Big Data Analytics Capability and Firm Performance in the Hotel Industry: The Mediating Role of Organizational Agility

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Abstract: - The emergence of the Covid-19 pandemic and restrictions on international mobility have negatively impacted the tourism market. Tourism players, particularly the hotel industry, have turned to big data analytics to mitigate uncertainties and offer better products and services. Nonetheless, the central question for researchers and practitioners is how the usage of big data analytics can help the hotel industry improve firm performance. Drawing on the resource-based view and dynamic capability theories, this study analyses the relationship between big data analytics capability and firm performance in the hotel industry. This study expands the current research by examining the role of organizational agility in mediating the relationship between big data analytics capability and firm performance. To empirically test the research model, the author used survey data from 115 star-rated hotels throughout Malaysia. Through partial least square equation modeling, the findings revealed that big data analytics capability positively affects organizational agility and firm performance. The result also demonstrated that organizational agility mediates the relationship between big data analytics capability and firm performance. This study can also guide hoteliers to identify resources required to build big data analytics capability and further highlight the significance of organizational agility in improving firm performance in the hotel industry.

Key-Words: Big data analytics capability, Firm performance, Organizational agility, Hotel industry

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1 Introduction

The growing digitalization of business processes has led to the abundance and viability of a large volume of data for analysis. A large volume of data is one of big data's key characteristics, including other characteristics such as variety, velocity, veracity, and value, [1]. Big data can be analyzed through statistical techniques and analytical tools to generate valuable business insight and predict future patterns, [2]. Consequently, the generated insight and information can eliminate the guesswork in decision-making and assist company executives in improving business operations, [3]. The usage of big data analytics also fosters innovation and efficiency in business operations that ensure an organization's long-term economic sustainability, [4], [5]. By adopting big data analytics, firms can enhance business decision-making, ultimately boosting their competitive advantage, [3]. According to IDC, [6], the global revenue for big data and analytics solutions was projected to surge around US215.7 billion in 2021, an increase of 10.1% from 2020. Hence, the reliance on data-driven decisions is essential for firms to maintain business resiliency during uncertain periods.

Specifically, the emergence of the Covid-19 pandemic and limitations on international mobility has negatively affected the tourism sector, [7]. The travel and tourism sector reported a loss of US$ 4.5 trillion globally in 2020, [8]. It is concerning given that the tourism industry is a significant contributor to the growth of the national economy and GDP. The economic benefits of the tourism industry include the generation of export revenue, local employment providers, and a source of foreign exchange, [9]. Big data analytics can assist firms in mitigating uncertainties, particularly during the Covid-19 pandemic, [10]. According to a report by UWNTO & ADB, [11], the usage of big data can aid in the recovery of tourism players by assisting in improving their products and services. One of the key tourism players is the hotel business, which is considered as one of the most significant drivers of employment and economic revenue in the tourism industry, [12].

Even though big data analytics benefits the tourism industry, there are limited studies examining firms' capability in its application and its impact on firm performance in the tourism industry. The majority of previous research that examines the relationship between big data analytic capability (BDAC) and firm performance is primarily conducted in the IT, technology, and manufacturing industries, [1], [2], [4], [13]. According to [14], the gap in firms' capability to use big data analytics warrants further research to assess the value of big data investment against firm performance. Hence, this study will examine the relationship between BDAC and firm performance centered on the tourism context. This study's findings could guide hoteliers on the importance of leveraging BDAC in daily hotel operations. It is important as the hotel industry is still reeling from past losses due to the COVID-19 pandemic.

The tourism industry is susceptible to changes in the economic and environmental landscape. Prior studies have reported a growing interest in studying organizational agility in unstable periods, particularly in the tourism landscape, [15], [16]. Agility relates to the adaptability of organizations to prosper in challenging periods or environments to improve firm performance, [17]. Consequently, it is important to examine how agile the hotel sector is in applying big data analytics to improve firm performance. In addition, several studies have indicated that BDAC indirectly affects firm performance through intermediate variables, [1], [18]. The authors in [3] further argue that BDAC is not an adequate prerequisite to influence firm performance, and this relationship must be subject to other factors. Hence, this study intends to analyze the mediating effect of organizational agility in the relationship between BDAC and firm performance in the tourism context. To conclude, this study will address the following two research questions based on the stated research gap:

*RQ1.*What is the impact of BDAC on firm performance in the tourism context?
RQ2. Is organizational agility a mediator in the relationship between BDAC and firm performance?

Based on the resource-based view and dynamic capability theories, this study will address the research questions highlighted above and further enrich big data studies in tourism and hospitality literature. Furthermore, [19] reported that big data literature in tourism is still lacking in theory-based research, and further explanations on the impact of big data on hotel performance based on theoretical perspectives are warranted.

2 Theoretical Background

2.1 Resource-based View

The resource-based view **(**RBV) theory measures the strategic value of organizational resources and explains why some firms exhibit superior performance compared to other firms, [20]. This theory states that firms managing their resources and capabilities would gain a competitive advantage based on two fundamental assumptions. The first assumption is based on resource heterogeneity, which assumes firms own diverse resources contributing to their competitive advantage, even though they may compete in the same industry, [21]. The second assumption relates to the firms' unique and long-lasting resources, which competitors find difficult to obtain and develop, [22]. The second assumption is coined as resource immobility. These resources include tangible and intangible assets, which could provide a competitive advantage for firms if these resources are rare, valuable, imperfect, imitable, and non-substitutable, [22].

Furthermore, firm resources can be combined to conduct a set of coordinated tasks to achieve specific purposes, [23]. This action is referred to as organizational capability, and it could become a point of competitive advantage as it is difficult to trade, copy and substitute. Competitive advantage can be achieved when organizations manage and exploit their capabilities and resources.

2.2 Dynamic Capability

The dynamic capability (DC) theory has been used extensively to understand the differential performance of an organization in a dynamic setting. This theory extends the RBV theory, which emphasizes the organization's ability to adapt and adjust its resources to attain a competitive advantage in a dynamic business environment, [24]. The DC theory is different from the RBV theory as the latter emphasizes utilizing resources and capabilities to achieve a competitive advantage based on a static market only, [2]. In addition, RBV theory does not sufficiently explain how competitive advantages and disadvantages can evolve. However, the DC theory covers the limitations of the RBV theory by considering the development of resources and capabilities over time, [24]. Based on the seminal paper in [25] the DC theory is further defined as the firm's capacity to combine, develop, and rearrange firm resources to respond to opportunities and threats in a fast-changing environment.

2.3 Big Data Analytic Capability (BDAC)

There are various definitions of big data analytics provided in the literature. Big data analytics has been described as the application of analytical tools, data mining, statistics, artificial intelligence, and machine learning to generate significant patterns from the data analyzed, [26]. According to [4], big data analytics is a multidisciplinary field that employs computer science, data science, statistics, and mathematical models to collect and evaluate data methodically. The latest definition by IBM states that big data analytics is the "use of advanced analytic techniques against very large, diverse big data sets that include structured, semi-structured and unstructured data from different sources, and in different sizes from terabytes to zettabytes", [27]. Despite the differences in meaning, the purpose of its use remains the same. Big data analytics is applied to determine meaningful insight and patterns, which can improve decision-making in a firm, [28], [29].

The current research extends the knowledge by examining big data analytics as an organizational capability. Scholars have provided different ranges of BDAC in the literature. According to Mikalef, BDAC is defined as "the ability of the firm to capture and analyze data towards the generation of insights by effectively deploying its data, technology and talent through firm-wide processes, roles and structure", [29]. Meanwhile [13] defined BDAC as the capability to gather, incorporate and utilize organizations' big data-specific resources. The majority of the previous studies have conceptualized BDAC as a multidimensional and hierarchical construct. Several studies demonstrated that BDAC is measured through dimensions such as big data analytics infrastructure flexibility, big data analytics management capability, and big data analytics personal expertise, [17], [30]. In other studies, BDAC comprises several organizational resources that include tangible (data, technology, basic resources), intangible (data-driven culture and organizational learning), and human skills (technical skills, managerial skills), [3], [28], [31]. The conceptualization of BDAC is grounded on RBV theory, whereby the usage of firm resources and capabilities will result in a competitive advantage. The following subsections explain the dimensions of BDAC.

2.3.1 Data

Data in the term 'big data' encompass structured, unstructured, and semi-structured data, which are large in volume and fast-moving, [13]. Organizations seek to boost their competitive advantage by effectively handling internal and external data so that they can make effective business decisions, [32].

2.3.2 Technology

Firms need technological resources that can compile, distribute, and analyze big data to generate insight, [18]. Technological resources such as non-relational databases, middleware, and data warehousing are able to extract, incorporate and analyze big data so that actionable insight can be formulated to assist in decision-making, [33]. In addition, firms are now moving away from relational databases to open-source software frameworks such as Apache Hadoop. This software provides distributed storage and allows parallel processing of big data based on a Java-based framework, [34].

2.3.3 Basic Resources

Firms need basic resources such as financial funding so that they can invest in technology and infrastructure to support big data initiatives, [35]. This investment requires time to provide the desired result, [13]. Thus, firms need to allocate appropriate time and funds for ventures into big data analytics.

2.3.4 Technical Skills

There are an increasing number of firms employing staff with technical skills in big data. This technical skill relates to the competency and know-how of employees in utilizing data and technology to obtain insight for company decision-making, [13]. A case in point is skills related to data extraction, data cleaning, and statistical analysis, [29].

2.3.5 Managerial Skills

Managers need to understand the insight extracted from big data to predict upcoming business growth and effectively apply the insight generated in making business decisions, [2], [13]. Managers also need to work and coordinate with other managers in the firm, suppliers, and customers in implementing big data-related initiatives, [36].

2.3.6 Data-Driven Culture

Employees from upper management, middle management, and lower levels should make any business action based on information gleaned from big data analytics and rely less on their experience, [13]. Employees also can obtain necessary information when data-driven culture is embedded in the internal process of the firm's decision-making, [29].

2.3.7 Organizational Learning

Organizational learning describes how organizations search, retain, distribute, and utilize knowledge, [13]. According to [4], the organizational learning encourages employees to upgrade their knowledge and enhance competitive advantage in firms.

2.4 Organizational Agility

Organizational agility is generally defined as the capability of firms to detect and respond to changes in the market with ease and speed, [37]. Similarly, the article in [38] relates organizational agility as the capacity of the organization to respond quickly to changes and opportunities in the market. Researchers have argued that organizational agility is the new management paradigm in which organizations are subjected to fluctuations in technology, customers, competitors, and climate, [16]. Due to changes in the environment, firms cultivate the ability to be agile in responsiveness, speed, and flexibility to maintain competitive advantage. According to [39], agile firms will survive and thrive in a globalized business setting as they are more aligned to increase their revenue and profit margin. Agile firms also can react rapidly to client demand, unexpected changes, and opportunities in the market, [40]. Consequently, firms can improve their business performance, [41].

Several studies have claimed that organizational agility is a part of dynamic capability, [18], [42], [43]. Organizational agility is viewed as a specific dynamic capability that assists firms in thriving in challenging environments, which competitors cannot easily replicate, [42]. Numerous previous studies have conceptualized organizational agility into several dimensions. These dimensions include market responsiveness agility and operational adjustment agility, [30], customer responsiveness, operational flexibility, and strategic flexibility, [38]. Additionally, other studies have conceptualized organizational agility as a unidimensional construct, [18], [44].

2.5 Firm Performance

Across the literature, there appears to be a consensus on the definition of firm performance among researchers. Firm performance is assessed based on a series of performance criteria in comparison with fellow rival firms. According to [45], the firm performance is defined as the extent to which a company performs better than its rivals. Similarly, [46] point out that the examination of inter-company comparison is vital in measuring firm performance. Many studies have studied firm performance as a multidimensional construct consisting of financial and non-financial indicators, [47], [48]. For example, firm performance is measured based on financial returns, customer perspective, and operational excellence, [49]. Also, several studies on big data have categorized firm performance into two separate and distinct dimensions, namely financial performance and market performance, [2], [13]. In these studies, market performance is measured by market shares, entrants to new markets, the introduction of product services, and its success rate. In contrast, operational performance relates to the firm's productivity, profit rate, financial goal, and return on investment. The research on the relationship between BDAC and firm performance in the tourism literature is still limited and warrants further study to improve understanding and generalizability.

3 Research Model & Hypotheses

The research model is developed by integrating both RBV and DC theories (Fig.1). Neither theory can theoretically support this study’s empirical result on its own. Both theories are required to explain the direct and mediating relationships in the research model. These include the direct relationship between BDAC and firm performance and between BDAC and organizational agility. This study also examines the role of organizational agility in mediating the relationship between BDAC and firm performance. The DC theory complements the RBV theory as the former examines firms’ use of resources to achieve competitiveness in a highly volatile market.

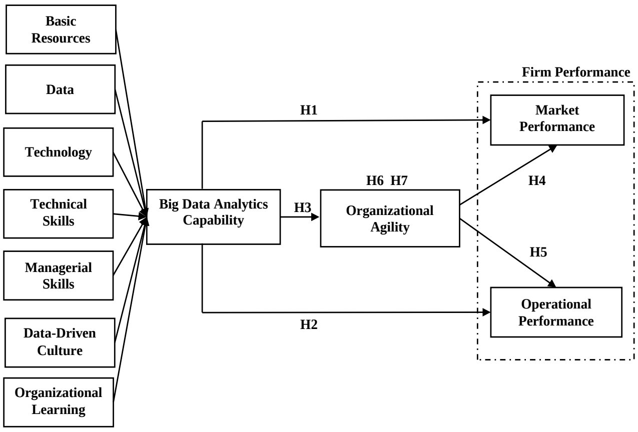

Fig. 1: Research Model

3.1 BDAC and Firm Performance

Every firm aims to maximize shareholder wealth by being competitive and profitable. Thus, firms seek to use every advantage, including using big data, to remain competitive, [28]. The authors in [50] stated that companies that applied big data in their daily operation could experience an increase of 5% in productivity and 6% in profitability in comparison to their rivals. Using big data analytics can assist companies in reducing operating costs and improving their product and services, [4]. Additionally, the market insight generated by big data analytics allows firms to focus on higher profit investment, [51]. Nevertheless, spending on big data does not necessarily lead to successful business outcomes, [35]. Several studies have pointed out that big data investment does not yield the intended results due to a lack of data-driven culture, [13], [52].

Companies that efficiently manage their resources to build BDAC would be able to improve firm performance, [2]. Based on RBV theory, firms' resources and capabilities, which might be valuable, rare, imperfectly imitable, and not substitutable, can create a competitive advantage. Significantly, most previous studies demonstrate that BDAC has a direct positive relationship with firm performance, [1], [2], [31]. Other studies also reported that BDAC significantly affects firm performance, where the latter construct is signified by market and operational performances, [2], [13]. Hence, the following hypotheses are proposed:

H1: BDAC is positively related to market performance.

H2: BDAC is positively related to operational performance.

3.2 BDAC and Organizational Agility

Previous empirical studies have established that IT capabilities are the enablers of organizational agility, [37], [39]. These studies show the importance of firms' capability to leverage IT-based resources, which positively impact organizational agility. Nonetheless, there is a shift toward examining BDAC as the antecedent of organizational agility in the literature. Big data analytics can generate market insight that would assist firms in identifying and reacting quickly to any market changes in terms of challenges and opportunities, [18]. The information generated would also assist firms in decision-making and managing risk during uncertain periods, [30]. Grounded on the DC theory, organizations operating in a dynamic market would continuously reconfigure and reshape their resources to achieve a competitive advantage.

A study, [53], highlighted that marketing-enabled data analytics capability has a significant positive relationship with organizational agility. In this study, the insight generated from data analytics would enable firms to react to emerging customer demand and potentially capitalize on new business opportunities. Several studies also reported that BDAC positively affects organizational agility, [17], [54]. Thus, the following hypothesis is developed in response to these studies.

H3: BDAC is positively related to organizational agility.

3.3 Organizational Agility and Firm Performance

Several studies have reported that organizational agility positively influences firm performance, [39], [55], [56]. Agility can boost performance by optimizing the firm's range of reactions toward market changes and reducing risk and uncertainty. This range of responses includes expansion into new territories, multiplying the rate of innovation, and making changes in products and services based on customer demand, [37]. As a result, agile firms can increase market share, reduce cost, and exhibit higher revenue and profitability. Similarly, [38] found that organizational agility positively affects firm performance. Firms that are agile and responsive to market changes would be able to formulate an effective business strategy to increase their competitive advantage in the market. Underlining the DC theory, organizational agility is recognized as a specific dynamic capability that can explain why firms reconfigure and reshape their resources to achieve competitive advantage in a dynamic environment, [17], [57]. The next postulated hypotheses are:

H4: Organizational agility is positively related to market performance.

H5: Organizational agility is positively related to operational performance.

3.4 Mediating Effect of Organizational Agility

Mediation relates to the concept that the effect of BDAC on firm performance is conveyed by organizational agility, [58]. The authors in [49] called for further research on the mediating effect of firm agility on the relationship between big data and firm performance. Firms can improve decision-making based on the insight generated through big data and rapidly react to opportunities and threats in the market. Consequently, agile companies can improve their bottom-line performance, [47]. In a dynamic business environment, the DC theory supports the mediating role of organizational agility as it emphasizes the company’s capability to adapt and adjust its resources to achieve a competitive advantage, [24]. Following the prior discussion, there is evidence in the literature supporting the positive effect of BDAC organizational agility. Likewise, organizational agility significantly affects firm performance, according to prior studies. Therefore, it is proposed that organizational agility is the mediational pathway through which BDAC affects firm performance. Our next postulated hypotheses are:

H6: Organizational agility mediates the relationship between BDAC and market performance.

H7: Organizational agility mediates the relationship between BDAC and operational performance.

4 Research Methodology

4.1 Instrument Design

The data collection was conducted by distributing self-administered questionnaires. The questionnaire items of the variables from this research were adapted from established articles from various journal publications. Big data analytics capability comprises seven dimensions: basic resources, data, technology, technical skills, managerial skills, data-driven culture, and organizational learning, adapted from, [4], and, [29]. Organizational agility was adapted from, [18], and, [37], while both market performance and operational performance were adapted from, [2], and, [13]. The dependent variable was measured using a five-point Likert scale, whereas the independent and mediating variables were measured using a seven-point Likert scale. Using two different Likert scales reduces the common method bias as the data collection was based on a single source and a single respondent. Common method bias can be described as the resultant bias due to independent and dependent variables measured using the same source or method, [59].

The developed questionnaire had gone through pre-testing before the actual data collection. This pre-test was conducted by four academic reviewers and another four respondents from the hotel industry. The pre-test was performed to review the clarity of the measurement item and confirm whether the target respondent could comprehend the question, [60]. Based on the comments from the pre-test, the survey was refined by amending the questions' wording, layout, and format.

4.2 Sampling and Data Collection

This study examines the relationship between BDAC and firm performance in the tourism context. Hence, the fitting unit of analysis for this study is hotel organizations. The respondents of this research came from middle to upper management of star-rated hotels in Malaysia. Malaysia is ranked second behind Thailand for the highest international tourist arrivals in Southeast Asia, with 26.1 million tourist arrivals in 2019, [61]. Since this research is focused on the hotel industry, applying the purposive sampling method was suitable for this study. This study focused on hotels rated 3-stars and above, as hotels with a higher star rating are more likely to have more professional and qualified staff and more inclined to apply innovation activities in their daily operation, [62]. Thus, it is more likely that higher-rated hotels would utilize big data analytics in their daily operation. Out of the 180 hotels that were contacted, 115 gave consent to take the survey, yielding a response rate of 64%. Among the hotels that participated, 76 respondents (66%) came from 5-star hotels, followed by 33 respondents (29%) from 4-star hotels, and six respondents from 3-star hotels (5%).

The sample size of the study was determined using the G*Power application. The G*Power is an independent program frequently used in social and behavioral studies to conduct statistical tests, [63]. Based on the application, the calculated minimum sample size was 103. As recommended by [64] the calculated value was based on seven predictors from the research model at medium effect size and the power of 80%. Since the number of responses collected was higher than the minimum sample size, this study proceeded with the data analysis.

5 Data Analysis and Results

Since the data collection was based on a single source, the collected data may be subject to common method bias. Full collinearity testing was performed to remedy the issue, [65]. In this test, all the constructs were regressed against a common construct, and it showed that there was no bias from the data. The VIF values of all constructs were below the recommended maximum limit of 5. Furthermore, as recommended by the authors in [66] this study examined the multivariate skewness and kurtosis, and the results indicated that the data collected was not multivariate normal with Mardia's multivariate skewness ($\beta = 3.184$, $p < 0.01$) and Mardia's multivariate kurtosis ($\beta = 26.779$, $p < 0.01$). The data analysis was conducted using Smart partial least squares (Smart PLS) software, which is a non-parametric analysis software.

The application of PLS-SEM is also ideal for analyzing formative constructs and hierarchical models in the theoretical framework, [67]. There are two main stages when applying PLS-SEM as the method of data analysis. The first stage is the measurement model analysis, which shows the association between the latent variable and its measurement items, [68]. After the measurement model is verified, the second stage, the structural model, is analyzed to test the hypotheses, [67].

5.1 Measurement Model

There is both reflective and formative construct in the research model, which has different assessment criteria. As for the reflective construct, two types of validity need to be assessed: convergent and discriminant. Convergent validity is confirmed when a particular item measures the construct that it is supposed to measure, [67]. Convergent validity was achieved as all loadings exceeded the minimum value of 0.5. Plus, all the average variance extracted (AVE) was larger than the minimum value of 0.5, and all composite reliability (CR) was larger than the minimum value of 0.7. Table 1 depicts the value of all the loadings, CR and AVE, which met the minimum threshold value to proceed with the discriminant validity. The discriminant validity would test the degree to which latent variables are exclusive and not represented by other variables [68]. As depicted in Table 2, the values of the Heterotrait-Monotrait ratio (HTMT) of all ten constructs were lower than the ceiling value of 0.9, which confirms the discriminant validity of this study, [69].

Table 1. Convergent Validity

Constructs	Items	Loadings	CR	AVE
Basic Resources	BR1	0.976	0.974	0.950
	BR2	0.974		
Data	D1	0.941	0.944	0.895
	D2	0.951		
Technology	T1	0.915	0.953	0.836
	T2	0.936		
	T3	0.895		
	T4	0.912		
Technical Skills	TS1	0.855	0.968	0.885
	TS2	0.974		
	TS3	0.970		
	TS4	0.958		
Managerial Skills	MS1	0.962	0.978	0.918
	MS2	0.970		
	MS3	0.972		
	MS4	0.927		
Data-Driven Culture	DDC1	0.847	0.919	0.739
	DDC2	0.841		
	DDC3	0.897		
	DDC4	0.851		
Organizational Learning	OL1	0.851	0.950	0.827
	OL2	0.933		
	OL3	0.930		
	OL4	0.921		
Organizational Agility	OA1	0.791	0.916	0.687
	OA2	0.843		
	OA3	0.862		
	OA4	0.902		
	OA5	0.736		
Market Performance	MP1	0.945	0.964	0.870
	MP2	0.929		
	MP3	0.958		
	MP4	0.899		
Operational Performance	OP1	0.945	0.973	0.898
	OP2	0.953		
	OP3	0.945		
	OP4	0.948		

Note: To get better discriminant validity, item D3 was dropped

BDAC was measured as a type II reflective-formative higher-order construct and required different criteria for examining the formative measurements. Firstly, the convergent validity was assessed using global single-item measurement through redundancy analysis, which produced a path coefficient higher than the minimum limit of 0.7, as shown in Table 3. Convergent validity is used to examine the extent to which the measurement items correlate with other items measuring the same latent variable, [70]. Subsequently, the formative measurement must be assessed on collinearity issues so that there would not be any two or more measurements that have high collinearity with each other, [68]. The VIF values of all the formative measurements were lower than the ceiling value of 5, [67]. Lastly, the formative measurements needed to be assessed individually on their significance and relevance through the bootstrapping technique, [70]. Based on Table 3, the lower-order constructs of Data, Technology, Managerial Skills, Technical Skills, and Organizational Learning were not significant based on the outer weight. Nonetheless, these constructs were kept in the model as all five had significant outer loading.

Table 2. Discriminant Validity

Construct	1	2	3	4	5	6	7	8	9	10
1. Basic Resources										
2. Data	0.891									
3. Data-Driven Culture	0.602	0.714								
4. Management Skills	0.793	0.706	0.588							
5. Market Performance	0.691	0.601	0.559	0.559						
6. Operational Performance	0.596	0.56	0.464	0.449	0.782					
7. Organizational Learning	0.315	0.426	0.661	0.463	0.285	0.251				
8. Organizational Agility	0.594	0.508	0.621	0.498	0.764	0.587	0.399			
9. Technical Skills	0.833	0.756	0.564	0.823	0.636	0.529	0.266	0.535		
10. Technology	0.779	0.891	0.679	0.755	0.597	0.522	0.453	0.546	0.789	

Table 3. Measurement Properties for Higher-order Construct

Higher Order	Lower Order	Convergent Validity	VIF	Weight	Sig.
BDAC	BR	0.873	4.684	0.723	0.002
	D		4.610	-0.246	0.179
	T		4.023	0.190	0.166
	TS		4.075	0.254	0.094
	MS		3.744	-0.200	0.175
	DDC		2.299	0.355	0.005
	OL		1.797	0.063	0.166

Note: BR= Basic Resources; D= Data, T= Technology; TS=Technical Skills;, MS=Managerial Skills; DDC= Data-driven Culture; OL=Organizational Learning.

5.2 Structural Model

Following confirmation of the measurement model, the next stage was to assess the structural model. The hypotheses developed in the research model were tested by looking into the path coefficient, standard errors, t-values, p-values, and confidence interval between the lower and upper levels. Before performing the analysis, the collinearity issue was checked in the structural model. Table 4 shows that all VIF values were well below the threshold value of 3.3, as recommended by the authors in [71]. This result showed that the collinearity issue was not significant in this study.

Subsequently, following the suggestion of [70] this study analyzed the structural model using the bootstrapping technique with a resampling of 5000. For the t-test, all five direct relationships were found to have t-values >2.33, thus significant at a 0.01 level of significance, as indicated in Table 4. Specifically, BDAC → Market Performance (β = 0.412, $p < 0.01$), BDAC → Operational Performance (β = 0.409, $p < 0.01$), BDAC → Organizational Agility (β = 0.629, $p < 0.01$), Organizational Agility → Market Performance (β = 0.443, $p < 0.01$) and Organizational Agility → Operational Performance (β = 0.289, $p < 0.01$). Furthermore, the confidence intervals bias-corrected 95% did not indicate any intervals straddling a 0, which confirmed our result. Hence, these findings support this study's **H1, H2, H3, H4,** and **H5**. The findings also show that the relationship between BDAC and market performance (f^2= 0.255) has a larger effect size than the relationship between BDAC and operational performance (f^2= 0.169). Next, based on the recommendation of [67] the mediating relationship in this study was tested by bootstrapping the indirect effect. As shown in Table 4, BDAC → Organizational Agility → Market Performance (β = 0.279, $p < 0.01$) and BDAC → Organizational Agility → Operational Performance (β = 0.182, $p < 0.05$) were all significant. In addition, the confidence intervals bias-corrected 95% also did not indicate any intervals straddling a 0, which confirmed our result. Hence, these findings support **H6** and **H7** of this study.

Table 4. Hypotheses testing

Hypothesis	Relationship	Beta	Se	T value	P value	LL	UL	f^2	VIF
H1	BDAC → Market Performance	0.412	0.099	4.169	0.001	0.230	0.551	0.255	1.655
H2	BDAC → Operational Performance	0.409	0.112	3.644	0.001	0.173	0.554	0.169	1.655
H3	BDAC → Organizational Agility	0.629	0.057	11.012	0.001	0.496	0.697	0.655	1.000
H4	Organizational Agility → Market Performance	0.443	0.092	4.824	0.001	0.314	0.608	0.294	1.655
H5	Organizational Agility → Operational Performance	0.289	0.120	2.410	0.008	0.124	0.509	0.084	1.655
H6	BDAC → Organizational Agility →Market Performance	0.279	0.069	4.025	0.001	0.179	0.408		
H7	BDAC → Organizational Agility → Operational Performance	0.182	0.082	2.212	0.014	0.068	0.343		

The predictive validity of the framework was assessed using PLS Predict. According to [72] the application of PLS Predict allows the examination of a model's out-of-sample predictive power through a holdout sample-based procedure. As illustrated in Table 5, all the LM model errors were higher than the PLS model, indicating that the research model had a large predictive power.

Table 5. PLS Predict

Item	PLS RMSE	LM RMSE	PLS-LM RMSE	Q²_predict
MP1	0.789	0.808	-0.019	0.367
MP2	0.829	0.843	-0.014	0.351
MP3	0.850	0.869	-0.019	0.333
MP4	0.864	0.892	-0.028	0.294
OP1	0.892	0.908	-0.016	0.305
OP2	1.031	1.061	-0.030	0.217
OP3	1.038	1.071	-0.033	0.195
OP4	1.085	1.134	-0.049	0.200
OA1	0.877	0.902	-0.025	0.152
OA2	0.841	0.877	-0.036	0.216
OA3	0.867	0.892	-0.025	0.232
OA4	0.829	0.877	-0.048	0.225
OA5	1.049	1.112	-0.063	0.251

Note: MP = Market Performance, OP = Operational Performance, OA = Organizational Agility

6 Discussion

This paper aims to assess BDAC's impact on firm performance in the tourism context. The empirical result shows that BDAC positively affects firm performance among star-rated hotels in Malaysia. Given that, empirical research between BDAC and firm performance has been mainly carried out in the IT and manufacturing industries. It fills the research gap by understanding the impact of big data on tourism players, particularly the hotel industry. The result of the study also implies that hotels with stronger BDAC will lead to better firm performance. A case in point is big data analytics have been used to improve revenue management techniques, which can boost hotel competitive advantage and improve sales revenue. The revenue management system analyzes internal and external data in order to provide reliable revenue decision-making to the hotel management, [73]. The findings are also consistent with past studies by [74] and [75], which examine the relationship between BDAC and firm performance in the IT and manufacturing industries. The results also show that BDAC has a larger effect size on market performance than operational performance. A possible explanation for this might be due to the adverse effect of the Covid-19 pandemic, which shows that financial indicators are considerably more affected than non-financial ones. In this study, the financial indicators are represented by operational performance, whereas non-financial indicators are represented by market performance.

Additionally, this study identifies and examines organizational agility as the mediating variable in the relationship between BDAC and firm performance. So far, research on the mediating effect of organizational agility on the relationship between BDAC and firm performance is limited. This study empirically tested the mediation analysis and found that the relationship between BDAC and firm performance is mediated by organizational agility. This finding indicates that hoteliers should be agile in their business operations to maximize BDAC's impact on firm performance. Given the insight generated from big data, hotels can optimize their reactions to market changes and uncertainty and improve their competitive advantage. This finding also corroborates with the past study by [17]. In the IT literature, [39] and [76] also demonstrated that organizational agility can act as a mediator between IT capability and organizational performance.

The empirical result demonstrates that BDAC is positively related to organizational agility. Previous studies by [30] and [54] supported this finding. Likewise, organizational agility is found to have a positive effect on firm performance. Prior studies have also reported the positive impact of organizational agility on firm performance, [37], [55].

6.1 Theoretical Contributions

The research model used the resource-based view and dynamic capability as the theoretical underpinning. Integrating both theories in a single framework broadened the scope of these theories and highlighted their importance. Consequently, this study contributes to theory-based studies of big data in tourism and hospitality literature. Past literature has shown that BDAC positively affects firm performance. However, what is less understood is the role organizational agility plays in this relationship. This study's results demonstrate the importance of organizational agility in mediating the relationship between BDAC and firm performance. In addition, based on prior studies, this study conceptualized BDAC as a multidimensional and hierarchical construct. Grounded on the RBV theory, this study identified that resources such as data, technology, basic resources, technical skills, management skills, organizational learning, and data-driven culture are needed to build and measure BDAC. Given that the studies of BDAC in tourism literature are limited, the empirical study on the conceptualization of BDAC based on a tourism setting further enriches the literature.

6.2 Managerial Contributions

From a management point of view, this study can create awareness among key management in the hotel industry on the importance of leveraging BDAC to improve hotel performance. The findings from this research can support hoteliers in justifying big data investment and initiatives. It is crucial as the hotel industry is still recovering from the losses due to the Covid-19 pandemic. This study could also guide hoteliers in identifying resources needed to build their BDAC. Hotel managers must drive and build resources such as data, technology, basic resources, technical skills, management skills, organizational learning, and data-driven culture. The combination of these resources can assist hotels in shaping their BDAC and consequently improve their bottom line. Having said that, hotels must be agile to react quickly to the information extracted from big data. They need to develop new strategies or reap new opportunities based on the knowledge gleaned from big data analytics. Hence, agility in hotel organizations is important as it improves competitive advantage and consequently boosts firm performance.

This study can provide a blueprint for policymakers on the way forward for the tourism industry. Despite the adverse consequences of the Covid-19 pandemic, tourism players should turn to emerging technology, such as big data analytics, to facilitate recovery. Thus, policymakers should incentivize industry players to apply big data analytics in their day-to-day business. Even the policymakers themselves need to formulate policies and directives based on big data so that it can benefit the tourism industry as a whole.

7 Limitations and Future Research

This paper has several limitations. First, the study samples were primarily drawn from managers in the hotel industry. Hence, it is uncertain whether the results of the study can be generalized to other tourism sectors, such as retail and restaurant businesses. Further research on the application of big data analytics in other tourism sectors can shed more light on its impact on the tourism industry. Second, this study is based on a cross-sectional design, and future research should focus on longitudinal studies to compare and generalize the results. The longitudinal design also has a stronger basis for deriving causal inference in testing mediation than cross-sectional data, [58]. Third, this study examined the mediating role of organizational agility in the relationship between BDAC and firm performance. Other variables, such as marketing capability, could be tested as a mediator in the relationship between BDAC and performance, [36]. Finally, this study's dependent variables (market performance and operational performance) are based on perceptual measures. Future research should base performance on objective measures to better comprehend BDAC's influence on firm performance.

8 Conclusion

This study further enriches the literature on big data by examining how BDAC influences firm performance in the tourism context. Based on the resource-based view and dynamic capability theories, these two theories are integrated to support and explain the relationship in the research framework. The study also conceptualized the organizational resources needed to build and measure BDAC and further tested the relationship between BDAC and firm performance in a tourism setting. The empirical results show that BDAC positively affects firm performance and organizational agility based on data from the hotel industry in Malaysia. The results also indicate that organizational agility mediates the relationship between BDAC and firm performance. These findings suggest that hotels must be agile in reacting to potential insight from big data to enhance their competitive advantage. Overall, the study results signify that BDAC and organizational agility are important drivers of hotel performance, particularly against the backdrop of the Covid-19 pandemic.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Norzalita Abd Aziz and Ahmad Azmi M. Ariffin carried out the research instrument development and data collection.
Muhamad Luqman Khalil managed the writing and editing.
Abdul Hafaz Ngah was responsible for Data Analysis.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.