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The Power of Big Data Analytics for the Competitive Performance of Digital Startups in an Emerging Economy

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Abstract

In emerging markets, digital startups (DS) play a critical role in driving innovation and addressing socio-economic and environmental challenges. Their importance extends beyond mere survival to achieving superior competitive performance (CP). A critical factor influencing the performance of DS is their resources and capabilities, with Big Data Analytics Capability (BDAC) emerging as particularly critical for startups that manage large volumes of data and aim to achieve operational and market success by strategically leveraging its power. However, the effectiveness of BDAC can vary, and deeper analysis is needed to understand these differences. Many DS failures can be attributed to an inability to systematically analyze data, which leads to poor decision making and underscores the need for stronger BDAC. Based on the Resource-Based View (RBV) theory, this study examines the level of BDAC in 270 Brazilian digital startups, all of which have been in operation for at least three years. Using Partial Least Squares (PLS) regression with PLS-SEM, the research shows that startups with higher levels of BDAC tend to have better operational and market performance, suggesting that investments in BDAC can yield significant returns in terms of sustainable competitiveness and growth; furthermore, investments in training programs to enhance the data analysis skills of DS personnel are important to leverage the quality job in Brazil.

Keywords: big data analytics, competitive performance, data-driven, digital startups, emerging markets, resource-based view

1. Introduction

Digital startups (DS) are key drivers of economic and social innovation, especially in emerging economies, where they make significant contributions by introducing disruptive solutions, creating quality employment opportunities, and addressing complex socioeconomic and environmental challenges (Autio, 2016; Liguori et al., 2020).

However, achieving sustainable success remains elusive for many digital startups. Success for DS is often defined by their ability to scale rapidly, either by expanding their customer base or quickly achieving profitability (Blank, 2010; Kuratko, Holt, & Neubert, 2019). The goal for many DS is to achieve "unicorn" status - being valued at a minimum of one billion dollars - before going public (Lee, 2013). Despite their potential, however, the reality is that less than 10% of DS achieve significant market success (Marmer, Herrmann, Dogrultan, & Berman, 2012). This disparity has spurred significant academic and practical interest in understanding the factors that drive success or precipitate failure among DS (Chatterji, Delecourt, Hasan, & Koning, 2019; Satish Nambisan, Lyytinen, Majchrzak, & Song, 2017).

Competitive performance (CP) in DS depends on several critical factors, including the formulation of a robust business model (Ferri, Spanò, & Tomo, 2020; Kunte & Promsiri, 2019; Ruggieri, Savastano, Scalingi, Bala, & D'Ascenzo, 2018), the composition of a capable founding team (Jinzhi & Carrick, 2019; Nair & Blomquist, 2019), and the infusion of strategic investments (Barot & Chhaniwal, 2018; Cavallo, Ghezzi, Dell'Era, & Pellizzoni, 2019; Cowden, Bendickson, Bungcayao, & Womack, 2020; Kenney & Zysman, 2019; Kuratko et al., 2019; Venkobarao, 2019). Moreover, effective management practices and data-driven decision making have emerged as key elements influencing CP, highlighting the critical role of analytics in shaping startup trajectories

(Barot & Chhaniwal, 2018; Huang, Henfridsson, Liu, & Newell, 2017; Jinzhi & Carrick, 2019; Say, Guo, & Chen, 2018; Yang, Sun, & Zhao, 2019).

Research highlights that data analytics significantly improves the decision-making capabilities of successful DS (Huang et al., 2017; Jinzhi & Carrick, 2019). For DS to cultivate a sustainable competitive advantage, the development of a robust big data analytics capability (BDAC) is essential. BDAC not only enables startups to leverage data as a strategic asset, but also fosters a culture of data-driven decision making at all levels of the organization (McAfee & Brynjolfsson, 2012). This data-driven approach enables startups to quickly capitalize on market opportunities and gain significant operational efficiencies, thereby increasing scalability and market competitiveness (Barot & Chhaniwal, 2018; Ferraris, Mazzoleni, Devalle, & Couturier, 2019; Henke et al., 2016; Huang et al., 2017; Jinzhi & Carrick, 2019). While existing research highlights the positive impact of BDAC on CP within established firms (Dubey et al., 2020; M. Gupta & George, 2016; Shivam Gupta, Qian, Bhushan, & Luo, 2019; Wamba et al., 2017), its specific implications for startups-particularly in emerging market contexts-remain underexplored. Moreover, one of the factors contributing to startup failures is the lack of BDAC, which leads to poor decision making, including the initial information gathering needed to build their business model and maintain customer centricity (Szathmári et al., 2024). In this context, the present study aims to fill this gap by investigating the level of BDAC in DS and whether BDAC has a relationship with their CP. As a thriving hub for startups even before the pandemic, Brazil has experienced significant growth in its startup ecosystem, supported by government policies and increased investment (Brasil, 2021; CB Insights, 2022; McKinsey & Company, 2019; Pacete, 2022).

The main theoretical contribution of this research was to verify the level of BDAC within DS and empirically validate the central role of BDAC in improving CP among Brazilian DS, filling a gap identified in case studies of Chinese unicorns (Huang et al., 2017; Jinzhi & Carrick, 2019). This revealed that the use of data analytics for operations and decision making contributes to superior CP for DS, providing a better understanding of these ventures (Shepherd & Gruber, 2020). The findings also highlight data as a key element of BDAC, surpassing even human resources in its impact on startup performance, a critical validation for startup leaders and policymakers alike (Bag, Pretorius, Gupta, & Dwivedi, 2021; Behl, 2020; Dubey et al., 2020). Moreover, this study contributes to a nuanced understanding of BDAC dynamics within the unique socioeconomic and cultural landscape of an emerging economy like Brazil (Akter, Fosso Wamba, Barrett, & Biswas, 2019; Chierici, Mazzucchelli, Garcia-Perez, & Vrontis, 2019; Ferraris et al., 2019).

In practical terms, this research provides actionable insights for startup accelerators, policymakers, and investors seeking to foster an enabling environment for DS growth. By highlighting the critical role of BDAC in shaping DS success, stakeholders can improve the design of support mechanisms that cultivate analytical capabilities within DS. This approach strengthens their resilience and competitiveness in the global marketplace, reinforcing the value of investing in this technology.

In this regard, the study underscores the imperative for DS to prioritize BDAC as a core competency in their growth strategies. By harnessing the transformative potential of data analytics, DS can not only more effectively navigate turbulent market landscapes, but also catalyze sustainable economic development and societal progress.

The remaining sections are organized as follows: Section 2 presents the theoretical background and research hypotheses, Section 3 details the research methodology and explains the data sources used in this study, Section 4 presents the results, followed by Section 5, which discusses the main research considerations, limitations, as well as suggestions for future studies. The paper concludes in Section 6 with the final remarks.

2. Theoretical Background and Hypothesis Development

2.1 Digital Startups and Competitive Performance

A startup is a temporary organization in search of a repeatable and scalable business model that is profitable even under conditions of extreme uncertainty (Blank & Dorf, 2014; Ries, 2011). For a startup to be digital, its business model is based on digital technologies (Kraus, Palmer, Kailer, Kallinger, & Spitzer, 2018; Steininger, 2019).

Repeatable means that processes can be replicated without customization, while scalable means that revenues and active customer base must grow without costs increasing at the same rate (Blank & Dorf, 2012) and the startup develops its capabilities and improves its competitive performance at low cost (S. Nambisan, 2017). Regarding the conditions of uncertainty, startups operate in a dynamic environment caused by technological evolution, data security, market creation, changing customer preferences, new forms of competition, globalization, and pressure from investors (Bohn & Kundisch, 2018; Kraus et al., 2018; Ojala, 2016).

Even small DS can contribute to a country's economy by attracting many customers with their disruptive solutions (Autio, 2016; Liguori et al., 2020). Moreover, during the COVID-19 pandemic, there was an acceleration of digital transformation, which increased the importance of DS and created jobs (Liguori et al., 2020). Another contribution to emerging economies occurs because increasing the number of successful startups in a region increases the ability of that region to produce other successful startups, thereby improving the local economy (Genome, 2020).

However, some authors have found that more than 90% of startups fail, less than 10% succeed, and the rest encounter many obstacles along the way (Blank & Dorf, 2012; Marmer et al., 2011).

To ensure the long-term continuity of DS, it is ideal for them to scale (Zhao & Di Benedetto, 2013). This includes rapidly increasing the number of customers or profitability (Blank, 2010; Kuratko et al., 2019), aiming to increase their market share (S. Shamim, Zeng, Shariq, & Khan, 2019), or achieving "unicorn" status (Zaheer, Breyer, & Dumay, 2019) by reaching a valuation of at least $1 billion before going public (Lee, 2013).

When DS demonstrate a solid competitive performance, they are able to grow sustainably and profitably (Picken, 2017; Sullivan, 2016), attracting more attention and additional investment (Behl, 2020; Jinzhi & Carrick, 2019), especially if they can demonstrate their market growth (Cowden et al., 2020).

Monitoring performance is critical to ensure that DS can sustain its growth and ensure its survival (Shepherd & Gruber, 2020). Declining performance jeopardizes the survival of the DS (Cavallo et al., 2019), and shaping the performance of digital ventures is key to achieving success (Satish Nambisan et al., 2017).

2.2 BDAC, RBV, and the Competitive Performance of the DS

RBV postulates that organizations possess multiple resources that must be leveraged to achieve CP (Teece, 2019; Tippins & Sohi, 2003) and that these resources must be aligned with strategy to provide competitive advantage (J. Barney, 1991; J. B. Barney, 1995; J. B. Barney, Ketchen, & Wright, 2011; Hart, 1995). This research followed the principles of RBV because the development of BDAC requires specific resources. BDAC involves the ability of DS to guide its decisions and processes with data, which depends on the availability of big data and analytic tools (BDA) within the organization. Furthermore, BDAC relies on the skills of the firm's professionals (HRS) to turn these analyses into actions that add value to the business (Bag et al., 2021; Dubey et al., 2020; Dubey, Gunasekaran, & Childe, 2019).

When data is scarce, such as in situations with few customers or inviable processes for obtaining it, as in the early stages of a DS, decision making may rely solely on intuition based on managerial experience (Hoffman & Yeh, 2019; McAfee & Brynjolfsson, 2012; Ries, 2011). Intuition and experience are not considered enemies in business management, they can be the difference for experienced decision makers to gain an advantage over using the same data that all competitors have access to (Dubey, Gunasekaran, & Childe, 2019; Saqib Shamim, Zeng, Khan, & Zia, 2020). However, as DS evolves through the stages of the lifecycle, they trigger several changes, such as a decrease in centralized decision making, hence the role of intuition. They also improve the formalization of their processes and communication (Picken, 2017), as well as the metrics for their evaluation (Hoffman & Yeh, 2019). The maturity of the indicator system can even lead to the use of artificial intelligence to identify market needs or opportunities (Chalmers, MacKenzie, & Carter, 2020).

2.2.1 Tangible Resources of Digital Startups in the Context of BDAC

In the context of BDAC, tangible resources are defined as data and analytical tools (Bag et al., 2021; Dubey et al., 2020; Dubey, Gunasekaran, & Childe, 2019; Gunasekaran et al., 2017; M. Gupta & George, 2016). Tangible Resources can be considered as the digital technology infrastructure for distributing, managing, processing, and visualizing data from various sources and formats (Bag et al., 2021; Benzidia, Makaoui, & Bentahar, 2020; Dubey, Gunasekaran, & Childe, 2019; Gunasekaran et al., 2017).

In general, DS follow the lean startup approach, starting with a minimum viable product (MVP) that offers as few features as possible to solve at least one customer problem (Blank & Dorf, 2012). From this MVP, DS implement an agile, iterative, and incremental process to test hypotheses in the marketplace with the goal of attracting and retaining more customers and consolidating a profitable, scalable, and sustainable business model. DS pursue defined goals with measurable outcomes (Huang et al., 2017).

Collecting data from DS social media (Agarwal, 2019) and customer preferences (Hokkanen & Väänänen-Vainio-Mattila, 2015) is critical. In addition, digitizing internal controls creates operational efficiency, productivity, and cost reduction (Ferraris et al., 2019; Henke et al., 2016; Scuotto, Santoro, Bresciani, & Del Giudice, 2017).

Therefore, digital native companies have an advantage in data analytics because they have more data than traditional companies and can therefore develop BDAC to optimize their CP (Behl, 2020; Ferraris et al., 2019) with the possibility of scaling (Huang et al., 2017; Jinzhi & Carrick, 2019). Furthermore, the lack of BDAC is identified as a significant factor contributing to startup failures, resulting in poor decision-making, including challenges in initial information gathering for business model development and maintaining customer centricity (Szathmári et al., 2024).

Considering data and analytical tools (BDA) as the raw material of digital business (Huang et al., 2017; Jinzhi & Carrick, 2019), these basic resources are expected to have a positive relationship with BDAC of DS, according to Hypothesis 1:

H1: BDA have a positive association with BDAC.

2.2.2 Human Resources of Digital Startups in the Context of BDAC

Human resources (HR) in the context of BDAC can be defined by the skills of professionals to strategically analyze big data to extract ideas and propose actions that bring value to the business (Bag et al., 2021; Dubey et al., 2020; Dubey, Gunasekaran, & Childe, 2019; Gunasekaran et al., 2017; M. Gupta & George, 2016). In general, DS hire competent, experienced, and highly specialized professionals because they rely on human resource capabilities to achieve competitiveness and business sustainability (Kuratko et al., 2019; Venkobarao, 2019). While resource utilization can be made more flexible through outsourcing and affected by automation (Bailey & Tatikonda, 2018; Chalmers et al., 2020), some DS prefer to develop capabilities in-house to build customized solutions that differentiate them from competitors (Behl, 2020).

All professionals involved in data analytics must understand the available BDA to capitalize on its potential and apply analytics in their areas (Côrte-Real, Oliveira, & Ruivo, 2017). Simultaneously, collaborating with business units, data professionals should comprehend the needs and risks that steer the data strategy (Behl, 2020; Rialti, Marzi, Ciappei, & Busso, 2019).

One of the potential advantages of DS over traditional enterprises is the ability of professionals to share data across departments, accelerate decision making, and prioritize market information to exponentially add value to customers (Barlette & Baillette, 2020; Mishra, Luo, Hazen, Hassini, & Foropon, 2019). Considering this, the literature reveals that the skills of professionals in big data analytics (HRS) are strategically important and provide new ways to create value for organizations. As a result, hypothesis 2 of this study suggests a positive relationship between HRS and the BDAC of DS.

H2: HRS have a positive association with BDAC.

2.2.3 Intangible Resources of Digital Startups in the Context of BDAC

Intangible resources in the context of BDAC can be defined as the BDAC itself (Bag et al., 2021; Dubey et al., 2020; Dubey, Gunasekaran, & Childe, 2019; Gunasekaran et al., 2017; M. Gupta & George, 2016).

The data-driven approach to decision making and operations means that leaders must align BDAC with business strategy to create competitive advantage (Mikalef, Krogstie, Pappas, & Pavlou, 2020; Singh & El-Kassar, 2019) and define data-driven business goals (Shaphali Gupta, Leszkiewicz, Kumar, Bijmolt, & Potapov, 2020), especially when operating in uncertain environments (Grandhi, Patwa, & Saleem, 2020).

Furthermore, unlike the use of traditional practices (Reis, Ruivo, Oliveira, & Faroleiro, 2020), BDAC allows firms to identify both opportunities and threats in the environment by better understanding their business and market to prepare their strategy (Irfan & Wang, 2019; Rialti, Marzi, et al., 2019).

By taking advantage of many opportunities, companies hope to get relevant results by discovering trends, forecasting production and sales demand, understanding the dynamics of the business, making accurate decisions (Ardito, Scuotto, Del Giudice, & Petruzzelli, 2019; Dubey et al., 2020; Dubey, Gunasekaran, & Childe, 2019; Rialti, Marzi, et al., 2019), improve their processes and generate organizational knowledge (Ferraris et al., 2019; Mikalef et al., 2020; Mishra et al., 2019; Rialti, Marzi, et al., 2019).

This allows them to improve performance by reducing their costs (Aydiner, Tatoglu, Bayraktar, Zaim, & Delen, 2019; Dubey et al., 2020; Dubey, Gunasekaran, & Childe, 2019), operate with resource optimization (Akter et al., 2016; Rialti, Marzi, et al., 2019; Wamba et al., 2017), avoid waste (Sivarajah et al., 2017), optimize internal operations and processes, and predict or simulate the impact of some unexpected factors (Arunachalam et al., 2018; Davenport, 2006; Dubey, Gunasekaran, Childe, et al., 2019; Rialti, Zollo, et al., 2019).

It also increases the relevance of real-time monitoring of the situation of the company, that is, the immediate detection of changes in its performance indicators, as opposed to retrospective actions, such as decisions based on historical data (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Rialti, Marzi, et al., 2019).

In general, organizations try to build sustainable performance by balancing market performance (MP) and operational performance (OP) in such a way that they capture markets while maintaining profit margins, both of which are important but different indicators (M. Gupta & George, 2016; Shivam Gupta, Drave, Dwivedi, Baabdullah, & Ismagilova, 2020; Nadali, Grilo, & Zutshi, 2018).

There is a tendency for corporate performance metrics to focus more on customers and less on revenue (Shaphali Gupta et al., 2020), with market share initially being more important than profitability (Autio, 2016; van Waes, Farla, Frenken, de Jong, & Raven, 2018).

As in other studies, performance can be measured based on the last three years (Behl, 2020; Dubey et al., 2020; Ferraris et al., 2019; Wamba et al., 2017), which is the same period used to determine whether a DS has reached the scale stage, that is, growing by at least 20% in revenue or number of employees for three consecutive years (OECD, 2007). Performance should also be measured against competitors, as competitive advantage is only achieved when the firm is more successful than its competitors in the same sector (M. Gupta & George, 2016; Jinzhi & Carrick, 2019).

In the context of DS, although there is a tendency for revenues to increase as the number of users increases (Henfridsson & Bygstad, 2013), it is recommended to monitor their OP and MP separately to understand their positioning relative to their peers and to determine whether the company is reaching more customers, minimizing the risk of losses and bankruptcy (Behl, 2020; Chierici et al., 2019; M. Gupta & George, 2016; Shivam Gupta et al., 2020, 2019).

Therefore, a possible positive relationship between BDAC and CP of DS is indicated. In this research, CP was adopted in its two dimensions, OP and MP, in line with the literature, in such a way that a DS should prioritize scalability, focusing on the growth of the customer base, without neglecting the monitoring of its internal indicators to understand its valuation (Autio, 2016; Behl, 2020; van Waes et al., 2018). Thus, hypotheses 3 and 4 are formulated:

H3: BDAC have a positive association with OP.

H4: BDAC have a positive association with MP.

Figure 1 presents the theoretical model based on the previous hypotheses to empirically test the relationship between BDAC and DS performance.

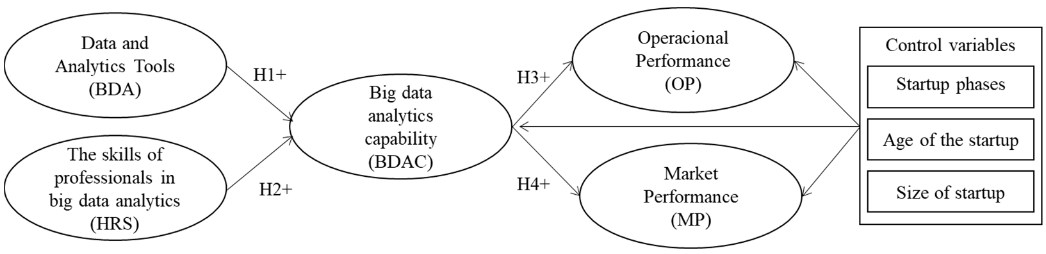

Figure 1. Theorical Model

Some decision-making variables identified as statistically significant in the literature review can influence DS behavior and affect their performance, namely size, age, and life cycle stage. The life cycle stage refers to the stage of product and market development of the DS and includes the stages of Ideation, Operation, Traction, and Scale. Consequently, control variables were established for the BDAC construct as well as for OP and MP (Wamba, Dubey, Gunasekaran, & Akter, 2020).

3. Method

3.1 The Sample

In this research, it was decided to study the Brazilian context because the country is considered a favorable market for DS, and before the pandemic, a study already pointed to the existence of more than 10,000 DS, generating more than 30,000 jobs, in a country with one of the highest connection rates in the world and a significant increase in the number of mobile devices (McKinsey & Company, 2019). Moreover, since 2018, the Brazilian government has adopted measures to promote the creation and growth of more DS in the country, including the approval of the legal framework for startups in 2021 (Brasil, 2021). Brazilian DS also received 2.5 times more investment in 2021 than in the previous year, according to a report by Distrito and Bexs (Pacete, 2022). In addition, Brazil had 15 unicorns in 2022 and ranked 9th out of 46 countries with a unicorn (CB Insights, 2022).

3.2 Survey Instrument

In Brazil, as noted in the OECD report (OECD, 2016), there was no official database available to identify digital startups. Therefore, this study created a database in two steps. First, 1,000 digital startups were identified on association websites, startup accelerators, and specialized media platforms (ABStartups, 2020; Cubo, 2020; Distrito, 2021; Gomes, 2019; Inovabra, 2020; PEGN, 2018, 2020, 2021). Representatives of each startup were then located on LinkedIn, following established research practices (Akter et al., 2016; M. Gupta & George, 2016). Founders, executives, or data analysts were selected to participate in the questionnaire, a method used by other researchers (Behl, 2020; Côrte-Real et al., 2017). Through this process, 1,802 potential respondents were identified.

The questionnaire was developed based on the existing literature and conceptual model, using a 7-point Likert scale (1=strongly disagree to 7=strongly agree). DS performance was measured subjectively based on the respondents' perceptions over the last three years (Dubey, Gunasekaran, & Childe, 2019). Operational performance (OP) was measured using four indicators adapted from Tippins and Sohi (2003) and Ravichandran and Lertwongsatien (2005). Market performance (MP) was assessed using four items from (Wang, Liang, Zhong, Xue, & Xiao, 2012). Big data analytics capability (BDAC), including big data analytics (BDA) and human resources (HRS), was assessed as defined by (Bag et al., 2021), and building on previous research (Dubey et al., 2020; Dubey, Gunasekaran, & Childe, 2019), this construct also assessed the level of BDAC in DS. These constructs were modeled as reflective latent variables, as detailed in Appendix A.

3.3 Data Collection Procedures

The data collection method selected was a survey. Between January and February 2022, the questionnaire was sent out individually, mainly via LinkedIn, but also through email, Facebook, and WhatsApp. Due to the short collection period and the individual sending, a non-response bias test was not necessary. The final sample consisted of 270 complete responses, with a response rate of 16%. The characteristics of the respondents and the organizations represented are shown in Table 1.

Table 1. Summary of the Sample's Characteristics

	Respondents	Number	% of Total
Position	Founder	114	42.2%
	President	35	13.0%
	Director	49	18.1%
	Manager	24	8.9%
	Coordinator/Information Technology Analyst	6	2.2%
	Director/Manager/Data Coordinator	16	5.9%
	Engineer/Analyst/Data Scientist	26	9.6%
Education	High School	8	3.0%
	College	89	33.0%
	Postgraduate	99	36.7%
	Master’s degree	61	22.6%
	Doctorate or Ph.D.	13	4.8%
Years of experience	0-4	105	38.9%
	5-9	118	43.7%
	10-14	36	13.3%
	15-19	5	1.9%
	> 20	6	2.2%
Age	18-24	7	2.60%
	25-30	58	21.50%
	31-35	63	23.30%
	36-40	60	22.20%
	41-45	37	13.70%
	46-50	19	7.00%
	>50	26	9.60%

Gender	Female	36	13.30%
	Male	234	86.70%
Digital Startups			
Age (Years)	2011	11	4.10%
	2012	24	8.90%
	2013	30	11.10%
	2014	23	8.50%
	2015	41	15.20%
	2016	49	18.10%
	2017	48	17.80%
	2018	44	16.30%
Size - Number of employees	Micro (0-9)	75	27.80%
	Small (10-49)	119	44.10%
	Medium (50-99)	41	15.20%
	Large (>100)	35	13.00%
Life Cycle Stage	Ideation	7	2.59%
	Operation	59	21.85%
	Traction	101	37.41%
	Scale	103	38.15%

4. Results

4.1 Assessing BDAC in Brazilian Digital Startups: Key Metrics

Significantly, the results showed that most DS are developing BDAC, with responses above 5 on nearly all items in the survey. To illustrate the level of BDAC in DS, items are presented in Figure 2: increasing decision-making power by analyzing available data (mean 6.215), providing a system for real-time monitoring of key performance indicators (mean 5.152), data visualization tools that support understanding of complex situations (mean 5.311), optimizing internal processes and resource utilization by analyzing available data (mean 5.444), analyzing available data to adapt to customer needs (mean 5.919), and regularly reviewing big data and analytics project goals based on the dynamic business environment (mean 5.004). The development and impact of these capabilities can vary widely, highlighting areas for further improvement.

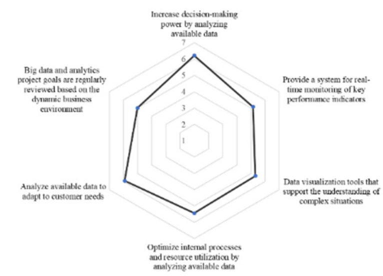

Figure 2. Level of BDAC in DS

4.2 Assessment of Sample Suitability for PLS-SEM

All sample checks for the method were performed. The absence of multicollinearity among the independent variables was verified as the linear regression analysis showed that all variance inflation factor (VIF) values were lower than 3 (J.F. Hair, Sarstedt, Pieper, & Ringle, 2012). The Kolmogorov-Smirnov test was performed to assess the normality of the data, and the p-value was insignificant for all items. In addition, Harman's single-factor test did not reveal any common method bias in the responses (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

This research developed a conceptual model based on the RBV theory to investigate the relationship between BDAC and CP of DS, controlled by the size of DS according to its number of employees, its age, and its life cycle stage. Smartpls 2.0 software was used to test the model. The results presented in Table 2 show that internal consistency was established, as all constructs have a Cronbach's alpha above the threshold of 0.70 and redundancy less than or equal to 0.30 (J.F. Hair, Hult, Ringle, & Sarstedt, 2014). In addition, the composite reliability of the model falls within the range of 0.7 to 0.9. Similarly, convergent validity was found, with AVE values for all constructs greater than 0.5 (Ringle, Da Silva, & Bido, 2014). Discriminant validity was established in the second round of testing according to the Fornell and Larcker criterion, as evidenced by Table 3, which shows that all values of the square root of the AVE on the diagonals exceed the correlation between constructs (Fornell & Larcker, 1981). Discriminant validity was also confirmed by the cross-loadings, as shown in Table 4, where the outer loadings of all items on their respective constructs are greater than their loadings on other constructs (Chin, 1998).

Table 5 also shows that the reliability of the items has been established. All items have outer loadings greater than 0.7 (J.F. Hair et al., 2014).

Table 2. Quality criteria of the model

Constructs	AVE	Composite Reliability	R^2	Cronbach's alpha	Communality	Redundancy
BDAC	0.556	0.833	0.502	0.736	0.556	0.091
MP	0.678	0.863	0.258	0.762	0.678	0.121
OP	0.712	0.881	0.246	0.799	0.712	0.090
HRS	0.596	0.855		0.775	0.596	
BDA	0.662	0.854		0.743	0.662	

Table 3. Discriminant validity FORNELL e LARCKER – 2ª. Round

Constructs	BDAC	MP	OP	HRS	BDA	VC_Stage	VC_Age	VC_Size
BDAC	0.745							
MP	0.429	0.823						
OP	0.371	0.782	0.844					
HRS	0.575	0.409	0.427	0.772				
BDA	0.688	0.416	0.412	0.734	0.814			
VC_Stage	0.301	0.372	0.411	0.168	0.266	1.000		
VC_Age	0.160	0.201	0.235	0.214	0.200	0.323	1.000	
VC_Size	0.046	0.146	0.126	0.100	0.074	0.200	0.172	1.000

Table 4. Discriminant validity - Cross Loadings

Item	BDAC	MP	OP	HRS	BDA	VC_Stage	VC_Age	VC_Size
BDAC_01	0.722	0.255	0.241	0.426	0.448	0.156	0.067	0.047
BDAC_02	0.750	0.342	0.295	0.446	0.627	0.276	0.121	0.038
BDAC_04	0.774	0.379	0.315	0.398	0.520	0.257	0.106	0.039
BDAC_05	0.735	0.284	0.244	0.449	0.424	0.185	0.186	0.010
MP_01	0.369	0.755	0.531	0.307	0.311	0.192	0.115	0.036
MP_03	0.382	0.849	0.679	0.347	0.378	0.326	0.131	0.142
MP_04	0.315	0.862	0.707	0.355	0.337	0.382	0.244	0.167
OP_01	0.318	0.629	0.837	0.366	0.346	0.368	0.171	0.047
OP_02	0.332	0.719	0.883	0.335	0.361	0.383	0.241	0.162
OP_04	0.287	0.627	0.811	0.390	0.338	0.280	0.177	0.107
HRS_01	0.453	0.353	0.341	0.755	0.585	0.157	0.179	0.077
HRS_02	0.478	0.356	0.386	0.747	0.575	0.183	0.158	0.081
HRS_03	0.437	0.303	0.309	0.803	0.548	0.109	0.186	0.129
HRS_04	0.395	0.238	0.269	0.783	0.554	0.055	0.135	0.014
BDA_02	0.575	0.305	0.288	0.600	0.838	0.217	0.176	0.049
BDA_04	0.588	0.356	0.379	0.625	0.857	0.261	0.189	0.051
BDA_05	0.514	0.359	0.341	0.565	0.742	0.167	0.118	0.083
VC_Stage	0.301	0.372	0.411	0.168	0.266	1.000	0.323	0.200
VC_Age	0.160	0.201	0.235	0.214	0.200	0.323	1.000	0.172

VC_Size	0.046	0.146	0.126	0.100	0.074	0.200	0.172	1.000

Table 5. Reliability of the items

BDAC		MP		OP		HRS		BDA	
BDAC_01	0.722	MP_01	0.755	OP_01	0.837	HRS_01	0.755	BDA_02	0.838
BDAC_02	0.750	MP_03	0.849	OP_02	0.883	HRS_02	0.747	BDA_04	0.857
BDAC_04	0.774	MP_04	0.862	OP_04	0.811	HRS_03	0.803	BDA_05	0.742
BDAC_05	0.735					HRS_04	0.783		

4.3 Structural Model Evaluation

Analyzing the coefficient of determination (R^2), the model in Figure 3 explains that the BDA construct and the HRS construct together explain 50.2% of the BDAC (Cohen, 1988). In addition, the BDAC construct explains 25.8% of MP and 24.6% of OP.

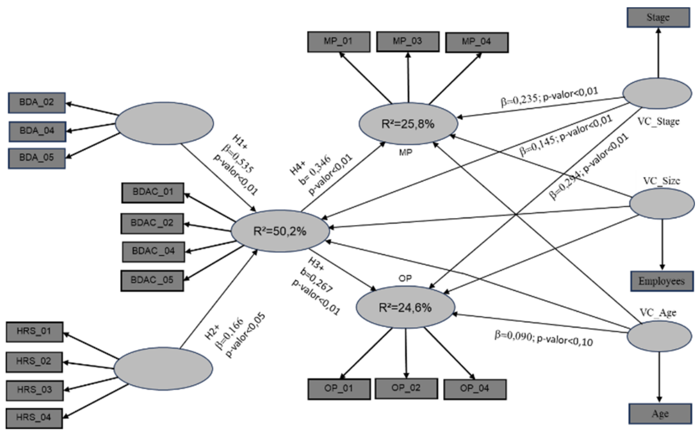

Figure 3. Model PLS-SEM

Table 6 presents the results of the verification of the hypotheses: all of them were confirmed in the context of DS. Thus, the BDA of DS is positively related to its BDAC (b=0.535 and p-value <0.01) and the HRS for strategic data analysis is positively related to the BDAC of DS (b=0.166 and p-value <0.05). BDAC is also positively related to the OP of DS (b=0.267 and p-value <0.01). Finally, BDAC has a positive relationship with the MP of DS (b=0.346 and p-value <0.01).

Table 6. Path analysis and hypothesis verification

Hypothesis	Path	b	t-test	p-value	Supported
H1	BDA -> BDAC	0,535	8,788	<0,01	Yes
H2	HRS -> BDAC	0,166	2,439	<0,05	Yes
H3	BDAC -> OP	0,267	4,290	<0,01	Yes
H4	BDAC -> MP	0,346	5,456	<0,01	Yes

O adjusted model presents predictive accuracy Stone-Geiser's value Q^2 values higher than zero are verified (BDAC=0.260, MP=0.173, OP=0.169).

With respect to the control variables, stage was found to be relevant at the 1% level with an effect on all dependent variables (MP b=0.235, p-value<0.01; OP b=0.294, p-value<0.01, and BDAC b=0.145, p-value<0.01). Age only at the 10% level in OP (b=0.090, p-value<0.10). On the other hand, the size of the DS, measured by the number of employees, was not relevant.

5. Discussion

The aim of this study was to investigate the level of BDAC in DS and its relationship with their OP and MP. Specifically, it examined whether the ability to analyze data can be considered a valuable resource associated with the superior performance of DS. In addition, this study examined whether this ability depends on BDA and HRS for strategic data analysis.

From an RBV perspective, regarding the question of whether one of the resources of DS is their ability to use big data (BDA), the results confirm what is recommended in the literature, that DS store and make available their data (Barot & Chhaniwal, 2018; Behl, 2020; Huang et al., 2017), both internally and from various external sources (Agarwal, 2019; Bosch, Holmström Olsson, Björk, & Ljungblad, 2013; Ferraris et al., 2019; Henke et al., 2016; Hokkanen & Väänänen-Vainio-Mattila, 2015), unlike small businesses in the traditional economy (Barot & Chhaniwal, 2018; Behl, 2020; Huang et al., 2017).

In terms of resources related to the profile of their employees (RHS), DS have professionals with the skills to strategically analyze large amounts of data. These findings are consistent with the literature on the characteristics of DS. They generally recruit competent, experienced, and highly specialized employees to achieve success (Kuratko et al., 2019; Venkobarao, 2019). In addition, most DS recognize that the use of data is aligned with their strategy (Barlette & Baillette, 2020; M. Gupta & George, 2016).

Analyzing the statistics, it is found that most of the DS develop BDAC. The results revealed that most DS develop BDAC by incorporating data analytics into their decisions and do not limit themselves to the opinions of managers (Venkobarao, 2019). Furthermore, there is a consensus among respondents that DS avoid wasting data (Barot & Chhaniwal, 2018; Behl, 2020; Huang et al., 2017). Almost all respondents agreed that DS improve decision making by analyzing their available data (McAfee & Brynjolfsson, 2012), which contributes to improving the accuracy of these decisions (Ardito et al., 2019; Dubey et al., 2020; Dubey, Gunasekaran, Childe, et al., 2019; Rialti, Marzi, et al., 2019).

It has also been confirmed that almost all DS analyze their available data to adapt to customer demands (Blank, 2013; Hoffman & Yeh, 2019; Ries, 2011; Shepherd & Gruber, 2020; Yang et al., 2019). In addition to having the necessary conditions to achieve marketing effectiveness (Barlette & Baillette, 2020; Irfan & Wang, 2019; Suoniemi, Meyer-Waarden, Munzel, Zablah, & Straub, 2020; Troisi, Maione, Grimaldi, & Loia, 2020; Zhou et al., 2018).

In addition to the relevance of the findings, most DS analyze the available data to optimize their internal processes and use of resources, as do other companies that have developed BDAC (Arunachalam, Kumar, & Kawalek, 2018; Dubey, Gunasekaran, & Childe, 2019; Rialti, Zollo, Ferraris, & Alon, 2019).

Similarly, most DS were able to monitor performance indicators in real time, quickly obtain information about their operations (Say et al., 2018), and adapt to changes in the operational scenario (Akter et al., 2016; Barlette & Baillette, 2020; Rialti, Marzi, et al., 2019).

In general, DS performed better on MP than OP, which is consistent with the theory that startups tend to focus on growth, often dominate markets before reaching profitability (Hoffman & Yeh, 2019; Sullivan, 2016), and can attract investment due to their disruptive nature (Kenney & Zysman, 2016). Thus, the sample followed the trend of achieving more expressive outcomes for MP (Autio, 2016; van Waes et al., 2018).

The results demonstrated that BDA, together with HRS, explained 50.2% of the development of BDAC in DS, indicating a large effect size (Cohen, 1988). In order to increase the explanatory power of the model, considering that this study has already shown that DS develop BDAC, it would be interesting to include more items in the BDA construct, especially those related to the use of tools such as artificial intelligence and machine learning (Mikalef, Boura, Lekakos, & Krogstie, 2019; Rialti, Marzi, et al., 2019). Furthermore, in this study with DS, BDA explains BDAC more than RHS, which supports recent studies such as BAG et al. (2021) and BEHL et al. (2019), which state that data is the most important asset of a company (Bag et al., 2021; Barlette & Baillette, 2020; Behl, 2020; Dubey et al., 2020; M. Gupta & George, 2016; Henke et al., 2016).

Significantly, BDAC explains 25.8% of MP and 24.6% of OP, indicating a moderate effect size (Cohen, 1988). However, it is important to note that this study focuses exclusively on this variable, although there are a wide range of other variables that influence a firm's performance that could be considered in future research.

The central hypothesis of the study, that BDAC is positively correlated with DS performance, was supported, indicating the existence of a relationship between BDAC and CP in the context of DS.

The model used included the following control variables: DS life cycle stage, age, and size. As for the DS stage, it was observed that this variable had a significant impact on both the CP and the BDAC of DS. It is important to note that most of the sample consisted of DS in the traction and scale phase (75.56%), where they are generally more mature, have better control over performance indicators and have more resources available, both in terms of data and people, and consequently tend to have higher levels of BDAC (Bailey & Tatikonda, 2018; Picken, 2017).

Regarding the age of the DS, most of the sample consisted of young firms between 3 and 6 years old, and this variable was only marginally significant at the 10% level in the OP. It should be noted that in the early stages of their life cycle, DS performance measures are uncertain. As time progresses, there is a tendency for accounting to become more organized and performance indicators to mature, providing greater certainty in assessing operating results. Regardless of the stage they are in, it is always important for DSs to closely monitor their performance metrics (Blank & Dorf, 2012; Ries, 2011).

In addition, the size of DS was found not to significantly affect the results for a sample composed predominantly of micro and small firms, even though DS can scale with few employees or be affected by automation and outsourcing (Chalmers et al., 2020; Josefy, Kuban, Ireland, & Hitt, 2015).

Furthermore, in response to one of its specific objectives, this research presented the level of BDAC in the DS sample on a scale of 1 to 7. It was observed that the DS obtained at least 5 as an average for each of the items of the construct. In addition, each participant can compare these results with their own responses and try to reach the maximum level as a guideline (M. Gupta & George, 2016).

The main theoretical contribution of this study was to identify, through a quantitative approach, that DS develop BDAC and that it is related to CP, confirming Huang et al. (2017) and Jinzhi and Carrick (2019), and demonstrating a decision-making behavior that is more analytical than intuitive. What provided more understanding of DS (Shepherd & Gruber, 2020). This implies the need to encourage DS to improve their BDAC by investing in data management and analysis to support operations and strategic decisions.

Therefore, given the wide diffusion and democratization of access to technology (M. Gupta & George, 2016; Henke et al., 2016), DS in emerging countries can enjoy the same opportunities for success as their counterparts in developed countries.

By recognizing that superior performance can lead to the success of DS, the BDAC expands the survival prospects of these companies and opens space for the emergence of new DS capable of addressing the socio-economic and environmental challenges of Brazil, an emerging economy (Genome, 2020).At the same time, countries have the potential to promote skilled jobs through BDA training programs for young people that meet the demands of these firms, and the more DS are active in the country, the more skilled jobs will be created (OECD, 2013, 2016). For example, the BDAC can even support the company's own strategic decisions, such as whether to invest more in hiring, thereby reducing the risk of future layoffs.

Moreover, this work addressed the performance of DS in early 2022 with assessments of the last three years, that is, through the period of the pandemic caused by COVID-19 (Liguori et al., 2020), in which DS increased its importance due to the accelerated digital transformation in the world (Genome, 2020).

As a practical contribution, the disclosure of the results of this study may reduce the fear of investing in BDAC, by confirming its effect on the performance of Brazilian DS (Suoniemi et al., 2020).

Another relevant practical contribution of this research relates to how to quantitatively measure BDAC in the DS segment, from maintaining data to creating a data-driven culture. New elements can be added in future research. For example, companies can self-assess their BDAC using the instrument constructed for this research. In this way, DS can use the items of the BDAC construct as a basis for BDAC development and should create an action plan to address the items with low scores to improve the current situation of their BDAC (M. Gupta & George, 2016).

The same tool can even be used by companies that offer big data solutions, which are looking for a diagnosis of the resources related to data analysis and the level of development of a company's BDAC, to select new customers and prepare their sales proposals (Urbinati, Bogers, Chiesa, & Frattini, 2019). It is also possible that BDAC could be addressed in both private and government DS accelerator programs (Huang et al., 2017; Jinzhi & Carrick, 2019).

As with any research, this study has several limitations. One limitation is the possibility that respondents may have an optimistic perception of the startup scenario, and with self-reported data, this could influence the results (Podsakoff et al., 2003). Furthermore, the cross-sectional nature of the research design limits the ability to observe changes in data levels, professional skills, BDAC, and performance of digital startups throughout their evolution in the life cycle, as the startup phase is relevant to the model. In addition, the results were specific to Brazilian digital startups, and there may be variations in different contexts. Therefore, it would be appropriate to apply the model to samples of digital startups in other countries to investigate the evolution of BDAC and its relationship with competitive performance. Moreover, the model could be tested on samples of startups based on different technologies to determine whether the factors affecting BDAC are unique to digital characteristics or a common need for companies created with the goal of solving problems and scaling quickly.

Another avenue for future research could be to explore how privacy and security concerns, particularly in the context of regulations such as the General Data Protection Regulation (GDPR), might influence BDAC by limiting data collection and use. Another suggestion for future research would be to deepen the understanding of BDAC by adding elements related to artificial intelligence and machine learning algorithms to the BDA construct, as this allows decisions to be made without human intervention. In addition, further studies could investigate the impact of BDAC development on the quality of decision making.

While this study provides insights into the technical and human resource factors that influence BDAC, future research could further explore the impact of organizational culture, leadership styles, and customer relationship management on the development and effectiveness of BDAC in improving startup performance. Crucially, the literature highlights several factors that can influence the CP of a DS that can be considered in future research. Among these factors, this study highlights the DS adopting a scalable business model (Ferri et al., 2020; Kunte & Promsiri, 2019; Ruggieri et al., 2018), the suitability of the founding team for the DS business(Jinzhi & Carrick, 2019; Nair & Blomquist, 2019), and the DS receiving investment at some stage of its lifecycle (Barot & Chhaniwal, 2018; Cavallo et al., 2019; Cowden et al., 2020; Jinzhi & Carrick, 2019; Kenney & Zysman, 2019; Kuratko et al., 2019; Venkobarao, 2019).

6. Conclusion

The originality of this study lies in its exploration of the critical role that BDAC plays in the CP of DS. Unlike previous studies that focus on traditional small businesses, this research examines the unique context of DS and demonstrates that BDAC is essential for their survival and growth in competitive markets. The study found that, despite the high-risk nature of digital entrepreneurship, where only 10% of startups achieve global success, participating startups exhibit significant levels of BDAC, which is critical for improving decision-making, optimizing operations, and adapting to market changes.

This data-driven capability enables startups to make more accurate decisions, reducing reliance on intuition and leading to better strategic planning and execution. In addition, the ability of DS to use the BDAC to gain deeper insights into customer behavior and preferences will not only improve customer satisfaction, but also strengthen customer relationships, which are critical to sustaining CP. The influence of organizational culture and leadership in fostering a data-centric environment further amplifies the impact of the BDAC, enabling startups to respond more effectively to market dynamics and customer needs.

Although big data analytics (BDA) was found to be more influential than human resources (HR), the need to train professionals in essential data skills remains critical, especially in emerging markets like Brazil. Investing in education and training to build a cadre of data-savvy professionals is essential to maintaining the competitive edge of DS.

Overall, this study validates the importance of BDAC in DS' CP and provides actionable insights for various stakeholders. By strategically integrating BDAC, digital startups can overcome traditional constraints, drive innovation, and contribute to economic development in emerging markets, positioning themselves at the forefront of socio-economic progress.

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Appendix A

Construct Measurement Instruments

Construct	Code	Items
OP	OP_01	The customer retention rate of the startup exceeded that of its competitors.
	OP_02	The sales growth rate of the startup exceeded that of its competitors.
	OP_03	The profit rate of the startup exceeded that of its competitors.
	OP_04	The return on investment of the startup exceeded that of its competitors.
MP	MP_01	The startup entered new markets faster than its competitors.
	MP_02	The startup introduced new products or services to the market faster than its competitors.
	MP_03	The startup has a success rate for new products or services that exceeded that of its competitors.
	MP_04	The startup has a market share that exceeded that of its competitors.
BDA	BDA_01	The startup uses appropriate technologies for storing and processing large volumes of data (such as cloud storage and Hadoop).
	BDA_02	The startup can integrate internal data, i.e. collect internally generated data and make it available for analysis by professionals.
	BDA _03	The startup can integrate external data, i.e. collect data from external sources and make it available to professionals for analysis.
	BDA _04	The startup provides tools that allow professionals to analyze data related to their areas and functions.
	BDA _05	The startup includes big data and analytics projects in its budget and strategic planning.
HRS	HRS _01	The startup provides training to employees so that they can perform data analysis related to their areas and functions.
	HRS _02	The startup hires new employees who can analyze data to make decisions.
	HRS _03	The startup's data analysis team has the education, skills, and experience to perform the work as expected.
	HRS _04	The leaders of the data analysis team have strong business knowledge and can effectively coordinate everyone involved in big data projects.
BDAC	BDAC_01	The startup increases its decision-making power by analyzing available data.
	BDAC_02	The startup provides a system for real-time monitoring of key performance indicators (dashboards) that allows understanding the root cause of its problems for continuous improvement of processes and activities.
	BDAC_03	The startup has data visualization tools that support the understanding of complex situations.
	BDAC_04	The startup optimizes its internal processes and resource utilization by analyzing available data.
	BDAC_05	The startup analyzes its available data to adapt to customer requirements.
	BDAC_06	The startup's big data and analytics project goals are regularly reviewed based on the dynamic business environment.