

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

3
4 **Abstract:**

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

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

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1 **1. Introduction**

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

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

25 Big data refers to data characterized by huge volume; velocity; variety; and value
26 (Ghasemaghaei & Calic, 2020). With the advanced mobile and Web 2.0 technology available,
27 tourism industries generate big data through devices and operations (Li et al., 2018). Big data
28 can be user/customer generated by using the platforms of tourist firms, such as hotels and
29 restaurants, and by third-party agents such as customer reviews on Expedia, Skyscanner and
30 Booking.com (Xiang et al., 2015). Big data can also be collected through social media like
31 Facebook, Twitter and LinkedIn (Chua, Servillo, Marcheggiani, & Moere, 2016) as well as
32 review sites such as TripAdvisor and Yelp (Viglia, Minazzi, & Buhalis, 2016). These data are

1 accessible to all tourism and hospitality firms, but the ability of firms at managing big data
2 varies. While some organizations do little about these data, others make full use of big data to
3 assist them with their product design and understanding of customer behaviour.

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

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

1 activity. Hence, we assume operational level BDMCs mediate the relationship of strategic level
2 BDMCs and knowledge creation.

3 Using the new knowledge gained through big data analysis, organizations are able to
4 adjust or radically change their current service to meet the demands of the external market
5 (Buhalis & Sinarta, 2019; Buhalis & Foerste, 2015). This value creation practice relies on the
6 organizations' dynamic capability of applying the knowledge extracted from big data to
7 improve service outcomes and co-create tourism experiences (Nieves, Quintana, & Osorio,
8 2016). This study investigates the influence of BDMCs (i.e. strategic and operational level) on
9 knowledge creation, and investigates the influence of knowledge creation on hotel service
10 innovation and customer quality ratings on www.booking.com, one of the most commonly
11 used infomediaries for hotel bookings. This study also examines how strategic level
12 capabilities indirectly influence knowledge creation through the mediation of operational level
13 BDMCs. Furthermore, the influence of knowledge creation through big data on a hotel's
14 service innovation and customer quality ratings on infomediaries (i.e. www.booking.com) is
15 also investigated. Sources of external knowledge can stimulate innovation (Khan, Lew, &
16 Marinova, 2019). By investigating these issues, this study aims to answer the research question
17 of how BDMCs enhance KBDCs i.e. service innovativeness which leads to better online quality
18 ratings?

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

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2. Literature review and hypotheses

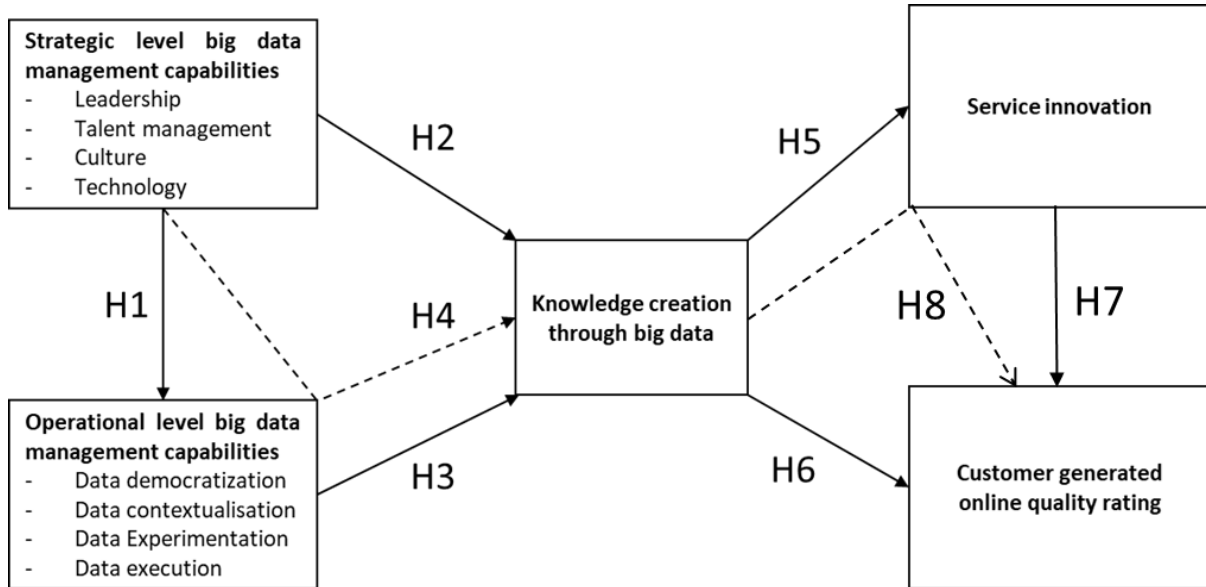
2.1. Knowledge-based dynamic capabilities view

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

1 creation (Uriarte, 2008). Existing studies have also used the KBDC framework to justify the
 2 relationship of strategic level capabilities, knowledge, and innovation (Zia, 2020). Based on
 3 these arguments and theoretical grounds we propose and test the conceptual model shown in
 4 figure 1.



5
 6 **Figure 1.** Conceptual model
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9 **2.2. Big data in tourism and the hospitality sector**

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

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

14

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

20 *2.3. Big data management capabilities*

21 BDMCs are the dynamic capabilities (Shaimm et al., 2019a), enabling organizations to sense
22 and seize opportunities to create value from big data. Dynamic capabilities can exist at all
23 levels in the organization such as individual, organizational, strategic, and operational levels
24 (Teece et al., 1997; Teece, 2007). Existing literature on big data mainly emphasises big data
25 analytics capability (Wamba et al., 2017), and studies investigating BDMCs are rare. Among
26 these few studies, Shamim et al. (2019a) pointed out that leadership, talent management,
27 technology and culture are important BDMCs to create value from big data, and these
28 capabilities are more strategic in nature. Zeng and Glaister (2018) and Shamim et al. (2019b)
29 examined the impact of operational level capabilities, i.e. data democratization, data
30 contextualization, experimentation, and execution on value creation. Most of the studies on
31 big data capabilities investigate organizational performance as an outcome (e.g. Dubey et al.,

1 2019; Wamba et al., 2017; Xiang et al., 2015), however less attention is paid to understanding
2 how big data can be applied to enhancement, such as service innovation and quality ratings.
3

1 Table 1.

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

1

1 The most recent studies on big data value creation are shown in Table 1. The inclusion
2 criteria for studies in Table 1 is the relevance with big data related capabilities published in last
3 five years. Most of these studies discussed big data analytics capability and very limited studies
4 paid attention to the management of big data, and most studies focused on theoretical
5 framework by using resource-based view (e.g. Dubey et al., 2019; Yasmin et al., 2020) and
6 dynamic capabilities (Erevelles et al., 2016). Shamim et al. (2019b) posited that dynamic
7 capabilities coming from big data are actually KBDCs because big data leads to new
8 knowledge, which in turn enables dynamic capabilities such as innovation. Firm performance
9 as an outcome of big data capabilities is the major focus of existing literature, whilst service
10 innovation and quality are the seldom discussed. Though Several studies on big data analytics
11 highlight the importance of management capabilities, but big data value creation is mainly
12 discussed in terms of performance; some exceptions are Ghasemaghahi and Calic's (2019)
13 study about innovation and decision-making as value creation from big data (Shamim et al.,
14 2019a), thus it indicates that service quality is a comparatively ignored area in big data value
15 creation literature. Consistent with Shamim et al. (2019a) and McAfee et al. (2012), this study
16 investigates leadership, talent management, technology management, and culture development
17 as BDMCs at the strategic level of organization. Furthermore, following Zeng and Glaister
18 (2018) and Shamim et al. (2019b), data democratization, contextualization, experimentation,
19 and execution are examined as operational level BDMCS. These BDMCs are explained in
20 more detail below.

21

22 *2.3.1 Strategic level big data management capabilities*

23

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

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

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

26 Whilst data become more affordable and accessible for most organizations nowadays,
27 data scientists become more valuable in the job market, where many organizations look for
28 candidates with skills in analysing big data and transferring statistic jargon into a language that
29 managers can understand (McAfee et al., 2012). However, it has been a challenge for many
30 organizations to recruit people with the appropriate IT knowledge, skills and experience to
31 adopt big data (Sivarajah et al., 2016). Maintaining the talent and continuously updating the
32 skills of data analysts becomes critical for many organizations (De Mauro, Greco, Grimaldi, &
33 Ritala, 2018). Due to the increasing value of big data experts, it is becoming increasingly

1 challenging for organizations to retain talented employees with big data analytic skills (Tambe,
2 2014). Additionally, fostering the IT workforce takes time (Kim et al., 2011). Hence,
3 organizations should maintain their key talents internally (Angrave et al., 2015). People are
4 considered to be a rare and non-substitutable resource; they give organizations a competitive
5 edge over competitors (Bharadwaj, 2000). Maintaining talented people also creates an internal
6 pool for future leaders with IT-orientation (De Mauro et al., 2018).

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

22 *Data-driven culture:* Organizational culture comprises prevailing values, norms and shapes
23 of behaviours that describe the core personality of the firm (Denison, 1984). Culture influences
24 leadership styles, management processes, working climates, organisational behaviours and
25 strategy formulations (Laforet, 2017). Data-driven organizations tend to develop a culture of
26 knowledge-based decision-making instead of relying on hunches and intuitions (McAfee et al.,
27 2012). Some organizations' decisions seem to be data-driven, but actually their decision is
28 based on gut feeling. Such decisions can be too abstract for employees to comprehend, so
29 leaders will have difficulty convincing others. Gupta and George (2016) stated that data-driven
30 culture affects data-driven decision-making at all levels in organizations. It is crucial for
31 decision-makers to actively engage in big data events and apply big data methodologies in their
32 daily business practice. The present literature on organizational culture in the perspective of
33 DC theory argues that culture can potentially influence organizations' dynamic capabilities

1 (Dubey et al., 2019). These arguments highlight the importance of management towards big
2 data in the development of dynamic capabilities.

3 2.3.2 *Operational level big data management capabilities*

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

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

24 *Big data contextualization:* The ability to contextualize data is about the capability of
25 assigning meanings to the data. Contextualize findings provided by big data to gain a complete
26 view can positively contribute to firms' ability at harnessing data for value creation (Zeng &
27 Glaister, 2018). With a large volume of data, organizations need to have a specific and clear
28 understanding of the context, so that options generated by business analysts can be applied
29 appropriated toward decision-making (Merendino et al., 2018). In order to contextualize the
30 data, organizations not only need human talent at designing algorithms, but also need human
31 intelligence at categorizing the context in which data will have an impact (Günther et al., 2017).

1 Organizations good at harnessing big data collect customer data from multiple channels and
2 magnify the context of their customer needs. Failing to integrate big data results into business
3 practices means that organizations could fail to benefit tremendously from data reports (Zeng
4 & Glaister, 2018).

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

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

24

25 Strategic management literature suggests that strategic level capabilities facilitate the
26 delivery of strategic objectives in daily operations (Witcher & Chau, 2014). This relationship
27 is also evident in the literature about big data and IT capabilities, which we discussed in the
28 above section. Big data demonstration; contextualization, experimentation and execution
29 require leaders to value the contribution of technology on business performance (Bharadwaj et
30 al., 2000) and create a data-driven culture in organizations through positing big data in the heart
31 of their decision-making (McAfee et al., 2012). Decision-making is context-based so that data-

1 driven organizations need to have talented experts, as they can provide multiple options in
2 accordance with different contexts of issues in organizations (Merendino et al., 2018).

3
4 With the overwhelming volume of data, it is important for organizations to have leaders
5 and an organizational culture which encourages employees to consider learning through errors.
6 These arguments suggest that strategic level BDMCs can influence operational level BDMCs.
7 This argument is consistent with strategic management literature (Witcher & Chau, 2014).
8 Wamba et al. (2017) argued that in the big data context, technology management and talent,
9 which are strategic level capabilities, could enhance big data analytical capabilities, and
10 process-oriented capabilities, which are operational in nature. Akter et al. (2016) also
11 emphasized that it is a prerequisite for organizations to have technology management and talent
12 management to gain insights from big data. Akter et al. (2016) further argued that without the
13 alignment of capabilities at different levels, organizations cannot reap the benefit of big data.
14 Zeng and Glaister (2018) also acknowledge the key role of leaders in benefiting data
15 democratization, contextualization, experimentation, and execution. Shamim et al. (2019a) is
16 also suggested that leadership, talent management, technology, and culture is associated with
17 operational level BDMCs. There is evidence in literature which suggests that strategic level
18 capabilities such as setting mission and value propositions influence operational level
19 capabilities in the given context, especially if these are KBDCs (Cepeda & Vera, 2007). Based
20 on these arguments, this hypothesis follows:

21
22 **H₁: Strategic level BDMCs are positively associated with operational level BDMCs.**

23 24 2.4 *Knowledge creation and Big Data Management capabilities*

25 Knowledge creation increasingly becomes a priority in organizations as it contributes to
26 improving organizations' performance and generate new knowledge (Sujatha & Krishnaveni,
27 2017). Knowledge creation refers to the generation, development, implementation, and
28 exploitation of novel ideas (Sujatha & Krishnaveni, 2017). According to the knowledge-based
29 view, an organization's value comes from its knowledge base (Grant, 1996). Knowledge is also
30 needed to reconfigure the resources to maintain a competitive advantage through innovation.
31 Hence, knowledge is essential for the development of dynamic capabilities (Fuchs et al., 2014)
32 and the most unique strategic assets are knowledge based (Grant, 1996; Donate & De Pablo,

1 2015). This phenomenon is well integrated in the KBDCs view of the firm, suggesting that
2 dynamic capabilities mainly rely on knowledge resources (Zheng et al., 2011).

3
4 Big data is crucial for IT-supported knowledge creation through data analysis. It allows
5 effective decision-making and advances business performance (Acharya, Singh, Pereira, &
6 Singh, 2018). In the tourism and hospitality sector, big data enables hotels to create knowledge
7 about customer preferences and generalize factors influencing loyalty and satisfaction (Xiang
8 et al., 2015). Aggregating real time, contextual information is also critical for the management
9 of customer experience (Buhalis & Sinarta, 2019). Management capabilities as a strategic
10 resource are crucial to create value out of knowledge (Teece, Pisano, & Shuen, 1997; Teece,
11 2007). This is echoed with many other researchers' findings which posit the importance of
12 leadership (Nonaka, Toyama, & Konno, 2000), talent monument (Jones, 2010) organisational
13 culture (Wang, Su, & Yang, 2011) and technologic management (Acharya et al. 2018). Shamim
14 et al. (2019a) suggest that in order to maximise value, there is a need for BDMCs at strategic
15 level, namely: leadership focus, talent and technology management, and data driven culture.
16 Cepeda and Vera (2007) also argued that strategic level capabilities enhance KBDCs and
17 enable the firm to acquire the required knowledge. These arguments are consistent with the
18 resource-based view and dynamic capabilities view of the firm that value creation from
19 strategic resources requires management capabilities (Teece, 2007; Barney, 1991). Big data is
20 an important strategic resource and based on these arguments, organizations need strategic
21 level management capabilities to create value from big data i.e. knowledge creation. These
22 arguments suggest the following hypothesis:

23
24 **H2: Strategic level BDMCs are positively associated with knowledge creation through big**
25 **data.**

26 Zeng and Glaister (2018) pointed out the importance of operational level BDMCs on
27 knowledge creation based on big data. Democratising, contextualizing, experimenting and
28 executing data can extract meaning from the data, which leads to knowledge creation (Shamim,
29 Cang, & Yu, 2016). Strategic level capabilities are facilitated by operational level capabilities
30 to achieve the desired outcomes such as knowledge creation by aligning the strategic objectives
31 with management and operations (Witcher & Chau, 2014). To achieve the desired
32 organizational outcomes, it is important to align strategic level capabilities with operational
33 competencies. Existing literature argues that most of the companies are good at developing

1 strategies, but they fail to execute the strategies, mainly because of lack of operational
2 alignment and capabilities at strategic level (Neilson et al., 2008).

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

18

19 **H₃: Operational level BDMCs are positively associated with knowledge creation through**
20 **big data.**

21

22 **H₄: Operational level BDMCs mediates the association of strategic level BDMCs and**
23 **knowledge creation through big data**

24

25 2.5 *Service innovation*

26 The role of service innovations in wellbeing and economic growth is well acknowledged (Den
27 Hertog, Van der Aa, & De Jong, 2010). Innovations refer to the introduction and
28 implementation of new concepts such as product, service and process. In the context of tourism
29 and hospitality, innovations are often developed by new technologies that enhance tourist
30 experiences, new hotel services, new attractions in a destination and improvement of the tours
31 using new technologies to enhance the tourist experience (Carlisle, Kunc, Jones, & Tiffin,
32 2013; Buhalis & Sinarta, 2019).

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

8 There is evidence of the positive effect of knowledge on innovativeness (Kim & Lee,
9 2013), particularly in the hospitality sector. Knowledge through the use of information
10 technology facilitates innovations (Garcia, 2015). Kim and Lee (2013) suggested that
11 knowledge positively affects the service innovativeness in the hospitality sector. Hu et al.
12 (2009) also suggest a positive association of knowledge and service innovation in the
13 hospitality sector. In hospitality operations, knowledge refers to knowledge of customers,
14 competitors, products and services, operational procedures, and job associates (Yang & Wan,
15 2004). Big data enables the firms to explore unanticipated patterns shown by customers,
16 businesses and marketplaces (Xie, Wu, Xiao, & Hu, 2016), which are crucial for their service
17 innovativeness (Kim & Lee, 2013). Learning from the customer, generated big data refers to
18 co-learning, which is a source of innovation (Jiménez et al., 2015). This suggests that big data-
19 driven knowledge creation can lead to service innovations. In the context of this study, big
20 data plays a vital role in knowledge generation to understand customer preferences. Based on
21 the improved understanding of customers' preferences, hotels use big data to adjust their
22 service to meet customers' needs. Furthermore, innovativeness in an established KBDC, and it
23 heavily relies on knowledge (Donate & de Pablo, 2015). These arguments suggest the
24 following hypothesis:

25
26 **H₅: Knowledge creation through big data is positively associated with service innovations**

27 28 2.6 Customer generated online quality ratings

29 Online ratings can influence organisations' revenue (Nieto-Garcia, Resce, Ishizaka,
30 Occhiocupo, & Viglia, 2019; Viglia, Minazzi, & Buhalis, 2016) and customer bookings in
31 hospitality sector (Gavilan, Avello, & Martinez-Navarro, 2018). In the era of internet, hotels
32 and their customers have access to unlimited information helping them to know each other
33 (Sheng et al., 2019; Rhee & Yang, 2015). Hotels can use online reviews and quality ratings to

1 advertise and improve their services, whilst customers can gain knowledge about hotels
2 through other customers' reviews and comments on websites such as Booking.com, Expedia,
3 TripAdvisor etc. (Rhee & Yang, 2015). Existing studies of online customer ratings either focus
4 on why customers' ratings are important, and what the business outcomes of online ratings are
5 (Gavilan et al., 2018; Nieto-Garcia et al., 2019; Filieri, Raguseo, & Vitari, 2018) or discuss
6 customer-related variables as predictors of online rating consideration, such as customer
7 sentiments (Geetha, Singha, & Sinha, 2017). However, little is known about what capabilities
8 are needed, and how big data-based knowledge creation and innovation can enhance customer-
9 generated online ratings.

10 Customer sentiments, whether positive, negative or neutral, lead to satisfaction or
11 dissatisfaction on the online quality ratings in the tourism and hospitality industry (Geetha et
12 al., 2017). Big data is a resource to help with the understanding of customer sentiments. For
13 example, online reviews enhance hotel managers' understanding of customer preferences,
14 emotions and their potential future buying behaviour (Xiang et al., 2015). The aggregated
15 online quality rating involves several dimensions, including value for money, staff attitude and
16 behaviour, location, service, cleanliness, facilities, and customer services (Nieto-Garcia et al.,
17 2019). Hotels can improve their online ratings if they know their customers' preferences based
18 on big data analysis.

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

32
33 **H₆: Knowledge creation through big data is positively associated with customer-**
34 **generated online quality ratings.**

1
2 **H7: Service innovation is positively associated with customer-generated online quality**
3 **ratings.**

4
5 **H8: Service innovation mediates the association of knowledge creation through big data**
6 **and customer-generated online quality ratings.**

7
8
9 **3 Methodology**

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

19 *3.1. Sample and data collection*

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

27 Questionnaires were distributed by post and via personal visits and emails to the hotels which
28 gave consent to participation in the research at the time of initial contact. We managed to
29 establish contact with senior managers of 364 hotels, out of which 287 hotels agreed to
30 participate in the survey. We collected data from hotels in all major cities of Pakistan. The
31 condition for participating hotels was that the hotel should be registered on www.booking.com.
32 Data was collected for hotels of all sizes enlisted in www.booking.com. Questionnaires were

1 distributed to these 287 hotels and 202 usable questionnaires were returned, with a response
2 rate of 70%. We ensured a high response rate through regular follow up emails and phone calls.
3 Our method of data collection is consistent with similar studies such as Shamim et al. (2017).
4 Senior managers, including general managers and directors representing their hotels, filled in
5 the questionnaires. Authors contacted the hotels several times i.e. to distribute and explain the
6 questionnaires, and to collect the questionnaires. During this time, the authors maintained
7 contact with participants through phone calls and emails. The whole process of data collection
8 took around one year.

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

16 *3.2. Measures*

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

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

29 Service innovation was measured by adapting five items from Donate and De Pablo (2015),
30 assessing the hotels' service innovation performance. Apart from subjective items such as
31 company results and performance, this measure also contained relative items such as
32 comparison of results with competitors. Relative measures are crucial, as innovation
33 effectiveness is explained on the basis of such comparisons (e.g., competitors' performance;

1 firms' own previous years' results) (Zahra & Das, 1993). For service innovation, items ranged
2 from 1 (very low) to 7 (very high). Secondary data on www.booking.com was used for
3 customer-generated online quality ratings. We noted the online quality rating on the
4 questionnaire before forwarding it to each hotel. Online quality ratings were collected from
5 Booking.com for each hotel in the sample. Details of measures for all the variables can be seen
6 in Appendix 1.

7

8 3.3 *Data analysis*

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

20 4 **Results**

21 4.1 *Reliability and validity*

22 Cronbach's alpha was used to measure the reliability of the constructs. To establish internal
23 consistency and reliability, Cronbach's alpha should be greater than 0.7 (Nunnally & Bernstein,
24 1994). Results indicate that Cronbach's alpha value for all the variables was higher than the
25 required value of 0.7. Table 2 results show that the factor loadings for all the construct were
26 higher than the required value of 0.65 and the AVE of all the constructs was higher than 0.50.
27 Table 2 also indicates that the CR of all the constructs exceeded the AVE value. Hence, the
28 convergent validity of all the variables was established. Discriminant validity was established
29 when the squared correlation among the constructs was less than the AVE of each construct
30 (Fornell & Larker, 1981). Table 3 shows that all the constructs met this requirement. The Chi-
31 square value is 421.52, R-square value for outcome variable is 0.34, and the SRMR value is also
32 less than 0.9, which reflected a good model fit. Values of skewness and kurtosis in table 2

1 indicate that data is normally distributed. Furthermore, the values of VIF in Table 3 suggested
2 that multicollinearity is not a concern in this study.

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1 **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			
	Culture	.76	.50	.80	.70
	Technology	.68			
Operational level BDMCs	Data democratization	.85			
	Data contextualization	.70			
	Data experimentation	.87	.66	.89	.83
	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			

1

2

3 **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

4 *Note:* AVE of each construct is at diagonal

5

6

7

8

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

5 **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

6

1 4.2 *Structural model and hypotheses testing*

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

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

15 Our results suggest that after entering the mediator in the model, the direct effect of
16 strategic level management capabilities on knowledge creation became insignificant ($\beta = -0.05,$
17 $p > 0.05$), which indicated full mediation; this led to the acceptance of H4. Results also
18 supported the positive association of knowledge creation through big data with service
19 innovation ($\beta = 0.658, p < 0.001$) and online customer rating ($\beta = 0.22, p < 0.001$). These
20 findings supported H5 and H6. Service innovation was also positively associated with the
21 online quality rating ($\beta = 0.36 p < 0.001$); furthermore, it also mediated the relationship of
22 knowledge creation through big data and the online quality rating ($\beta = 0.21, p < 0.001$). After
23 entering service innovation as the mediator into the model, the direct association of knowledge
24 creation and online quality rating became insignificant ($\beta = 0.01, p > 0.05$); this showed that
25 there was a full mediation of service innovation in this relationship. These findings support
26 H7 and H8.

27

28

Table 5. Path analysis

Path	Direct effects	Indirect effects	Total effects	Hypotheses	Result
	β /t-value	β /t-value	β /t-value		
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

1 5. Discussion

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

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

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

15 *5.1. Theoretical Contribution*

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

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

32 Third, this study empirically tested the role of knowledge creation through big data on
33 service innovation and customer-generated online quality ratings in the hospitality industry.

1 Existing studies on big data in the hospitality industry mainly focus on illustrating the
2 importance of predicting customers' behaviour through data mining (see a literature review
3 carried out by Mariani et al., 2018). Instead of focusing on techniques of analysing big data
4 like many previous studies, this is one of the rare studies examining service innovation as value
5 creation through big data by showing that knowledge creation through big data can enhance
6 dynamic capability, such as service innovation in the hospitality sector.

7 8 *5.2. Implications for practice*

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

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

24 In the hospitality sector, big data can be used for value creation such as improved
25 customer satisfaction, loyalty, understanding the patterns of customer behaviour (Xiang et al.,
26 2015), helpfulness, and ratings (Xiang et al., 2017). Based on the knowledge created through
27 big data, hospitality firms can improve their service innovativeness. The findings of this study
28 also suggest that hotels should now limit the value of big data to knowledge creation, but they
29 must translate that knowledge into service innovation. Only then, big data capabilities and
30 knowledge created through big data, leads to better online quality ratings. Without service
31 innovation, the link is missing. However, achieving these outcomes using big data is not
32 simple.

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

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

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

30 At operational level, managers should ensure that employees have the ability to access,
31 understand, interpret, and contextualize big data. Mangers should encourage employees to do
32 experiments with big data to monitor changes and come up with new things to test big data.
33 “Trial and error” with the data should be a routine matter. Mangers should ensure that
34 employees are able to transform big data insights into action. Employees should be able to

1 respond to the data in a timely manner, by observing the abnormalities emerging from data and
2 monitoring market trends and customer activities.

4 *5.3. Limitations and Future Studies*

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

6 Secondly, cross-sectional research design is subject to common method bias. However,
7 appropriate measures were taken to reduce this possibility. Harmon's one-factor test explains
8 38% of total variance, which indicates that common method bias is not significant and is
9 unlikely to contaminate the results (Yang et al., 2018). Another limitation of this study is the
10 low value of R-square i.e. 3.4 which indicates a low explanatory power of the model, so a large
11 part of the variability is still unexplained by the model. This could be due to some factors not
12 being included in the model. For instance, big data analytics capability (Wamba et al., 2017).
13 Thus, future research is needed in order to better the understanding of big data value creation
14 in relation to BDMCs.

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

24 *5.4. Conclusion*

25 This study concludes that strategic level BDMCs (leadership, talent management, technology,
26 culture) and operational level BDMCs (data democratization, contextualization,
27 experimentation, and execution) are interrelated. Organizations looking to create value from
28 big data will need both strategic and operational level BDMCs. without either level of the
29 BDMCs will not be sufficient for organizations to create knowledge from big data. The results
30 of this study indicate strategic and operational level BDMCs enable the hospitality firms to
31 create new knowledge through big data and enhance innovativeness and online quality ratings.

- 1 Knowledge creation through big data can boost the online quality ratings through the mediation
- 2 of service innovation in the hospitality sector.
- 3

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1 Appendix 1

2 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.