International Journal of
Financial Studies

MDPI

Article

Examining the Effects of Big Data Analytics Capabilities on Firm Performance in the Malaysian Banking Sector

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Abstract: Banks' primary goal is to gain profit for survival and to thrive. Therefore, they have to take various measures, such as data analysis, to maintain their sustainable competitiveness. Along with the rapid development of information technology, big data analytics capabilities (BDAC) is considered essential for banks in the highly dynamic market. To gain an in-depth understanding of the economic importance of BDAC in the banking sector in Malaysia, this research examines the relationship between BDAC and firm performance (i.e., market performance and operational performance) based on the resource-based view (RBV) and the contingent resource-based view (CRBV). The partial least squares structural equation modelling (PLS-SEM) was adopted to analyse the collected data from 162 bank managers in Malaysia. The findings verify that BDAC is composed of seven tangible/intangible resources and human skills, and it significantly influences firm performance in the banking sector.

Keywords: big data analytics capabilities; firm performance; bank; Malaysia

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Citation: Aziz, Norzalita Abd, Fei Long, and Wan Mohd Hirwani Wan Hussain. 2023. Examining the Effects of Big Data Analytics Capabilities on Firm Performance in the Malaysian Banking Sector. *International Journal of Financial Studies* 11: 23. https://doi.org/10.3390/ijfs11010023

Received: 10 November 2022
Revised: 19 January 2023
Accepted: 20 January 2023
Published: 28 January 2023

1. Introduction

Big data has been considered "the next frontier for innovation, competition and productivity" (Manyika et al. 2011, p. 1), and its usage is expected to become a crucial factor for organizations concerning business forecasting and strategic decision-making in the near future (Appelbaum et al. 2017; Goasduff 2021; Ram and Zhang 2022). Therefore, organizations pay more attention to big data analytics (BDA) to keep up with business changes. The importance of BDA is to boost organization operations and decision making via information technology and quantitative analysis. Through BDA, organizations (e.g., banks) can improve their capabilities in understanding the market and finding business opportunities.

The value of BDA application has been widely accepted among academic scholars. Many organizations have also put considerable efforts and investments into related infrastructures, technologies, talents, and business practices, aiming to keep their competitive advantages in the market (Ciampi et al. 2020, 2021). Thus, it is pivotal to look at how BDA magnifies business operations and facilitates marketing activities in the service context (Leung et al. 2019; Ram and Zhang 2022). Despite the importance of BDA, most prior studies focused on the manufacturing sector (Wamba et al. 2017) and technology-oriented organizations (Meire et al. 2017; Troisi et al. 2020) rather than the service sector. Furthermore, it remains unclear how to effectively acquire BDA for a firm and transform it to a data-driven organization that is capable of turning big data into actionable insight (Behl et al. 2022). Hence, it is necessary to explore what underlying factors construct big data analytics capabilities (BDAC) and the impacts of BDAC on business performance in the financial services context, the banking sector in particular. BDAC could be interpreted as a firm's abilities to transform big data into meaningful knowledge and insight via related tangible and intangible resources (Mikalef et al. 2019).

According to Sivarajah et al. (2020), SMEs and large organizations could gain competitive advantages through BDA by analysing data from multiple channels, including social media, online businesses, and informational portals. However, there is insufficient research examining the effects of BDA in the context of financial services. Specifically, studies focusing on the effects of BDAC on business performance in the banking sector are still underdeveloped. Meanwhile, the Malaysian banking sector must face new challenges along with large scale crises that may reoccur (e.g., the 1997 Asian financial crisis and the 2008 global financial crisis). In such turbulent market environments, the Malaysian banking sector must continuously update itself and embrace digital transformation for competitive advantages. The adoption of BDA is proliferating, but many organizations are still struggling to produce quality insights (Ransbotham et al. 2016). Thus, there is a necessity for furthering research examining the factors of BDAC or adopting analytics in organizations. (Aziz 2018; Kim and Lui 2015; Wang and Wang 2020). Research on BDAC in financial services organizations is considered to be fragmented in scope and limited in methodologies. Therefore, it is crucial to further understand the adoption of industry 4.0 to gain optimal outcomes for the banking sector in Malaysia. Banks need to keep abreast with the current and latest situation from many angles, including multiple economic perspectives in decision making, and integrating BDAC could facilitate this.

Based on the stated research problems and gaps, there are two research questions to address, as follows:

Q1: What are the enablers needed to build BDAC in the financial services industry, particularly banks?

Q2: How does BDAC impact business performance?

By addressing the research questions above, this research makes a contribution to the extant literature in twofold. Firstly, it clarifies how to effectively transform a firm into a data-driven organization in the context of Malaysia's banking sector. In another word, what core resources are necessary to develop BDAC, which could facilitate banks' transformation to data-driven organization in the current fast-changing market? Secondly, this study empirically demonstrates the direct impacts of BDAC on marketing performance and operational performance among financial firms in Malaysia, which justifies the importance and necessity of developing BDAC, thus encourages banks to make investments in big-data-related infrastructure, technology, and talent and make strategic decisions based on BDA-centric knowledge/insight in the financial sector.

2. Literature Review

2.1. Big Data Analytics Capabilities

The financial sector is a data-intensive industry concerning data generation and utilization. The advancement of technology allows for the connections of different physical elements, services, and spaces and facilitates real-time approximation and the generation of a large volume of data. Big data analytics (BDA) is critical for any commercial organization with the belief that data collection, analysis processes, technology deployment and talent resources are needed to capitalize on its values and increase its business performance in the current emerging data economy. The recent technologies have empowered customers to seek out and compare an endless array of products and services from around the globe (Kiron et al. 2014; Srinivasan and Kurey 2014). Thus, it is vital to understand the adoption of BDA to gain the optimal outcomes for the banking sector.

BDA has become a significant trend in today's businesses and has emerged as a new frontier for academic and practical research. The application of big data is developing into a management revolution that affects commercial organizations' strategies, processes, and systems (George et al. 2016). BDA plays a crucial role in business operation and extends commercial organizations' capabilities in developing international markets (Doh et al. 2016; Watson et al. 2018). BDA involves discovering meaningful data patterns using pattern-recognition techniques, statistics, machine learning, artificial intelligence, and data mining (Abbott 2014). By scrutinizing big data, service organizations can develop actionable insights and new knowledge to establish competitive advantages in the market.In particular, BDA has become a significant differentiator between high-performance and lowperformance firms as it allows companies to have a long-term vision, decreases customer acquisition costs by 47 percent, and raises firm revenue by about eight percent (Liu 2014).

Due to the increasing digitalization of business in every aspect, BDA is crucial for organizations to gain competitive advantages and enhance their performances (Akter et al. 2016). Big data has been defined primarily with five Vs: volume, variety, velocity, veracity, and value, and its application could deliver sustainable values to customers and improve firm performance (Wamba et al. 2017). The application of BDA involves assisting firms in making strategic decisions on sourcing, supply chain network design, and product design and development. This involves many service organizations, including finance, telecommunications, internet service, mobile apps, and tourism (Wang et al. 2015, 2016). Current information technological innovations (e.g., smartphones, digital devices, scanning devices, cloud computing, and Internet of Things) improve business productivity and generate a variety of extensive data, which helps service firms build analytics capabilities.

Organizations in the service industry must enhance and improve their big data analytics capabilities (BDAC) to sustain their competitiveness amid the current economic situation and intense market competition (McDermott and Prajogo 2012), as BDAC is a dynamic and continuous process of "data-insights-behaviors-value" (Zheng and Zhou 2019). Drawing from prior studies, this research argues that big data analytics capabilities are composed of tangible resources, human skills, and intangible resources (Gupta and George 2016; Jeble et al. 2018; Mikalef et al. 2019). Specifically, tangible resources refer to data, technology, and some other basic resources; human skills contain managerial skills and technical skills; and intangible resources include data-driven culture and organizational learning. The seven resources/skills are the main components of BDAC, and BDAC is extremely important for a firm's survival and success (Su et al. 2022). Nevertheless, there is still a lack of academic studies and empirical evidence about BDA and its usage among companies (Wang et al. 2015). As a result, adopting BDA and developing BDAC are relatively slow in the service sector, and the whole sector generally has no clear direction or guidance for digital development (Stylos et al. 2021). Involving messy, massive, and real-time unstructured data can cause significant risks to companies. Thus, Tan et al. (2015) state that BDA is crucial in assisting a company in designing its operations strategy and making wiser decisions in enhancing capabilities.

2.2. Firm Performance

Firm performance refers to "the degree to which a focal firm has superior performance relative to its competition" (Rai et al. 2006, p. 229). Several studies, such as Gunasekaran et al. (2017), Sivarajah et al. (2020), and Su et al. (2022), suggest that big data analytics capabilities (BDAC) positively impact a firm's performance and precisely its organizational position in the market. BDAC also facilitates a firm's achievement of distinctive consequences, and improves the robustness of its performance (Wamba et al. 2017; Watson et al. 2018). To fully measure the differences regarding firm performance among financial organizations, particularly banks in Malaysia, this study considers two distinct components of firm performance, namely market performance and operational performance. Market performance refers to the actual outcomes of a firm, such as market share, and operational performance is defined as the strategic dimensions in which companies choose to compete, such as profits and return on assets (Liu et al. 2020; Richard et al. 2009; Upadhyay and Baber 2013).

2.3. Conceptual Framework and Hypotheses

The study draws on the resource-based view (RBV) and contingent resource-based view (CRBV) to explain the effects of significant big data analytics capabilities (BDAC) on performance (please refer to Figure 1). At the same time, dominant quality logic will be referred to discuss the role of BDAC in terms of quality. Barney's (1991) RBV supports the consideration of knowledge as a competitive asset. Barney (1991) argued that a firm's competitive advantages derive from its valuable and irreplaceable resources and capabilities. In addition, the RBV has been identified as a functional theory for explaining big data's impacts through knowledge generation in marketing as it explains how a firm integrates tangible and intangible resources and human skills to gain a unique competitiveness in the market (Erevelles et al. 2015). The data revolution is changing market dynamics and behaviours. Whilst the contingent resource-based view (CRBV) relates to firms possessing resources and capabilities to achieve a competitive advantage, it depends on specific conditions and addresses the static nature of RBV (Aragón-Correa and Sharma 2003; Brandon-Jones et al. 2014). Adopting a dynamic and evolutionary view, this research argues that BDAC facilitates commercial organizations in repositioning themselves amid constantly changing business environments.

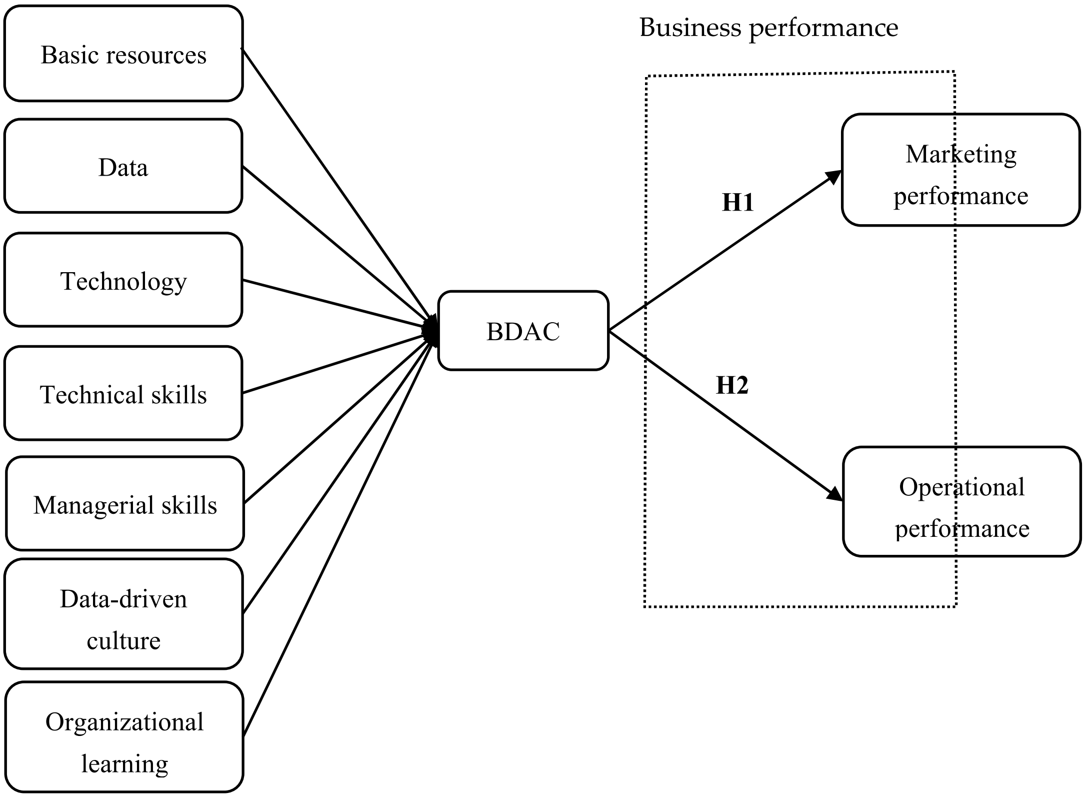

Figure 1. Conceptual framework and proposed hypotheses.

In such business environment, companies must continuously reconfigure their resources and capabilities for competitive advantages (Mikalef et al. 2019). Furthermore, they must respond to both external and internal changes in a quick and effective way, which entails them to identity opportunities and challenges for continuity and growth in its marketplace (Kiron et al. 2014). Prior studies, with empirical evidence, suggested that companies are able to produce meaningful insights from big data, and these data-generated insights could help them in identifying threats and opportunities (Erevelles et al. 2015).

RBV is consistent with IS success theory (DeLone and McLean 2003) as both focus on the competencies of internal management systems to influence firm performance. Wixom and Todd (2005) and Nelson et al. (2005) presented the quality dominant logic in technology usage theory by putting forward two fundamental dimensions of information systems. In addition, Sivarajah et al. (2020) highlighted that organizations need to rethink and reconfigure their operations to be customer-centric based on data analytics in the current technology advancement. In this research, we propose that companies need to combine tangible, human, and intangible resource to develop BDAC. With a competent BDAC, organizations can have a smoother process for coordinating, integrating, learning, and reconfiguring. As a result, they can have a better performance in the market (Wamba et al. 2017). Therefore based on the conceptual framework (refer to Figure 1) the following hypotheses are proposed.

Hypothesis H1. *BDAC positively influences a firm's marketing performance in the banking sector of Malaysia.*

Hypothesis H2. *BDAC positively influences a firm's operational performance in the banking sector of Malaysia.*

3. Methodology

The population of this study was banks that had adopted big data analytics (BDA) in Malaysia. Low-level to top-level managers were targeted as survey respondents because they were arguably more familiar with their banks' marketing and operational performance. Furthermore, they knew the latest technology deployment for survival in the marketplace.

This study designed a self-administered questionnaire that closely matched the reality of the banking sector. The measurement items were adopted/adapted from relevant studies and further refined via a pre-test with five bank managers and three academic scholars before the finalization of the questionnaire for data collection. From 1 October 2021 to 31 December 2021, 162 valid responses were collected (the response rate was 81%).

This study used a filter question: does your firm use BDA? This ensured that only banks that adopted BDA were chosen for analysis. The instrument was developed based on an extensive review of the existing literature. Some measurement items were modified to be more suitable for the study. All of the items used to measure the constructs corresponded to their theoretical definitions. We adopted/adapted measurement items from previous studies to tailor them to the context of the banking sector. The questionnaire included three sections. The first section contained twenty-five items measuring BDAC (including seven dimensions) from Mikalef et al. (2019) and Jeble et al. (2018) The second section included four descriptive questions for banks (e.g., business type and category). The third section contained four items measuring market performance from Gupta et al. (2018) and four items measuring operational performance from Wamba et al. (2017) and Gupta et al. (2018). The descriptive questions were placed between predictive and criterion variables, which aimed to minimize common method bias (Podsakoff et al. 2012). For measurement scales, a 7-point Likert scale was used for predictive variables (i.e., BDAC) and a 5-point Likert scale was used for criterion variables (i.e., marketing performance and operational performance). The rationale for the arrangement was to reduce the effect of common method bias (Podsakoff et al. 2012).

3.1. Data Analysis

This research adopted partial least squares structural equation modelling (PLS-SEM) and specifically software package SmartPLS 3.3.3 for data analysis. There are two main approaches in structural equation modelling (SEM), namely the co-variance-based approach (CB-SEM) and the variance-based approach (PLS-SEM). The former one aims to reproduce a theoretical co-variance matrix, and the latter one aims to maximize the variance of endogenous variables. Hair et al. (2021) summarized five important criteria, such as research goal and measurement model specification, when choosing CB-SEM or PLS-SEM. Given that this research had formative and reflective variables, PLS-SEM was applied rather than CB-SEM (Nair et al. 2018). Meanwhile, both G*Power and the "10 times rule" were used to check sample size requirements. The results indicated that the 162 samples satisfied the minimum size requirement for using PLS-SEM. To assess the hypothesis, the measurement and structural measurement models of the research needed to be confirmed. This study followed the data-analysis procedure suggested by Hair et al. (2019), and the detailed steps are reported as follows:

3.2. Measurement Model Assessment

Regarding the assessment of the measurement model, the internal reliability, convergent validity, and discriminant validity had to be confirmed. Given the existence of reflective and formative variables in the research framework, different assessment criteria were applied (Hair et al. 2021). To establish the reliability and convergent validity of the first-order reflective variables (seven dimensions of BDAC, marketing performance, and operational performance), factor loadings, composite reliability (CR), and average variance extracted (AVE) values needed to surpass the cut-off threshold values at 0.7, 0.7, and 0.5 respectively. As shown in Table 1, the reliability and convergent validity of all of the first-order reflective variables were confirmed.

Table 1. Validation of the measurement scales.

Construct/ Dimension	Type	Items	Loadings	CR	AVE
Basic Resources	Reflective			0.946	0.915
		BR1	0.950		
		BR2	0.934		
Data	Reflective			0.931	0.819
		DA1	0.927		
		DA2	0.877		
		DA3	0.910		
Technology	Reflective			0.943	0.805
		TE1	0.891		
		TE2	0.904		
		TE3	0.887		
		TE4	0.907		
Technical Skills	Reflective			0.947	0.914
		TS1	0.941		
		TS2	0.954		
		TS3	0.955		
		TS4	0.942		
Managerial Skills	Reflective			0.947	0.916
		MS1	0.935		
		MS2	0.947		
		MS3	0.948		
		MS4	0.947		
Data-driven Culture	Reflective			0.882	0.651
		DC1	0.782		
		DC2	0.809		
		DC3	0.786		
		DC4	0.849		
Organizational Learning	Reflective			0.950	0.83
		OL1	0.939		
		OL2	0.932		
		OL3	0.898		
		OL4	0.874		
Marketing Performance	Reflective			0.942	0.831
		MP1	0.919		
		MP2	0.938		
		MP3	0.915		
		MP4	0.873		

Table 1. *Cont.*

Construct/ Dimension	Type	Items	Loadings	CR	AVE
Operational Performance	Reflective			0.931	0.773
		OP1	0.794		
		OP2	0.905		
		OP3	0.911		
		OP4	0.900		
Big Data Analytics Capabilities	Composite (2nd order construct)		Weights	CI	VIF
		BR_BDAC	−0.189	[−0.423, 0.044]	3.635
		DA_BDAC	0.842	[0.415, 1.229]	4.824
		TE_BDAC	0.109	[−0.162, 0.303]	2.376
		TS_BDAC	−0.161	[−0.515, 0.190]	3.828
		MS_BDAC	0.240	[−0.141, 0.622]	4.407
		DC_BDAC	0.049	[−0.244, 0.360]	1.848
		OL_BDAC	0.292	[0.076, 0.480]	1.265

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

Regarding the discriminant validity of the first-order reflective variables (including the seven dimensions of BDAC), this research applied Heterotrait–Monotrait of correlations (HTMT) for assessment (Henseler et al. 2014). To confirm discriminant validity, HTMT should be no more than 0.90 (Gold et al. 2001). According to Table 2, all the HTMT scores were less than the cut-off threshold. Therefore, the discriminant validity of the research was confirmed.

Table 2. Discriminant validity (HTMT).

Constructs	BR_BDAC	DA_BDAC	DC_BDAC	MP	MS_BDAC	OL_BDAC	OP	TE_BDAC
DA_BDAC	0.885							
DC_BDAC	0.605	0.684						
MP	0.503	0.656	0.486					
MS_BDAC	0.832	0.881	0.679	0.562				
OL_BDAC	0.220	0.260	0.452	0.289	0.258			
OP	0.424	0.533	0.384	0.805	0.453	0.388		
TE_BDAC	0.727	0.804	0.585	0.552	0.696	0.379	0.426	
TS_BDAC	0.818	0.850	0.653	0.508	0.852	0.273	0.396	0.695

Note: Discriminant validity established at $HTMT_{0.90}$.

Apart from the first-order reflective variables, BDAC is a reflective-formative 2nd order composite construct. The assessment procedure of formative measurement, involving three steps, is different from the one of reflective measurement above. Firstly, the convergent validity is examined by performing redundancy analysis (Chin 1998). As shown in Figure 2, the path coefficient between the formative BDAC and the same construct being measured reflectively by a global single item was 0.904, which was much higher than the cut-off threshold at 0.70. Therefore, the convergent validity of the formative construct was confirmed (Hair et al. 2021).

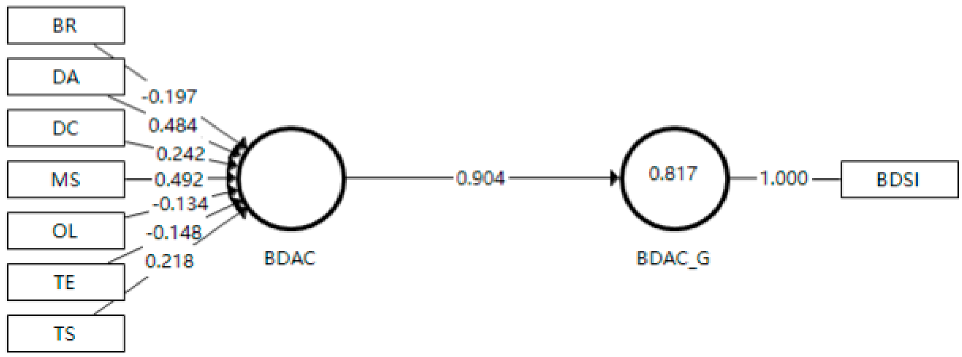

Figure 2. Results of redundancy analysis.

Then, collinearity issues among indicators (dimensions) have to be ruled out by checking the variance inflation factor (VIF). BDAC is a 2nd-order formative construct, so its dimensions are not inter-changeable. Significantly, high correlations among dimensions are not expected as high collinearity can lead to incorrect estimations of weights (Hair et al. 2019). As shown in Table 1, all VIF scores of BDAC's dimensions were lower than 5. Thus, BDAC, as a formative composite construct, does not have a potential collinearity problem (Hair et al. 2021).

Thirdly, the significance and relevance of formative indicators (dimensions) had to be confirmed via a bootstrapping technique for estimating the outer weight significance of BDAC's dimensions (Hair et al. 2021). The outer weight of each dimension indicates its relative importance to forming BDAC. Whether an outer weight is significant can be assessed by confidence interval bias corrected with significance at 0.95 (Gannon et al. 2021). According to Table 1, the outer weights of BR_BDAC, TE_BDAC, TS_BDAC, MS_BDAC, and DC_BDAC were not significant, and DA_BDAC and OL_BDAC were significant. The results suggest that the latter two dimensions were relatively more important than the first five dimension in forming BDAC. Meanwhile, as shown in Table 3, the outer loadings were all higher than the cut-off threshold of 0.5, which confirms the absolute importance of the seven dimensions in forming the construct (Hair et al. 2021). Therefore, all the dimensions were kept, regardless of outer weights.

Table 3. Formative indicator's outer loading.

	BDAC
BR	0.722
DA	0.933
DC	0.670
MS	0.822
OL	0.529
TE	0.774
TS	0.733

3.3. Structural Model Assessment

After confirmation of the measurement model of the research, the structural model was assessed via t-value, *p*-value, confidence intervals, coefficient of determination (R2), effect size (f2), and predictive relevance (Q2) (Hair et al. 2021). By conducting a bootstrapping procedure with 5000 resamples, it was found that H1 and H2 were supported at 95% confidence intervals (see Table 4). To be specific, BDAC positively influences marketing performance (β = 0.630, t = 11.463, p = 0.000, LL = 0.515, CL = 0.703) and BDAC also positively influences operational performance (β = 0.547, t = 9.239, p = 0.000, LL = 0.411, CL = 0.619) in the banking sector of Malaysia.

Table 4. Results summary for the direct effect testing.

Hypothesis	Relationship	Beta	SD	T Value	*p* Value	LL	UL	Decision
H1	BDAC -> MP	0.630	0.055	11.463	0.000	0.515	0.703	Supported
H2	BDAC -> OP	0.547	0.059	9.239	0.000	0.411	0.619	Supported

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

The model's predictive accuracy was examined via the coefficient of determination (R2). As shown in Table 5, the R2 values of marketing and operational performance were 0.400 and 0.299, respectively, which indicated that BDAC had a substantial level of predictive accuracy (Cohen 1988). To assess the relative impact of a predicting variable on an endogenous variable, the effect size (f^2) is examined. The f^2 scores of BDAC on marketing and operational performance were 0.666 and 0.426, indicating a substantial effect size (Cohen 1988). Concerning the predictive validity of the path model, Stone and Geisser' Q^2 was checked via a blindfolding technique. It was found that the Q^2 scores were greater than 0, indicating that BDAC had a predictive relevance on marketing and operational performance (Hair et al. 2021).

Table 5. Assessment of R^2, f^2 and Q^2.

	R^2	f^2	Q^2
		BDAC	
MP	0.400	0.666	0.301
OP	0.299	0.426	0.203

4. Discussion and Implications

A thorough understanding of extensive data analytics capabilities (BDAC) facilitates financial organizations (e.g., banks) to make better strategic decisions concerning new market exploration and product/service innovation. This study provides evidence of the outcomes of big data analytics (BDA) in the banking sector. Thus, this study derived the research model that statistically validates the gap in the related literature. Therefore, it makes significant contributions to filling up the identified research gaps and provides practical implications to managers in the banking sector.

This study finds that the dimensions of data and organizational learning dominate extensive BDAC in the banking sector. Furthermore, the analysis shows that about 40% of marketing performance and 30% of operational performance is explained by BDAC, respectively, among financial services organizations in the proposed model. The data analysis evidence shows that data and organizational learning help to enhance the quality of sales of new and current products and improve decision-maker engagement strategies. Ransbotham et al. (2016) stated that organizations could enhance their competitive advantage through BDA. Concerning the marketing of financial organizations (e.g., banks), big data provides insights into what is accessible to data through multiple internal and external sources in facilitating high-value analyses.

Organizational learning can be achieved through knowledge assimilation and applying the new knowledge from big data. For example, financial organizations can decide to understand the most effective data at each stage of a sales cycle, how to improve investments in customer relationship management (CRM) systems, and how to effectively adjust strategies for increasing conversion rates, prospect engagement, revenue, and customer lifetime value. Furthermore, banks can analyse and predict various phenomena, such as customer purchase behaviour and forecasting stock prices, market trends, market share, competitor moves, and profitability (Pappas et al. 2018). The application of BDA throughout financial products' life cycles facilitates extending customers' value and prompting value-generating behaviours. By setting customer value as an underlying goal, financial services firms can improve their profitability by targeting the right customers, maintaining good customer relationships, enhancing the share of wallet, and reducing the cost of customer acquisition/retention.

The BDAC in the organization must determine the extent to which analytics will help improve a customer's experience, reducing the dissonance in a customer's mind about competing for brand choices in financial services that build customer loyalty. Financial services organizations should integrate the data from external and internal sources to facilitate high-value analyses. Financial services organizations need to optimize the analytics requirements to map out the scope of use across various customer and marketing processes. Significant BDAC may offer a unique advantage over competitors that could improve the existing marketing and operational performance by providing valuable insights.

From the organizational perspective of big data analytics, the banks may treat big data as an asset in decision making. Financial organizations should start with segmentation to build a comprehensive view of existing customers, as all targeting decisions are based on insights derived from segmentation. For example, a large bank can build a strategic segmentation model to capture its customers' changing financial outlooks and design a new value proposition and prospect marketing program. Banks should use lead management techniques to score potential customers and focus acquisition efforts on those with high values. They can leverage knowledge from electronic networks through data from other organizations, customers, and workers to improve their business performance (Aziz and Omar 2013).

BDA is related to demand generation, and it not only increases conversion rates but also reduces direct marketing costs. Banks that issue credit cards can route their inbound calls to the authorized agent or outsource a call centre to create a customized experience for each caller, which assists in conversion rates and revenue through increased call-centre productivity. Bank marketers should reduce the costs of mailing and outbound marketing campaigns through acquisition modelling that will produce the likelihood of response in attracting potential customers and increasing long-term customer profitability simultaneously. For example, a bank could monitor and inspect customer feedback from various sources, such as call centre comments, user-generated content (e.g., social media), and firm-generated content (e.g., bank website) to improve their products and services.

5. Conclusions

With ever-changing and expanding customer expectations and high competition in the financial services sector, financial services organizations should not ignore the untapped amount of big data they have (e.g., users of ATMs, account holders, mobile banking users, social media users) whereby banks should leverage the existing and new data sets to maximize customer understanding and gain a competitive advantage. Big data analytics drives the pattern analysis for prediction, supports automatization of organizational processes, creates opportunities, and generates value for the organization through exploiting various capabilities in developing knowledge (Gupta and George 2016).

This study extends the literature from its conceptualization by emphasizing the lack of theoretically grounded evidence of the prominent data analytics roles in business performance, particularly in a financial services organization. The results will enable practitioners and academics from various areas, such as business and marketing e-commerce-related research, to further develop a shared understanding of big data analytics roles that will benefit the service industry. Thus, the study's findings advance the business and management literature on technology assimilation in organizations based on the resource-based view and the dynamic capability view on the Malaysian banks as the foundation for services organizations. Therefore, the research focus and the findings from these Malaysian financial organizations may bring new insights to advance related theories.

6. Limitations and Future Research

Like any other research, this study has some limitations, even though it does provide a foundation for further investigation on BDAC in the services sector. First, the current research is limited to the financial services organizations based in Malaysia. There may be considerable differences across industries and countries. Thus, generalizing the findings of the research should be carried out with care. Future research should further validate this study's findings empirically in different sectors and countries. Furthermore, future studies are advised to make comparisons for similarities and differences, which could further improve our understanding of BDAC's role on firm performance. Second, this research collected data from bank managers through a self-administered questionnaire, and the collected data only reflects respondents' perceptions. Future studies should also consider objective data, such as financial statements, to examine the effects of BDAC on firm performance. Thirdly, the dimensions of BDAC identified by this study are neither exhaustive nor complete, and other elements should be considered. Therefore, more in-depth research is needed.

Author Contributions: Conceptualization, N.A.A. and F.L.; methodology, N.A.A. and F.L.; software, F.L.; validation, N.A.A., F.L. and W.M.H.W.H.; formal analysis, F.L.; investigation, N.A.A. and F.L.; resources, N.A.A. and F.L.; data curation, N.A.A.; writing—original draft preparation, F.L.; writing—review and editing, W.M.H.W.H.; visualization, F.L.; supervision, N.A.A.; project administration, N.A.A.; funding acquisition, N.A.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by [RHB-UKM Endowment] grant number [RHB-UKM-2020-002] And The APC was funded by [RHB-UKM Endowment]. Information regarding the funder and the funding number should be provided. Please check the accuracy of funding data and any other information carefully.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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