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RESEARCH ARTICLE

Predicting Small- and Medium-Sized Enterprise Competitive Firm Performance From Big Data Analytics Capabilities

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ABSTRACT

The objective of this research was to determine if, and to what extent, the tangible resources, human skills, and intangible resources components of big data analytics capability, collectively and individually, significantly predict competitive firm performance among small- and medium-sized enterprises (SMEs) in the United States. This research applied the resource-based theory (RBT) posited by Barney (1991). A quantitative correlational-predictive survey was executed among small- and medium-sized enterprises in the United States. The results of the multiple regression model confirmed that the components of BDAC collectively and individually influence the competitive firm performance of SMEs. Additionally, the research also contributed to affirming the relevance of the resource-based theory as a foundational framework. The primary insight was that tangible resources should be regarded as a foundational priority. Secondly, the non-technological resources, human skills and intangible resources together should be the next priority. Thirdly, within the non-technological factors, the creation of a culture of data-driven decision-making and organizational learning is relatively more consequential than human skills. There were few, if any, quantitative correlational-predictive research focused on SMEs in recent years in the United States that related BDAC to competitive firm performance (CFP) as guidance for SME leadership. This research filled that gap.

Keywords: *big data, big data analytics (BDA), big data analytics capability (BDAC), SMEs, competitive firm performance, correlational, predictive, quantitative.*

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I. INTRODUCTION

A brief history of big data and big data analytics (BDA) is essential to appreciate the problem associated with big data analytics capabilities (BDAC) and firm performance among small- and medium-sized enterprises (SMEs). The advent of Web 2.0 in 2005, which enabled users to interact with websites and contribute their content, set off the social media trend. This trend generated vast quantities of digital data and gave rise to the concept of big data (Lee, 2017). Digital data is ubiquitous today, permeated by social media, mobile apps, and sensor-embedded goods that we use (Henriques et al., 2020). Coming into prominence in the early 2010s, BDA emerged to extract value from big data (Henriques et al., 2020; Sena et al., 2019). BDAC, on the other hand, represents an organization's ability to apply and leverage the BDA technology effectively.

Research on BDAC is a recent phenomenon. Henriques et al. (2020) confirmed 2010 as the year of inflection in BDAC research production. In the nascent years, BDAC demanded a high initial investment both in terms of technology and associated capabilities. Therefore, early business models of BDA applications evolved mainly in the domain of large firms and data centers (Olufemi, 2019). Consequently, research also focused on determining the relationship between the use of analytics for data-driven decisions and elements of firm performance among large corporations (Asad et al., 2020; McAfee & Brynjolfsson, 2012). Only six of the 17 recent quantitative research studies relating BDAC to firm performance reviewed for this research (refer to Appendix A) focused on SMEs.

The SME-focused studies were geographically dispersed, and all were located outside the United States. They were conducted in a variety of economic conditions and tended to be sector-specific. For example, Dubey et al. (2019) and Maroufkhani, Wan Khairuzzaman, and Ghobakloo (2020) studied manufacturing SMEs, while Saleem et al. (2020) focused on technology startups. These studies showed direct or indirect effects of BDAC on various dependent measures, such as firm performance, organizational performance, financial performance, and market performance. Extant research in this domain is nascent, not only in applying research models but also in defining variables.

Research-based guidance for leveraging BDAC among SMEs was, therefore, considered an opportunity to advance knowledge in this domain. There is little empirical quantitative research relating BDAC to competitive firm performance among SMEs specific to the U.S. conditions. Such research could provide SME leaders in the U.S. with valuable insights and confidence for investing in BDAC. The research problem can be stated as follows: It is not known if, and to what extent, tangible resources, human skills, and intangible resources, components of big data analytics capability (BDAC), collectively and individually, significantly predict competitive firm performance (CFP) among small- and medium-sized enterprises (SMEs) in the United States.

A. Why SMEs?

SMEs make substantial contributions to the economies of the countries they operate in. The U.S. Small Business Administration - Office of Advocacy (2019) stated that small businesses accounted for two-thirds of net new jobs created, drove innovation, and accounted for 44% of the country's economic activity. However, the Office of Advocacy further noted that the contribution of small businesses to the economy had eroded from 48% to 43.5% in recent years. These compelling SME statistics made a case for supporting this segment with BDAC research that could help them achieve competitive firm performance.

B. Literature Review

Literature for this research was collated from the following sources: (a) EBSCOhost, (b) Google Scholar, (c) ERIC, (d) Sage Research Methods, the Web of Science, and (f) Laerd Statistics. The materials included were peer-reviewed papers, conference presentations, and textbooks. The keyword search terms used for assembling the literature included the following terms, which were used either individually or in various combinations: *SME*, *big data*, *big data analytics*, *BDA*, *big data analytics capabilities*, *BDAC*, *business intelligence*, *evolution of big data*, *enterprise data analytics*, *prescriptive analytics*, *firm performance*, *technology adoption*, *technology implementation*, *outcomes*, *success factors*, and *failure factors*.

Additionally, reference lists from reviewed papers were used to complete the reviewed literature. Peer-reviewed empirical research studies were drawn from the years 2016 to 2023. Date ranges were expanded to source other seminal references.

II. THEORETICAL FRAMEWORK

This research applied the resource-based theory (RBT), also referred to as the resource-based view (RBV) by some researchers, as the theoretical foundation. The theory was posited by Barney (1991) and has been used widely in technology research (Kim et al., 2011). BDAC research, drawing substantially from IT and business value research approaches, has also widely applied RBT as a theoretical underpinning. RBT posited that a firm could gain a competitive advantage by leveraging internal resources to respond to marketplace opportunities (Barney, 1991).

The theory made two assumptions. Firstly, strategic resources within a given industry are heterogeneously distributed across firms. Secondly, some of these resources may not be mobile across firms. A firm's resources were defined as physical capital, comprising technology, plant, and equipment; human capital, comprising experience and skill of staff; and organizational capital, comprising formal and informal structures and processes (Barney, 1991). Further, the theory recognized that not all resources were equally relevant for delivering competitive advantage.

To contribute to a firm's competitive advantage, resources must be (a) "valuable" in the firm's competitive context, either contributing to exploiting an opportunity or negating a threat; (b) "rare" among its competitive set; (c) imperfectly "inimitable"; (d) non-substitutable or must have no resource of equivalent capability (Barney, 1991). Several research papers refer to these resources as valuable, rare, inimitable, and non-substitutable or VRIN (Eller et al., 2020; Gupta & George, 2016). Other papers have used an evolution of the resource definition, namely, VRIO, which stands for valuable, rare, inimitable, and organizationally embedded (Ardito et al., 2021; Grover et al., 2018). To summarize, a firm can gain a competitive advantage by harnessing its VRIN or VRIO resources to exploit opportunities and negate threats in its business environment.

In their bibliometric analysis of co-cited documents, Henriques et al. (2020) discovered that Barney (1991) was frequently referenced by papers linking BDA to firm performance. Gupta and George (2016) observed that RBT was the only theory offering a unifying framework for disparate resources contributing to competitive advantage. Maroufkhani et al. (2019) noted that the RBT was the most frequently applied theory in BDA and firm performance research. RBT was, therefore, considered the appropriate theoretical foundation for this research. A schematic relationship between resources, competitive advantage, and CFP is represented in Figure 1.

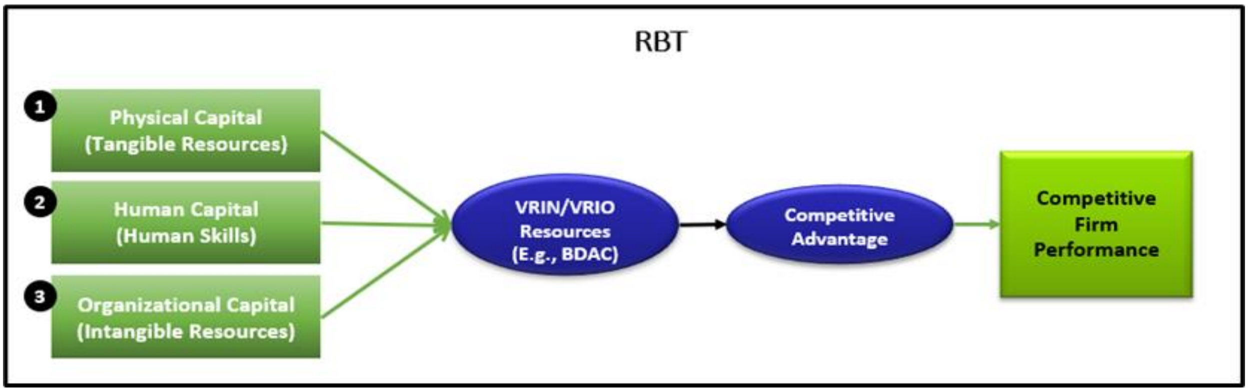

Figure 1. Representation of Linkage Between Resources, Competitive Advantage, and Competitive Firm Performance

III. REVIEW OF THE LITERATURE

This section is organized along the lines of the research model's proposed variables. BDAC is represented by its three components as the independent variables, and CFP, the dependent variable. The constituent components of each variable and their application in recent research are discussed. Gupta and George (2016) empirically validated all indicators representing each of the three components of BDAC. Further, their research also statistically confirmed the relationship between BDAC and firm performance.

A. Tangible Resources

Gupta and George (2016) defined tangible resources as data, technology, and essential resources. The data subcomponent in tangible resources was expressed in terms of the integration of large data sets from external and internal sources to create value for the business (Gupta & George, 2016). For technology, the second subcomponent of tangible resources, the authors referenced the need for firms to adopt new methods and technologies to capture, store, and process vast quantities of data — particularly unstructured data arriving at high speed —and to develop tools for visualizing outputs. Essential resources, the third subcomponent of tangible resources, were defined as the adequacy of monetary and time investment in BDAC to gain benefit from this capability.

B. Human Resources

The second component of the BDAC model comprised both technical and managerial skills required for applying appropriate analytic technology and effectively leveraging analytic outputs for business needs. The technical skills component focused on the training and technical competence of the BDA staff (Gupta & George, 2016). Managerial skills represented the notion that BDA managers would work as agents, bridging the gap between the output of BDA and business decision-makers by being knowledgeable about business needs within and outside the firm, such as suppliers and customers. Therefore, the effectiveness of technical and managerial skillsets is a critical component of BDAC.

C. Intangible Resources

The third component was considered central to the delivery of competitive advantage for the firm (Gupta & George, 2016). The nature of these resources is such that they are not documented and, therefore, not tradable. That makes them VRIN in RBT parlance (Gupta & George, 2016). Data-driven culture, one of the two subcomponents of intangible resources, represented the extent to which managers and staff in the firm made decisions based on analytic output rather than intuition. The second subcomponent, the intensity of organizational learning, represented the firm's ability to effectively leverage current knowledge alongside the creation and assimilation of new knowledge to meet the challenges of the changing business environment. This subcomponent reflects elements of dynamic capabilities and the knowledge-based view, which are adopted as separate variables by other researchers.

D. Competitive Firm Performance

Competitive firm performance (CFP) was applied as the dependent variable for this research. Taouab and Issor (2019) observed that although firm performance was used frequently in research as a dependent variable, there was little consensus on its definition and measurement. Further, the concept of firm performance also evolved to reflect the changing business principles, business environments, and business philosophies of the time (Taouab & Issor, 2019). For example, the word “performance” has been described as a “bag” word, which includes wide-ranging concepts of growth, profitability, efficiency, and competitiveness. Given the breadth of interpretation, scholarship proposed that the components of firm performance could be classified as financial, nonfinancial, tangible, and intangible, reflecting the dimensions of efficiency and effectiveness of a firm (Taouab & Issor, 2019). Consequently, researchers have often chosen a subset of firm performance components depending on the context of their research.

RBT was developed to support the achievement of competitive advantage. Therefore, research studies based on RBT also defined firm performance in competitive terms (i.e., being either more efficient or effective than the competition). Mikalef et al. (2020) defined competitive performance as the degree to which a firm achieves its objectives relative to its competitors. The items most commonly appearing across RBT-based research studies to represent competitive firm performance are sales, profit, return on investment (ROI), market share growth, and improved customer satisfaction or retention. Secondarily, studies make occasional reference to cost reduction. These scales reflect the set of outcomes that BDAC is most likely to influence (Grover et al., 2018; Maroufkhani, Tseng, et al., 2020; Maroufkhani, Wan Khairuzzaman, & Ghobakloo, 2020; Mikalef et al., 2020). Firstly, the influence on a firm's internal processes will likely reduce costs, thereby increasing profit. Secondly, influencing consumer experience is likely to improve customer satisfaction and increase customer retention. Thirdly, tracking the development of consumer trends and demand will likely influence the success rate of innovation, thereby contributing to increasing market share and sales growth. The items outlined above are a fair representation of financial and non-financial outcomes influenced by BDAC, making them suitable for representing CFP.

IV. METHODOLOGY

The purpose of this quantitative correlational-predictive research was to determine if, and to what extent, tangible resources, human skills, and intangible resources components of big data analytics capability (BDAC), collectively and individually, significantly predict competitive firm performance (CFP) among a sample of small- and medium-sized enterprises (SMEs) in the United States. The paucity of empirically derived quantitative research on the impact of BDAC on CFP among U.S. SMEs was the primary reason for recommending a quantitative methodology with a correlational-predictive, regression-based design. A regression analysis will assess the extent to which the predictor components, individually or collectively, predict the criterion variable. In practice, a successful predictive model would also help practitioners simulate the outcomes of the criterion variable, CFP, by varying the predictor variables, which in this case are BDAC's components (Siedlecki, 2020).

The BDAC instrument reflected the three types of resources enunciated by RBT, namely, physical capital, human capital, and organizational capital. Correspondingly, Mikalef et al. (2019) proposed the three components of the BDAC instrument as: technological resources representing physical capital; human skills representing human capital; and intangible resources representing organizational capital. Each of these components was, in turn, defined by a set of items representing different facets of its respective component.

Further, an argument for measuring the impact of BDAC as a collective variable was put forward by Akter et al. (2016). Citing the tenets of the entanglement view of the sociomaterialism theory, Akter et al. (2016) argued that BDA components worked in unison and were so interwoven that it would be difficult to measure their contribution in isolation. This is why the purpose statement includes determining the relationship between the collective components of BDAC and CFP. This study applied the instrument used by Mikalef et al. (2019) to measure BDAC.

Competitive firm performance (CFP) was the dependent variable in the research model. Mikalef et al. (2020) conceptually defined CFP as the degree to which a firm achieves its objectives relative to its competitors. The CFP scale, validated by Mikalef et al. (2020), appropriately comprises items that represent aspects of both financial and market performance, given BDAC's potential to impact a wide range of a firm's performance metrics.

A. Research Question, Hypotheses, And Variables

The purpose statement provides the basis for determining the variables of this research. The research question and the hypotheses derived from the purpose statement can be stated as follows:

RQ: If, and to what extent, do the tangible resources, human skills, and intangible resources components of big data analytics capability, collectively and individually, significantly predict competitive firm performance among small- and medium-sized enterprises in the United States?

H10: The tangible resources, human skills, and intangible resources components of big data analytics capability collectively do not significantly predict competitive firm performance among small- and medium-sized enterprises in the United States.

H20: Individually, controlling for all other components of the model, the tangible resources component of big data analytics capability does not significantly predict competitive firm performance among small- and medium-sized enterprises in the United States.

H30: Individually, controlling for all other components of the model, the human skills component of big data analytics capability does not significantly predict competitive firm performance among small- and medium-sized enterprises in the United States.

H40: Individually, controlling for all other components of the model, the intangible resources component of big data analytics capability does not significantly predict competitive firm performance among small- and medium-sized enterprises in the United States.

The conceptual and operational definitions of these variables are outlined in the following table, along with the levels of measurement for each. Each component will be represented by a scale drawn from Mikalef et al. (2019, Appendix A). Competitive firm performance (CFP) will be represented by a single scale as prescribed by Mikalef et al. (2020, Appendix A). All items will be measured using the 7-point Likert scale.

Table 1. Summary of Study Variables

Variable	Conceptual Definition	Operational Definition	Measurement level	Instrument source
Tangible Resources (TR)	Will be operationalized as access to large, unstructured or fast-moving data from multiple sources including external sources; adequate funding and time for projects, and the adoption of hardware and software tools to run BDA.	Derived from the 3 Data, 2 Basic Resources, and 5 Technology questions, each rated on a 7-pt Likert scale.	Ordinal, approximated to interval. Aggregate mean range 1-7	Big Data Analytics Capability *Mikalef et al. (2019).*
Human Skills (HS)	Will be operationalized as managerial skills to coordinate big data projects with the business and the availability of relevant technical skills.	Derived from the 4 Managerial Skills, and 4 Technical Skills questions, each rated on a 7-pt Likert scale.	Ordinal, approximated to interval. Aggregate mean range 1-7.	Big Data Analytics Capability *Mikalef et al. (2019).*
Intangible Resources (IR)	Will be operationalized in terms of decisions driven by data rather than intuition, and the assimilation of relevant knowledge.	Derived from 3 Data-driven Culture, and 4 Organizational Learning questions, each rated on a 7-pt Likert scale.	Ordinal, approximated to interval. Aggregate mean range 1-7.	Big Data Analytics Capability *Mikalef et al. (2019).*

Variable	Conceptual Definition	Operational Definition	Measurement level	Instrument source
Competitive Firm Performance (CFP)	Will be operationalized as "better" performance than main competitors on key financial metrics such as profitability, ROI, and market performance metrics such as market share and sales growth.	Derived from 7 Competitive Performance questions, each rated on a 7-pt Likert scale.	Ordinal, approximated to interval. Aggregate mean range 1-7.	Competitive Performance *Mikalef et al. (2020).*

B. Research Methodology

Three factors influence the choice of research design. Firstly, the research problem statement, questions, and associated hypotheses influenced the choice. Secondly, the fit between the problem statement and the characteristics of the research design influences the choice. Finally, the widespread application of the method in recent research is revealed by the literature review on this topic.

The research problem, the first factor, is stated as: It is not known if, and to what extent, tangible resources, human skills, and intangible resources, components of big data analytics capability (BDAC), collectively and individually, significantly predict competitive firm performance (CFP) among small- and medium-sized enterprises (SMEs) in the United States. This statement requires determining the relationship between the components of BDAC and CFP and measuring the extent of their influence, if any. The research question, which originates from the problem statement, also seeks to test the existence and strength of relationships, indicating the need for a quantitative, correlational method. Sackett and Wennberg (1997) asserted that the question being asked must determine the choice of research strategy and tactics. Finally, the term "predict" implies the need for a correlational-predictive research design.

The second factor is the fit between the problem statement and the characteristics of the research design. Correlational-predictive designs are applied when the research aims not only to discover relationships between variables, if any, but also to determine whether one variable (the predictor variable) could predict another variable (the criterion variable). The correlational-predictive analytical method represents the next advancement from the application of simple correlation. It entails the application of regression, or its flavors, when multiple predictor variables need to be examined jointly (Siedlecki, 2020). Such a design is appropriate for this research because the research model defines a set of variables based on prior research and focuses on determining the existence and strength of the relationship.

The third factor is applying a research design similar to recent research on the topic. Most recent studies on the influence of BDAC on facets of firm performance used a correlational-predictive method, applying a flavor of regression. Examples of these studies are Olabode et al. (2022), Bahrami and Shokouhyar (2021), Razaghi and Shokouhyar (2021), C. H. Liu and Mehandjiev (2020), Behl (2020), and Mikalef et al. (2020). Therefore, the regression-based correlational-predictive research design was chosen for this research.

C. Instrumentation and Validity

BDAC was measured using Mikalef et al.'s (2019) 25-item, SME-focused version of Gupta and George's (2016) BDAC scale. This instrument has been used and validated in multiple research studies. The instrument was foundationally developed and validated by Gupta and George (2016), and subsequently revalidated by Mikalef et al. (2019), Dubey et al. (2019), Mikalef et al. (2020), and C. H. Liu and Mehandjiev (2020). This research also used a validated scale for CFP. A seven-item set for CFP was proposed by Mikalef et al. (2020). It was a single scale covering both financial and non-financial facets. The seven-item CFP scale was validated by Mikalef et al. (2020).

D. Population and Sample

The Small Business Administration sets standards for small businesses in the United States. Small businesses are defined as establishments or firms with fewer than 500 employees for manufacturing businesses or those with annual receipts of less than $7.5 million for non-manufacturing businesses (US Small Business Administration - Office of Advocacy, 2019). These businesses are also required to run for profit, operate primarily in the United States, have a place of business in the United States, and be independently owned (What Is a Small Business? - United States Department of State, 2019). Businesses with 10 or fewer employees are considered small offices or microbusinesses (Small and Medium-Sized Enterprises - Wikipedia, n.d.). Review of the literature confirmed that the adoption of BDA and BDAC commenced with larger firms and then migrated to smaller firms as various barriers to adoption were overcome (Asad et al., 2020; Liu et al., 2020; Maroufkhani, Tseng, et al., 2020; Olufemi, 2019; Persaud & Zare, 2023). Further, Persaud and Zare (2023) favored a larger SME firm-size based on the number of employees to ensure adequate representation of BDA operations. Therefore, the population for this research was defined as SMEs with 100-499 employees. Additionally, to ensure that firms in the sample represent SME businesses with a high propensity to access and leverage big data, specific sectors were identified from the NAICS codes (U.S. Census Bureau, 2022). These sectors are accommodation and food services, construction, healthcare and social assistance, manufacturing, retail trade, and wholesale trade.

To summarize, the target population for this research was defined as: independently owned and run for-profit SMEs, with operations primarily in the United States, having 100 to 499 employees, operating in the Accommodation and Food Services, Construction, Healthcare and Social Assistance, Manufacturing, Retail Trade, and Wholesale Trade, and having applied analytics to at least one big data source for at least the past 3 years. In this context, big data is defined as "large, unstructured, or fast-moving data" (Mikalef et al., 2019) that may be generated by any or a combination of the following sources: software logs, sensors, usually in production lines and warehouses, business and customer digital interactions, usually through APIs, click streams, the internet of things, Industry 4.0 intelligent digital technology in manufacturing and industrial processes, product or services reviews on social media, and e-commerce operations (Asad et al., 2020; Persaud & Zare, 2023; Saleem et al., 2020). Finally, the stipulation of 3 years of experience with big data analytics ensured that sufficient time had been invested in the capability for the SME to assess its impact on the business.

G*Power 3.1.9.7 was used to estimate the minimum sample size required for this research. The options chosen to arrive at the minimum sample size were a linear multiple regression fixed model, R-square deviation from zero, a test family of F tests with an effect size of 0.15, an alpha error probability of 0.05, a power of 0.95, and three predictors. The minimum sample size for these specifications was 119. It is normal practice to plan for various sources of attrition to the final sample size and, therefore, 35% was added to the minimum estimated sample to achieve a target sample of 161 for this research.

E. Data Collection

The research question and hypotheses were answered by setting up a quantitative survey among small- and medium-sized enterprises in the United States. A questionnaire was developed using appropriate, validated Likert scales discussed above. The Informed Consent and a set of masked screening questions preceded the Likert scale questions. Only those who agreed to participate in the survey and qualified were allowed to progress to the main questionnaire.

To confirm that the questionnaire was working as intended, it initially included an additional open-ended question at the end, which probed the ease or difficulty with the language of the questionnaire, ease of understanding, and the overall flow. This pilot phase consisted of 10 complete questionnaires. The survey was paused at this stage to examine the quality of data delivered and the open-ended responses. The review showed that the skip pattern of the questionnaire was working, and the open-ended responses did not indicate any difficulty with the language or the overall questionnaire.

Given the positive feedback from the pilot phase, QuestionPro (n.d.), the survey provider, then mailed out the survey invitation to a larger number of potential respondents drawn from the developed sample frame. In total, the survey provider mailed out 2,300 survey invitations to their panel of SME businesses. In response to the invitations, the survey received 619 views, 480 respondents began the survey, and 186 completed it. Fully complete questionnaires meant that respondents accepted the Informed Consent, met the target sample criteria, and had no missing values. The pilot completes were also included as part of the final sample because their data was valid.

V. RESULTS AND DISCUSSION

A. Data Preparation

Upon receipt of the 186 completes, the data was examined for quality. “Straight-liners” [respondents that gave the same score for all Likert items], “zippers” [respondents that completed the survey in inordinately short times, e.g., two to four minutes] were eliminated first; 22 records were removed in this process. Next, an initial regression analysis was run on the sample of 164 records to identify outliers from case-wise diagnostics and cases with points of unusual influence; two case-wise and four unusual points records were identified. Six outliers were identified.

Before deciding on the removal of the six outliers, additional regression analyses were run with and without the outliers. The results showed that the inclusion of the outliers distorted conclusions from the analysis. Given the benefit of a large over-sample (a minimum of 119 was required), the outlier records were eliminated from further analysis. Tests of assumptions were re-run on the final sample of 158 to validate the data. The multiple regression analysis was executed on the final sample of 158 to support or reject the research hypotheses outlined above.

B. Tests of Assumptions

A total of eight tests of assumptions relevant to regression analysis were conducted to validate the data. These tests are: (a) Assumption #1 - confirming that the criterion variable is continuous, (b) Assumption #2 - confirming that the predictor variables are continuous, (c) Assumption #3 - confirming the independence of observations, (d) Assumption #4 - confirming that there is a linear relationship between the predictor variables and the criterion variable, (e) Assumption #5 - confirming the presence of homoscedasticity, (f) Assumption #6 - confirming the absence of multicollinearity (g) Assumption #7 - confirming the absence of unusual points, and (h) Assumption #8 - confirming the normality of residual errors. All tests of assumptions were met.

C. Descriptive Findings

Appendix B provides a description of the sample characteristics, and Appendix C shows the variety of big data sources applied in their operations. All firms were for-profit SMEs with primary operations in the United States. They all confirmed the use of at least one source of the nominated big data and had the ability to combine internal and external data sources. Respondents primarily responsible for managing the analytics function within the firm answered the survey.

The purpose of this quantitative, correlational predictive study was to determine if, and to what extent, the tangible resources, human skills, and intangible resources components of big data analytics capability

(BDAC), collectively and individually, significantly predict competitive firm performance (CFP) among a sample of small- and medium-sized enterprises (SMEs) in the United States. It was, therefore, critical to demonstrate that the three components, or predictor variables, represented BDAC. Cronbach's alpha is used most often to measure reliability or internal consistency. This statistic measures the extent to which scales measure the underlying construct (Laerd Statistics, n.d.). A score of 0.7 or higher is considered a good level (Laerd Statistics, n.d.).

Although the three components of BDAC—tangible resources (TR), human skills (HS), and intangible resources (IR)—have been tested for reliability in multiple previous studies, as explained earlier, they were tested again with data from this study. Table 2 confirms the reliability of the three components with a Cronbach alpha score of .789. It can be concluded that these three components collectively represent BDAC.

Table 2. Cronbach's Alpha for the 3 Components Representing BDAC (TR, HS, IR)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.789	0.791	3

D. Data Analysis Procedures

The prepared data from 158 questionnaires was put through the standard multiple regression procedure in the SPSS Statistics V29.0.2.0 software package using the enter method. The outputs of the analysis were three tables. The first, Table 3, was a model summary table that explained the variance in the criterion variable that the total model, comprising the three predictor variables, accounted for. The second, Table 4, ANOVA, confirmed whether the model was significant, thereby supporting or rejecting H10. The third, Table 5, provided the coefficients of the predictor variables and indicated whether they were significant, thereby addressing each of the other three hypotheses. These results are discussed in the following section.

Table 3. ***Model Summary[b]: Variance for the Complete Model***

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.734[a]	0.538	0.530	0.375	1.552

[a] Predictors: (Constant), IR, TR, HS
[b] Dependent Variable: CFP

Table 4. ***ANOVA[a] for the Overall Model***

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25.292	3	8.431	59.897	<.001[b]
	Residual	21.676	154	0.141		
	Total	46.968	157			

[a] Dependent Variable: CFP
[b] Predictors: (Constant), IR, TR, HS

Table 5. ***Coefficients of the Predictors: Tangible Resources (TR), Human Skills (HS), and Intangible Resources (IR)***

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B

		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.515	0.290		5.218	0.000	0.941	2.088
	TR	0.397	0.063	0.448	6.354	0.000	0.274	0.521
	HS	0.163	0.064	0.187	2.566	0.011	0.038	0.289
	IR	0.180	0.055	0.226	3.263	0.001	0.071	0.288

Dependent Variable: CFP

E. Presenting Results

The primary motive for undertaking this research was to provide the managements of small- and medium-sized enterprises in the United States with quantitative, empirical evidence about the factors that contribute to the effective application of big data analytics capabilities (BDAC) for competitive firm performance (CFP). To achieve this goal, data from a sample of 158 respondents, which included the three predictor components of BDAC—tangible resources (TR), human skills (HS), and intangible resources (IR)—and the criterion variable of competitive firm performance (CFP), were analyzed using multiple regression. Table 4 confirms whether the model is significant and is the basis for supporting or rejecting H10. Table 5 provides the beta values for each of the predictor variables and whether they are significant. The significance of the beta values of each predictor variable is the basis for supporting or rejecting H20, H30, and H40.

1) Testing of Null Hypothesis for the Collective Model ($H1_0$): Table 3, the Model Summary, shows an R value of 0.738, which is indicative of a positive and strong correlation (Cohen, 1992). The R2 is 0.538, which indicates that the addition of the three predictor variables explained 53.8% of the variance in the criterion variable, CFP. The adjusted R2, which provides an estimate of the variance expected in the population, is 0.530. Alternatively, R2 suggests that 53% of the variance in CFP is likely to be explained by the three predictor variables in the population. An R2 of 53.8% and an adjusted R2 of 53% are considered a large effect according to Cohen (1992). Table 4, the ANOVA, provides the statistical significance of the model. It shows that tangible resources (TR), human skills (HS), and intangible resources (IR) collectively statistically significantly predicted competitive firm performance (CFP), F(3, 154) = 59.897, p < .001. The hypothesis H10 is, therefore, rejected.

2) ***Testing of Null Hypothesis for Tangible Resources Controlling for others ($H2_0$)*:** Table 5 presents the coefficients of the three predictor variables and their statistical significance. Results show that tangible resources (TR) had a positive impact and statistically significantly predicted competitive firm performance (CFP) with a coefficient of 0.397 (p < 0.0005) and a 95% CI [0.274, 0.521] while controlling for the other components. Thus, H20 is rejected. The standardized coefficient for TR is 0.448 (refer to Table 5), which represents a nearly strong correlation (Cohen, 1988). A comparison of the standardized coefficients across the predictor variables suggests that TR had twice the impact on CFP relative to the other predictor variables.

3) Testing of Null Hypothesis for Human Skills Controlling for Others ($H3_0$): Similarly, Human skills (HS) had a positive impact and statistically significantly predicted CFP with a coefficient of 0.163 (p < 0.05) and a 95% CI [0.038, 0.289] while controlling for the other components (refer to Table 5). H30 is also rejected. The standardized coefficient for HS is 0.187, which is a weak correlation (Cohen, 1988).

4) ***Testing of Null Hypothesis for Intangible Resources Controlling for Others ($H4_0$):*** Intangible resources (IR) also had a positive impact and statistically significantly predicted CFP with a coefficient of

0.180 ($p < 0.005$) and a 95% CI [0.071, 0.288] while controlling for the other components (refer to Table 5). Thus, H40 is also rejected. The standardized coefficient of IR is 0.226, which is a weak correlation (Cohen, 1988).

The regression equation of this model can be expressed as: predicted CFP = 1.515 + (0.397 x TR) + (0.163 x HS) + (0.180 x IR)

The equation indicates that while controlling for the other components, an increase in one unit of TR will increase CFP by 0.397 units; similarly, an increase in one unit of HS will increase CFP by 0.163 units; and an increase of one unit in IR will increase CFP by 0.180 units.

F. Discussion of Results, Limitations, and Recommendations for Future Study

1) The Collective Model $H1_0$: Results of the regression analysis confirmed that the three variables representing BDAC collectively significantly predicted competitive firm performance, $F(3, 154) = 59.897$, $p< .001$ (see Table 6). Thus, H10 was rejected. The model explained 53.8% of the variance in the criterion variable, competitive firm performance (CFP) (Table 5). We can, therefore, conclude that BDAC impacts the competitive firm performance of small- and medium-sized enterprises in the target population in the United States.

The outcome that BDAC impacts firm performance is not unexpected. All 17 recent research studies reviewed (refer to Appendix A) that related BDAC, or its variations, to firm performance, or its variations, reported significant direct or indirect effects. Five of the 17 studies measured the direct impact of BDAC, or its variations, on aspects of firm performance; eight studies measured the direct and indirect impact on aspects of firm performance; and four studies only measured the indirect effects.

The purpose of this study was to demonstrate the effects of BDAC on competitive firm performance among small- and medium-sized enterprises (SMEs) in the United States. Six of the 17 studies focused their research on SMEs; four were in Asia, and one each in Italy and Canada. These studies have variously confirmed the direct and indirect effects of BDAC, or BDA, on aspects of firm performance. The significant effect of BDAC on competitive firm performance among SMEs in the United States, as reported by this research, is therefore a valuable addition to the body of knowledge in this domain.

2) Individual Components of BDAC ($H2_0$, $H3_0$, $H4_0$): These three hypotheses were designed to test the significant effects of the three components of BDAC—tangible resources, human skills, and intangible resources—on competitive firm performance. Most studies do not include this aspect. Citing the tenets of the entanglement view of the sociomaterialism theory, Akter et al. (2016) asserted that BDA components worked in unison and were so interwoven that measuring their individual contribution in isolation would be difficult. Usually, studies demonstrated that the three individual components loaded significantly onto the latent variable, BDAC, which was then used as the independent variable to confirm the relationship with firm performance. H10, discussed above, represents the sociomaterialism view of BDAC as a composite variable. The addition of relating the individual components of BDAC to firm performance incorporated in this study is, therefore, a source of incremental insights to the existing body of knowledge.

3) Impact of Tangible Resources ($H2_0$): The tangible resources (TR) component statistically significantly predicted competitive firm performance (CFP) while controlling for the other components, with a positive coefficient of 0.397 ($p < 0.0005$) and a 95% CI [0.274, 0.521] (refer to Table 5). Thus, H20 was rejected. TR had a standardized coefficient of 0.448, indicating a nearly moderate effect on the criterion variable, CFP (Cohen, 1992). Standardized coefficients also represent the relative importance of the predictor variables in explaining variance in the criterion variable (Bring, 1994; Gravetter & Wallnau, 2013). The standardized coefficient of 0.448 accounts for 52% of the total variance explained by the model, which is 53.8%. Therefore, tangible resources explain 28.0% of the variance in the criterion variable, CFP.

4) Impact of Human Skills (H3$_0$): The human skills (HS) component statistically significantly predicted competitive firm performance (CFP) while controlling for the other components, with a positive coefficient of 0.163 ($p < 0.05$) and a 95% CI [0.038, 0.289] (refer to Table 5). Thus, H30 is also rejected. Human skills had a standardized coefficient of 0.187, which is a very weak but positive correlation with the criterion variable. HS accounted for 22% of the variance explained by the model (53.8%). Therefore, HS explains 11.7% of the variance in the criterion variable, CFP. The human skills component contributed the least of the three components in explaining variance in CFP.

5) Impact of Intangible Resources (H4$_0$): The intangible resources (IR) component also statistically significantly predicted competitive firm performance (CFP) while controlling for the other components, with a coefficient of 0.180 ($p < 0.005$) and a 95% CI [0.071, 0.288] (refer Table 5). Thus, H40 was also rejected. The intangible resources component had a standardized coefficient of 0.226, which represents a weak but positive correlation with the criterion variable, CFP. IR accounted for 26% of the model variance (53.8%). Thus, it explained 14.1% of the variance in the criterion variable, CFP.

The relatively high importance of the intangible resource's component is not surprising, given that prior studies have demonstrated the relevance of knowledge management and organizational culture in the context of big data analytics. Ferraris et al. (2019) and Shabbir and Gardezi (2020) demonstrated that when BDAC is defined purely in terms of technology and skill, it only has an indirect effect through the mediating variable of knowledge management. Persaud and Zare (2023) also showed that analytics culture has a significant mediating role between the BDAC components and strategic business value.

All four null hypotheses are rejected, indicating that BDAC and its components have a significant effect on competitive firm performance for SMEs in the target population. When these results are viewed in totality, the non-technological aspects—human skills and intangible resources—are as relevant as the technological aspects. Human skills (11.7%) and intangible resources (14.1%) explained 25.8% of the variance in CFP, the criterion variable, while tangible resources accounted for 28%. These results demonstrate the value of BDAC to competitive firm performance for SMEs in the target population. Results also suggest that SME managements should pay attention to the technological aspects (tangible resources) and the non-technological aspects (human skills and intangible resources) to harness the benefits of BDAC effectively. The research question raised was answered, contributing to the advancement of knowledge in the domain.

6) Theoretical Implications: Additionally, the research also contributed to affirming the relevance of the resource-based theory (Barney, 1991) as a robust foundational framework. The theory proposes that a firm's resources are a source of its competitive advantage. Firm resources are defined as physical capital, which includes technology, plant, and equipment; human capital, which includes the experience and skills of staff; and organizational capital, which includes formal and informal structures and processes (Barney, 1991). Study results demonstrated that the three components —physical capital (tangible resources), human capital (human skills), and organizational capital (intangible resources) —collectively and individually had significant effects on competitive advantage (competitive firm performance).

RBT also posits that not all resources are equal; only those that are VRIN deliver competitive advantage (Barney, 1991). The three components of BDAC, individually and collectively, had a significant effect on CFP, confirming that they are VRIN resources. The appropriate investment and nurturing of this capability could prove valuable for SMEs.

7) Practical Implications: Several practical insights emerge from this research for SME leadership. Firstly, tangible resources should be regarded as a foundational priority given their relative importance (28%) in impacting competitive firm performance. Secondly, to fully leverage the benefits of BDAC, it is essential to equally nurture the non-technological resources (25.8% contribution), which include human skills and intangible resources. Thirdly, among the non-technological factors, the creation of a culture of data-driven decision-making and organizational learning is relatively more consequential (14.1%) than human skills (11.7%) in fully realizing the benefits of BDAC.

As stated above, tangible resources lay the foundation for implementing BDAC. Specifically, this means funding for relevant fast-moving, structured, and unstructured data, supporting the capability to integrate multiple sources of internal and external data, adopting cloud-based and open-source software solutions for big data analytics, and ensuring appropriate visualization tools that foster timely business decisions. Additionally, it is important to allow the big data analytics teams adequate time to achieve their objectives.

Within intangible resources, a data-driven culture involves relying on data rather than instinct to make decisions, being willing to override intuition when data contradicts opinions, and continuously coaching teams to use data for decision-making. Organizational learning is about creating a culture of seeking and applying new and relevant existing knowledge for improved performance. The two dimensions of intangible resources, data-driven culture and organizational learning, build upon each other to leverage relevant data-driven information for enhanced performance.

The human skills component encompasses management as well as technical skills. This component includes such aspects as identifying and prioritizing target areas for the application of big data analytics for the greatest gains, the ability to translate the outputs of big data analytics to business managers effectively for decision-making, to ensure the coordination of data-related activities with suppliers as well as customers, and continually enhancing technical competence through training. Unquestionably, the elements outlined for this component represent good management practices and will likely play a key role in fully realizing the benefits of BDAC.

8) Limitations, Strengths and Weaknesses of the Study: No matter how carefully a research study is planned, limitations could arise from the delimitations defined and the assumptions made. The primary delimitations for this research were the choice of a single theory to frame the research questions and hypotheses, the definition of the target sample, definitions of the variables, the choice of the research design, which was a cross-sectional study, data collection, and measurement error due to the use of an online survey. The choice of RBT (Barney, 1991) as a single foundational theory to frame this research was robust and not unusual. However, the literature review showed that studies based on single theoretical frameworks generally explained around 55% of the variance in the criterion variable. In contrast, those that applied additional theories and developed research models with mediators, and in some instances moderators, tended to explain around 65% of the variance.

The definition of the sample is often a source of limitation for any research. The target population was defined as U.S.-based SMEs with 100-499 employees operating in accommodation and food services, construction, healthcare and social assistance, manufacturing, retail and wholesale trade, and that have applied big data analytics in the past three years. The results of this study can be generalized only to this population. Another limitation of this research is the definition of the variables. The predictor variables, TR, HS, and IR representing BDAC, were sourced from Gupta and George (2016) and Mikalef et al. (2019, Appendix A), while the criterion variable, competitive firm performance (CFP), was sourced from Mikalef et al. (2020, Appendix A). Therefore, results should be interpreted in the context of the variable definitions outlined in this research.

This study is potentially the first quantitative correlation-predictive research relating BDAC and its components to competitive firm performance, focusing on small- and medium-sized enterprises in the United States, as defined by the target population. The research model was developed from a thorough review of recent peer-reviewed studies on BDAC and firm performance. The study was founded upon the resource-based theory (RBT), a robust framework applied widely in prior BDAC research. The variable scales adopted for this study have been validated multiple times. The minimum a priori sample size estimated for the research was 119, but the final sample analyzed was 158, yielding greater precision of estimates and reliability. Systematic random sampling, using masked screening questions, was employed to recruit the sample from a business-to-business sampling frame. The application of systematic random sampling supports the potential for generalizability to the target population (Andrade, 2020). Results were derived by the application of multiple regression, an analytic approach widely used for predictive research. Statistical rigor ensured that all tests of assumptions relevant to regression analysis were met. The rigorous approach to research represents its strengths. The positive effect of BDAC on competitive firm performance among SMEs, as shown by this research, reaffirms conclusions from similar studies in other countries. Quantifying the contribution of BDAC components to competitive firm performance variance offers practitioners incremental value in prioritizing their resources.

Overall, three potential weaknesses stand out. The first is the choice of one theoretical foundation, the second is the choice of a survey-based method for data collection, and the third is the choice of not including objective measures as dependent variables. The addition of one or more complementary theoretical foundations markedly improves the model's explanation of the dependent variable. However, it also adds complexity. As one of the earliest quantitative, correlation-predictive studies focused on SMEs in the United States, a decision was made to explore relationships using a simpler yet robust approach. Secondly, the choice of a survey-based method for data collection was based on the literature review. All studies relating BDAC to firm performance that have been reviewed have applied this method. Hence, this approach was considered appropriate. Thirdly, including objective firm performance measures as dependent variables would require sourcing information from third parties that track SME performance. Preliminary discovery efforts in this direction indicated that no single third party had all the data. Therefore, a researcher would have to append data from multiple sources to the survey data using propensity matching. However, such an approach could be attempted by other researchers with sufficient resources. On balance, many aspects of this study were robust.

9) Recommendations for Future Research: The most obvious and immediate opportunity to deepen knowledge in this domain is to expand the definition of the target population to determine if similar results are obtained for other industry sectors of SMEs. Another theme to pursue would be to apply a more sophisticated research model by augmenting RBT with complementary theories, such as the dynamic capability theory and absorptive capacity theory, among others. A third theme could focus on uncovering barriers to the adoption of BDAC. This theme could comprise both qualitative and quantitative approaches. The qualitative exploration would parse out the factors that still hold back the adoption of BDAC, and the quantitative research could help quantify them. These results would be valuable for sellers as well as buyers of BDAC technology. An important fourth theme is to revalidate the items and sub-scales of BDAC to ensure that they reflect the current state of the art.

VI. CONCLUSION

The purpose of this study was to demonstrate the effects of BDAC on competitive firm performance among small- and medium-sized enterprises (SMEs) in the United States. Six of the 17 studies focused their research on SMEs; four were in Asia, and one each in Italy and Canada. These studies variously confirmed the direct and indirect effects of BDAC, or BDA, on aspects of firm performance. The significant effect of BDAC on competitive firm performance among SMEs in the United States, as reported by this study, is a valuable addition to the body of knowledge in this domain.

H20, H30 and H40. These three hypotheses were designed to test the significant effects of the three components of BDAC —tangible resources, human skills, and intangible resources — on competitive firm performance. Except for one study, none of the studies reviewed for this research related each of the three components to aspects of firm performance. Citing the tenets of the entanglement view of the sociomaterialism theory, Akter et al. (2016) asserted that BDA components worked in unison and were so interwoven that measuring their individual contribution in isolation would be difficult. Usually, studies demonstrated that the three individual components loaded significantly onto the latent variable, BDAC, which was then used as the independent variable to confirm the relationship with firm performance. H10, discussed above, represents the sociomaterialism view of BDAC as a composite variable. The addition of relating the individual components of BDAC to firm performance incorporated in this study is, therefore, a source of incremental insights to the existing body of knowledge.

Several practical insights emerge from this research for SME leadership. Firstly, tangible resources should be regarded as a foundational priority given their relative importance (28%) in impacting competitive firm performance. Secondly, to fully leverage the benefits of BDAC, it is essential to equally nurture the non-technological resources (25.8% contribution), which include human skills and intangible resources. Thirdly, among the non-technological factors, the creation of a culture of data-driven decision-making and organizational learning is relatively more consequential (14.1%) than human skills (11.7%) in fully realizing the benefits of BDAC.

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