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Do Big Data Analytics Competencies Improve Banks' Financial Performance? An Investigation using Portuguese data

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Dissertation presented as partial requirement for obtaining the Master's degree in Statistics and Information Management

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Do Big Data Analytics Competencies Improve Banks' Financial Performance? An Investigation using Portuguese data

By

Jéssica Martins

Dissertation report presented as partial requirement for obtaining the Master's degree in Statistics and Information Management, with a specialization in Risk Management and Analysis

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DEDICATION

A walk of this nature was only possible with the help of three of the pillars of my life to whom I dedicate this work: my mother Júlia, my brother Frederico and Nuno, my boyfriend.

To my mother, who teaches me every day to fight and never give up, is the most hard-working person I know, who gives me the right values and who tells me that it's from work that everything comes, our dreams, the our achievements.

To my brother for always being there and with a smile and he says that I can reach everything I want, that it inspires me to be better and to be the example for him in his life.

I also dedicate it to Nuno, my greatest partner and the person without whom this thesis would not exist, because it was he who encouraged me to risk and enroll in this master. In all moments of life, personal or professional, even the most challenging, he keeps the amazing spirit, encourages me to get out of my comfort zone and makes me grow every day.

ABSTRACT

Over the last few years, big data has been a popular technological advancement in games and changes as a virtual 'border' of a wide variety of IT-driven technologies and information-enabling possibilities. Due to technological advances, the internet, handheld machinery, decision support systems, transmission, and computations, the idea of big data was propelled by rapids in data processing and storage. The aim of our study is to determine how Portuguese banks' big data analytics capabilities will help them to improve their financial performance: the efficacy of the audit committee as a mediator and process-oriented dynamic capabilities (PODC) as a moderator. Companies have recently met with unpredictable environmental factors and shifts, and increasingly competitive trends. To obtain a competitive edge, attain superior performance and success and increase long-term survival and longevity, they have to apply, introduce and apply suitable techniques and strategies. Techniques and methods from a variety of fields have been examined rigorously and analytically. In this report, the audit committee is one of the most effective tools and procedures used by businesses, and it is a key driver of successful organizational mechanisms. In comparison, the audit committee's monitoring functions have been considerably greater and more effective.

The study adopted a survey research design. Simple random sampling was used to ensure that those employees were found at their workplaces who were used for the study. This design was quantitative to allow for descriptive and inferential analysis. The data has been collected within one month (i.e., February 2021 to May 2021). As it was collected at one time so the design is cross-sectional in nature. Scholars received data from 330 target respondents, including hardcopies and softcopies due to the COVID-19 pandemic in the different public and private banks of Portuguese.

The current study makes a substantial addition to big data analytics management and firm performance, and it has a wide range of applications. Because no previous study has directly addressed the moderating behavior of Process-oriented dynamic capability and the mediating role of audit committee effectiveness in this setting, the function played by the current study is quite important. Furthermore, the convergence of organizational resources examined in this study to assess a firm's big data analytics competency has never been attempted before. Using the resource-based Theory (RBT) and dynamic capabilities view (DCV) as theoretical lenses, the study investigates the relationship between BDA capabilities and firm performance. The main justification for adopting these two points of view is that the technological capability of utilizing BDA requires various additional firm-specific resources that can eventually contribute to increased performance.

KEYWORDS

Big Data Analytics Competency; Process-oriented dynamic capabilities; Audit committee effectiveness; Firm Financial performance; Portuguese.

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LIST OF ABBREVIATIONS AND ACRONYMS

Abbreviations	
DCV	Dynamic Capabilities View
RBT	Resource-Based Theory
BDA	Big data Analytics
BDAC	Big data Analytics View
IT	Information Technology
PODC	Process-Oriented Dynamic Capabilities
FPER	Firm Performance
ACE	Audit Committee Effectiveness
RBV	Resource-Based View
VIF	Variance Inflation Factor
SEM	Structural Equation Modelling
LLCI	lower limit confidence interval
ULCI	upper limit confidence interval
HTMT	Heterotrait–monotrait

1. INTRODUCTION

The introduction part explains the background of the study, gap analysis, problem statement, significance of the study, research questions, research objectives, supporting theory, definitions of studying variables used in this research study are all explained in the introduction section.

BACKGROUND OF THE STUDY

BDA (big data analytics) is becoming a common subject among academics and practitioners. BDA is a systematic method to handling, collecting, and evaluating five vs. of data (i.e., volume, variety, velocity, veracity, and value) to generate practical ideas for sustainable value, success measurement, and competitive advantages (Fosso Wamba et al., 2017; Gupta et al., 2021). Any practitioners and students have so far suggested that BDA is the 'fourth scientific paradigm (Strawn, 2012), "The latest information resources model" or "the next boundary for creativity, competitiveness, and productivity" (Manyika et al., 2011). This is mostly motivated by the widespread use and adoption of BDA-enabled tools, technology, and networks, including social media, smart devices, automated Internet recognition technologies, and cloud-based services for businesses to gain competitive benefits and maintain them (Maheshwari, Gautam, & Jaggi, 2021). Big data is one of the latest industries and technological developments. Big data is extremely important in many areas of study, but in the finance sector, it is especially important (Hasan, Popp, & Oláh, 2020). In this context, the most recent developments require companies to recruit finance specialists, particularly accountants, who also have Information Technology (IT) skills, especially because this is required in modern market dynamics. Around the same time, finance experts and accountants with relevant knowledge of their field will take advantage of this (once only highly qualified professionals) to integrate big data into decision-making processes.

Over the last few years, big data has been a popular technological advancement in games and changes (Dos Santos et al, 2014) as a virtual 'border' of a wide variety of IT-driven technologies and information-enabling possibilities (Chen & Chiang, 2012). Due to technological advances, the internet, handheld machinery, Decision support systems, transmission, and computations, the idea of big data was propelled by rapids in data processing and storage (Kacfah Emani et al., 2015). Adding more to it, Raguseo (2018) has shown that this rise in data is motivated by different sources that are generally classified as data produced by the machine and human data (Davenport, 2014); where data generated by machines are used to create digital machines automatically for big data so that there is no direct human-enabled intervention (for example audio, video, image and speech data, sensor data, safety cameras, medical device data, etc.). In contrast, human-generated data involve creating big data by direct human-computer interactions (e.g., social media posts-generated data, click-streams data, web content, etc.). Big data is now known to be one of the quickest changing future developments, not just due to its distinguishing existence in scale and speed, but also due to five basics 'V's that make it 'big' in a real sense (Gupta & George, 2016). Furthermore, only the use of high-volume data will ensure efficiency; high quality and data relevance are the key features to improve the decision-making process (Sukumar & Ferrell, 2013).

For specific reasons, bankers choose various banks. Banks want to know their consumers since they have the skills, they need to make better choices in their organization (for example, whether or not a customer is fit to receive a high-value loan) (Coetzee, 2018; ALI et al., 2020). The recent economic crisis has also affected how consumers, especially in Portugal, engage with banks (Cabrita et al., 2017; Neves et al., 2021). Customers would like to find out more about the institution they believe in, to which they want to be sure that the money will not suddenly disappear, but they also want to use it in a way that maximizes profit.

The literature that exists indicates that analytical abilities, domain expertise (Waller & Fawcett 2013), and analytical tools are among the most essential variables that can annul, if not used correctly and efficiently, the beneficial effect of big data on company results (Davenport, 2013). Organizations then race to get competent Big Data Analysts (Erevelles et al., 2016) to validate and analyze the data and to intensify their big Data Analytics competence (Gupta & George, 2016). In the study of big data, it is beneficial for companies to be alert to rising prospects and trade decisions (Tian et al., 2015). This promotes the interest of the current survey to fill this gap by taking into consideration Portuguese telecommunications and banking industries to investigate the expertise of big data analytics and its effect on business efficiency.

The aim of our study is to determine how Portuguese banks' big data analytics capabilities will help them to improve their financial performance: the efficacy of the audit committee as a mediator and process-oriented dynamic capabilities (PODC) as a moderator. Companies have recently met with unpredictable environmental factors and shifts, and increasingly competitive trends. To obtain a competitive edge, attain superior performance and success and increase long-term survival and longevity, they have to apply, introduce and apply suitable techniques and strategies. Techniques and methods from a variety of fields have been examined rigorously and analytically. In this report, the audit committee is one of the most effective tools and procedures used by businesses, and it is a key driver of successful organizational mechanisms. In comparison, the audit committee's monitoring functions have been considerably greater and more effective.

GAP ANALYSIS

The current study contributes to the big data analytics competency literature in a variety of ways. For example, it looks at the effect of firm success on big data analytics, which has been overlooked in previous studies. The study also recognizes possible mediators and moderators in the big data analytics and firm performance relationship (audit committee effectiveness and Process-oriented dynamic capabilities).

Process-oriented dynamic capabilities are described as a company's ability to adjust (improve, adapt, or reconfigure) a business process more effectively than the competition in integrating operations, cutting costs, and leveraging business intelligence/learning. They have a wide range of changes in business procedures, ranging from continuous modifications and enhancements to dramatic one-time changes. While most improvements can be gradual, the ability of a company to adapt quickly often means it is willing to make drastic changes if necessary (Kim et al., 2011).

Moreover, in previous research, firm performance plays a vital role as a dependent or independent variable (Masood Fooladi Chaghadari et al., 2011; Mahfuzah et al., 2012; Fosso Wamba, et al., 2017). Similarly, many researchers used process-oriented dynamic capability as a mediator (Fosso Wamba, et al., 2017; Zhou et al., 2018), but it can't be used as a moderator (Misbah Ejaz, 2018). So, the purpose of this research is to use the process-oriented dynamic capability as a moderator in this paper. This research uses an exceptional data set to test the framework on quantitative data and provide crucial data by following an entire explanatory methodology.

PROBLEM STATEMENT

In the context of BDA, a recent study found that various BDA benefits, particularly BDA's advanced analytical capacity, create different dynamic capabilities in the organization, which ultimately aid success. Organizations in developed countries, especially those in Portuguese, are facing dire financial circumstances, and BDA is likely to be one of the possible solutions to this problem. "A conceptual distinction between ordinary capabilities and the firm's large resource base, on the one hand, and dynamic capabilities, on the other," according to the literature on dynamic capabilities. Ordinary capabilities (also known as operational or zero order' capabilities) decide how a company makes money in the present, while dynamic capabilities enable the company to change" (Winter, 2003; Zollo & Winter, 2002).

The study's problem statement is: How does big data analytics competency influence firm output through process-oriented dynamic capability? By examining the relationships between variables, the effect of BDA on financial performance can be determined, and the current literature on BDA and financial performance can be improved.

While all of these variables are taken into account in the literature, researchers are not modeling them all together in a single logical model. The current study builds a model of these variables by analyzing how big data analytics competency causes firm output with Audit committee effectiveness as a mediating role, and process-oriented dynamic capabilities as a moderating role in Portuguese bank's competency on big data analytics improve their financial performance and context setting of Portuguese.

SIGNIFICANCE OF THE STUDY

Our research also contributes to the existing BDA and firm performance literature. Our research can help project-based organizations confidently integrate imagination and inventiveness into their proposals. It can be accomplished by looking for market opportunities and taking chances (financial industry, for example) to turn certain ideas into practice. It will not only help them increase profitability by successfully executing their innovations, but it will also give them a competitive advantage.

THEORIES SUPPORTING RESEARCH

The resource-based theory (RBT) has been developed (Penrose, 1959). RBT proposes that the company can acquire a competitive edge over its competitors by possessing strategic resources (Penrose, 1959). The theory on resources examines the resources available to companies as a set of dynamic capabilities and competitive advantage competencies. Mishra and Yadav (2021) claimed that companies operate in a competitive environment and need to use their unique resources, skills, and capabilities, take up new opportunities, expel threats, and meet the customers' wants.

The resource-based paradigm divides the organization's resources into two: tangible and intangible resources. Tangible resources comprise material, commodities, physical resources, and financial reserves. Intangible business resources include reputation, technology, and staff. According to Oliveira et al. (2011), if the company possesses rare, unique, valuable, and unique resources, it achieves a competitive advantage. RBT notes that the competitive advantage is within the environment and the company and its resources and competencies. This strategy was then mostly criticized for its static characteristics and poor explaining power of the conditions under which companies in highly dynamic environments can have a competitive advantage (ul Rehman et al., 2021).

Dynamic capabilities generate new methods for generating value by changing ordinary capabilities (Ringov, 2017). Some scholars, however, argue that "While dynamic and ordinary capabilities are specified locally, the line between them is unnecessarily blurry" (Winter, 2003). Following the RBT study, the potential of a company to accomplish the targeted goals, i.e., greater integration and exploitation of resources into developing big data analytics skills, would be higher. Furthermore, the efficacy of an audit committee that acts as a mediator in the present study is another resource-based feature of a company that plays an important part in business performance (Phornlaphatrachakorn, 2020).

In addition, the process-oriented dynamic capabilities of a firm as a moderator in this study impact resources-driven dimensions, as resources are among the main challenges on which organizational decisions (Kim et al., 2011). Although the Resource-based Theory takes into its circle of impact all the dimensions examined during this study, it justifies its implementation in current research.

DEFINITIONS OF STUDYING VARIABLES

1.1.1. Firm Performance

The level to which a firm exploits its resources to enter new markets and provide new products and services to the market is referred to as market performance. In contrast, the level to which a firm exploits its resources to improve productivity, profitability, and financial performance is referred to as operational performance. The term "firm performance" has several concepts (Miller et al., 2013).

1.1.2. Big data Analytics Competency

The popularity of big data has been boosted by technological advances in both software and hardware (Sena et al., 2019). Big data has piqued academics and practitioners' interest as the next big thing in management, with some also proposing it as the next management movement (Brynjolfsson & McAfee, 2012; Misbah Ejaz, 2018). Big data (BDA), which has superseded conventional statistic instruments, and has valued businesses, in financial and non-financial terms, is an emerging hot topic among scholars, business communities and public institutions (Chen, Roger, & Chiang, 2012; Aydiner et al. 2019a; Sena et al., 2019; Ashofteh & Bravo, 2021). The firm's integration and deployment of big data-specific resources to make it capable of conducting a methodical and action-oriented analysis of detailed data are referred to as "Big-Data Analytics Competency" (Gupta & George, 2016).

1.1.3. Audit committee effectiveness

According to Hermanson and Rittenberg (2003), the auditor's primary responsibility is to monitor and report on the efficacy of corporate governance to the board of directors. They anticipate a potential conflict between the internal audit functions and the audit committee's roles, which could impact organizational outcomes. In cooperation with (Gramling et al., 2004), it is suggested that we have to understand how the internal audit function interacts to provide effective corporate governance with the audit committee, management, or external auditors.

1.1.4. Process-oriented dynamic Capabilities

"The power of the organization to reconfigure, integrate, and coordinate internal and external talents to deal with rapid turbulence in commercial environments" is how dynamic capacity is defined (Teece, Pisano, & Shuen, 1997; Eriksson, 2014). The company will employ specialized methods to implement and express dynamic capabilities to establish, enhance, or transform organizational capabilities. They relate to a company's ability to improve its organizational processes to lower costs and boost business intelligence. The company should optimize the effectiveness of these operational procedures, improve knowledge management, and better align its resources with the firm's mission by integrating PODC (Tallon & Kraemer, 1999; Kim et al., 2011; Wamba et al., 2017).

1.1.5. Research Questions

The research question describes the broader problem area, which is also described in our problem statement. The following research questions are taken from our study's problem definition.

1. Does big data analytics competency is positively associated with firm financial performance?
2. Does big data analytics competency is associated with Audit committee effectiveness?
3. Does audit committee effectiveness is associated with firm financial performance?
4. Does audit committee effectiveness play a significant role as a mediator between big data analytics competency and firm financial performance?
5. Do process-oriented dynamic capabilities play a significant role as a moderator between big data analytics competency and firm financial performance?

6. Do process-oriented dynamic capabilities play a significant role as a moderator between big data analytics competency and Audit committee effectiveness?

1.1.6. Research Objectives

The research goals include the rationale for studying specific correlations. We have achieved the following aims in our research based on the typology of the study objectives.

1. To examine the relationship between the big data analytics competency and firm financial performance.
2. To examine the relationship between the big data analytics competency and Audit committee effectiveness.
3. To examine the relationship between Audit committee effectiveness and firm financial performance.
4. To examine the mediating effect of Audit committee effectiveness between big data analytics competency and firm financial performance.
5. To examine the moderating effect of Process-oriented dynamic capabilities on the relationship between big data analytics competency and firm financial performance.
6. To examine the moderating effect of Process-oriented dynamic capabilities on the relationship between big data analytics competency and Audit committee effectiveness.

1.1.7. Hypotheses

The study research hypotheses are:

H1: Big data analytics competency is positively associated with firm financial performance.

H2: Big data analytics competency is positively associated with Audit committee effectiveness.

H3: Audit committee effectiveness is positively associated with firm financial performance.

H4: Audit committee effectiveness as a mediator on the relationship between big data analytics competency and firm financial performance.

H5: Process-oriented dynamic capabilities as moderator on the relationship between big data analytics competency and firm financial performance.

H6: Process-oriented dynamic capabilities as moderator on the relationship between big data analytics competency and Audit committee effectiveness.

2. LITERATURE REVIEW

TANGIBLE RESOURCES

2.1.1. Data

Organizations nowadays aren't just interested in their unique structured data when it comes to making decisions. Rather, they aim to obtain every bit of information available, regardless of its structure, size, or rate of production (Manyika et al., 2011). (i) Public data, (ii) Private data, (iii) Data exhaust, (iv) Community data, and (v) Self-quantification data are the five key sources of high-volume data generation (George et al., 2014).

Data sets controlled by the government and local communities are known as public data, and they include information on transportation, healthcare, energy use, and climate change, among other topics. In contrast to public data, private data refer to data sets collected and owned by businesses and individuals but not freely accessible by public sources. Consumer transaction data, mobile phone usage data, and other types of private data are all examples of personal data (Pantelis & Aija, 2013). Next, data exhaust refers to data sets generated from an individual's behaviors, which are passively gathered and contribute value when combined with other data sources to provide new insights. Log files generated by a web browser are examples of data exhaust (Oleary & Storey, 2017). The last category is self-quantification which is data sets formed by quantifying individuals' behaviors and actions, such as data from intelligence wristbands on movement (Almalki et al., 2015).

2.1.2. Technology

Digital technologies are transforming markets, corporate contexts, and communication marketing techniques substantially (Foltean et al., 2019). Digitalization has changed the interactions and exchanges between firms and customers, generating new contact and market cooperation pathways. While increased digitization might bring corporate opportunities, it is also a major challenge. Managers encounter complicated and fast-changing markets and lack the specific knowledge to recognize and manage these changes (Leeflang et al., 2014). To address these difficulties, companies need to grasp the strategic use of digital technology and the ability they require to rapidly respond to market changes by changing the value creation process (Quinton et al., 2018; Chanias et al., 2019).

The fundamental qualities of big data that distinguish it from traditional data, according to the most generally used 3Vs dimensional framework, are (i) Volume, which emphasizes the amount or quantity of generated data, and the minimum size of data generation to be labeled big data is one terabyte (Gandomi & Haider, 2015); (ii) Velocity, which shows the rate at which data is produced and processed; big data velocity is high enough to be referred to as near-real-time creation (Ertemel, 2015) and (iii) Variety, which refers to the development of various forms of data from various sources, and big data, which comprises the development of three forms of data: structured, unstructured, and semi-structured data from various sources such as humans and robots (Abbasi et al., 2016).

These three characteristics distinguish big data from ordinary data, necessitating the development of new systems capable of handling the gigantism, diversity, rapid generation, and transport of big data. Organizations rely on certain technology for data storage and insight. Technology has always played an important part in acquiring a competitive advantage and making an organization (Nicholas, 2003). However, factors like personnel movements, informal meetings and talks from various firms, reverse engineering, etc., it's not easy for firms to keep their unique technologies hidden (Mata et al., 1995).

2.1.3. Basic Resources

Alongside data and advanced technologies, organizations are required to invest adequately in basic resources to develop their big data analytics competencies. Taking the uniqueness and novelty of big data and the opposite technologies, jobs and duties into consideration, most organizations are still on their way yet to make standard strategies and procedures in this domain. There exists, therefore, a probability that organizations practicing big data analytics in their system may not achieve immediate desired results. What matters is firm pertinacity and determination to achieve their analytical goals, thus devoting sufficient resources.

In addition to data and innovative technologies, firms must invest in essential resources to improve their expertise in big data analytics. In the light of the uniqueness and innovation of big data and relevant technologies, roles and obligations, most businesses are still pursuing typical strategies and procedures. Therefore, it is likely that enterprises conducting big data analytics on their systems cannot get the intended outcomes immediately. What matters is the firm relevance to their analytical goals and desire to devote sufficient resources to them. Tangible resources play a crucial role in establishing an adequate big data analysis competence or a subjective gain to a company's constant commitment to investing in those resources (Mata et al., 1995; Wixom & Watson, 2001).

2.1.4. Human Resources

Human capital is seen as a long-term growth factor that is sustainable (Camps, 2016). Human capacity depends on education, talent, health, opportunity and other services (Saad et al., 2013). There is a lack of congruence between human capital and company demands (Hult & Olsan, 2018), including workers, income, job fulfillment, training, and productivity (Kampelmann and Rycx, 2012; McGuinness, 2006).

2.1.5. Technical Skills

Employees' technical analytics abilities refer to their knowledge and advanced technology for dealing with large amounts of data. A few technical skills required to examine large data include data cleansing and extraction, machine learning, data analysis, and programming paradigms (Davenport, Thomas, 2014; Russom, 2011). According to recent literature, educational institutions have taken such courses to instill big data specific competencies in individuals, owing to the escalation of big data analytics and its use in enterprises; nonetheless, scarcity still exists (Chen et al., 2012).

On the other hand, analysts with insufficient technical analysis skills could consider the delaying of things that cause waste of time, resources, make mistakes that still are incapable of handling the difficulties before them (Ghasemaghaei et al., 2015). So legitimizes the essential role played by technical analytics in building skills and influencing company performance.

As a result, the critical importance of technical analytics abilities in developing competency and influencing firm performance is validated. In addition, there is a domestic and international conflict between faculty and industry, which is needed to provide the most competent people to meet the needs of the sector (Khan & Mohammad, 2018). Stoner and Milner (2010) have stated that the participants do not generally develop or engage in the entire range of courses they underline. The authors found it challenging for students to handle their time, solve problems, and be involved in the modeling activity.

For a business practitioner, technical abilities and professional qualifications are more important. In the absence of operational activities, tasks are not adequately performed, which leads to delayed growth in the banking industry.

2.1.6. Managerial Skills

Though technical, analytical skills were considered an important aspect of competence in Big Data Analytics, management abilities are also of equal importance. While businesses can improve their workforce's technical skills by training and recruiting new experts, management skills are created and enhanced throughout a while with organizational experience (Mata et al., 1995). It is consequently immensely important for enterprises that their managers comprehend the application of the recently found values, which can provide optimum benefits for a company by analyzing data in such areas.

Big data managers must have a profound understanding of the current and future requirements of other business units, partners and customers to do that (Mata et al., 1995). Thus, management skills are a field that cannot be ignored while analyzing organizational skills. A thorough survey of existing research has influenced all these dimensions, and in the current study, they are being used to explore the field of big data analysis skills.

2.1.7. Domain Knowledge

In addition to the technical and analytical abilities of the employees, domain knowledge is another aspect to focus on. Domain knowledge and analytical skills make ineffective data and task performance analysis competent for employees (Draganidis & Mentzas, 2006). It has been found that several firms engage extensively in the development of staff knowledge in uncovering new business insights out of data (Waller & Fawcett, 2013).

Human knowledge is one of the most difficult resources for the organization to replicate, according to the resource-based view (RBV) (Peteraf, 1993). While the growth of modern technology cannot withhold knowledge, new fields must always be explored, and organizational goals and capacities updated to maintain an unexpected world of business must be updated (Teece, 2015). Analyzers' ability to identify key strengths and weaknesses, risks and opportunities so that efficient business solutions to issues are found (Sukumar & Ferrell,

2013) and have a better impact on company performance. Therefore, domain knowledge is regarded as a key element in developing the competence of large data analysis (Bharadwaj, 2000; Maryam Ghasemaghaei et al., 2018).

INTANGIBLE RESOURCES

2.1.8. Bigness of Data

The value of data indicates an enormous growth in data availability around which data analytics are required (Lycett, 2013). Increased digital content generation by increasing smart devices adds tons of data volume every day (Newell & Marabelli, 2015). In 2011, an estimate of the rise in data generation to 50 times by 2020 was made (Ertemel, 2015). Volume increases are not just developed by one sort of data, but rather by different variants, for example, structured data, semi-structured data, and unstructured data (Abbasi et al., 2016; Li & Zhai, 2018).

Organizations are now interested in their own particular internal and external information to derive new trends and patterns that contribute to the volume and the range of data. The velocity of big data is the third most outstanding characteristic. Big data is produced at near-real-time speed. By discovering hidden patterns exposed through the processing and analysis of large data, near-real times with huge volumes and variants are highly useful to organizations for their performance (Fern'andez et al., 2014). This essential role of data bigness makes it a critical aspect of analyzing huge data (Bharadwaj, 2000).

2.1.9. Data Quality

Its fit defines data quality, correctness and dependability for usage, amount of details, integrity, and various other features. Although new analytical methods and technologies are sufficiently progressed to detect usable and important data (Cai & Zhu, 2015), the data quality still affects analytic data findings (Popovi alternatives, 2014). Therefore, firms should employ only quality data to get valuable insights and make smart decisions to improve corporate performance (Lycett, 2013). Bharadwaj (2000) described it as an essential aspect of large data analysis competence, given the crucial significance of data qualities.

2.1.10. Data-Driven Culture

When it comes to defining organizational culture, there are a variety of viewpoints. Existing research reveals that different management researchers have different perspectives on corporate culture, with some believing it to be a glair that binds an organization together (Iivari & Huisman, 2007) and others considering it to be a glair that defines all domains of an organization (Dowling, 1993); consequently, there is a lack of consensus in this area (House et al., 2002).

Accordingly, recent studies in the field of big data have found that an organization's culture plays a critical role in the success or failure of BDA initiatives and that the unproductivity of big data-related projects is tied more to the organization culture than to data qualities and technological inadequacy (LaValle et al., 2011). Furthermore, organizational culture is said to have the power to improve an organization's ability to use big data analytics and acquire a competitive advantage (Ross et al., 2013).

With the growth of research in the field of big data, it is now known that despite gathering a large amount of data, only a few firms have realized the anticipated return from their investment in big data analytics (Ross et al., 2013). The underlying reason for this is that, although businesses have begun to use big data analytics in their decision-making units, these entities are still reliant on the experience and intuition of their top executives (Andrew McAfee & Brynjolfsson, 2012). All of a company's efforts to gather vast amounts of data, adopt modern technologies, and develop staff capabilities are in vain if choices are made based on designations rather than data (Andrew McAfee & Brynjolfsson, 2012). It establishes data-driven culture as the most critical aspect of big data analytics expertise.

BIG DATA ANALYTICS COMPETENCY AND FIRM FINANCIAL PERFORMANCE

The term "big data" was used to describe databases that were too large for conventional methods to handle. The term "big data" was coined in the 1990s and became popular in the mid-2000s. The concept ‘big data,' which has essentially been generalized in the long term, refers to both the data and various other elements, including—but not limited to—social trends, diagnostic or ability advances, periods, and structures (Mishra, Gunasekaran, Papadopoulos, & Childe, 2018).

With the introduction of IT, financial activities have increased, including internet banking and payment systems, savings options, insurance, and creativity in corporate banking and finance services. The banking industry is primarily relying on emerging technologies to provide the majority of its services. It has also been embedded in key policy systems, such as organizational and individual risk analysis, transaction management, and corporate reporting. The specification of such information communication technology (ICT) is regulated by local laws and rules in financial services (Andriosopoulos et al., 2019). Big data is used in all industry fields as an evolving phenomenon. Big data also contribute significantly to an improved interpretation of the general public's financial market mechanisms (Shen, Chen, 2018). To make short and long-term decisions, endless information is exchanged regularly in the stock market (Ewen, 2019). The biggest explanation is that in the financial services market, this is a new avenue.

Further analysis is also essential to help us clarify these problems in the banking sector. This study focuses on ways scholars have not investigated and examines the effect of Big Data on financial markets as the main new feature of this report. Our analysis suggests RBT as a strong mechanism for combining different BDA aspects, their synergistic impact on FPER, and the continuity of the approach linked to this general performance-capacity partnership. It seems that the conception of the capacity requirements, which are crucial for the success predictions, can be seen in just a small part of big data research (Phillips-Wren et al., 2015; Abbasi et al., 2016).

Therefore, we support RBT that company success in a data economy can be increased only if skills are important, rare, imperfectly replicable, and the organization or management of the company exploits the potential resources.

Kim et al. (2012, p.341) identified corporate success as a company's ability, in terms of coordination/integration, cost reduction, business intelligence/learning, to improve its capacity to adjust current business processes.' Centered on RBT, IT capabilities literature acknowledges that IT capability is a strategic advantage and differentiating business success (Bharadwaj, 2000a; Piccoli & Ives, 2005). As robust IT capabilities are core dimensions in a big data set, their implementations will distinguish company success in different business functions (Davenport, 2006). This increasingly enlightens scholars on the role of distinguishing IT capacity in conjunction with organizational capital and capacities to influence the performances of companies to organize and deploy IT-based resources.

H1: Big data analytics competency is positively associated with firm financial performance

BIG DATA ANALYTICS COMPETENCY AND AUDIT COMMITTEE EFFECTIVENESS.

The concept of big data in the industry comes from the literature, which includes many articles conducted in reputable research journals. Many industry sectors are now linked to big data. Big data has a crucial impact on various market aspects, for example, in terms of management, analysis, and growth of human capital (Blackburn et al., 2017); Management processes (Grover, Kar, 2017; Arunkumar et al., 2018), company, advertisement and marketing processes (Holland et al., 2020; Liu et al., 2020), mechanical assembly (Huang et al., 2019; Dubey et al., 2020), organizational efficiencies (Shamim et al., 2019), policy-making (Aragona, De Rosa, 2019) and supply chain management (Bag et al., 2020).

This study also examined three complex approaches (analysis, proactive, and prescription) to improve the measure of customary knowledge analysis. A firm's ability to collect and analyze data to generate insights by effectively orchestrating and deploying its data, technology, and talent is known as a big data analytics capability (Mikalef et al., 2017). As a result, businesses must acquire and grow a mix of data, technical, human, and organizational capital to develop a difficult-to-copy and transfer capability (Vidgen et al., 2017).

The audit committee also supports their senior management, managers, and auditors in managing and dealing with potential risks and enhancing financial reporting in line with accounting practices and other relevant legislation regarding correct and full transparency. Audit board is a tool to track financial statements, external auditors, and the internal management force (Dobija, 2015). The audit committee is also a critical corporate governance tool and can directly contribute to promoting the integrity, transparency, accuracy, and added value of financial reporting. It plays a major role in reducing the asymmetry of information and enhancing the consistency of transparency. As a result, greater audit committee efficacy is favorably linked to more corporate performance in complex, competitive environments (Grange, Ackers, & Odendaal, 2021). The audit committee's performance becomes a valuable determinant of the internal audit results of companies, financial reporting efficiency, and corporate progress. In addition, the efficiency of the audit committee will help the corporate operations and strategies of companies that are linked to their results attained and sustained profitability in the long run. Companies whose effectiveness is improved by the audit committee tend to have more corporate success.

The theoretical structure of the present thesis is focused on the principle of socio-materiality and RBT, which relates to the ontological unification of society and materials. This view does not prove that the material affects the social (i.e., technological determinism) or social effect of the material or recursive connection between the social and the material (i.e., social constructions) (i.e., socio-technical view). Rather, the research includes the relationship ontology of socio materialism that makes it impossible to quantify individual contributions on a single basis in such an interwoven manner as the organization's (i.e., the administration of BDAs), physical (i.e., IT infrastructure), and human (e.g., analytic ability or skill) (Orlikowski and Scott, 2008).

Orlikowski (2007) clarifies "inextricably linked to social and content." We disagree with this principle that the aspects of the BDA do not act in isolation; they act jointly instead. We argue that the superior FPER in the big data environment is the product of unique combined organizational (i.e., management of BDA), physical (i.e., IT infrastructure), and human (i.e., analytical or knowledge) resources consistent with RBT (Barney, 1991; Grant, 1991) and related ontologies of socio materialism (Orlikowski, 2007; Orlikowski and Scott, 2008; Kim et al., 2012). These resources are divided into three categories, according to RBT: (i) Tangible Resources, (ii) Intangible Resources, and (iii) Human Resources. Tangible resources are not physical, like knowledge-based assets, whereas human resources include training employees, skills, relations, experiences, etc. (Grant, 2002). Tangible ones are the assets that can either be acquired or sold.

H2: Big data analytics competency is positively associated with Audit committee effectiveness.

AUDIT COMMITTEE EFFECTIVENESS AND FIRM PERFORMANCE

The word audit is a Latin word and is called as official financial inspection of (a company or its accounts). The primary data auditor easily understands the financial expense and net asset and net growth of financial services and less chance of fraud include in big data because all necessary information is already provided in big data (Al-Adeem, 2015). The audit committee's primary role is to track the company's financial statements and results.

In that respect, the appointment, dismissal, and remuneration of auditors, the auditing work's content and scope, auditor integrity, and the settlement of conflicts between auditors and corporate management are likely to be heavily affected by audit commissions. Audit commissions may also study the selected accounting policies and settle on them (Grange et al., 2021). As well as persuasion for the strategy, level of information, and commitment to the normal practice of an organization in financial statements.

In addition, the audit committee can track the effectiveness of business accounting systems to ensure that organizational practices, including maintaining preventive fraud controls, are complied with (Turley & Zaman, 2004). "Big data brings to additional analytics measurements. It provides improved insight prospects, but it needs new human and technological resources because of its special features. Therefore, one noteworthy finding is that few scholars agree with including BDA, and BDA talent as core dimensions of the BDA management capacity (Al-Adeem, 2015).

Auditing aims to confirm the accuracy of the management's financial statements. Supervision in this simple statement may raise a concern about the skills of the accounting profession and thus reduce public confidence in the profession (Edelman & Nicholson, 2011; Belkaoui, 2017b). The auditor's position has become more prominent, with the company activities expanding internationally, and the increased volume of data collected resulted in huge transaction volume (Kim, 2000). The collection of transaction data in real-time, including location, time, quantity, and medium, will make it easier to collect materials for an audit opinion.

Previous studies also imply that the auditor should be qualified to conduct a high-quality audit and have previous experience (e.g., Brody et al., 1998). Boo and Koh's study (2004) showed that the audit team's quality and qualities correspond to their abilities to advise improvements in the internal control systems. For internal auditors, previous experience is vital as many judgments on supervision are subjective, and management measures might have pervading impacts.

H3: Audit committee effectiveness is positively associated with firm financial performance

AUDIT COMMITTEE EFFECTIVENESS AND FINANCIAL PERFORMANCE

After the audit of financial sector audit committee make an objection book is called annexure book the main purpose of auditor is to write down all the missing and overlook mistake about employees' level and standard operating procedure (Sops) level of financial institutions which solve and rectify by the management of an organization in a specific time when organizations exercise to remove the objection its positive sign of financial organization. Fichtner (2010) pointed out that the auditing committee originated in the late 1930s after bribery involving McKesson & Robbin Inc. when the New York Stock Exchange (NYSE) and Securities and Exchange Commission (SEC) suggested that a special committee of non-officer board members should appoint foreign auditors (Barney, 1991). Valuable, rare and inimitable resources are provided by organizational framework and procedure to improve corporate efficiency.

The auditors in practice are concerned with using Big Data more efficiently to gather important and accurate information from their audit (Brown-Liburd & Vasarhelyi, 2015; Appelbaum et al., 2017). Data may not be of low importance to companies alone; that is if more attempts are taken to interpret it for sound decision-making, thus demonstrating the need for analytics. The data are of limited value. Data analytics and data analytics methods help audit teams review both customer data and identify areas requiring further analysis early in the audit process. Audit teams may adjust audit methods by changing their audit plans (IFAC, 2017). Data analytics explore the transmission of dynamic information to arrive at decisive decisions. The field of data analysis determines when data differs from comparable industry and current circumstances (Yeo & Carter, 2017). This correspondence includes methods and strategies informative, diagnostic, predictive, and prescriptive. Such methods identify causal factors that can prevent potential consequences and thus recommend appropriate behavior and strategies. That is, through visualization and data interpretation, they provide insights into key market activities (Quinton et al., 2018).

Furthermore, data remain more meaningful to represent importance while analytics and technologies for complex data requirements are used (KPMG, 2018). Big data analysis is increasingly revolutionizing many areas, and it is only a matter of time for the audit profession to follow related methods of analysis (Cao, Chychyla, & Stewart, 2015). Big data analytics can enhance the data and expertise of accountants by their experience with organized data sets (Richins et al., 2017).

There is a need to take a dominant role in strategic decision-making for financial accountants, especially auditors. Big data allows auditors to analyze the data-generating processes, including complete population testing, that add value to and benefit the auditing and accounting profession (Gepp et al., 2018). Therefore, experts must gain knowledge of the underlying strategies and strategies of the company for the endless benefits and potential of big data to be successfully used.

H4: Audit committee effectiveness as a mediator on the relationship between big data analytics competency and firm financial performance.

RESOURCE-BASED THEORY (RBT)

Two main conclusions are made in RBT concerning corporate capital to demonstrate that some companies do better than others and improve corporate efficiency. Resources complementarity within a firm means that rivals have difficulty duplicating the resources (Morgan et al., 2009). Complementarity of resources happens as one resource allows another to make use of firm efficiency. In conclusion, the organizational aspect focuses on managing useful, uncommon, and imitation capital properly to make the most of their maximum potential competitively (Barney & Clark, 2007).

The main components of RBT are resources and skills. Whereas 'capital' means tangible and incorporeal assets (e.g., technology, human and organizational), 'capacity' are subsets of non-transferable resources of a company that serves to increase the efficiency of other resources (Makadok, 1999). The ability to use other tools and boost total output is often described as tangible or intangible. Overall, skills are a particular category of resource that aims at the efficiency of other company capital (Morgan et al., 2009). RBT says that the skill of an enterprise is based on the ability to handle its key capital (both human and other resources) successfully to achieve firm efficiency (Grant, 2002).

PROCESS-ORIENTED DYNAMIC CAPABILITIES AS MODERATOR ON THE RELATIONSHIP BETWEEN BIG DATA ANALYTICS COMPETENCY AND FIRM FINANCIAL PERFORMANCE

Alignment capabilities to the business strategy are the critical path for BDA to enable organizations to accomplish FPER. The function of process-oriented dynamic capacity may have a moderating effect on organizational success. The large capacity for data analysis (BDA) is generally recognized as an important factor in improving the success of businesses and companies (FPER) (Wixom et al., 2013). For instance, price optimization and benefit maximization (Davenport and Harris, 2007a; Schroeck et al., 2012); revenue, profitability, and market share are shown by the connection between BDA and FPER in this literature reports (Manyika et al., 2011).

We argue that the superior FPER in the big data environment is the product of unique combined organizational (i.e., management of BDA), physical (i.e., IT infrastructure), and human (i.e., analytical or knowledge) resources consistent with RBT (Barney, 1991; Grant, 1991) and related ontologies of socio materialism (Orlikowski & Scott, 2008; Kim et al., 2012).

Firms must use effective processes to activate the potential BDA benefit and diverse BDA into concrete perspectives based on the data dimensions. This procedure is considered a method of analytics. Analytic processes may explain what has happened before (descriptive analytics), predict what is going to be happening (predictive analysis). Predictive and prescriptive analytics, which BDA regards as the key function (Watson 2012).

The literature from BDA reveals that business leaders gradually take evidence rather than intuition-based decisions (Davenport 2006; Lavalle et al. 2011). In addition, the analytical approach transforms the way companies operate and compete (Kiron et al., 2012). In Value Development (BDA), Manyika et al. (2011) consider the position of BDA to provide accountability, enhance decision-making, creativity and segment people for action. Dynamic capacity is a special organizational mechanism for integrating, reconfiguring, gaining, and distributing environmental dynamism capital (Fornell and Larcker, 1981). (Tippins and Sohi 2003; Mithas et al., 2011). According to the findings of this study, the market importance of big data analytics tools directly impacts a firm's results, with a mediating or moderating effect (Ji-fan Ren et al., 2016).

Furthermore, having BDA capability alters corporate processes, and the way companies operate. As a result of these capabilities, firm success is influenced by evolving operating processes and financial and industry performance. (Kim et al., 2012) used a hierarchical socio-materialistic conceptualization of IT capacity to discover a constructive and important connection between IT capability and firm performance.

Based on this finding, our research suggests examining the direct effects of BDA on FPER and the moderating effects of PODC on the BDA-FPER relationship. A positive association between the deployment of consumer analytics and company performance has been observed in the burgeoning literature on BDA (Germann et al., 2014). For instance, BDA enables companies to examine and manage strategies via data lenses (Brands, 2014). The effects of BDA in several industries are predicted to be enormous. For instance, large retail organizations use Big Data to improve their customer experience, decrease fraud and offer just-in-time recommendations (Tweney, 2013). BDA is intended to lower operating costs and improve the quality of life in the healthcare sector (Liu, 2014). BDA is regarded as a facilitator for assets and business process monitoring in manufacturing and operational management (Davenport et al., 2012b), visibility of the supply chain, improving manufacturing and industrial automation (Wilkins 2013), and improving business transformation (Gardner, 2013).

H5: Process-oriented dynamic capabilities as moderator on the relationship between big data analytics competency and firm financial performance.

THE MODERATING EFFECT OF PROCESS-ORIENTED DYNAMIC CAPABILITIES

According to recent studies, big data is a key predictor of market growth in various sectors (McAfee et al., 2012). To accelerate their digital market models to change supply chains, organizations are investing significant capital in big data projects in their quest for value generation opportunities (Chen et al., 2012), being reached results to allow them to make more educated business decisions and to ultimately boost firm performance (Ji-fan Ren et al., 2016).

"Because of its strong organizational and strategic value, big data analytics is now regarded as a game-changer that can allow increased market performance and effectiveness." (Wamba, Gunasekaran, et al., 2017). This study, drawing on the processes and emerging literature of the BDA (Barton and Court, 2012, McAfee et al., 2012a, Davenport et al., 2012a, Kiron et al., 2012). The new technical phenomena are necessary, and auditing officials will have no choice but to improve their expertise and skills as an important element in their business activities in the field of big data technology and analytics.

Auditors consider the need "not because they trust Big Data's analytical capacity, but because of their customers" (Alles, 2015, p. 4). The argument was refuted by (Gepp et al., 2018, p.110) by pointing out that, as early as possible, auditors have already been given the advantage of their customers, 'either large data is used by their customers or not.' The auditors must consider the definitions and directives of terms for the database. Data creation and management competencies to support risk assessments, analytic processes, and informative audit processes, auditors need to know how to effectively archive, organize, use, manage, and analyze different kinds of information.

The expertise includes technological fields (e.g., data aggregation, mining, interpreting, and modeling), procedures and database information. Big data analysis Applications, including Hadoop, Relational, and Web Analytical Modeling, is in this group (OLAP) (Deloitte, 2018; E-Skills UK, 2013). Financial reporting, internal controls to assess risk, and auditor activity are all under the purview of the audit committee (DeZoort, Hermanson, Archambeault and Reed, 2002). As a governance mechanism, the audit committee reduces information asymmetry between stakeholders and managers, thereby mitigating agency issues. (Dechow, Sloan, and Sweeny, 1996) found that companies without audit committees are more likely to have fraudulent financial reporting and earnings overstatement. Based on the above argument we hypothesis that (see Figure 1):

H6: Process-oriented dynamic capabilities as moderator on the relationship between big data analytics competency and Audit committee effectiveness.

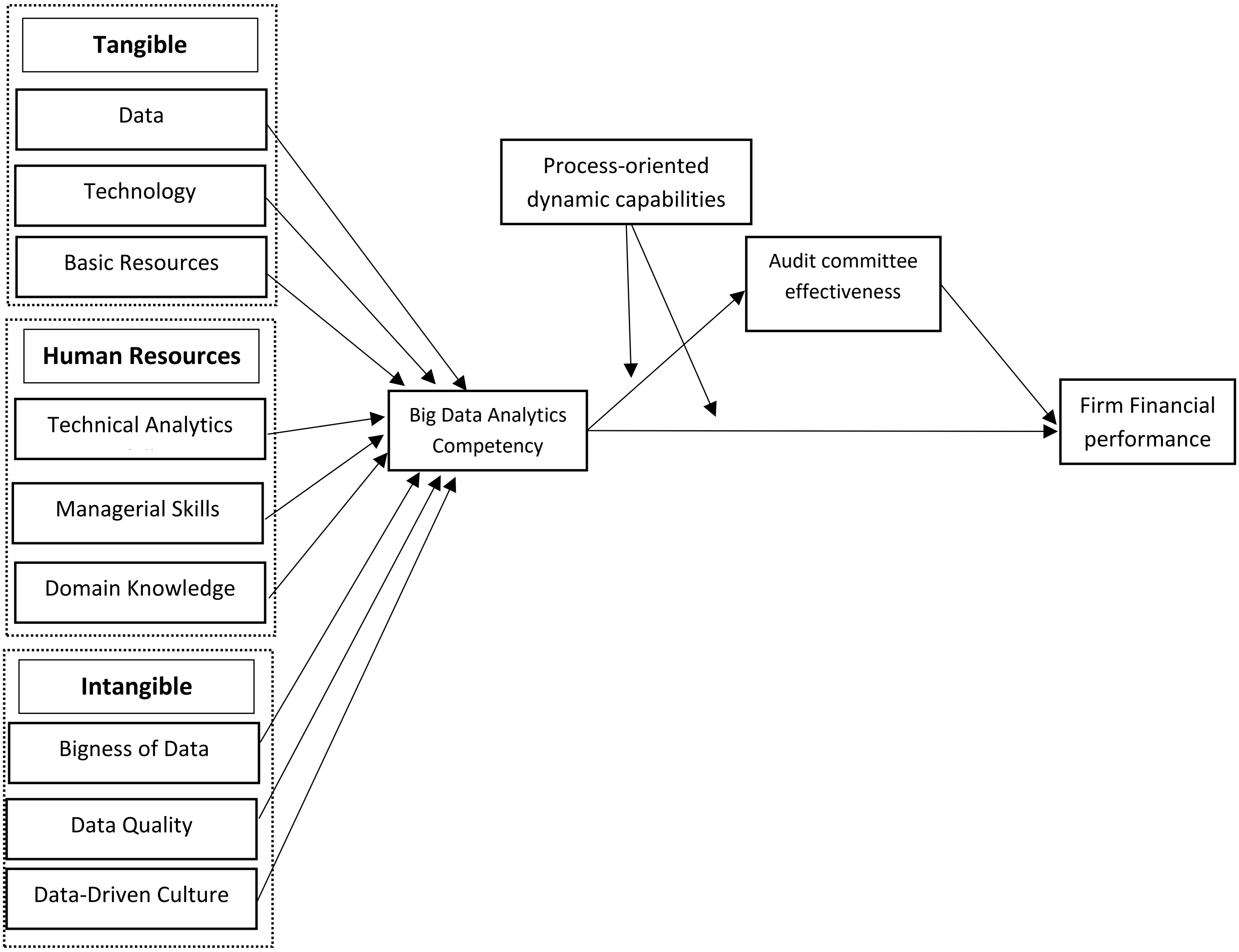


FIGURE 1: CONCEPTUAL MODEL

Source: Author's preparation

3. METHODOLOGY

INTRODUCTION

The purpose of this study was to investigate the effects of big data analytics competency on financial performance through audit committee effectiveness as a mediator and process-oriented dynamic capabilities as a moderator in the Portuguese banking sector. The survey research is used in this study for justifying the results and described the target population. This chapter tells how we have selected the target population and the collection of data was made possible for interpretation. This research also determines that the demographic variables i.e., gender, age, designation, marital status, and experience in the banking sector. The studied variables are derived from the literature review and deeply taken the analysis of these variables also determine in this study.

RESEARCH DESIGN

The study adopted a survey research design. This survey research design, according to Saris and Gallhofer (2014), is important since it helped the researcher attain systematic data on different respondents at the same time. Simple random sampling was used to ensure that those employees were found at their workplaces who were used for the study. This design was quantitative to allow for descriptive and inferential analysis (Schreiber & Asner-Self, 2011).

This examination is descriptive as it tries to articulate, enlighten and translate the present responses of representatives about big data analytics competency, financial performance, audit committee effectiveness, and process-oriented dynamic capabilities. An essential component of research design is to decide on the use of either quantitative or qualitative research approaches or both. Schreiber et al. (2011) avowed about quantitative research approaches where:

- Testing and authentication are weighted
- Evidence and causes related to the social affair are emphasized
- The analytical and particular approach
- Organized quantities
- Hypothetical analysis
- Concerned with consequence
- Circumstantial and logical rationalization through population participation.

The present study deals with the quantitative approach to research. Procedures towards quantitative approach involve well-organized protocols, verbal or composed managed questionnaires consist of restricted prearranged reactions.

RESEARCH STRATEGY

3.1.1. Time Horizon

The data has been collected within one month (i.e., February 2021 to May 2021). As it was collected at one time so the design is cross-sectional in nature.

3.1.2. Population and Sampling

A population is a collection of events, things and people that are associated with an interest that the researcher wants to analyze. Workers of the banking sector were contacted and questionnaires were completed during work hours in their natural work environment so it’s a field study. The sample is a configuration of the population that depicts the entire population for the study we utilized a simple random sampling technique was used.

We distributed 450 questionnaires including hardcopies and softcopies due to the COVID-19 pandemic in the different public and private banks of Portuguese. An introductory letter alongside the goal of the study was given to the administrators and representatives of the organizations. A different measure of surveys was given to them. Scholars received data from 330 target respondents, from these 330 questionnaires 30 was excluded based on missing information and incorrect answers, which make these questionnaires inconclusive and thus excluded. However, only 300 usable surveys were received, resulting in a 66.66% response rate.

At any time during the one month’s when the study was being conducted, participants could respond to the online questionnaire by entering the URL provided on the message, which also outlined the aim of the study, provided a hyperlink to the survey form, I likewise went to the workplaces to meet the administrator and clarify the reason for the study and information gathering in a printed version. I guaranteed them that if they needed the results; it will be given to them. During these face-to-face meetings, I educated the organizations that the information will be gathered from the representatives. For this investigation, we utilized cross-sectional information. Table 1 summarizes the sample demographics.

TABLE 1: DEMOGRAPHICS

Demographics	Categories	Frequency	Valid Percent	Cumulative Percent
Gender	Female	71	23.7	23.7
	Male	229	76.3	100.0
Age	20-30	106	35.3	35.3
	31-40	135	45.0	80.3
	41-50	55	18.3	98.7
	>50	4	1.3	100.0
Education	Bachelor	77	25.7	25.7
	Masters	143	47.7	73.3
	Post Graduation	69	23.0	96.3

	Any Other	11	3.7	100.0
Current Organization Experience	<3	26	8.7	8.7
	3-5	124	41.3	50.0
	6-10	96	32.0	82.0
	>11-15	54	18.0	100.0
Experience	<3	22	7.3	7.3
	3-5	100	33.3	40.7
	6-10	99	33.0	73.7
	>11-15	79	26.3	100.0
Bank Type	Public	67	22.3	22.3
	Private	233	77.7	100.0
Position	Auditors/accountants	70	23.3	23.3
	Middle management	35	11.7	35.0
	Senior managers (vice presidents)	91	30.3	65.3
	Human resource directors	77	25.7	91.0
	CEOs/presidents	27	9.0	100.0

Source: Author's preparation Perform & Analyses on SPSS

3.1.3. Measures

Data were complied with by means of questionnaires from various sources. The questionnaire consisted of a total of 48 items, including: a 28-items scale developed by Gupta et al. (2016) was used to measure big data analytics competency the independent variable, and a 04-item scale was used for dependent variable Financial Performance adopted from Shashi et al. (2019). For mediator the audit committee effectiveness was used the 12-items scale was developed by Phornlaphatrachakorn (2020), and moderator process oriented dynamic capabilities based on 4-items scale was used developed by Kim et al. (2011). All scale evaluated based on five-point Likert scale, comprising 1 (strongly disagree), 2 (disagree), 3 (neutral), 4 (agree) and 5 (strongly agree).

STRUCTURAL EQUATION MODELLING (SEM)

SEM is called "second-generation" technique, which is used simultaneously to analyses multiple variables (Sarstedt et al., 2019). The term "soft modulization" (Henseler et al., 2015) was also developed by Herman Wold in 1970s because of his soft assumptions. In many fields including organizational management, human resources administration, marketing, etc., it has received significant attention (Hair et al., 2016). SEM is divided into "covariance-based" and structural equation modelling Partial Least Squares (PLS).

PLS is used as the "component-based approach" to SEM in exploratory study for forecasting and explaining the variance of criterion variables (Hair et al., 2016).

PLS-SEM is the most important functionality:

A. The size of the small sample

B. Efficient management of complex models

C. No assumption for normality of data.

D. Management of a one-point building.

E. Measurement of training structures

There are two components to the PLS-SEM. The first component is called a measuring model (or external model) which demonstrates the relationship between constructs and their indicators. The second component is the structural model (or internal model), which shows the connection between one construction and another (Hair et al., 2016). The building is exogenous or endogenous.

Exogenous buildings are separate variables and there is no arrow pointing towards them. Endogenous buildings are those explained by other variables (i.e., arrows are pointing towards them). The independent variable becomes if the endogenous construction is placed among two variables (Hair et al., 2014). Two stages of PLS results are assessed. The first phase examines the measurement model and evaluates the structural model in a second phase if the results are satisfactory.

4. RESULTS

In this chapter, the statistical methods used to analyze data obtained will be discussed. Two different software systems were used for data analysis; IBM SPSS Statistical version 28 and Smart PLS version 3.2.8. It starts with a brief introduction to PLS-SEM and describes how descriptive analysis, reliability analysis, validity analysis, mediation and measurement analysis assess the measurement and structural model. Tables and graphs illustrated the results.

MEASUREMENT MODEL

The measurement model is analyzed through the validity of the constructs, convergent and discriminating (internal consistency reliability). Since the structure for entrepreneurial guidance is reflective-formative, two stages have been implemented. The external loading of reflective construct indicators was first examined (i.e., first-order construct). Only the items that satisfied the criteria were maintained. Generally, the external load value must exceed 0.70 (Hair et al.,2014). Those items whose external loads are 0.40-0.70 should only be removed if removal increases the reliability of the composites or average variance extracted (AVE) (Hair et al., 2016). Moreover, the amount of items in an area that can reduce the credibility of the scale depends on Cronbach alpha (Hair et al., 2017). Composite reliability, therefore, provides an appropriate reliability measure and varies between 0 and 1. As threshold values exceeding 0.70 are recommended (Hair et al., 2016). AVE is another way of determining the validity of convergence. It explains how much the element and its corresponding structure are variable (Hair et al., 2017). The AVE threshold is 0.50 or higher, based on the criteria of (Fornell & Larcker, 1981).

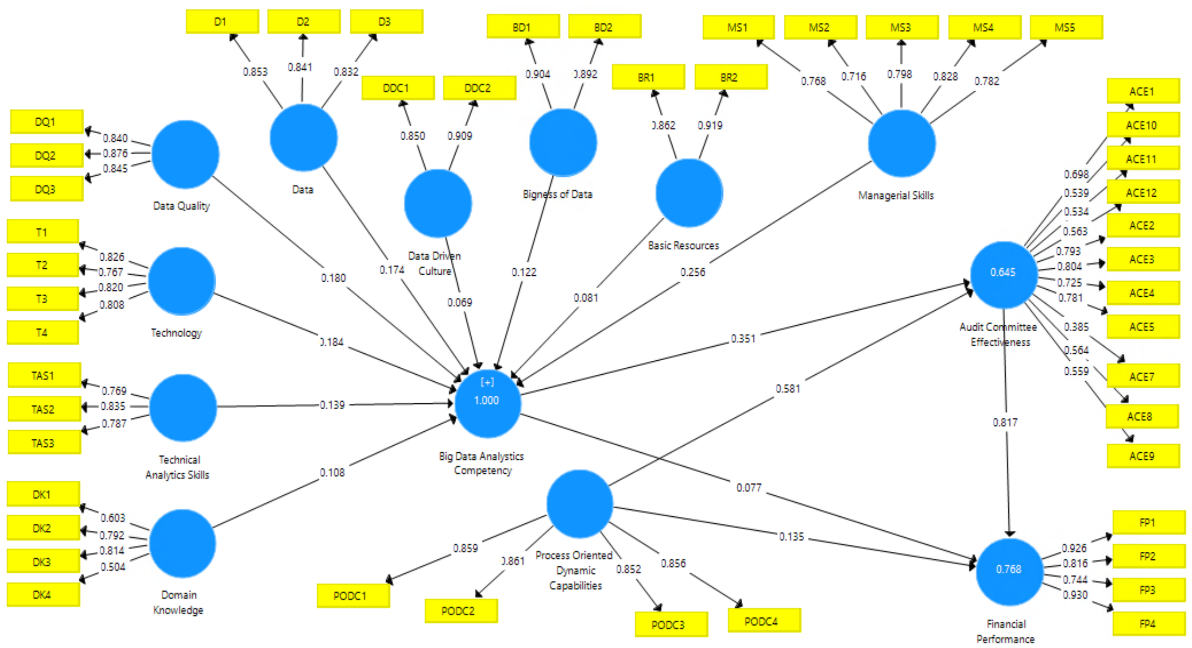


FIGURE 2. MEASUREMENT MODEL ANALYSIS.

Source: Author's preparation by SmartPLS Sofwtare

TABLE 2: MEASUREMENT MODEL

Constructs	Items	Factor Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Big Data Analytics Competency					
Managerial Skills	MS1	0.768	0.838	0.885	0.608
	MS2	0.716			
	MS3	0.798			
	MS4	0.828			
	MS5	0.782			
Basic Resources	BR1	0.862	0.743	0.885	0.793
	BR2	0.919			
Technical Analytics Skills	TAS1	0.769	0.713	0.839	0.636
	TAS2	0.835			
	TAS3	0.787			
Technology	T1	0.826	0.819	0.881	0.649
	T2	0.767			
	T3	0.820			
	T4	0.808			
Bigness of Data	BD1	0.710	0.760	0.893	0.806
	BD2	0.892			
Data	D1	0.853	0.795	0.880	0.709
	D2	0.841			
	D3	0.832			
Data Driven Culture	DDC1	0.850	0.711	0.872	0.774
	DDC2	0.909			
Data Quality	DQ1	0.840	0.814	0.890	0.729
	DQ2	0.876			
	DQ3	0.845			
Domain Knowledge	DK1	0.603	0.618	0.779	0.477
	DK2	0.792			
	DK3	0.814			
	DK4	0.504			
Financial Performance	FP1	0.926	0.876	0.917	0.735
	FP2	0.816			
	FP3	0.744			
	FP4	0.930			
Audit Committee Effectiveness	ACE1	0.698	0.860	0.882	0.415
	ACE2	0.793			
	ACE3	0.804			
	ACE4	0.725			
	ACE5	0.781			
	ACE7	0.385			
	ACE8	0.564			
	ACE9	0.559			
	ACE10	0.539			
	ACE11	0.534			
	ACE12	0.563			
Process Oriented Dynamic Capabilities	PODC1	0.859	0.879	0.917	0.734
	PODC2	0.861			
	PODC3	0.852			
	PODC4	0.856			

Source: Author’s preparation by SmartPLS Sofwtare version 3by SmartPLS Sofwtare

To determine the validity of formative constructs, several latent variables from all the lower-order buildings were derived (i.e., second-order construct). The initial Path Model estimate for external loads is shown in Figure 2. External loadings for each item, Cronbach alpha, composite reliability, and average variance are representable in Table 2.

Multicollinearity is checked when two or more components are closely linked and measured by the "Variance Inflation Factor" (VIF) (Hair et al., 2016). In multicollinearity, the formative structure was examined. Multicollinearity issues occur when a value is greater than 5. The second-order VIF values shown in Table 3 show that in current research there is no multi collinearity problem. Outer weights of formational indicators have been assessed. In addition, bootstrapping tested the significance of the weights. The weights of indicators are significant as indicated in Table 3.

Table 3 shows significant outer weights of Basic Resources, Bigness of Data, Data, Data-Driven Culture, Data Quality, Domain Knowledge, Managerial Skills, Technical Analytics Skills and Technology all were significant as its lower limit confidence interval (LLCI) and upper limit confidence interval both have the same sign. If the weight is small but the loading is above 0.50, the item is to be retained (Hair et al. 2016). According to the article. The item should be removed if the outer load is also less than 0.5.

TABLE 3. OUTER WEIGHTS AND VARIANCE INFLATION FACTOR VALUES

Relationship among Constructs	Original Sample	Sample Mean	VIF	LLCI 2.5%	ULCI 97.5%
Basic Resources -> BDAC	0.091	0.091	2.367	0.069	0.111
Bigness of Data -> BDAC	0.123	0.123	2.270	0.108	0.139
Data -> BDAC	0.175	0.175	2.372	0.157	0.194
Data Driven Culture -> BDAC	0.059	0.058	2.772	0.033	0.081
Data Quality -> BDAC	0.172	0.171	2.302	0.156	0.188
Domain Knowledge -> BDAC	0.138	0.138	2.270	0.110	0.164
Managerial Skills -> BDAC	0.257	0.257	2.659	0.236	0.279
Technical Analytics Skills -> BDAC	0.132	0.132	2.584	0.114	0.149
Technology -> BDAC	0.173	0.172	2.444	0.148	0.197

Source: Author's preparation by SmartPLS Sofwtare version. Abbreviations: Big Data Analytics Competency (BDAC).

4.1.1. DISCRIMINATORY VALIDITY

For discriminatory validity the Heterotrait–monotrait **(**HTMT) techniques was used presented by Henseler et al., (2015). This is the average correlation ratio of the indicators between the various structures and the average correlation of the associated structure indicators. According to Hair et al. (2017) model with similar structures have a threshold of 0.90 while constructs with a threshold of 0.85 or below are non-related. In Table 4, it can be observed that not a single value is more than 0.85. Therefore, discriminatory validity was established.

TABLE 4. HETEROTRAIT–MONOTRAIT RATIO (HTMT)

Constructs	1	2	3	4	5	6
1. Audit Committee Effectiveness						
2. Big Data Analytics Competency	0.810					
3. Financial Performance	0.837	0.564				
4. Moderating Effect 1	0.173	0.106	0.154			
5. Moderating Effect 2	0.173	0.106	0.154	0.137		
6. Process Oriented Dynamic Capabilities	0.738	0.507	0.802	0.174	0.264	

Source: Author's preparation by SmartPLS Sofwtare

STRUCTURAL MODEL EVALUATION

The standard method for bootstrapping with subsample 5000 was used in this study to acquire significant associations among the structure. We followed the methods recommended by Henseler et al (2015) to review the mediating results of audit committee effectiveness. Four specific criteria were used to analyze the direct and indirect effects of the structural equation models. Firstly, to calculate the amount of variation elucidated by all constructs, to estimate R^2 in endogens of latent variables (Hair et al., 2018). Although, the satisfactory evaluation for R^2 depending on the setting of the study (Cohen, 1998) shows a high, moderate and low evaluation of 0.26, 0.13, and 0.09 respectively. The R^2 value for Financial Performance was 0.759, which was large and shows that BDAC, ACE and PODC had elucidated 75.9% of Financial Performance variation.

Similarly, Table 5 and Figure 3 indicates the R^2 value for audit committee effectiveness was also high at 0.688, which mean 68.8% change occur in audit committee effectiveness due to BDAC and PODC.

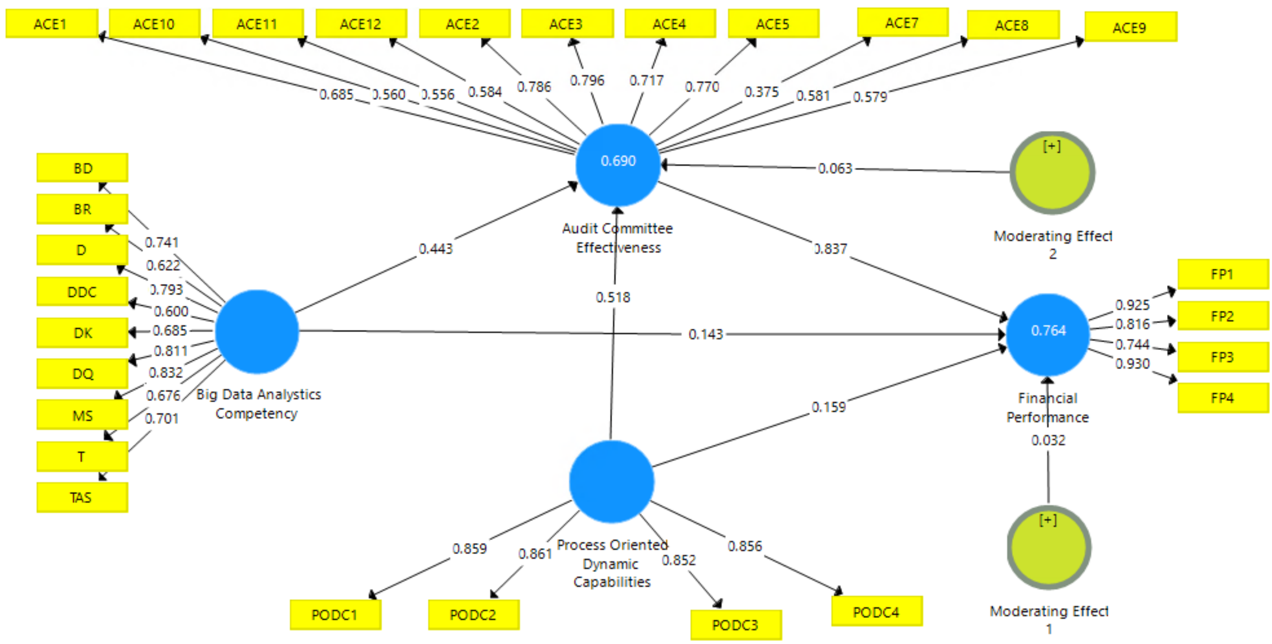
TABLE 5. COEFFICIENT OF DETERMINATION

Constructs	R Square	R Square Adjusted	Q^2 (=1-SSE/SSO)
Audit Committee Effectiveness	0.688	0.685	0.254
Financial Performance	0.759	0.756	0.549

Source: Author's preparation by SmartPLS Sofwtare

Second, the predictive relevance measure (Q^2) was also used to measure the evaluated meaning of the investigation model using a cross-validation redundancy measure (Hair et al., 2014). Table 5 shows the appropriate estimates of direct effect model value since the endogenous latent variable value of Q^2 is greater than zero, both direct and indirect endogenous constructs FP ($Q^2 = 0.549$) and ACE ($Q^2 = 0.254$) values greater than zero and can be considered as an acceptable predictive relevance of the model (Henseler et al., 2015).

Figure 3 and Table 6 shows that the direct effect of BDAC on FP was positive and significant ($\beta = 0.144$, $p < 0.001$). The path coefficient indicates that one-unit change BDAC occur 14.4% change in FP. Furthermore, the direct effect of BDAC on ACE ($\beta = 0.433$, $p < 0.000$) and ACE on FP ($\beta = 0.853$, $p < 0.000$) was also positive and significant. Therefore, all direct hypotheses H1, H2 and H3 were accepted.



Source: Author's preparation by SmartPLS Sofwtare

FIGURE 3: PLS (N = 5000 BOOTSTRAPPED SAMPLES) PATH ANALYSIS

Analysis of mediation is the phenomenon that explains the relationship between independent constructs and dependents. In the current study, the Audit Committee Effectiveness mediates the relationship between BDAC and FP. Table 6 illustrated that the indirect effect results of ACE on BDAC and FP also positive and significant (β = 0. 369, $p < 0.000$). Lastly, the moderator Process-Oriented Dynamic Capabilities positively and significantly moderate the relation between BDAC and ACE (β = 0. 063, $p < 0.021$). But insignificant between BDAC and FP (β = 0. 034, p= 0.109) because p-value greater than 0.05. Therefore, Hypotheses H4 and H6 were accepted and H5 was rejected.

TABLE 6. RESULTS OF THE STRUCTURAL EQUATIONS MODEL

	Hypotheses/ Relationship between Variables	B	Sample Mean	Standard Deviation	T Values	P Values	Remarks
	Direct Effect						
H1	BDAC -> FP	0.144	0.142	0.043	3.325	0.001	Supported
H2	BDAC -> ACE	0.433	0.434	0.052	8.344	0.000	Supported
H3	ACE -> FP	0.853	0.856	0.045	19.105	0.000	Supported
	Indirect Effect						
H4	BDAC -> ACE-> FP	0.433*0.853=0.369	0.372	0.048	7.645	0.000	Supported
H5	Moderating Effect 1 -> FP	0.034	0.032	0.021	1.602	0.109	Not Supported
H6	Moderating Effect 2 -> ACE	0.063	0.058	0.026	2.310	0.021	Supported

Source: Author's preparation by SmartPLS Sofwtare. Abbreviations: Big Data Analytics Competency (BDAC), Financial Performance (FP), Audit Committee Effectiveness (ACE), Process-Oriented Dynamic Capabilities (PODC).

SUMMARY OF HYPOTHESES

The proposed hypotheses for the study are summarized in Table 7 below.

TABLE 7. SUMMARY OF ACCEPTED AND REJECTED HYPOTHESIS

Hypothesis	Statement	Results
H_1	Big data analytics competency is positively associated with firm financial performance.	**Accepted**
H_2	Big data analytics competency is positively associated with Audit committee effectiveness.	**Accepted**
H_3	Audit committee effectiveness is positively associated with firm financial performance.	**Accepted**
H_4	Audit committee effectiveness as mediator on the relationship between big data analytics competency and firm financial performance.	**Accepted**

H_5	Process-oriented dynamic capabilities as moderator on the relationship between big data analytics competency and firm financial performance.	**Rejected**
H_6	Process-oriented dynamic capabilities as moderator on the relationship between big data analytics competency and Audit committee effectiveness.	**Accepted**

Source: Author’s preparation

5. DISCUSSION

Past literature has shown that important study in big data analytics and company performance has been carried out (Maryam Ghasemaghaei et al., 2015; Collymore et al., 2017 Raguseo et al., 2018; Song et al., 2018). Furthermore, research has shown that company performance, audit committee effectiveness, and process-oriented dynamic capacities are critical to investigate and impact firm performance (Guangming et al., 2015; Lopez-Cabarcos et al., 2015; Ringov, 2017). Following, earlier research and conclusions, the primary goal of this study was to investigate the relationship between big data analytics competency and financial performance in the context of the Portuguese banking industries. Furthermore, in the relationship between big data analytics competency and financial performance, the mediating role of Audit committee effectiveness and the moderating role of process-oriented dynamic capability was investigated.

H1: Big data analytics competency is positively associated with firm financial performance.

Hypothesis 1 anticipated that big data analytics competency is positively associated with financial performance and results ($\beta = 0.144$, $p < 0.001$) has also emphasized a significant bond among the variables. In the last few decades, large data have arisen as a new field of research. Worldwide companies are extremely interested in making full use of the BDA's capacity (Ross et al., 2013). Literature has found that big data analytics continue to evolve, and firms want to have the big data analytics capacity that can substantially impact corporate performance (Akter et al., 2016, Gupta & George, 2016). Furthermore, recent studies have highlighted the competence of big data analysis as a generator of value for companies to help gather insights from collected data and provide them with information on current and future patterns to keep them current and make their actions accordingly (Saggi & Jain, 2018). Moreover, numerous studies examined and determined that big data analysis played a major role in gaining competitive advantages (Kubina et al., 2015; Morabito, 2015b). In addition, competitive advantage leads to improved performance, keeping them ahead. Big data analytics competence is very important in the Portuguese banking sectors since the current study has empirically proved that BDA enables companies to operate at a high level. However, organizations need to concentrate on various dimensions to build a high BDA level.

H2: Big data analytics competency is positively associated with Audit committee effectiveness.

Hypothesis 2 anticipated that Big data analytics competency is positively associated with Audit committee effectiveness and results ($\beta = 0.433,\ p < 0.001$) has also emphasized a significant bond among the variables. All dimensions of big data analytics are observed to increase the efficiency of organizational choice in the context of quick decision making except the bigness of data (Maryam Ghasemaghaei et al., 2018). As previously stated, big data analytics is all about collecting and supplying relevant information about customer wants and desires, markets, suppliers, and other factors.

H_3: Audit committee effectiveness is positively associated with firm financial performance.

Hypothesis 3 anticipated that Audit committee effectiveness is positively associated with firm financial performance and results ($\beta = 0.853$, $p < 0.001$) has also emphasized a significant bond among the variables. Auditors devote a lot of time and effort to recognizing item separation and providing higher-quality audits (Suryanto, 2014). Because they have superior competencies to find out industry abnormalities and distortions, a high-quality audit by an industry specialist audit company may boost the acceptance and creditability of a firm's financial reporting (Sirois et al., 2016). Their ability to provide high-quality audits stems from their ability to serve multiple customers within the same learning, industry and share best practices across the organization. Previous research has shown that audit quality improves an organization's performance (Mandzila et al., 2016). As a result of the findings of this study, the premise that there is a link between audit committee effectiveness and firm performance also holds in the Portuguese banking industries.

H4: Audit committee effectiveness as a mediator on the relationship between big data analytics competency and firm financial performance.

Hypothesis 4 anticipated that Audit committee effectiveness plays a role of mediator with big data analytics competency and firm financial performance and results ($\beta = 0.\ 369$, $p < 0.001$) has also emphasized that there is a significant bond among the variables. Audit quality is one of the most fundamental challenges in today's auditing profession. The joint possibility that a current material error is recognized and reported by an auditor has been defined as audit quality (Jordan et al., 2017). Big accounting firms are typically regarded as professional, independent, dependable, and skilled in delivering superior audit quality (Lokatt, 2018). Firms with more inherent instability (i.e., larger information asymmetry between the firm and customers) have a stronger incentive to talk about their distinctive quality by hiring an extra solid, top-notch auditor. According to previous research, it is not only the size of data that causes improved firm performance; it is how firms create insights from big data and improve their performance that impacts firm performance (Thirathon et al., 2017).

H5: Process-oriented dynamic capabilities as moderator on the relationship between big data analytics competency and firm financial performance.

Hypothesis 5 anticipated that process-oriented dynamic capabilities play a role of moderator among big data analytics competency and Firm financial performance. However, the results indicates that PODC is insignificant ($\beta = 0.\ 034$, $p= 0.109$) among the variables. In terms of coordination, integration, cost reduction, business intelligence, and learning connected to BDA initiatives, PODC refers to the extent to which a firm can create or acquire essential skills to transform its existing business processes in a more robust way than its competitors (Kim et al., 2011). The term "dynamic" refers to the company's capacity to renovate its capabilities for compliance by producing inventive answers to the changing business environment. The term "capacity" shows how organizational skills and resources are adjusted, integrated, and reconfigured to meet the needs of a changing environment. Capability development requires the concerted work of individuals and organizing teams and is crucial for companies in changing marketplaces today (Helfat and Peteraf, 2003). Improved performance comes by using technical resources and the addition of organizational resources to generate distinctive capabilities (Trainor et al., 2014). Although the moderating role of process-oriented dynamic had not been investigated previously in this domain, existing research offered the ground to investigate this behavior in the specified correlation, with favorable results confirming the predicted relationship.

The results show that there is a negative impact of process-oriented on financial firm performance and big data analytics. The firm's capacity to recruit and keep consumers and improve sales, profitability, and return on investment (ROI) is measured by FPER (Tippins and Sohi, 2003, Mithas et al., 2011). The RBV and dynamic capabilities views and recent big data analytics research are used in this study. The empirical findings emphasize the need to invest in all complementary big data resources (tangible, human, and intangible) that contribute to the development of a BDAC. Firms achieve evolutionary fitness due to BDAC-generated knowledge, which enhances a firm's dynamic capacities, resulting in increased operational capabilities. To summarize, this study demonstrates that a) big data is more than just the data itself, b) developing a capability necessitates the consideration of several complementary resources, and c) capturing BDAC performance gains necessitates identifying the mechanisms and main enablers/hindrances that influence performance.

H6: Process-oriented dynamic capabilities as moderator on the relationship between big data analytics competency and Audit committee effectiveness.

Hypothesis 6 anticipated that Process-oriented dynamic capabilities play a role of moderator among big data analytics competency and Audit committee effectiveness and results ($\beta = 0.433$, $p < 0.001$) have also emphasized that there is a significant bond among the variables. Process orientated dynamic capacities are defined as the ability of a company, in terms of integrating operations, cutting costs, and capitalization on business intelligence/learning, to alter (improve, adapt, or reconfigure) business processes rather than the competition. They cover various company process changes, from constant modifications and enhancements to radical once-in-a-lifetime changes. Although most of the adjustments can be modest, the ability of a company to adjust promptly also suggests its willingness to make drastic adjustments whenever necessary. Although the moderating role of process-oriented dynamic capabilities had not been investigated previously in this domain, existing research offered the ground to investigate this behavior in the specified correlation, with favorable results confirming the predicted relationship.

RESEARCH IMPLICATIONS

The current study makes a substantial addition to big data analytics management and firm performance, and it has a wide range of applications. Because no previous study has directly addressed the moderating behavior of Process-oriented dynamic capability and the mediating role of audit committee effectiveness in this setting, the function played by the current study is quite important. Furthermore, the convergence of organizational resources examined in this study to assess a firm's big data analytics competency has never been attempted before. Furthermore, earlier research has revealed a paucity of literature in big data analytics on the Portuguese banking environment; hence, the current study has contributed to filling this gap in the literature.

Results from this study showed that the direct and indirect link between Big Data Analysis and firm performance is influenced by the performance of the audit board and process-oriented dynamics, and alone, BDA is not sufficient to generate strong, equally important performance for research. BDA makes the job simple and reduces the adverse effect. There is a tendency around the world to use BDA rather than relying on intuition and experience to take effective decisions. To benefit from Big Data, researchers provide strategic and practical guidance. However, the perspectives on the application of big data continue to expand through rigorous academic research and theory. In addition, BDA-based internal mechanisms are not completely studied. Many investigations to date have explored the BDA's performance-related advantages. This research contributes in several ways to BDA research. While BDA research and practice has mostly focused on industrialized countries, empirical study in other country contexts, particularly emerging markets, appears to be lacking. Portuguese provides a rich setting for expanding this line of research, as it has become critical for businesses in all sectors to build BDA capabilities to compete with other economies. Even though most emerging economies have institutional gaps in economic, legal, and financial infrastructure, BDA experts in emerging markets have discovered that BDA can help both public and private enterprises deal with the demands of global competitiveness.

THEORETICAL IMPLICATIONS

Using the resource-based Theory (RBT) and dynamic capabilities view (DCV) as theoretical lenses, the study investigates the relationship between BDA capabilities and firm performance. The main justification for adopting these two points of view is that the technological capability of utilizing BDA requires various additional firm-specific resources that can eventually contribute to increased performance. Another important feature of this research is that it is conducted in an important emerging market, Portuguese, which is undeniably a fast-growing market with characteristics similar to other emerging significant country markets like Canada, Australia, and France. Although audit committees are also part of a firm's internal control system, this paper aims to see if audit committee independence influences the relationship between Process-oriented dynamic capability, BDA, and growing firm financial performance.

The firm's RBV identifies two potential competitively advantageous sources: the variety of its strategic resources and the firm's total immobility (Barney, 1991). An efficient mix of physical, human, and business capital, as proposed by (Hambrick 1987), is a rare and imperfectly imitative resource. The interpersonal relationship between managers, the company culture, and the reputation of a company between suppliers and customers and information processing systems can avoid the imitation of a business's resources (Barney, 1991). By developing BDA capabilities, companies can thereby attain imperfect imitability, creating an evidentiary decision environment and data-driven culture.

The drawbacks of RBV are highlighted by (Teece and Pisano, 1994), who claim that it is rather static and incompatible with the continually changing corporate environment. They argue that dynamic capabilities are the source of competitive advantage, arguing that competitive success requires both the exploitation of existing internal and external firm-specific talents and the development of new ones. Because a firm's behavior, methods, and operations are difficult to replicate, the core premise of dynamic capability is tacit knowledge; this is the nexus of coordinative management processes. Another flaw with RBV is that it does not account for resource evolution over time.

6. CONCLUSIONS

The research is based on the Resource-Based Theory, which states that improved resource integration and deployment leads to improved organizational outcomes. It first looked into integrating and deploying big data analytics-specific resources, which are the driving force behind BDA, and then its impact on firm performance in Portuguese banking sectors. Statistical tests are used to assess the proposed model's reliability and validity. In addition, other tests such as correlation analysis, regression analysis, and mediation analysis are used to determine if claimed relationships are accepted or rejected. The current study hypothesized that BDA and firm performance are positively related, and the findings confirmed this, implying that companies with a high level of big data analytics competency also have a high level of firm performance.

The results of this study are compatible with a recent Portuguese study (Yeo and Carter, 2017), which states that auditors must be more trained and data analytics applied to improve their research capability. Next, this study stated that big data analytics competency is related positively to Audit committee effectiveness, and the findings supported this claim, demonstrating that if an organization's competence in big data analytics is high, so is its performance. Furthermore, the results of a study have offered support for another theory, which predicts that audit committee effectiveness is favorably correlated with firm performance. Furthermore, the study's hypotheses suggested that Audit committee effectiveness mediates the relationship between BDAC and firm performance, and the results showed that Audit committee effectiveness mediated the relationship. By examining the mediating behavior of Audit committee effectiveness and process-oriented dynamic capability in the Portuguese banking sectors, this study tried to present a holistic understanding of the impact of big data analytics competency on firm performance.

Analysis, however, has shown that in auditing research, auditors in more developed countries are at least fairly comfortable with Big Data Analytics (Brown-Liburd & Vasarhelyi, 2015). It has also been stressed that overall technical progress (including the professional skills of auditors) in the application of audit data analytics would be guided by progress in the US and the international audit standards (see Alles, 2015). As they are responsible for reviewing financial reporting, the board audit committee has a function to play in the business and to provide openness information or outcomes, either directly or indirectly. In the meantime, this has a substantial impact on the firm's success. The audit committee and accounting firms play an important role in determining the validity, acceptance, and dependability of high quality. These findings have consequences for the practice of Portuguese auditors.

Auditing their client's or businesses' dynamic business activity records, the auditors will have to make further attempts to do in-depth risk analyses using Big Data Analytics. If the firm improves its results, it will rely mostly on how the company and its analysts use the critical incentive. The company sales can be improved dramatically using automated processes and the right changes at the right time, along with the integration of big data processing (Cockcroft & Russell, 2018). Big data is used for digitizing the financial industry. Digital revolution increases the company's competitiveness and uses these innovations to satisfy consumer needs in major companies. Most companies hold the current and vital records, and the effects and consequences of this collected knowledge in the financial sector is an increasingly important issue. Financial services are technologically innovative in hindsight and treat data as a core element in the company. Therefore, the results of the study indicate that the financial sector was revolutionized by the use of big data, particularly by the shift in trade and investments due to the real insight in stocks and fraud detection and prevention, as well as by the use of machine-learning algorithms to analyze the risks more precisely. The services delivered by big data analytics change and improve customer loyalty, deliver sales, minimize response time for manual operations, ensure efficient device processing, enhance the direction of acquisition, analyze the financial success of the company and improve and monitor products and development of the business.

7. LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORKS

Like any other research, this study has some limitations:

1. This research is limited to the banking industries in Portuguese. Future studies can test this model in different industries i.e., manufacturing, Hospital, and construction sector,
2. The current study is cross-sectional in terms of time interval; nevertheless, because this is a capabilities-based study, researchers should consider longitudinal data in the future to investigate this relationship, which may yield different results.
3. The current study has only included a few of the available dimensions to investigate an organization's big data analytics competency; nevertheless, additional dimensions may have a significant impact. Researchers must use other variables in the future.
4. Although using objective measurements of firm performance would be beneficial, acquiring access to such measurements that include multiple dimensions of firm performance is a huge challenge. As a result, future research should combine hard and soft measurements to assess firm performance better. In addition to this, new research is needed, including additional capabilities or external factors influencing BDA development. In addition, BDAC's impact on the firm's corporate performance has been examined while researchers can explore the influence of BDAC in certain departments or fields such as supply chain management.

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9. APPENDIX (OPTIONAL)

Questionnaire

Dear respondent,

I am a student of MS (Statistics and Information Management) at NOVA information management school, wishing to conduct research on "*Portuguese Banks Competency on Big Data Analytics Improve Their Financial Performance: Audit committee effectiveness as Mediator and Process-Oriented Dynamic Capabilities as Moderator*" for the completion of my research thesis.

In this regard, I have prepared following questionnaire, please note down that your identity as respondent is concealed. You can freely express whatever the ground realities you see and face. It will take your 10-15 minutes to answer the questions; any information obtained for this research will only be used for academic purpose.

For more queries, please email jessicanunesmartins@gmail.com. I really appreciate your time for filling up this questionnaire.

Thanks a lot for your help and support!

Sincerely

Regards

Jéssica Martins

DEMOGRAPHICS

1. Gender

Male ☐ Female ☐

2. Age

21 to 30 years ☐ 31 to 40 years ☐ 41 to 50 years ☐ More than 50 years ☐

3. Experience

Less than 3 years ☐ 3 to 5 years ☐ 6 to 10 years ☐ 11 to 15 years ☐

4. Education Level

Bachelor ☐ Master ☐ Post Graduat☐ Others (please specify)

____

5. Bank Type

Public ☐ Private ☐

6. Experience in Current Organization

Less than 3 years ☐ 3 to 5 years ☐ 6 to 10 years ☐ 11 to 15 years ☐

7. Position

1. Auditors/accountants ☐
2. Middle management ☐
3. Senior managers (vice presidents) ☐
4. Human resource directors ☐
5. CEOs/presidents ☐

Keeping in view your employer, please indicate the extent of your agreement and disagreement by entering the appropriate option.

Strongly Disagree = 1, Disagree = 2, Neutral = 3, Agreed = 4, Strongly Agreed = 5

Big data analytics competency Scale					
Data	**Strongly Disagree**	**Disagree**	**Neutral**	**Agreed**	**Strongly Agreed**
BDAC1: We have access to very large, unstructured, or fast-moving data for analysis.	1	2	3	4	5
BDAC2: We integrate data from multiple internal sources into a data warehouse or mart for easy access.	1	2	3	4	5
BDAC3: We integrate external data with inter-nal to facilitate high-value analysis of our business environment.	1	2	3	4	5
Bigness of Data					
BDAC4: In our organization, we process high-volume of data.	1	2	3	4	5
BDAC5: In our organization, we process Realtime data.	1	2	3	4	5
Data Quality					
BDAC6: In our organization, data used in data analytics is reliable.	1	2	3	4	5
BDAC7: In our organization, data used in data analytics has an appropriate level of details.	1	2	3	4	5
BDAC8: In our organization, data used in data analytics is relevant to the task at hand.	1	2	3	4	5
Technology					
BDAC9: We have explored or adopted parallel computing approaches (e.g., Hadoop)to big data processing.	1	2	3	4	5
BDAC10: We have explored or adopted different data visualization tools.	1	2	3	4	5
BDAC11: We have explored or adopted cloud-based services for processing data and performing analytics.	1	2	3	4	5
BDAC12We have explored or adopted newforms of databases such as Not Only SQL (NoSQL) for storing data.	1	2	3	4	5
Basic Resources					

BDAC13: Our big data analytics projects are adequately funded.	1	2	3	4	5
BDAC14: Our big data analytics projects are given enough time to achieve their objectives.	1	2	3	4	5
Technical Analytics Skills					
BDAC15: We provide big data analytics training to our own employees.	1	2	3	4	5
BDAC16: We hire new employees that already have the big data analytics skills.	1	2	3	4	5
BDAC17: Our big data analytics staff has the right skills to accomplish their jobs successfully.	1	2	3	4	5
Managerial Skills					
BDAC18: Our big data analytics managers understand and appreciate the business needs of other functional managers, suppliers, and customers.	1	2	3	4	5
BDAC19: Our big data analytics managers are able to work with functional man-agers, suppliers, and customers to determine opportunities that big data might bring to our business.	1	2	3	4	5
BDAC20: Our big data analytics managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers.	1	2	3	4	5
BDAC21: Our big data analytics managers have a good sense of where to apply bigdata.	1	2	3	4	5
BDAC22: Our big data analytics managers are able to understand and evaluate the output extracted from big data.	1	2	3	4	5
Domain Knowledge					
BDAC23: In our organization, there is a high level of knowledge of the external environment (e.g., government, competitors, suppliers, and customers).	1	2	3	4	5
BDAC24: In our organization, there is a high level of knowledge of the organizational goals and objectives.	1	2	3	4	5
BDAC25: In our organization, there is a high level of knowledge of the core capabilities of the organization	1	2	3	4	5
BDAC26: In our organization, there is a high level of knowledge of the key factors that must go right for the organization to succeed.	1	2	3	4	5
Data-Driven Culture					
BDAC27: We are willing to override our own in-tuition when data contradict our view-points.	1	2	3	4	5
BDAC28: We continuously assess and improve the business rules in response to in-sights extracted from data	1	2	3	4	5

Financial Performance	**Strongly Disagree**	**Disagree**	**Neutral**	**Agreed**	**Strongly Agreed**
FP1: The return on investment of our company is higher compared to competitors.	1	2	3	4	5
FP2: The return on assets of our company is higher compared to competitors.	1	2	3	4	5
FP3: The sales growth and profitability of our company are higher compared to competitors.	1	2	3	4	5
FP4: The total operating costs of our company are lower compared to competitors	1	2	3	4	5

Audit committee effectiveness	**Strongly Disagree**	**Disagree**	**Neutral**	**Agreed**	**Strongly Agreed**
ACE1: Audit committee has encouraged firms to provide good corporate practices.	1	2	3	4	5
ACE2: Audit committee has strengthened the roles and effectiveness of non-executive directors.	1	2	3	4	5
ACE3: Audit committee has assisted directors in discharging their statutory responsibilities as regards financial reporting.	1	2	3	4	5
ACE4: Audit committee has preserved and enhanced the independence of internal auditors.	1	2	3	4	5
ACE5: Audit committee has assisted the auditors in the reporting of serious deficiencies in the control environment or management weaknesses.	1	2	3	4	5
ACE6: Audit committee has improved communications between the board and internal auditors.	1	2	3	4	5
ACE7: Audit committee has improved communications between the board and external auditors.	1	2	3	4	5
ACE8: Audit committee has increased the confidence of the public in the credibility and objectivity of financial statements.	1	2	3	4	5
ACE9: Audit committee has assisted management to discharge its responsibilities for the prevention of fraud, other irregularities and errors.	1	2	3	4	5
ACE10: Audit committee has increased the confidence of investment analysts in the credibility and objectivity of financial statements.	1	2	3	4	5
ACE11: Audit committee has provided a forum for arbitration between management and auditors.	1	2	3	4	5

ACE12: Audit committee has concerned the possibility of legislative pressure.	1	2	3	4	5

Process-oriented dynamic capabilities	**Strongly Disagree**	**Disagree**	**Neutral**	**Agreed**	**Strongly Agreed**
PODC1: Our company is better than competitors in connecting (e.g., communication and information sharing) parties within a business process.	1	2	3	4	5
PODC2: Our company is better than competitors in reducing cost within a business process.	1	2	3	4	5
PODC3: Our company is better than competitors in bringing complex analytical methods to bear on a business process.	1	2	3	4	5
PODC4: Our company is better than competitors in bringing detailed information into a business process	1	2	3	4	5