handle/10315/35957

Ajayi, O. M., Odusanya, K., & Morton, S. (2017). Stimulating employee ambidexterity and employee engagement in SMEs. *Management Decision, 55*(4), 662-680.

Akhtar, P., Frynas, J. G., Mellahi, K., & Ullah, S. (2019). Big Data- Savvy teams' skills, big data- driven actions and business performance. *British Journal of Management*, *30*(2), 252-271.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment. *International Journal of Production Economics, 182*, 113-131.

Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: Why HR is Set to Fail the Big Data Challenge. *Human Resource Management Journal*, *26*(1), 1-11. Baharuden, A. F., Isaac, O., & Ameen, A. (2019). Factors Influencing Big Data & Analytics Learning Intentions with Transformational Leadership as Moderator Variable: Malaysian SME Perspective. *International Journal of Management and Human Science*, 3(1), 10-20.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99-120.

Bharadwaj, A. (2000). A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation. *MIS Quarterly*, *24*(1), 169-196.

Buhalis, D., & Sinarta, Y. (2019), Real-time co-creation and nowness service: lessons from tourism and hospitality, *Journal of Travel and Tourism Marketing*, *36*(5), 563-582.

Buhalis, D., Harwood, T., Bogicevic, V., Viglia, G., Beldona, S., Hofacker, C. (2019). Technological disruptions in Services: Lessons from Tourism and Hospitality, *Journal of Service Management*, (4), 484-506.

Buhalis, D., & Foerste, M. (2015). SoCoMo Marketing for Travel and Tourism: empowering co-creation of value, *Journal of Destination Marketing & Management*, *4*(3), October, 151–161.

Cepeda, G., & Vera, D. (2007). Dynamic capabilities and operational capabilities: A knowledge management perspective. *Journal of business research*, *60*(5), 426-437

Chen, C. P., & Zhang, C. (2014). Data-intensive applications, challenges, techniques and technologies: A survey on big data. *Information Sciences, 275*, 314-347.

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least square latent variable modelling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research, 14*(2), 189-217.

Chua, A., Servillo, L., Marcheggiani, E., & Moere, A. V. (2016). Mapping Cilento: Using geotagged social media data to characterize tourist flows in southern Italy. *Tourism Management, 57*, 295-310.

De Mauro, A., Greco, M., Grimaldi, M., & Ritala, P. (2018). Human resources for big data professions: A systematic classification of job roles and required skill sets. *Information Processing & Management*, *54*(5), 807-817.

Den Hertog, P., Van der Aa, W., & De Jong, M. W. (2010). Capabilities for managing service innovation: Towards a conceptual framework. *Journal of Service Management, 21*(4), 490-514.

Denison, D. R. (1984). Bringing corporate culture to the bottom line. *Organizational Dynamics, 13*(2), 5-22.

Donate, M. J., & de Pablo, Jess D Sanchez. (2015). The role of knowledge-oriented leadership in knowledge management practices and innovation. *Journal of Business Research, 68*(2), 360-370.

Dubey, R., Gunasekaran, A., Childe, S, Blome, C., Papadopoulos, T. (2019), Big data and predictive analytics and manufacturing performance: integrating institutional theory, resource-based view and big data culture, *British Journal of Management*, *30,* 341-361.

E Silva, F. B., Herrera, M. A. M., Rosina, K., Barranco, R. R., Freire, S., & Schiavina, M. (2018). Analysing spatiotemporal patterns of tourism in Europe at high-resolution with conventional and big data sources. *Tourism Management*, *68*, 101-115.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research*, *69*(2), 897-904.

Filieri, R., Raguseo, E., & Vitari, C. (2018). When are extreme ratings more helpful? Empirical evidence on the moderating effects of review characteristics and product type. *Computers in Human Behavior*, *88*, 134-142.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Fuchs, M., Höpken, W., & Lexhagen, M. (2014). Big data analytics for knowledge generation in tourism destinations – A case from Sweden. *Journal of Destination Marketing & Management*, *3*(4), 198-209.

García-Álvarez, M. T. (2015). Analysis of the effects of ICTs in knowledge management and innovation: The case of Zara Group. *Computers in Human Behaviour*, *51,* 994-1002.

Gavilan, D., Avello, M., & Martinez-Navarro, G. (2018). The influence of online ratings and reviews on hotel booking consideration. *Tourism Management*, *66*, 53-61.

Geetha, M., Singha, P., & Sinha, S. (2017). Relationship between customer sentiment and online customer ratings for hotels-an empirical analysis. *Tourism Management*, *61*, 43-54.

Ghasemaghaei, M., & Calic, G. (2020). Assessing the impact of big data on firm innovation performance: Big data is not always better data. *Journal of Business Research*, *108*, 147-162.

Ghasemaghaei, M., & Calic, G. (2019). Does big data enhance firm innovation competency? The mediating role of data-driven insights. *Journal of Business Research*, *104*, 69-84.

Grant, R. M. (1996). Toward a knowledge- based theory of the firm. *Strategic Management Journal*, *17* (S2), 109-122.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, *70*, 308-317.

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*, 1049–1064.

Gutierrez-Gutierrez, L. J., Barrales-Molina, V., & Kaynak, H. (2018). The role of human resource-related quality management practices in new product development: A dynamic capability perspective. *International Journal of Operations & Production Management*, *38*(1), 43-66.

Hashem, I. A. T., Yaqoob, I., Anuar, N. B., Mokhtar, S., Gani, A., & Khan, S. U. (2015). The rise of "big data" on cloud computing: Review and open research issues. *Information Systems*, *47*, 98-115.

Imran, M. (2018). Influence of industry 4.0 on the production and service sectors in pakistan: Evidence from textile and logistics industries. *Social Sciences*, *7*(12), 246.

Jiménez-Zarco, A. I., González-González, I., Martínez-Ruíz, M. P., & Izquierdo-Yusta, A. (2015). New service innovation success: Analyzing the influence of performance indicator nature. *Computers in Human Behavior*, *51*, 1024-1031.

Khan, Z., Lew, Y. K., & Marinova, S. (2019). Exploitative and exploratory innovations in emerging economies: The role of realized absorptive capacity and learning intent. *International Business Review*, *28*(3), 499-512.

Kim, Gimun; Shin, Bongsik; Kim, Kyung Kyu; & Lee, Ho Geun. (2011). IT Capabilities, Process-Oriented Dynamic Capabilities, and Firm Financial Performance, *Journal of the Association for Information Systems*: *12*(7), 487-517.

Kim, T. T., & Lee, G. (2013). Hospitality employee knowledge-sharing behaviours in the relationship between goal orientations and innovative work behaviour. *International Journal of Hospitality Management*, *34*, 324-337.

Kiumarsi, S., Isa, S. M., Jayaraman, K., Amran, A., & Hashemi, S. (2020). The effect of service innovation on service loyalty in post offices. *International Journal of Business Innovation and Research*, *21*(1), 108-127.

Laforet, S. (2017). Effects of organisational culture on brand portfolio performance. *Journal of Marketing Communications*, *23*(1), 92-110.

Lerner, M., & Almor, T. (2002). Relationships among strategic capabilities and the performance of women- owned small ventures. *Journal of small business management*, *40*(2), 109-125.

Li, J., Xu, L., Tang, L., Wang, S., & Li, L. (2018). Big data in tourism research: A literature review. *Tourism Management*, *68*, 301-323.

Li, X., Pan, B., Law, R., & Huang, X. (2017). Forecasting tourism demand with composite search index. *Tourism Management*, *59*, 57-66.

Luu, T. T. (2019). Can diversity climate shape service innovative behaviour in Vietnamese and Brazilian tour companies? The role of work passion. *Tourism Management*, *72*, 326-339.

Mariani, M. M., & Borghi, M. (2018). Effects of the booking.com rating system: Bringing hotel class into the picture. *Tourism Management*, *66*, 47-52.

Matzler, K., Renzl, B., Muller, J., Herting, S., & Mooradian, T. A. (2008). Personality traits and knowledge sharing. *Journal of Economic Psychology*, *29*(3), 301-313.

McAfee, A., Brynjolfsson, E., & Davenport, T. H. (2012). Big data: The management revolution. *Harvard Business Review*, *90*(10), 60–68.

Memon, A. N. (2010). *Analysis of presumptive income tax for small business in informal economies: a case of Pakistan* (Doctoral dissertation, PhD Thesis, University of New South Wales).

Merendino, A., Dibb, S., Meadows, M., Quinn, L., Wilson, D., Simkin, L., & Canhoto, A. (2018). Big data, big decisions: The impact of big data on board level decision-making. *Journal of Business Research*, *93*, 67-78.

Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2018). Big data analytics capabilities: a systematic literature review and research agenda. *Information Systems and e-Business Management*, *16*(3), 547-578.

Ministry of commerce (2019). E-commerce policy of Pakistan. http:// www. Commerce . gov .pk / ecommerce – policy - 2019/

Neilson, G. L., Martin, K. L., & Powers, E. (2008). The secrets to successful strategy execution. *Harvard business review*, *86*(6), 60.

Nieto-Garcia, M., Resce, G., Ishizaka, A., Occhiocupo, N., & Viglia, G. (2019). The dimensions of hotel customer ratings that boost RevPAR. *International Journal of Hospitality Management*, *77*, 583-592.

Nieves, J., Quintana, A., & Osorio, J. (2016). Organizational knowledge, dynamic capabilities and innovation in the hotel industry. *Tourism and Hospitality Research, 16*(2), 158-171.

Nonaka, I., Toyama, R., & Konno, N. (2000). SECI, ba and leadership: A unified model of dynamic knowledge creation. *Long Range Planning, 33*(1), 5-34.

Nunnally, C. & Bernstein, I. (1994). The assessment of reliability. *Psychometric Theory, 3,* 248-292.

Peters, T. & Waterman, R. (2004). In search of excellence: lessons from America’s best-run companies. USA: Harper Business Essentials.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology*, *88*(5), 879.

Presenza, A., Petruzzelli, A. M., & Sheehan, L. (2019). Innovation through tradition in hospitality. The Italian case of Albergo Diffuso. *Tourism Management*, *72*, 192-201.

Raun, J., Ahas, R., & Tiru, M. (2016). Measuring tourism destinations using mobile tracking data. *Tourism Management*, *57*, 202-212.

Rhee, H. T., & Yang, S. B. (2015). Does hotel attribute importance differ by hotel? Focusing on hotel star-classifications and customers' overall ratings. *Computers in Human Behavior, 50*, 576 587.

Shah, N. Irani, Z. & Sharif, A. (2017). Big data in an HR context: exploring organizational change readiness, *Employee Attitudes and Behaviour*, *70,* 366-378.

Shamim, S., Zeng, J., Shariq, S. M., & Khan, Z. (2019a). Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capabilities view. *Information & Management*, *56*(6), 103135.

Shamim, S., Zeng, J., Choksy, U. S., & Shariq, S. M. (2019b). Connecting big data management capabilities with employee ambidexterity in Chinese multinational enterprises through the mediation of big data value creation at the employee level. *International Business Review*, 101-604.

Shamim, S., Cang, S., & Yu, H. (2017). Impact of knowledge-oriented leadership on knowledge management behaviour through employee work attitudes. *The International Journal of Human Resource Management*, 1-31.

Shamim, S., Cang, S., & Yu, H. (2016). Influencers of information system usage among employees for knowledge creation. A future research agenda. In *10th International Conference on Software, Knowledge, Information Management & Applications (SKIMA)* (pp. 134-141). IEEE.

Sheng, J., Amankwah- Amoah, J., Wang, X., & Khan, Z. (2019). Managerial responses to online reviews: A text analytics approach. *British Journal of Management*, *30*(2), 315-327.

Shoval, N., & Ahas, R. (2016). The use of tracking technologies in tourism research: The first decade. *Tourism Geographies, 18*(5), 587-606.

Spencer, A., Buhalis, D., Moital, D., (2012). A hierarchical model of technology adoption for small owner-managed travel firms: An organizational decision-making and leadership perspective, *Tourism Management*, *33*, 1195-1208.

Sujatha, R., & Krishnaveni, R. (2017). Knowledge creating ba as a determinant of work performance of employees: An empirical analysis among pump manufacturing firms in south India. *Asia Pacific Management Review, 23(1),* 45-52.

Talon-Ballestero, P., Gonzalez-Serrano, L., Soguero-Ruiz, C., Munoz-Romero, S., & Rojo-Alvarez, J. L. (2018). Using big data from customer relationship management information systems to determine the client profile in the hotel sector. *Tourism Management*, *68*, 187-197.

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal, 28*(13), 1319-1350.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509-533.

Uriarte, F. (2008). Introduction to knowledge management. *Jakarta: ASEAN Foundation,*

Viglia, G., Minazzi, R., Buhalis, D., 2016, The influence of e-word-of-mouth on hotel occupancy rate, *International Journal of Contemporary Hospitality Management*, *28(9),* 2035–2051.

Vu, H. Q., Li, G., & Law, R. (2015). Exploring the travel behaviors of inbound tourists to Hong Kong using geotagged photos. *Tourism Management*, *46*, 222-232.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70*, 356-365.

Wang, D., Su, Z., & Yang, D. (2011). Organizational culture and knowledge creation capability. *Journal of Knowledge Management, 15*(3), 363-373.

Witcher, B. J., & Chau, V. S. (2014). *Strategic management: Principles and practice*, Cengage Learning.

Xiang, Z., Du, Q., Ma, Y., & Fan, W. (2017). A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism. *Tourism Management, 58*, 51-65.

Xiang, Z., Schwartz, Z., Gerdes Jr, J. H., & Uysal, M. (2015). What can big data and text analytics tell us about hotel guest experience and satisfaction? *International Journal of Hospitality Management, 44*, 120-130.

Xie, K., Wu, Y., Xiao, J., & Hu, Q. (2016). Value co-creation between firms and customers: The role of big data-based cooperative assets. *Information & Management, 53*(8), 1034-1048.

Xu, Z., Frankwick, G. L., & Ramirez, E. (2016). Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. *Journal of Business Research, 69*(5), 1562-1566.

Yasmin, M., Tatoglu, E., Kilic, H. S., Zaim, S., & Delen, D. (2020). Big data analytics capabilities and firm performance: An integrated MCDM approach. *Journal of Business Research, 114*, 1-15.

Yang, Y., Secchi, D., & Homberg, F. (2018). The relationship between personality and organisational learning. *Journal of Business Research, 85*, 155–164.

Zahra, S. A., & Das, S. R. (1993). Innovation strategy and financial performance in manufacturing companies: An empirical study. *Production and Operations Management, 2*(1), 15-37.

Zeng, J., & Glaister, K. W. (2018). Value creation from big data: Looking inside the black box. Strategic Organization, 16(2), 105-140.

Zheng, S., Zhang, W., & Du, J. (2011). Knowledge-based dynamic capabilities and innovation in networked environments. *Journal of Knowledge Management, 15*(6), 1035-1051.

Zia, N. U. (2020). Knowledge-oriented leadership, knowledge management behaviour and innovation performance in project-based SMEs. the moderating role of goal orientations. *Journal of Knowledge Management,*

Appendix 1

Questionnaire

Answer these questions using the following scale
1=Strongly disagree, 2=Disagree, 3=Slightly disagree, 4=Neither disagree nor agree, 5=Slightly agree, 6=Agree, 7=Strongly agree

Knowledge creation through big data

1. Big data helps us to understand our customers in better way
2. In our hotel, big data play a crucial role in IT-supported knowledge creation
3. We take decisions based on the analysis of big data
4. Big data analysis often leads to new knowledge related to our business
5. Big data increases our knowledge of customer preferences

Strategic level big data management capabilities *(Shamim et al., 2019a)*

Leadership
1. Our leadership provides a clear vision
2. Our leadership sets clear goals
3. Our leadership encourages big data decision-making
4. Our leadership shows great interest in the big data chain
5. Our leadership shows concern for the use of big data
6. Our leadership is very active in managing big data

Talent management
1. We prefer to hire employees who understand big data
2. We have the ability to recruit expert users of big data
3. We plan to enhance the big data management skills of our staff
4. We take special care in the retention of big data experts in our organisation

Technology
1. We use the latest technology to manage big data
2. Our technological competency helps us to enhance big data management
3. We use a variety of technological tools to manage big data
4. Our big data technological tools are more effective than those used by others in the industry
5. We face technological problems in managing big data*

Culture
1. Our decisions are based on data
2. A dependency on hunches for decision-making is strongly discouraged in our organisation
3. Depending on data is part of our organisational routine
4. We have a culture of data driven work
5. Our executives use lots of data to justify decisions they have already taken through traditional approaches*

Operational level big data management capabilities *(Shamim et al., 2019b)*

Data democratization
1. We have the ability to access big data when it is needed at any given time
2. We have the ability to understand big data where it is needed

3. The sheer volume of big data creates problems for us to deal with it*
4. We have the ability to understand the data of different departments
5. We can use a wide range of big data applications
6. We have the ability to break down data barriers

Data contextualization

1. We have the ability to interpret big data
2. We can identify contextual clues in big data
3. Based on the data, we can see the connection between "individual customers" and "their everyday lives"
4. Based on the data, we can understand the scenarios that drive customers to make decisions
5. It is difficult for us to understand the context of big data

Data experimentation

1. We do experiments with big data to monitor changes
2. We have the ability to come up with new things to test big data
3. "Trial and error" with the data is a routine matter for us
4. For us, data are a scary set of numbers*
5. We do not know how to start experimentation with data*
6. We prefer not to mess with the data*

Data execution

1. We can transform big data insights into actions
2. We often use big data to modify our decisions
3. We respond to the data in a timely manner
4. When we observe any abnormality emerging from the data, we react to the situation in real time
5. We monitor market trends/customer activities through data tools based on historical and real time data

Service innovation *(Donate & De Pablo, 2015)*

Assessment of the level of innovation performance in the last year for this hotel with regard to: **(from 1–very low to 7–very high):**

1. Development of new services.
2. Modification and/or improvement of existing services.
3. Introduction of more innovative services than major competitors.
4. Introduction of more innovative services than the industry average.
5. Introduction of more innovative services than three years ago.

1