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What factors affect firm performance in the hotel industry post-Covid-19 pandemic? Examining the impacts of big data analytics capability, organizational agility and innovation

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ABSTRACT

The Covid-19 pandemic has had an adverse effect on the global economy, particularly the hotel industry. Industry players have turned to big data to recover and improve their business performance. This paper aims to identify the key resources to develop and build big data analytics capabilities (BDAC). Drawing upon the knowledge-based and dynamic capability views, this research also examines the interplay among BDAC, organizational agility, marketing and organizational innovations, and firm performance in the hotel industry. The partial least square structural equation modeling is used for the data analysis, while quota sampling is used for the sampling design. Based on the statistical data analysis from 115 star-rated hotels in Malaysia, BDAC positively impacts organizational agility, marketing and organizational innovations, and firm performance. Likewise, organizational agility positively impacts firm performance, marketing and organizational innovations. The empirical findings provide researchers and industry players with meaningful insights for improving firm performance in the hotel industry using big data.

1. Introduction

The digitalization of business processes has produced a large volume of big data with key features, including variety, velocity, veracity, and value (Wamba et al., 2017). Big data is generated anywhere and anytime, providing valuable business insight through appropriate analysis. The generated business insight can improve daily operations and assist organizations' strategic decision-making process (Ram and Zhang, 2022). A growing number of firms are using big data analytics (BDA) to provide insight that can improve their competitive advantage (Mikalef et al., 2020). By utilizing BDA, insight and patterns can be formulated through statistical techniques, analytical tools, and computer algorithms that can improve business performance (Gupta et al., 2018). Particularly, firms can utilize the insights generated by BDA to predict consumer demand and preference, consequently improving their product and services. According to Huo and Vesset (2022), in 2021, the market value of big data and analytics software was about USD 90 billion, and it is forecasted to increase that number twofold by 2026.

Significantly, BDA can facilitate commercial organizations to maintain resiliency during uncertainty and crisis. In particular, the tourism industry is seriously affected by the COVID-19 pandemic. The restriction to global mobility paralyzed the tourism industry and the local economy. Global travel and tourism spending has been reduced dramatically from USD 6.25 trillion in 2019 to USD 3.65 trillion in 2021 (Statista, 2022). Before the Covid-19 pandemic, the tourism economy accounted for about 7 % of global trade and was classified as the third largest export category in 2019 (UNWTO, 2023). The tourism industry is also one of the main contributors to the national GDP, besides providing job opportunities and a source of foreign exchange.

Thus, the recovery and revitalization of the tourism industry are essential for the national economy as more and more countries start opening their borders to international tourists. UNWTO, and Asian Development Bank (2021) states that BDA can expedite tourism recovery by assisting tourism players to boost competitive products and services. Lin and Lin (2023) also claimed that organizations that adopt digital technology would be able to generate business value. In the case of the hospitality industry, hoteliers can use big data tools to review online reviews and user-generated content to measure guest experience

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and satisfaction (Zarezadeh et al., 2022). Besides that, BDA can assist hotels in revenue management by calculating the best daily room rate (Egan and Haynes, 2019).

Due to its service-based nature, the tourism industry is susceptible to market changes. Thus, relevant players (e.g., hotels) must continuously adjust their organizational processes and structures to deliver new products/services through innovation, which big data can facilitate. Agile organizations also can stay competitive in an uncertain environment by recognizing and rapidly reacting to customer needs (Ravichandran, 2018). Prior studies indicate the importance of agility and innovation during uncertain and unstable times, particularly in the tourism context (Melián-Alzola et al., 2020; Nieves and Diaz-Meneses, 2016). Nonetheless, there are insufficient studies examining how to efficiently and effectively leverage big data analytics capability (BDAC) to improve organizational agility, innovation, and firm performance. Particularly, there is a gap in the literature on the impact of big data in influencing firm performance during a crisis period (Mariani et al., 2023).

Most previous studies on the relationship between BDAC and firm performance are conducted in the information technology and manufacturing industries (Awan et al., 2022; Gupta et al., 2018; Jeble et al., 2018; Wamba, 2022). There are limited studies that examine this relationship in the tourism industry. Also, Mariani et al. (2023)call for further studies on the interaction of BDAC with innovation capabilities. There are four types of innovations that are primarily used in research at the firm level (Cinar et al., 2020). Many prior studies on innovation center on product and process innovation, while marketing and organizational innovation are under-researched (Joueid and Coenders, 2018; Maqdliyan and Setiawan, 2023). Both marketing and organizational innovations are fundamental to improving firm performance (Chen et al., 2020; Kafetzopoulos et al., 2020). Nevertheless, various scholars argue that further studies on the antecedents of marketing and organizational innovations are needed to understand both innovations (Prasad and Junni, 2016; Ramirez et al., 2018). Based on the stated research gaps, this research aims to address the following four research questions:

Q1: What key resources are needed to build BDAC in the tourism industry, particularly hotels?

Q2: How does BDAC affect organizational agility, marketing and organizational innovations, and firm performance?

Q3: How organizational agility influences marketing and organizational innovations?

Q4: How organizational agility, marketing and organizational innovations affect firm performance.

By addressing the research questions above, this study contributes to the current literature in several ways. Theoretically, the existing research applied knowledge-based and dynamic capability view theories to explain the theoretical relationship among BDAC, organizational agility, innovation, and firm performance. Regarding empirical contribution, the findings show that BDAC has a positive relationship with marketing and organizational innovation. Both direct relationships are rarely tested in the literature. In terms of practical contribution, this study highlights to hotel managers the key resources needed to build their BDAC, which they can leverage to improve their hotel performance after sustaining losses due to the Covid-19 pandemic.

2. Literature review

2.1. Knowledge-based view (KBV) and dynamic capability view (DCV) as the theoretical foundation

The resource-based view (RBV), proposed by Barney (1991), is one of the most important theories to measure the strategic value of an organization's internal resources. This theory explains how an organization achieves a competitive advantage by reconfiguring its internal resources (Erevelles et al., 2016). Nonetheless, RBV is a static theory as it overlooks dynamic changes in the market (Kraaijenbrink et al., 2010). Thus, Teece et al. (1997) proposed the dynamic capability view (DCV) as an extension of the RBV in strategic management. DCV argues that an organization must combine internal and external resources to improve its capabilities in a dynamic market environment (Gupta et al., 2019). Nevertheless, not every organization is capable of achieving its strategic goals. In order to sustain competitive advantage, firms must be agile to adjust their resources and capabilities to fit in a rapidly changing market (Arsawan et al., 2022; Ghasemaghaei et al., 2017).

The limitation of RBV also leads to the introduction of the knowledge-based view (KBV). KBV stresses that a firm can achieve a competitive advantage by attaining and sharing knowledge. Grant (1996) further highlights that knowledge is an important resource in an organization, and it is important that firms can integrate this resource. KBV and DCV have been used in dynamic market settings to explain organizational competitive advantage (Côrte-Real et al., 2017). Hence, this research adopts KBV and DCV as the grounded theory in order to have a holistic understanding of the factors affecting firm performance in the hotel industry.

2.2. Big data analytic capability (BDAC)

The main characteristic of big data can be summarized in "5Vs", including volume, variety, velocity, veracity, and value (Wamba et al., 2017). However, big data itself barely has crucial business values without suitable analytical tools (Aziz et al., 2023). Thus, it is necessary for an organization to perform big data analytics (BDA). There are various definitions of BDA in the literature. According to Jeble et al. (2018), BDA is a multidisciplinary discipline involving computer science, data science, and mathematical models for systematically collecting and evaluating data. BDA has also been referred to as the capability to collect, analyze and interpret big data to extract business insights and transform this information into competitive advantages (Ferraris et al., 2019; Wamba et al., 2017).

An organization must deploy various resources and capabilities to develop big data analytics capabilities (BDAC). Mikalef et al. (2019) defined BDAC as “the ability of a firm to capture and analyze data towards the generation of insight by effectively orchestrating and deploying its data, technology, and talent” (p. 274). According to Akter et al. (2016), BDAC is a hierarchical construct with three main blocks: management capability, technology capability, and talent capability. Nonetheless, Mikalef et al. (2019) argue that BDAC comprises three main blocks: tangible resources, human skills, and intangible resources. Specifically, tangible resources include data, technology, and basic resources; human skills include technical and managerial skills; and intangible resources include data-driven culture and organizational learning.

The human, tangible, and intangible resources are interrelated, and many synergies exist among these essential resources for developing BDAC. Given the potential benefits of data analytics, many commercial organizations pour financial resources into technology and data infrastructure and spend time aligning big data initiatives with their strategic goals (Gupta and George, 2016). Although data and technology are essential for developing BDAC, they cannot provide competitive advantages without incorporating human and intangible resources (Jeble et al., 2018). Regarding human resources, both technical and managerial skills are necessary for implementing big data analytics initiatives (Mikalef et al., 2020). Davenport (2014) argues that managerial skills, such as interpersonal communication, largely determine whether a data analytics project will be successful. Also, data-driven culture and organizational learning are key resources for building BDAC (Mikalef et al., 2019). For instance, it is essential to have a data-driven culture to ensure the successful implementation of big data projects across the workforce (Gupta and George, 2016).

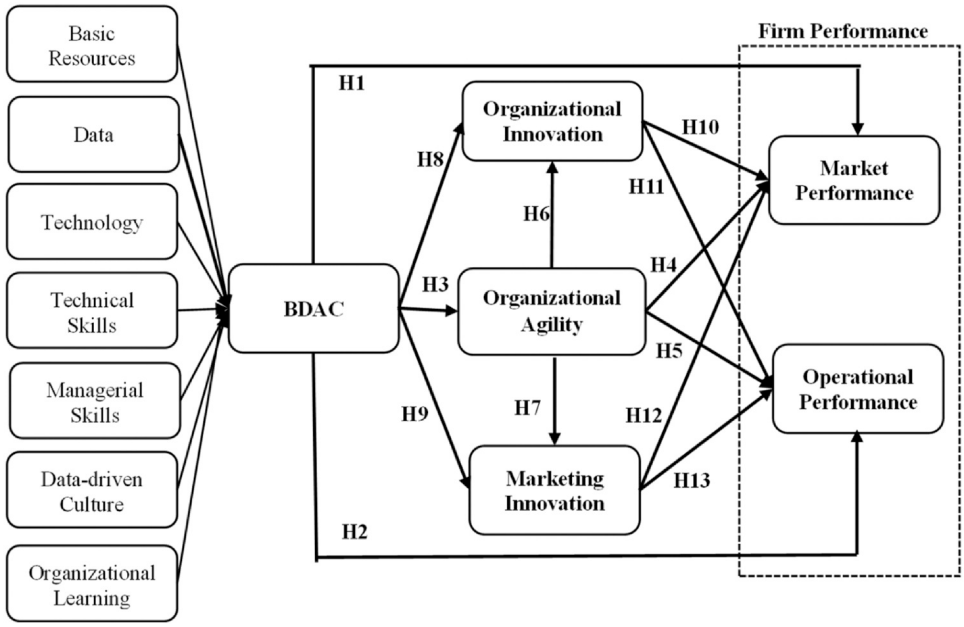

Fig. 1. Conceptual framework and hypotheses development.

2.3. Innovation

Innovation is a crucial component of competitiveness. It determines how an organization competes with its competitors and responds to market changes. Innovation is widely reflected in products, services, operations, processes, and organizational structures (Gunday et al., 2011). Damanpour and Evan (1984) described innovation as "the implementation of an internally generated or a borrowed idea whether pertaining to a product, device, system, process, policy, program or service that was new to the organization at the time of adoption" (p. 393). Furthermore, there are different types of innovation in the current literature. Based on the 3rd edition of the Oslo Manual, there are four main types of innovation: product, process, marketing, and organizational (OECD and Eurostat, 2005). According to Cinar et al. (2020), these four types of innovation are commonly used in the study of innovation at the firm level. Nonetheless, this study would focus on marketing and organizational innovations as there is a lack of study regarding these two types of innovation in the big data literature.

Marketing innovation is defined as a new marketing technique for improving product design, placement, promotion, and pricing (Nieves and Diaz-Meneses, 2016). Setting up new distribution channels to offer products and services to customers is an example of marketing innovation in terms of product placement (Nieves and Diaz-Meneses, 2016). Marketing innovation can also include the introduction of a new brand symbol or the promotion of new items through placement in films (OECD and Eurostat, 2005). Any improvement or introduction of a new marketing method does not necessarily have to be original, as firms could copy from competitors and incorporate them into their marketing goals.

Regarding organizational innovation, this innovation refers to the adoption of new organizational methods in terms of firm-wide processes, practices, and structure (OECD and Eurostat, 2005). Gunday et al. (2011) provide examples of organizational innovation, including adopting a new organizational structure to promote cooperation between employees and adopting new processes and procedures that can assist organizations in innovatively conducting work activities. One of the main antecedents of organizational innovation is the firm's culture of innovation. Management support and staff training would facilitate the promotion of an innovation culture in a company (Cinar et al., 2020). Also, the changes in market conditions can force organizations to change or establish new organizational practices and structures (Cinar et al., 2020).

2.4. Organizational agility

Organizational agility is generally defined as an organization's ability to detect market changes (e.g., opportunities and challenges) and react accordingly in a quick manner (Wamba, 2022). According to Conboy (2009), the driving force for agility is an ability to sense, capture and transform new business opportunities as they emerge. As a dynamic capability, organizational agility is considered a new paradigm for organizational management (Côrte-Real et al., 2017; Ghasemaghaei et al., 2017). The agility paradigm is related to critical elements, such as interpersonal and cross-cultural relationships (Gonçalves et al., 2021). Therefore, it is important for an organization to have a firm-wide culture of change to achieve sufficient organizational agility. With high organizational agility, organizations are more likely to have continuous innovations (Gonçalves et al., 2021). Agile organizations can act quickly in response to customer demand, unanticipated developments, and market possibilities (Darvishmotevali et al., 2020). As a result, businesses can increase their bottom-line performance.

2.5. Firm performance

In the literature, there are various definitions of firm performance. According to Rai et al. (2006), firm performance refers to "the degree to which a focal firm has superior performance relative to its competition" (p. 229). Regardless of the differences in definitions, most studies measure firm performance as a multidimensional construct composed of financial and non-financial components. For example, Wamba et al. (2017) measured firm performance based on two perspectives (i.e., financial and market performance). Also, prior research measures firm performance by two separate constructs, namely market performance and operational performance (Gupta and George, 2016; Gupta et al., 2018). Based on the literature, market performance measures a commercial organization's actual outcomes (e.g., market share and new markets), and operational performance refers to an organization's productivity (e.g., profits and return on investment) (Aziz et al., 2023; Liu et al., 2020).

3. Research framework and hypotheses development

This current study draws on the knowledge-based view (KBV) and the dynamic capability view (DCV) to develop the research framework (see Fig. 1). Both theories are adopted to explain the interplays among BDAC, organizational agility, innovation, and firm performance. According to Barney (1991), an organization can gain competitive advantages over its competitors if it possesses valuable, rare, imitable, and unsubstitutable resources and capabilities. Commercial organizations aim to maximize their shareholders' benefits, taking all possible measures, including applying BDA, to remain competitive in the market (Ciampi et al., 2021; Wamba, 2022). Meaningful insights and patterns can be generated through BDA, which can be used for decision-making and ultimately improve firm performance (Ansari and Ghasemaghaei, 2023; Jeble et al., 2018; Ram and Zhang, 2022). Specifically, Wamba and Akter (2019) investigate the role of BDAC in the supply chain, and their finding found that BDAC has a positive influence on firm performance.

Similarly, Ferraris et al. (2019) examined the relationship between BDAC, knowledge management, and firm performance, and the result showed a positive association between BDAC and firm performance. Furthermore, Gupta et al. (2018) examine the relationship between Cloud-based ERP and BDAC, and they conclude that BDAC positively influences both market performance and operational performance. Therefore, the following hypotheses are proposed:

H1. BDAC positively influences market performance.

H2. BDAC positively influences operational performance.

The study by Ghasemaghaei et al. (2017) found that a firm can increase its organizational agility by using big data analytics. This finding is supported by another study conducted by Ciampi et al. (2022). The rationale behind this positive interaction is that BDA can produce meaningful insights for organizations to quickly identify market changes and react appropriately (Côrte-Real et al., 2017). The organization’s ability to respond rapidly to market opportunities and threats would boost its competitive advantage (Ravichandran, 2018). Consequently, firms can increase business performance in terms of market share and profit (Zhou et al., 2019). In the context of the hotel industry, Melián-Alzola et al. (2020) revealed that IT application positively impacts organizational agility. Correspondingly, Wamba (2022) concludes that organizational agility positively affects firm performance. Thus, the following hypotheses are proposed:

H3. BDAC positively influences organizational agility.

H4. Organizational agility positively influences market performance.

H5. Organizational agility positively influences operational performance.

Organizational agility refers to a firm's ability to sense and respond to market changes so that it can gain competitive advantages (Wamba, 2022). A commercial organization's responses to market changes include entering new markets and innovations in terms of products, services, processes, and routines (Chen et al., 2014; Ciampi et al., 2022). Gonçalves et al. (2021) examine the digital innovation of automotive startups, and they find that a firm with high organizational agility is more likely to innovate continuously. Organizational agility, as a dynamic capability, explains how a firm reconfigures its resources to gain market competitiveness through various measures (e.g., innovation). Dahms et al. (2023) also reported that organizational agility is an antecedent to innovation performance in the study of foreign-owned subsidiaries. Therefore, the following hypotheses are proposed:

H6. Organizational agility positively influences organizational innovation.

H7. Organizational agility positively influences marketing innovation.

Thus far, a number of studies have reported a positive relationship between BDAC and innovation (Ciampi et al., 2021; Shuradze et al., 2018). Specifically, knowledge-driven organizations are more likely to conduct innovative activities, and the implementation of innovative activities requires relevant knowledge resulting from internal resources and skills within an organization. Moreover, Nieves and Diaz-Meneses (2016) argue that knowledge-based resources positively influence an organization's innovative activities. Grounded on the knowledge-based view theory, BDAC enhances an organization's innovation ability as it facilitates the organization to take full advantage of new information to improve its competitive advantage (Mikalef et al., 2019, 2020). With regard to empirical evidence, Ciampi et al. (2021) found that BDAC has a positive effect on business model innovation. Mikalef et al. (2019) also reported that BDAC positively influences both incremental and radical innovation. Thus, the following hypotheses are proposed:

H8. BDAC positively influences organizational innovation.

H9. BDAC positively influences marketing innovation.

According to OECD and Eurostat (2005), a commercial organization can increase its sales revenue via marketing innovation (e.g., repositioning products). Marketing innovation would assist firms in better satisfying consumers' changing needs through innovation in product design, placement, promotion, and pricing. Several studies also suggested that there is a positive impact between marketing innovation and firm performance (Hussain et al., 2020; Kafetzopoulos et al., 2020; Nieves and Diaz-Meneses, 2016). Furthermore, prior studies have reported that organizational innovation positively influences firm performance (Cinar et al., 2020; Prasad and Junni, 2016). The rationale is that innovative organizations are more likely to adjust their organizational routines and practices based on market changes to achieve their strategic goals. Specifically, OECD and Eurostat (2005) state that a firm could reduce operational expenditure and increase employee satisfaction through organizational innovation. Chen et al. (2020) examined 265 Chinese companies based in the Pearl River Delta region, concluding that organizational innovation positively impacts firm performance. Therefore, the following hypotheses are proposed:

H10. Organizational innovation positively influences market performance.

H11. Organizational innovation positively influences operational performance.

H12. Marketing innovation positively influences market performance.

H13. Marketing innovation positively influences operational performance.

4. Methodology

4.1. Data source and design

Based on the quantitative method, this research utilized self-administered surveys for data collection. The data collection is based on a single source and single method. Hence, the data collected could be subjected to common method variance (CMV). As Hulland et al. (2018) recommended, this study employs procedural methods to reduce CMV by using two different Likert scales for the predictor and criterion variables in the study. For instance, BDAC, organizational agility, marketing and organizational innovation are measured using a 7-point Likert scale. In contrast, market and operational performance are measured using a 5-point Likert scale. Another procedural method applied to lessen common method bias is placing the descriptive/demographic question between predictor and criterion variables in the questionnaire design (Hulland et al., 2018). Furthermore, the cross-sectional design of this study may limit the causal inference between variables and could be subject to non-response bias (Wang and Cheng, 2020). Nonetheless, the cross-sectional design allows this study to examine multiple variables simultaneously and is inexpensive to conduct. Plus, non-response bias is not applicable in this study as there is no accurate sampling frame of the study's population (Hulland et al., 2018).

Before the actual data collection, the authors conducted two rounds of pre-testing with four academic researchers and another four hotel managers as respondents. The pre-test was conducted to ensure that the respondents could easily comprehend the survey items and understand the questionnaire the same way the authors designed it. A few items were modified based on the feedback from the first round of the pre-test. Subsequently, four hotel managers had reexamined the refined questionnaire. Some wording and structure of survey items were further amended based on the comment from the managers.

4.2. Variable measurement

All the measurement items of the questionnaire are either adopted or adapted from previous studies. The survey is divided in three different sections. The first one includes items measuring big data analytics capability (BDAC), organizational agility (OA), marketing innovation (MI), and organizational innovation (OI). BDAC is comprised of seven dimensions, including basic resources (BR), data (DA), technology (TE), technical skills (TS), managerial skills (MS), data-driven culture (DC), and organizational learning (OL). There are 25 items measuring the seven dimensions of BDAC, which had been adopted from Mikalef et al. (2019). For organizational agility (OA), five items were adopted from Côrte-Real et al. (2017). As for innovation, five items were adopted from Nieves and Diaz-Meneses (2016) to measure marketing innovation (MI), while five items were adopted from Prasad and Junni (2016) to measure organizational innovation (OI). The second section contains a few descriptive questions for hotels (e.g., star rating and number of employees). The third section includes four items measuring market performance (MP) from Gupta and George (2016) and four items measuring operational performance (OP) from Gupta et al. (2018).

4.3. Population and sampling design

This research aimed to examine the impacts of BDAC, organizational agility, and innovation on firm performance in the hotel industry. Managers of star-rated hotels (middle to upper levels) in Malaysia were targeted for data collection. The selection of star-rated hotels as the study population is because the local authority has verified that these particular hotels have reached a certain standard in quality, facilities, and service. This study focused on 3-star, 4-star, and 5-star hotels because such hotels are more likely to engage in big data analysis and innovation activities to improve business performance (Nieves et al., 2014). Thus, this study used quota sampling to gather information from specific target groups. According to Rowley (2014), using non-probability samples is common in social science research, as achieving a 100% response rate is difficult. Also, even though there is an available sampling frame from the Ministry of Tourism, Arts and Culture Malaysia, the list is not updated as many hotels are not on the list, and some hotels have closed down.

The study distributed questionnaires to 210 star-rated hotels from September 2021 to February 2022. By the end of February, 115 usable surveys had been collected, which yielded a response rate of 55 %. Among the 115 responses, 75 are from 5-star hotels, 33 are from 4-star hotels, and 7 are from 3-star hotels. Table 1 presents the descriptive statistics of the sample population.

Table 1
Descriptive statistics.

Hotel characteristics	Categories	N	Percentage (N = 115)
Star Rating	3-star	7	6.1 %
	4-star	33	28.7 %
	5-star	75	65.2 %
Hotel Age	1–3 years	14	12.2 %
	4 – 6 years	10	8.7 %
	7–10 years	16	13.9 %
	> 10 years	75	65.2 %
Number of Employees	26–50	8	7.0 %
	51–75	5	4.3 %
	76–100	17	14.8 %
	> 100	85	73.9 %
Brand Ownership	Local brand	52	45.2 %
	International brand	63	54.8 %

5. Results

The partial least squares structural equation modeling (PLS-SEM) technique is adopted for data analysis. PLS-SEM is an alternative method to the covariance-based approach (CB-SEM) (Marcoulides et al., 2009). The core difference is that CB-SEM focuses on reproducing the theoretical covariance matrix, and PLS-SEM focuses on explaining the variance of endogenous latent variables (Hair et al., 2021). For this study, PLS-SEM is selected compared to CB-SEM because CB-SEM is normally used for reflective constructs only, and the current research has both formative and hierarchical order variables. The SmartPLS software package was used to analyze the collected data based on the PLS-SEM technique (Rezvani et al., 2022). Regarding the sample size, G*Power software was utilized. The results showed that this study's sample size (115 samples) exceeds the minimum requirement to run PLS-SEM (Hair et al., 2021). The research's measurement and structural measurement model must be assessed to test the proposed hypothesis (Ramayah et al., 2018). Furthermore, BDAC is operationalized as a 2nd order reflective-formative latent variable, which requires different criteria for assessing its reflective and formative measurement items.

5.1. Measurement model assessment (Reflective Items)

To examine the reflective measurement model of the research, three main criteria (i.e., internal consistency reliability, convergent validity, and discriminant validity) are used (Hair et al., 2021). Cronbach's alpha and composite reliability (CR) are widely applied by researchers to assess indicator reliability. Typically, Cronbach's alpha and CR underestimate and overestimate the true reliability, so they should be seen as the lower and higher boundaries of the internal consistency reliability (Sijtsma, 2009). To better measure reliability, rho_A is introduced, as it usually lies between Cronbach's alpha and CR (Henseler et al., 2016). As shown in Table 2, all the rho_a values (including dimensions of BDAC) are higher than 0.7 and lower than 0.95, which indicates sufficient internal consistency (Chin, 2010). Convergent validity refers to the degree to which a latent variable explains the variance of its associated indicators (Hair et al., 2021). Factor loadings and average variance extracted (AVE) are checked to examine the convergent validity (Hair et al., 2021). According to the results in Table 2, there is no loading value lower than 0.708, and no AVE value is less than 0.50. Therefore, the convergent validity of the research is confirmed.

With regard to discriminant validity, this validity examines whether the latent variables under investigation are truly different from each other (Hair et al., 2021). Henseler et al. (2015) state that the Heterotrait-Monotrait of Correlations (HTMT) is a better approach to detect discriminant validity in common research situations. The discriminant validity results (including dimensions of BDAC) are summarized in Table 3. It could be seen that all the HTMT values are lower than the cut-off threshold at 0.90, so the discriminant validity of the research is confirmed.

5.2. Measurement model assessment (Formative Items)

For the formative measurement model, this research follows the three-step procedure suggested by Hair et al. (2021). First, redundancy analysis is performed to examine convergent validity. Hair et al. (2021) specifically state that redundancy analysis can be conducted by

Table 2
Validation of the measurement scales.

Construct/Dimension	Type	Items	Loadings	rho_a	AVE
Basic Resources (BR)	Reflective			0.950	0.953
		BR1	0.976		
		BR2	0.974		
Data (DA)	Reflective			0.930	0.863
		DA1	0.902		
		DA2	0.955		
		DA3	0.930		
Technology (TE)	Reflective			0.944	0.851
		TE1	0.920		
		TE2	0.938		
		TE3	0.909		
		TE4	0.922		
Technical Skills (TS)	Reflective			0.943	0.892
		TS1	0.875		
		TS2	0.935		
		TS3	0.969		
		TS4	0.956		
Managerial Skills (MS)	Reflective			0.948	0.915
		MS1	0.958		
		MS2	0.941		
		MS3	0.969		
		MS4	0.928		
Data-driven Culture (DC)	Reflective			0.892	0.755
		DC1	0.860		
		DC2	0.865		
		DC3	0.908		
		DC4	0.842		
Organizational Learning (OL)	Reflective			0.926	0.812
		OL1	0.854		
		OL2	0.925		
		OL3	0.917		
		OL4	0.906		
Organizational Agility (OA)	Reflective			0.887	0.687
		OA1	0.794		
		OA2	0.846		
		OA3	0.863		
		OA4	0.900		
		OA5	0.733		
Marketing Innovation (MI)	Reflective			0.927	0.764
		MI1	0.791		
		MI2	0.910		
		MI3	0.879		
		MI4	0.879		
		MI5	0.904		
Organization Innovation (OI)	Reflective			0.945	0.819
		OI1	0.880		
		OI2	0.918		
		OI3	0.943		
		OI4	0.892		
		OI5	0.891		
Market Performance (MP)				0.946	0.889
		MP1	0.953		
		MP2	0.937		
		MP3	0.951		
		MP4	0.919		
Operational Performance (OP)				0.947	0.899
		OP1	0.949		
		OP2	0.953		
		OP3	0.930		
		OP4	0.951		
Big Data Analytics Capabilities	Composite (2nd order construct)		Weights	CI	VIF
		BR_BDAC	0.314	[0.063, 0.614]	4.828
		DA_BDAC	0.024	[− 0.316, 0.317]	4.709
		TE_BDAC	-0.072	[− 0.267, 0.130]	4.000
		TS_BDAC	0.341	[0.153, 0.570]	4.430
		MS_BDAC	0.057	[− 0.161, 0.277]	4.061
		DC_BDAC	0.432	[0.289, 0.581]	2.439
		OL_BDAC	0.073	[− 0.082, 0.245]	1.882

Note: CR = composite reliability; AVE = average variance extracted; CI = confidence intervals; VIF = variance inflation factor.

correlating the formative items against a single global item. As shown in Fig. 2, the path coefficient is 0.865. The value is much higher than 0.70, so the convergent validity is confirmed for the formative measurement model. Second, the variance inflation factor (VIF) is checked to assess potential collinearity issues. No VIF value of BDAC's dimensions is higher than the suggested threshold at 5 (refer to Table 2), so the

Table 3
Discriminant validity (HTMT).

Constructs	BR	DA	DC	MI	MP	MS	OA	OI	OL	OP	TE
DA	0.878										
DC	0.640	0.738									
MI	0.631	0.596	0.734								
MP	0.728	0.725	0.628	0.658							
MS	0.809	0.779	0.635	0.678	0.619						
OA	0.594	0.567	0.621	0.590	0.764	0.498					
OI	0.649	0.652	0.748	0.775	0.760	0.647	0.746				
OL	0.376	0.462	0.675	0.563	0.361	0.519	0.399	0.462			
OP	0.625	0.628	0.523	0.506	0.778	0.510	0.587	0.648	0.301		
TE	0.791	0.892	0.692	0.587	0.625	0.774	0.546	0.609	0.503	0.552	
TS	0.849	0.816	0.618	0.676	0.684	0.845	0.535	0.66	0.337	0.572	0.795

Note: Discriminant validity established at HTMT $_{0.90}$

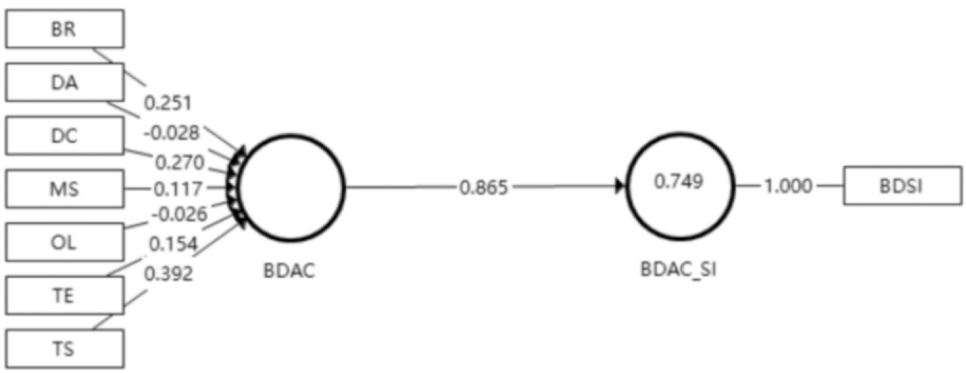

Fig. 2. Results of redundancy analysis.

formative measurement model of the research is not likely to have a collinearity problem (Hair et al., 2011).

Third, BDAC's outer weight significance is examined to assess the formative variable's significance and the relevance of its dimensions/indicators. Hair et al. (2021) state that outer weight is the result of a multiple regression measuring the latent variable and its formative dimensions/indicators. According to Table 2, the outer weights of DA_BDAC, TE_BDAC, MS_BDAC, and OL_BDAC are insignificant. Nonetheless, all four dimensions' outer loadings exceed the threshold of 0.5 in Table 4. Therefore, it is concluded that all the dimensions are significant in forming BDAC. However, the four dimensions are less important than the three dimensions with high outer weight significance. Given that the results of the three-step procedure meet all the criteria, the formative measurement model is confirmed.

5.3. Structural model assessment

As a pre-requisite to assessing the structural model of the research, it is crucial to rule out the lateral collinearity problem. Although the vertical collinearity (discriminant validity) is properly addressed earlier, lateral (predictor-criterion) collinearity could mislead the findings of the research as indicators of two latent variables may casually measure the same variable (Kock and Lynn, 2012). The results of inner VIF are summarized in Table 5, and it can be seen that no VIF value is higher than 5. Thus, this research has ruled out the lateral collinearity problem (Hair et al., 2011).

Table 4
Formative indicator's outer loading results.

Constructs	Loadings	T Value	P Value
BR	0.882	25.454	0.000
DA	0.864	21.181	0.000
DC	0.861	19.113	0.000
MS	0.834	20.681	0.000
OL	0.562	7.573	0.000
TE	0.793	18.806	0.000
TS	0.876	22.068	0.000

Table 5
Results of inner VIF values.

	MI	MP	OA	OI	OP
BDAC	1.550	2.320	1.000	1.550	2.320
MI		2.187			2.187
OA	1.550	1.995		1.550	1.995
OI		2.751			2.751

Then, the significance and relevance of the structural model relationships are assessed by using a bootstrapping technique with 5000 resamples. Using the bootstrapping technique, the relationships' t-value, p-value, and confidence intervals, bias-corrected, are obtained (Hair et al., 2021). As shown in Table 6, 11 proposed hypotheses are supported, and another two are not.

To further confirm the results of hypothesis testing, the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) are assessed (Hair et al., 2021). As shown in Table 7, the R^2 values of MI, MP, OA, OI, and OP are 0.470, 0.609, 0.349, 0.579, and 0.408, respectively, which indicates the research model has a moderate level of predictive accuracy (Hair et al., 2021). The results of f^2 confirm that marketing innovation does not significantly influence operational performance and market performance; BDAC has a substantial effect size on MI, OA, and OI, and OA has a substantial effect size on MP and OI (Cohen, 1988). With regard to Q^2, the values range from 0.305 and 0.453. They are all greater than the threshold value at 0, so the exogenous variables have predictive relevance for their associated endogenous variables (Hair et al., 2021).

Table 6
Results of hypothesis testing.

Hypothesis	Relationship	Beta	SD	T Value	P Value	LL	UL	Supported
H1	BDAC - > MP	0.247	0.112	2.208	0.027	0.083	0.445	Yes
H2	BDAC - > OP	0.289	0.141	2.054	0.040	0.073	0.531	Yes
H3	BDAC - > OA	0.596	0.061	9.760	0.000	0.481	0.683	Yes
H4	OA - > MP	0.350	0.095	3.682	0.000	0.206	0.519	Yes
H5	OA - > OP	0.198	0.128	1.646	0.098	0.001	0.420	Yes
H6	OA - > OI	0.428	0.099	4.317	0.000	0.251	0.581	Yes
H7	OA - > MI	0.203	0.126	1.649	0.092	0.002	0.423	Yes
H8	BDAC - > OI	0.430	0.098	4.381	0.000	0.271	0.595	Yes
H9	BDAC - > MI	0.552	0.123	4.485	0.000	0.328	0.742	Yes
H10	OI - > MP	0.269	0.111	2.430	0.015	0.094	0.456	Yes
H11	OI - > OP	0.313	0.134	2.334	0.020	0.100	0.534	Yes
H12	MI - > MP	0.040	0.100	0.402	0.688	-0.119	0.206	No
H13	MI - > OP	-0.072	0.121	0.595	0.552	-0.273	0.122	No

Note: LL (lower limit) and UL (upper limit) at 95% confidence intervals.

Table 7
Assessment of R^2, f^2 and Q^2.

	R^2	f^2				Q^2
		BDAC	MI	OA	OI	
MI	0.470	0.378		0.051		0.435
MP	0.609	0.070	0.002	0.162	0.070	0.426
OA	0.349	0.550				0.333
OI	0.579	0.288		0.285		0.453
OP	0.408	0.063	0.004	0.034	0.063	0.305

6. Discussion

The current study examines the interplays among big data analytics capability (BDAC), organizational agility, innovation, and firm performance in the tourism industry. A holistic understanding of the interaction among these factors facilitates hotels to make better strategic decisions for improving firm performance. By examining the aforementioned interplays, this research attempts to address four research questions: (1) how a hotel reconfigures its key resources and skills to obtain BDAC; (2) how digital evolution (i.e., BDAC) affects organizational agility, marketing and organizational innovations, and firm performance; (3) how organizational agility influences marketing and organizational innovations; and (4) how organizational agility and marketing and organizational innovations affect firm performance.

6.1. Theoretical contributions

This research has made several significant theoretical contributions to the existing literature regarding the relationship between BDAC, organizational agility, marketing and organizational innovations, and firm performance. First, this study confirmed that basic resources, data, technology, technical skills, managerial skills, data-driven culture, and organizational learning are needed to develop effective BDAC. These findings confirm previous studies by Mikalef et al. (2019) and Ciampi et al. (2021), which used the seven dimensions mentioned to form BDAC. Moreover, the dynamic capability view has been applied as the theoretical underpinning to justify the formation of BDAC. In line with this theory, organizations should continuously reconfigure their resources and skills to adapt to the rapidly changing market (Teece et al., 1997).

Second, the empirical findings revealed that there is a positive impact between BDAC and firm performance in the hotel sector. This result corroborates the finding by Yadegaridehkordi et al. (2020), which examines the relationship between big data adoption and hotel performance. Based on the findings, hotels that leverage BDAC can gain meaningful insights and respond to new market opportunities and threats. BDAC can also facilitate organizations to improve customer satisfaction and consequently build brand loyalty (Aziz et al., 2023). Brand loyalty directly increases customer purchase intention (Heidari et al., 2023). Consequently, hotels are more likely to make better decisions and improve their marketing and operational performance. Moreover, Previous studies mainly discussed the impacts of BDAC on firm performance in the fields of information technology and the manufacturing industry (Gupta et al., 2018; Mikalef et al., 2019; Ciampi et al., 2021). This study, however, extends the literature on tourism and hospitality, particularly in the hotel sector.

Third, the result showed that BDAC positively impacts organizational agility. This finding matches previous studies by Ghasemaghaei et al. (2017) and Xie et al. (2022). Similarly, this study also finds that BDAC has a positive impact on organizational innovation and marketing innovation. Thus far, no prior research has investigated BDAC's influence on marketing and organizational innovation. Grounded on the knowledge-based view theory, BDAC improves a firm's ability to utilize new information to improve its competitive advantage (Mikalef, 2019). Hence, knowledge-driven organizations would conduct more innovative activities. Furthermore, this study confirms that organizational agility positively influences marketing and organizational innovations. Thus far, research on the impact of organizational agility on marketing and organizational innovations has been limited. Nonetheless, Gonçalves et al. (2022) argue that agile organizations are more likely to participate in continuous innovations to sustain their competitiveness.

Fourth, this research examines the relationship between organizational agility and firm performance. The positive relationship between these two variables corroborates with past studies by Wamba (2022) and Zhou et al. (2019). This finding also implies that hotels should fully use BDAC to improve their agility and business performance. In addition, the result showed that organizational innovation has a positive impact on firm performance, which aligned with past literature by Chen et al. (2020) and Prasad and Junni (2016). However, marketing innovation does not have any effect on firm performance, which contradicts past studies by Hussain et al. (2020) and Nieves and Diaz-Meneses (2016). This inconsistent result warrants further research on the relationship between marketing innovation and firm performance. A possible avenue to strengthen this relationship is by introducing a moderator.

6.2. Managerial implications

This study provides awareness to the hotel industry on the importance of big data, especially during unstable periods. The study identifies resources such as data, technology, basic resources, technical skills, managerial skills, data-driven culture, and organizational learning that must be developed to build BDAC. The findings of the study highlighted the critical role of BDAC in improving hotel performance and boosting agility and innovation. Specifically, insight and information gleaned from big data allow hotels to be agile and effectively react to market opportunities and threats from competitors. Agility in hotel firms is crucial since it increases competitive advantage and therefore enhances firm performance. In addition, the result of the study also shows that BDAC has a significant impact on both marketing and organizational innovation in hotels. With the knowledge gleaned from big data, hotels can innovate by adopting new organizational structures and practices or introducing new marketing methods in pricing, distribution, and promotion. Finally, the findings of the study also show that organizational agility influences innovation in the hotel industry. The result indicates that hotels need to be agile in innovating, which can boost market share through market innovation while achieving strategic goals through organizational innovation.

6.3. Big data and open innovation in the tourism industry

The research on open innovation has primarily involved organizations as the unit of analysis (Bogers et al., 2017). Chesbrough and Bogers (2014) define open innovation as "a distributed innovation process based on purposively managed knowledge flows across organizational boundaries" (p. 17). The relationship between big data and open innovation has been widely discussed by researchers in the literature (Arias-Pérez et al., 2022; Del Vecchio et al., 2018a; Fortunato et al., 2017; Kim et al., 2022; Yun et al., 2020). As big data is a knowledge generator, firms would utilize this technology to improve innovation across their organizations (Ali et al., 2020). Nonetheless, there are still limited studies on the relationship between big data and open innovation in the tourism industry (Egger et al., 2010). The proliferation of user-generated content in social media and online travel websites would provide valuable insight using big data analytics (Del Vecchio et al., 2018b). These insights and information would help tourism players, such as the hotel industry, better understand customer sentiments and improve their products and services.

7. Conclusion

Most previous studies examine the relationship between big data and firm performance in the IT, electronics, and manufacturing industries. The present study extends the literature by examining BDAC, organizational agility, marketing and organizational innovation, and firm performance in the hotel industry. Marketing and organizational innovation are under-research in the literature, even though these types of innovation can assist organizations during unstable periods. Theoretically, the existing research applied knowledge-based and dynamic capability view theories to explain the theoretical relationship among the construct in the research model. The data analysis is based on collected surveys from 115 star-rated hotels in Malaysia. Using SmartPLS software, the study's findings revealed that BDAC positively impacts organizational agility, marketing and organizational innovations, and firm performance. Similarly, organizational agility positively impacts firm performance, marketing and organizational innovations. In terms of innovation, organizational innovation has a positive effect on firm performance, whereas marketing innovation does not have a significant relationship with firm performance. The result of the study also highlights to hotel managers the key resources needed to build their big data analytics capabilities, which they can leverage to improve their hotel performance.

7.1. Limitations and future research directions

This study has significant theoretical and practical contributions but is subject to limitations. First, this research used a quota sampling method for data collection from the star-rated hotels in Malaysia. The non-probability samples analyzed could not be easily generalized to the population of the study, but the main objective of this study is to test the validity of the suggested theoretical relationships. Future studies should aim to obtain an accurate sampling frame in order to do a probability sampling design. Second, this research collected data from a single source, which may lead to common method variance (CMV). The study took a few procedural measures to minimize the negative impacts of CMV, but it is better to use multiple sources, including objective data, for data collection. Third, this research is based on a cross-sectional design, which may limit causal inference. Future studies are encouraged to adopt a longitudinal data collection design to compare possible differences before and after embracing BDAC. Fourth, this study is based on the tourism sector, particularly the hotel industry situated in Malaysia. Future studies may run the same research on BDAC, organizational agility, innovation, and firm performance across multiple industries to increase generalizability. Also, cross-national studies to compare results would further enhance understanding of the relationships between the constructs.

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