The Role of Analytical Skills in Big Data-Driven Decision-Making in African Firms: Evidence from Morocco

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Abstract

The purpose of the study was to investigate the impact of analytical skills on enhancing the decision-making process within Moroccan enterprises. Using a research questionnaire, the study obtained primary data from data profiles operating in 49 Moroccan companies. To analyze the data and test the hypotheses developed, we adopted and applied the partial least squares (PLS) method. The results of this study confirmed the overall hypothesis that analytical skills (technical and managerial) contribute to better decision making within the company at strategic, operational and administrative levels. The managerial contributions of this study are that managers can develop a deep understanding of how an information processing capability in a Big Data environment can help their firm make optimal decisions, and potentially give their firm a competitive advantage. Similarly, this work provides a good deal of guidance to managers and consultants involved in the implementation of Big Data analytics projects in companies to consider the technical and managerial skills needed to support the implementation project.

Keywords: Skills, Big Data, Firm, Analytical, Decision, Structural Equations.

JEL Classifications: O15, M15

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1. Introduction

In the past, technological resources offered firms a competitive advantage due to proprietary rights. However, the emergence of social media-based groups, workforce mobility, and reverse engineering make it challenging to maintain technological exclusivity (Gupta & George, 2016; Mata et al., 1995). Furthermore, technological resources only become a source of competitive advantage when the firm develops analytical skills. These skills are the result of a combination of the quality of the data, an analytical culture within the firm, and the degree to which data analysis is integrated into decision-making (Batko, 2017).

Thus, the emergence of Big Data has acted as a catalyst for BI systems to evolve from a simple reporting tool for executives to a robust system that allows employees at all levels to be guided by data. As a result, BI systems have evolved into creative and innovative analyses for problem-solving and decision support (Noah & Borkovich, 2014).

Furthermore, Albaum et al. (1995) presented the firm as a system that, unlike the individual, is embedded in a perspective where decision-making is a collective responsibility of all stakeholders and that the performance of the firm is dependent on the style of decision-making (Russ et al., 1996). Therefore, the quality of decisions made by managers is fundamental to boosting the firm's competitiveness (Chan & Chan, 2005; Limsila & Ogunlana, 2008; Toor & Ofori, 2008). In his theory of competitive advantage, Porter (1980; 1985) identified and developed the core competencies required to achieve sustainable competitive advantage. Thus, an optimal competitive strategy must involve three levels of strategic decision-making: organizational, commercial, and functional (Pearce & Robinson, 2007).

Morocco is no exception to the rule; like several countries globally, Morocco has embarked on a process of social and economic digitalization, as evidenced by the technological readiness indices issued by the World Economic Forum. Technological progress at the regulatory, infrastructure, accessibility, and skills levels (Dutta & Lanvin, 2020). Furthermore, the study of the evolution of internet, mobile and social network use in Morocco during the period 2017 to 2020 offers an index of the state of data in circulation in Moroccan society, with penetration rates; The penetration rates of internet, active users in social networks, mobile subscription and active users in social networks via mobile; respectively 69%, 49%, 118% and 46% of the Moroccan population, these effective rates prove the omnipresence of digital in the daily life of the Moroccan citizen (Dataportal, 2017, 2018, 2019, 2020).

The diffusion and popularization of information technologies in recent years means it is no longer critical which technology a firm will adopt but how it will exploit it (Carr, 2004). The Mckinsey Global Institute study indicated a gap of 140,000 to 190,000 people with in-depth analytical skills, as well as 1.5 million managers and analysts capable of analyzing Big Data and making data-driven decisions (De Mauro & Grimaldi, 2016; Manyika et al., 2011).

The emergence of Big Data in the Moroccan economic environment has gained momentum with several public and private initiatives. Firstly, the Haut Commissariat au Plan (HCP), the official institution responsible for statistics, adapted its statistics to technological change through a study on Big Data in 2020. Secondly, several multinationals (IBM, ATOS, SAS, & Microsoft) have joined forces with Moroccan universities through public/private partnerships to support Big Data training courses (Benkaraache & Salam, 2016). The results of the survey on the maturity of Big Data in Morocco presented at the Med-IT trade show reveal the state of market observation by the players. An analysis of the results by sector of activity reveals: a predominance of the public sector with 39%, just fewer than 12% for the Banking and Insurance sector, and 7.5% for the distribution sector (Med-IT, 2016).

Ghanouane and Benkaraache(2022) surveyed Moroccan IT recruitment agencies, showing that 84% of Moroccan companies require a moderate level of Big Data skills, which boils down to performing advanced analyses using specialized software or analysis tools. Furthermore, 63% of the recruitment agencies worked for banks or insurance firms. Of the 24 agencies surveyed, 90% of IT recruitment agencies said they had been approached by Moroccan firms to recruit Big Data profiles. This finding proves that Moroccan firms are increasingly interested in analytical skills to adopt data-driven decision-making. This research paper aimed to determine the impact of analytical skills on the decision-making of Moroccan firms.

2. Theoretical Background

2.1. The resource-based theory

The resource-based theory has been widely used in research on information systems and related fields (Bharadwaj, 2000; Mata, Fuerst & Barney, 1995; Otto, 2015). Research fields have covered: the use value of information to reduce uncertainty in decision-making (Otto, 2015), the cost of production value, and the exchange value of information (Otto, 2015). Thus, information management is seen as a form of resource management (Bharadwaj, 2000; Otto, 2015) or a strategic activity (Otto, 2015). Other authors have focused on the quality of data and how this quality affects the value of information to gain or maintain a competitive advantage (Otto, 2015). Thus factors such as timeliness, format, content, or cost of data impact the value of information (Otto, 2015).

Indeed, the development of Big Data analysis capabilities requires the firm to mobilize material resources (data, technology) and human resources (technical and managerial) (Gupta & George, 2016). Similarly, Kiron et al. (2012) define Big Data analytics capability as the competence to produce information using data management, technology infrastructure, and human skills to improve the competitiveness of firms. The resource-based theory has been used to justify and understand the relative contribution of resource availability and capability involving organizational characteristics, people skills and enabling technology, towards the diffusion of Big Data analytics implementation for effective decision making (Adrian et al., 2018).

2.2. Analytical Skills

A firm's human skills include experience, knowledge, business acumen, problem-solving abilities, leadership qualities, and relationships with other employees (Gupta & George, 2016; Barney, 1991; Ross et al., 1996). Previous research on IT skills has suggested that technical and managerial skills are the critical dimensions of IT human resources (Gupta & George, 2016; Barney, 1991; Ross et al., 1996). In a similar line, this paper proposes Big Data-specific technical and managerial skills as two important aspects of a firm's Big Data analytical skills. Otherwise, Big Data analytics requires new talent and training of internal employees in Big Data-specific technical and managerial skills (McAfee & Brynjolfsson, 2012; Chen et al., 2012).

2.3. Technical Skills

Technical skills include machine learning, data mining, data cleaning, statistical analysis, and understanding programming paradigms such as MapReduce (Gupta & George, 2016; Davenport, 2014; Russom, 2011). Similarly, data scientists need to be comfortable speaking the language of business and helping leaders reformulate their challenges so that Big Data can be addressed (McAfee & Brynjolffson, 2012). Indeed, technical capability involves integrating various analytical tools with other systems in the organization, converting data into information through visualization and reporting systems, and using advanced statistical tools to discover patterns, anticipate trends, and optimize business processes (Batko, 2017; Olszak, 2014).

Extracting useful information from Big Data requires human capabilities. Namely, technical knowledge, including operational systems, statistics, programming languages, and systems for managing the low data (Davenport & Patil, 2012; Ghanouane, 2020). Similarly, the firm should have the technological knowledge specific to Big Data. Ramaswamy (2013) cites the example of Netflix, which leverages a demand visualization and analysis tool to understand consumer behavior and preferences. Furthermore, the team in charge of handling Big Data should know the different functions of the firm and its environment and have relational knowledge to communicate and work with people from other functional teams (Wamba et al., 2016).

2.4. Managerial Skills

While technical skills can be acquired by recruiting new talent or by training employees internally, managerial skills are company-specific and require time to be developed by people working in the same firm (Gupta & George, 2016; Mata et al., 1995). Managerial skills represent tacit knowledge heterogeneously dispersed across firms (Gupta & George, 2016; Mata et al., 1995). In the context of Big Data, the implication of managers is imperative for exploiting the potential of the newly extracted information. Thus, managers need to identify how and where to apply the information extracted by their technical teams (Gupta & George, 2016). In addition, the teams responsible for extracting and analyzing Big Data need to understand the current and future needs of other business units, customers, and partners (Ghanouane & Benkaraache, 2022; Gupta & George, 2016; Mata et al., 1995). For Gupta and George (2016), gaining a competitive advantage from people skills requires mutual trust and a good working relationship between Big Data teams and other functional teams.

Finally, leaders determine the success of a Big Data project by setting clear objectives, asking the right questions, and being present throughout the Big Data implementation process (McAfee & Brynjolffson, 2012).

2.5. The Role of Big Data Analytics in the Decision-Making Process

The decision-making process can be divided into several phases. The first is the intelligence phase, during which internal and external data can be used to identify problems and opportunities. During this phase, Big data must be identified, collected from different sources, processed, stored, and transferred to the end user (Elgendy & Elragal, 2016).

Many authors agree that intensive and innovative use of information as an essential and strategic resource determines business success (Batko, 2017; Olszak, 2016; Webster, 2014; Davenport & Harris, 2017; Erickson & Rothberg, 2013). This resource supports the decision-making processes through the data stored in the business and its environment, and analyzing this data can help create value for the business (Batko, 2017).

This paper examines the impact of Big Data analysis on the decision-making process at strategic, operational, and administrative levels.

2.6. Impact of Big Data Analytics on Strategic Decisions

Reducing uncertainty, anticipating risk, and adapting to change: The Big Data movement has responded to all firms in all sectors; data exists everywhere in production, transportation, consumption, or customer collaboration (Strengell, 2017; Davenport, 2013). Exploiting this mass of data benefits customers on the one hand and the optimization of business decisions on the other (Strengell, 2017; Davenport, 2013; Benkaraache and Ghanouane, 2020). Indeed, integrating different formats of structured and unstructured data combined with predictive and prescriptive models allows for the efficiency of the firms' route network, the reduction of costs, and the reduction of risks (Strengell, 2017; Davenport, 2013; Ghanouane, 2022).

Product and process innovation: Exploiting Big Data provides firms with better knowledge of customer behavior. Thus better meeting customer needs through personalized products and services (Vloet, 2016). Alternatively, measuring customer buying patterns allows firms to determine which methods are most effective in serving customers (McAfee & Brynjolfsson, 2012; Spenner & Freeman, 2012). In addition, Big Data makes process optimization possible, as the firm has more information about processes and the supply chain bottleneck. It can also provide a better understanding of when unnecessary costs occur (Vloet, 2016; Frizzo-Barker et al., 2016 ; Ghanouane, 2022).

Big Data analysis allows product specificities to be integrated into the design of the supply chain structure. Indeed, Big Data analytics improves product adaptability through data on customer purchase records or online purchase behaviours to understand customer requirements (Jin & Liu, 2016).

The originality of Big Data compared to traditional data is to exploit interesting combinations of structured and unstructured data, both internal and external (Bloem et al., 2013). Peristeris and Redzepovic (2015) cite the case of data collected from a telecommunications company, and a financial services institution can enable the innovation of a new product or service suited to a completely different market. Similarly, the emergence of Big Data has enabled the emergence of new firms whose business is creating and exploiting new types of data for commercial purposes using social networks (Davenport, 2013).

Improving customer knowledge: Big Data analytics can detect the demand signal, determine optimal prices, track consumer loyalty, detect new market trends, and determine the root causes of failures, problems, and defects (Tiwari et al., 2018). Similarly, Big Data analysis could support business service innovation by predicting customer behavior (Tiwari et al., 2018). Similarly, the models developed can predict future customer demands based on the data, which leads to less intuition-based decisions (McAfee & Brynjolfsson, 2012).

In addition to predicting future customer behavior, Big Data analysis provides insight into the customer situation. This way, the company can address specific customer needs through closer customer segmentation, leading to customer-centric sales activities (Vloet, 2016).

Thus, we hypothesize that:

H1: Analytical skills will have a positive impact on the effectiveness of strategic decisions

2.7. Impact of Big Data Analytics on Operational and Administrative Decisions

Cost control, optimization, and mobilization of resources: Big Data also offers benefits through increased margins and profits - for example, den Boar (2015) cites dynamic pricing to better coordinate supply and demand and position itself against the competition. Thus, based on the number of visits or the number of purchases, the firm lowers or raises its prices to obtain higher margins on sales (Vloet, 2016). Otherwise, adopting Big Data has the advantage of cost reduction by achieving economies of scale and scope. Cost reduction also comes through a learning and education environment, thus enabling employees to perform tasks more efficiently (Sharma, 2016).

In addition, Big Data enables human resource structures to access all relevant information and communicate with every employee, no matter where they are (Scholz, 2017). In addition, Big Data management offers possibilities in the field of recruitment to assist in the search for candidates and provide information on the recruitment process (Scholz, 2017; Armstrong, 2014).

Increasing productivity: Big Data analytics can support supplier selection and management decisions, and provide accurate information on firm spending patterns, return on investment (ROI), and in-depth analysis of potential suppliers (Tiwari et al., 2018; Panchmatia, 2015). Similarly, predictive and prescriptive analysis of Big Data can help solve planning problems, improve transportation capabilities and provide seamless supply chain integration (Tiwari et al., 2018; Mehmood & Graham, 2015; Burnson, 2013).

At the production level, Big Data analytics can support logistics planning and scheduling on the factory floor, anticipate production, and design intelligent systems to improve production efficiency (Tiwari et al., 2018; Zhong et al., 2015; Stich et al., 2015). Indeed, the analysis of production data can lead to an optimized use of resources such as time, human resources, and input materials (Peristeris & Redzepovic, 2015). Furthermore, combining production data with data from different functions provides analysts with important information on how to improve effectiveness and efficiency (Peristeris & Redzepovic, 2015).

Thus, we hypothesize that:

H2: Analytical skills will have a positive impact on the effectiveness of operational and administrative decisions

Therefore, we propose a conceptual model (see Figure 1) with three key variables:

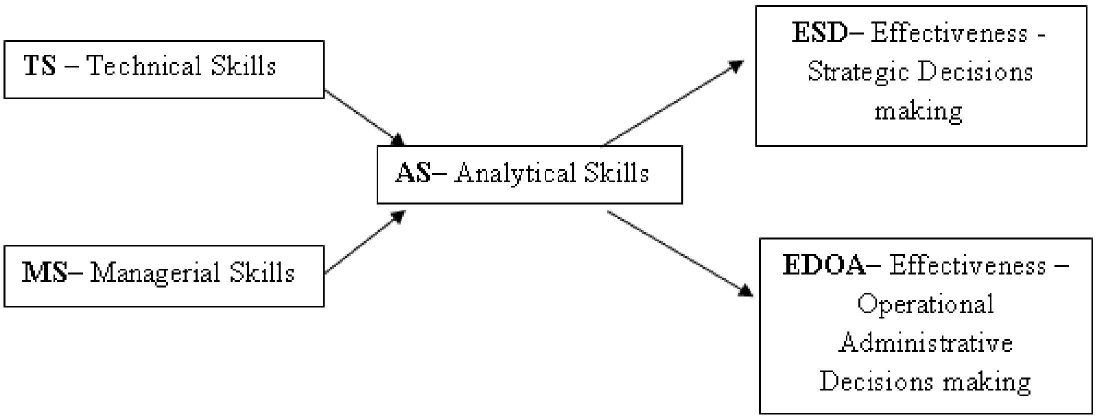

Figure 1. Conceptual framework of this study

3. Research Methodology

3.1. Research design

To test our conceptual model, a questionnaire survey is the appropriate type of research to achieve this objective.

3.2. Population and sample of the study

219 Moroccan firms were identified as the sampling frame. The respondents are "Data" profiles operating in different sectors of the Moroccan economy. Our questionnaire was sent electronically to "Data" profiles during the period from 08/06/2021 to 13/07/2021; only 49 were retained for analysis on the SMART PLS software (i.e., a sampling rate of 41%).

3.3. Sampling technique

We chose a non-probability quota sampling technique to ensure the diverse representation of samples. Chin (1998) sets the sample size; to optimize the partial least squares (PLS) method; to the number of predictors involved in the multiple regressions in the inner and outer approximation. Otherwise, it is a matter of:

- Identify the block with the largest number of manifest variables and count them; in our model, the maximum manifest variables per block are of order 4.
- Identify the endogenous latent variable with the largest number of exogenous latent variables and count them; in our model, this number is of order 2.
- And to take the maximum of two numbers and multiply it by ten to get the minimum sample size. Thus, our model should have a minimum size of 40 firms.

3.4. Source of data collection

In addition, we introduced our electronic survey approach, the development of the survey, and our sampling frame based on our LinkedIn database; created in 2018; to identify Moroccan firms that have adopted Big Data analysis.

3.5. Instrument of data collection

We have designed a questionnaire based on information from the literature reviewed. The questionnaire includes the following:

A section on technical skills with the measures:

Table 1. Measures of Technical skills

ID	Questions	Authors
TS1	We have a sufficient number of competent data analysis staff to achieve our analysis objectives.	(McAfee and Brynjolfsson, 2012), (Davenport et al., 2014) (Wamba et al., 2016), (Guptaa & Georgeb, 2016)
TS2	Our data analysis team acts as trusted consultants to our executive managers for crucial decisions and data-driven innovation.	
TS3	Our data analytics team understands the business processes to which Big Data and analytics apply.	
TS4	Our data analytics team operates effectively in teams to handle Big Data analytics projects.	

A section on managerial skills with the measures:

Table 2. Measures of Managerial Skills

ID	Questions	Authors
MS1	Our executive managers regularly explore the opportunities that Big Data and analytics capabilities could bring to our business.	(McAfee & Brynjolfsson, 2012), (Davenport et al., 2014) (Wamba et al., 2016), (Guptaa & Georgeb, 2016)
MS2	Our executive managers challenge business units and functional leaders to integrate Big Data and analytics capabilities into their business processes and decision-making.	
MS3	Non-executive managers use Big Data analytics capabilities to drive their decisions.	
MS4	Our process for prioritizing and deploying our Big Data resources (data, human resources, technology) is driven and reviewed by management.	

A section on effectiveness of strategic decision making with the measures:

Table 3. Measures of effectiveness of strategic decision making

ID	Questions	Authors
SD1	Develop new product and service offerings based on the data.	(McAfee & Brynjolfsson, 2012), (Chen et al 2012), (George et al, 2014), (Davenport, et al, 2014), (Zhong et al, 2015), (marr et al, 2015), (Ji-fan Ren et al, 2016), (Wamba et al, 2016), (Erevelles et al, 2016), (Wang et al, 2016), (Kitchin, 2017).
SD2	Better predictions and thus better decisions.	
SD3	Optimisation of product or service prices.	
SD4	Better forecasting of consumer needs and feelings, thus better market segmentation.	

A section on effectiveness of Operational and Administrative decision making with the measures:

Table 4. Measures of effectiveness of Operational and Administrative decision making

ID	Questions	Authors
OAD1	Reduction in the cost of implementing Big Data technologies compared to traditional technologies.	(McAfee & Brynjolfsson, 2012), (Chen et al 2012), (George et al, 2014), (Davenport, et al, 2014), (Zhong et al, 2015), (marr et al, 2015), (Ji-fan Ren et al, 2016), (Wamba et al, 2016), (Erevelles et al, 2016), (Wang et al, 2016), (Kitchin, 2017).
OAD2	Productivity: reduction in the time needed to complete specific core business processes.	

The measurement instruments were structured in the modified Likert method, on a 5 – point scale, ranging from “strongly agree”, through “agree”, "neither disagree nor agree", “disagree” to “strongly disagree”. Firms were then instructed to respond to their degree of agreement with the statements contained in the instrument.

3.6. Data analytical procedures

The complex nature of organizational behavior research reflected in this study requires a model that accommodates a large number of variables and nested constructs, whereby the partial least squares analysis approach is most appropriate (Hair et al., 2017). Similarly, the PLS approach is appropriate for causal-predictive analysis that maximizes the variance explained in the dependent variables (Anderson and Gerbing, 1988; Hair et al., 2017). Thus, this approach is justified for our study, which seeks to predict the significance of the relationship between analytical skills and decision-making effectiveness within the firm.

In the figure below, we present our conceptual model in the form of the partial least squares (PLS) method using the SMART PLS 3.0 software.

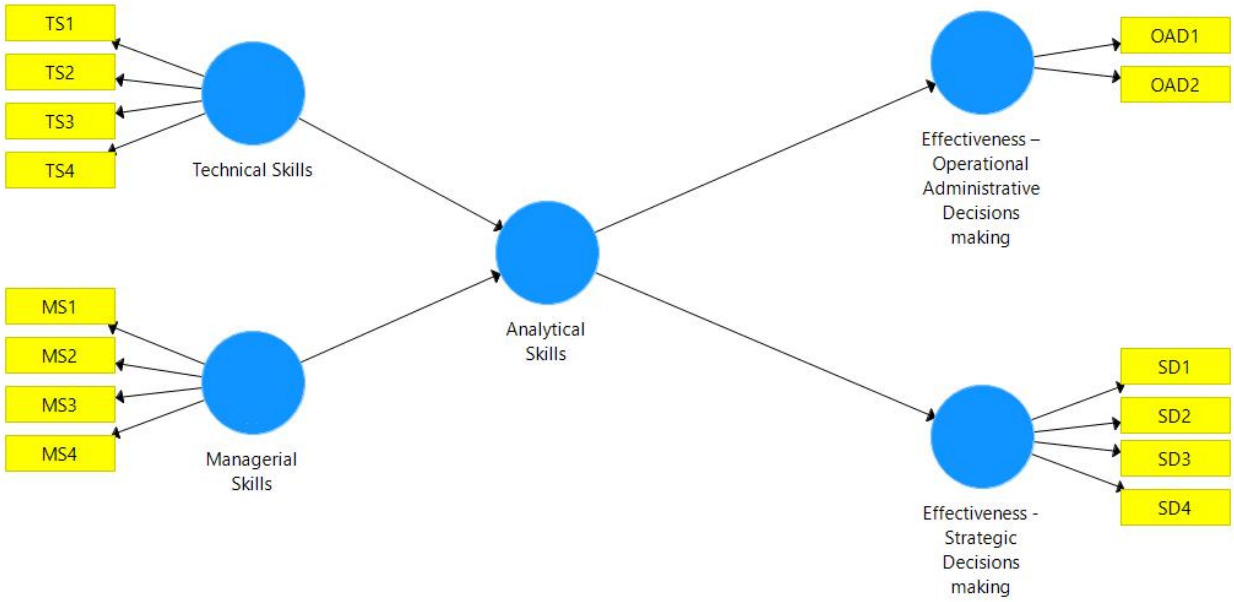

Figure 2. Conceptual framework under SmartPls

4. Research Results

4.1. Respondents

The respondents are as follows: 82% are from the Information Technology, Professional Services, and Finance and Insurance sectors, with 41%, 27%, and 24% of the respondents, respectively (see Figure 3).

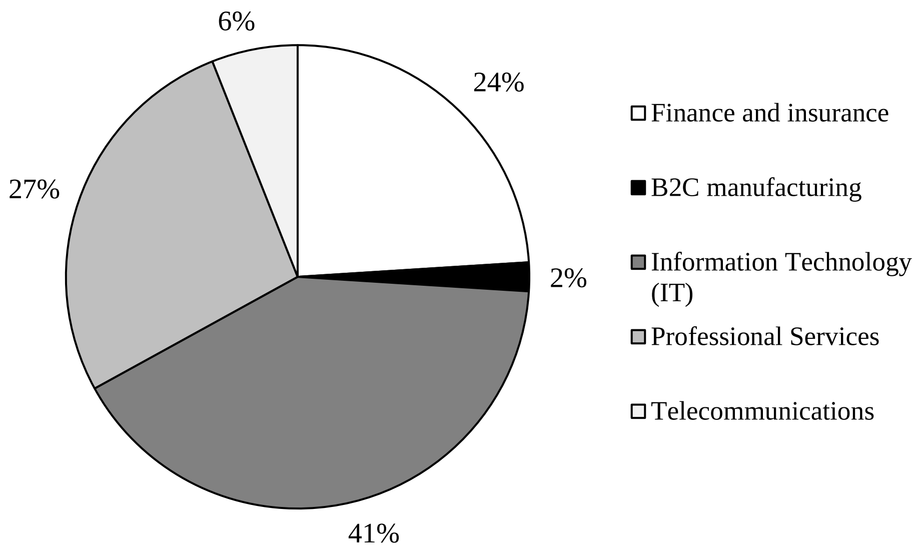

Figure 3. Distribution of respondents by sector

4.2. Assessment of the reflective measurement model

Convergent validity analysis (see Table 5) indicates; that each indicator through external charges confirms; the saturation of all indicators being above the 0.7 thresholds, except for the ST1 and ST3 indicators being close to this level. Furthermore, Chin (1998) states that values must be significant at the 0.05 and above 0.70 levels.

The analysis of the composite reliability for all the constructs is higher than 0.6. The measure of internal consistency via Cronbach's Alpha indicates that all the constructs have excellent reliability with values higher than 0.6. Finally, the average variance extracted (AVE) for all constructs meets the requirement of a minimum of 0.5.

Table 5. Summary of results for the reflective measurement model.

Construct	Indicator	Outer Loadings	Composite Reliability	Cronbach's Alpha	Average Variance Extrated (AVE)
		>0.70	0.60-0.90	0.60-0.90	>0.50
Technical Skills	ST1	0.63	0.79	0.65	0.50
	ST2	0.75			
	ST3	0.60			
	ST4	0.81			
Managerial skills	MS1	0.81	0.88	0.81	0.64
	MS2	0.79			
	MS3	0.83			
	MS4	0.77			
Strategic decisions making	SD1	0.84	0.90	0.85	0.69
	SD2	0.79			
	SD3	0.87			
	SD4	0.81			
Operational and Administrative decisions making	OAD1	0.96	0.93	0.85	0.87
	OAD2	0.91			

Discriminant validity tends to check whether the indicators have a higher factor load with the same construct than the other constructs (see Table 6). This validity is verified for all reflective constructs. Furthermore, the square root of the mean of the extracted variance (AVE) for each construct is higher than the inter-construct correlation (see Table 7). Thus, we can conclude that the reflexive model provides satisfactory reliability and convergent validity.

Table 6. Cross-factor loadings and construct reliability

	Technical Skills	**Managerial skills**	**Strategic decisions making**	**Operational and Administrative decisions making**
MS1	0.54	0.81	0.45	0.53
MS2	0.50	0.79	0.42	0.37
MS3	0.43	0.83	0.37	0.48
MS4	0.49	0.77	0.51	0.44
TS1	0.63	0.41	0.06	0.00
TS2	0.75	0.50	0.49	0.24
TS3	0.60	0.43	0.20	0.38
TS4	0.81	0.45	0.17	0.33
OAD1	0.38	0.60	0.49	0.96
OAD2	0.23	0.43	0.53	0.91
SD1	0.40	0.46	0.84	0.37
SD2	0.18	0.40	0.79	0.41
SD3	0.27	0.48	0.87	0.52
SD4	0.25	0.47	0.81	0.50

Table 7. Correlation matrix of reflexive constructs.

	Technical Skills	**Managerial skills**	**Strategic decisions making**	**Operational and Administrative decisions making**
Technical Skills	0.70			
Managerial skills	0.61	0.80		
Strategic decisions making	0.34	0.55	0.83	
Operational and Administrative decisions making	0.34	0.57	0.54	0.93

4.3. Evaluation of the formative measurement model

The analysis of the validity of the formative constructs (see Table 8) does not reveal any multicollinearity problem in the results (all VIF are less than 5). Similarly, the bootstrapping procedure confirms that all indicators contribute to their construct.

Table 8. Validity analysis of the formative constructs

Construct	**ID**	**VIF**	**Outer weights (Outer loadings)**	**Construct**	**ID**	**VIF**
Analytical Skills	TS1	1.98	0.10 (0.52)	2.59	0.00	Yes
	TS2	1.64	0.18 (0.66)	7.48	0.00	Yes
	TS3	1.50	0.13 (0.49)	3.14	0.00	Yes
	TS4	2.18	0.16 (0.63)	5.78	0.00	Yes
	MS1	1.89	0.23 (0.78)	7.55	0.00	Yes
	MS2	2.03	0.21 (0.75)	7.56	0.00	Yes
	MS3	2.57	0.21 (0.75)	7.14	0.00	Yes
	MS4	2.35	0.22 (0.74)	6.91	0.00	Yes

The validity analysis of the reflective and formative constructs of the measurement model was conclusive with satisfactory levels of quality. Thus, we can proceed to the evaluation of the structural model.

4.4. Structural model and hypothesis testing

Measurement of Coefficient of Determination and predictive relevance: The analysis of the explained variances of the latent variables with their total value through the calculation of the Coefficient of Determination (see Table 9) shows solid values for the variable "analytical skills." The coefficient of determination for the variables "effectiveness of strategic decisions" and "effectiveness of operational and administrative decisions" is moderate according to the standard of Chin (1998).

The Q^2 statistic is positive for all latent variables in the structural model. These results confirm the predictive relevance of our structural model.

Table 9. Estimation of the coefficients of determination and predictive relevance

Latent variables	**R^2**	**R Square adjusted**	**Q^2**
analytical skills	0.94	0.93	0.41
Strategic decisions making	0.41	0.39	0.23
Operational and Administrative decisions making	0.38	0.37	0.30

Measuring Path Coefficients and Effect Size: Our model shows significant path coefficients and effect sizes between the variable "analytical skills" and the variables "effectiveness of strategic decisions" and "effectiveness of operational and administrative decisions." These high values are evidence of significant impact (see Table 10).

Table 10. Estimation of path coefficients between latent variables

Variables latentes	Analytical skills	
	Path coefficients	**Effect sizes**
Strategic decisions making	0.64	0.68
Operational and Administrative decisions making	0.62	0.62

Hypothesis testing: The bootstrapping procedure provided a significance level for each hypothesized relationship (see Table 11).

Table 11. Estimation of the parameters of the causal model by the bootstrapping procedure.

N°	Hypotheses	β (Correlation coefficient)	t-Student (Bootstrap)	P value	Significant
H1	Analytical skills will have a positive impact on the effectiveness of strategic decisions making	0.71	7.74	0.00	Accepted
H2	Analytical skills will have a positive impact on the effectiveness of operational and administrative decisions making	0.72	7.78	0.00	Accepted

The analysis of the bootstrapping report allows us to verify that all the hypotheses are confirmed with significant correlation coefficients.

5. Discussion of findings

To empirically validate our conceptual model, we employed the partial least squares approach using Smart PLS 3 software. We began by validating the measurement models for the reflective and formative constructs. This validity analysis was conclusive, demonstrating satisfactory levels of quality. Furthermore, the evaluation of the structural model confirmed the absence of critical problems related to collinearity between the latent variables. Similarly, the validity of the model was meticulously checked, considering coefficients of determination, path coefficients, effect size, and predictive relevance. Finally, the bootstrapping method was utilized to validate all our initial hypotheses. These steps underscore the significance of analytical skills within Moroccan companies in optimizing decision-making effectiveness.

Drawing on the resource-based theory (RBT) approach, this study seeks to decipher the contribution of Big Data analysis. While many contributions from Big Data practitioners have enriched the literature, they have predominantly focused on the technical aspects of the field (Gupta & George, 2016). This research fills this gap by highlighting the crucial importance of human, technical, and managerial dimensions in the development of analytical skills, which are indispensable for data-informed decision-making.

Focusing on Moroccan companies, this study is situated within a global context where the development of analytical skills holds vital importance for strategic decision-making. These skills contribute to creating new products or services based on data, enhancing prediction and optimization of products or services, and gaining a better understanding of consumer needs (Ji-fan Ren et al, 2016; Wamba et al, 2016; Erevelles et al, 2016; Wang et al, 2016; Kitchin, 2017). Moreover, bolstering analytical skills within Moroccan companies enhances operational decision-making, resulting in cost reductions and heightened productivity (Ji-fan Ren et al, 2016; Wamba et al, 2016; Erevelles et al, 2016; Wang et al, 2016; Kitchin, 2017).

However, it is worthwhile to go beyond this internal analysis and contextualize our results in relation to similar research. Compared to prior research conducted by Gupta and George (2016) and Ji-fan Ren et al. (2016) in similar contexts, our findings demonstrate a more robust correlation between analytical skills and improved decision-making in Moroccan firms. While Gupta and George (2016) observed positive yet moderate relationships, our results reveal a significantly stronger association between these variables. Likewise, our results deviate from those of Ji-fan Ren et al. (2016), who suggested that analytical skills might exert lesser influence on strategic decision-making. Conversely, our study highlights a potent relationship between these skills and decision-making effectiveness, thereby underscoring their indispensable role in the distinct context of Moroccan companies. These disparities could stem from cultural nuances, business practices, or economic policies specific to each context, emphasizing the necessity of considering contextual factors in future research.

5.1 Practical implications of the study

In the context of Moroccan companies, the successful application of analytical skills and Big Data can indeed play a key role in enhancing decision-making and operational performance. The findings of this study suggest that companies can adopt the following approaches to leverage these skills:

Optimizing Decision-Making Strategy: By cultivating robust analytical skills, companies can gather, analyze, and interpret available data to make more informed, evidence-based decisions. This involves employing advanced data processing techniques to uncover trends, patterns, and opportunities that might have previously gone unnoticed.

Personalizing the Customer Experience: Through the utilization of customer data, companies can construct detailed profiles and specific segments, enabling a higher degree of personalization in products, services, and interactions. This has the potential to result in heightened customer satisfaction and loyalty.

Improved operational efficiency: Analytical skills can be used to optimize operational processes, reduce inefficiencies and minimize costs. For example, predictive analytics can help forecast product demand, enabling companies to manage inventory efficiently.

Identifying growth opportunities: By analyzing market data and consumer behavior, companies can identify new growth opportunities, develop new products or services, and enter new markets.

Proactive risk management: Analytical skills can help companies anticipate and manage potential risks by analyzing relevant data. This can include the early detection of negative market trends or the identification of risk factors within the company.

Enhanced competitiveness: Companies that invest in the development of analytical skills and Big Data can gain a competitive edge by making more informed decisions and remaining agile in an ever-changing business environment.

In summary, Moroccan companies can apply analytical skills and Big Data to transform their approach to decision-making, improve their operational performance and maintain their competitiveness in the market. Drawing on the lessons learned from this study, they can craft context-specific strategies and embark on initiatives aimed at fortifying these skills within their teams.

6. Conclusion

In conclusion, this study aimed to explore the contribution of Big Data analytics using a Resource-Based Theory (RBT) approach. Throughout the study, we examined the impact of developing analytical skills on decision-making at strategic and operational levels within Moroccan firms. Our results showed that the development of analytical skills improves decision-making.

By achieving these objectives, our study provides valuable insights into the role of analytical skills in exploiting Big Data for decision-making in the Moroccan context. These results imply that organizations should focus not only on the technical aspects of Big Data but also on developing the human and managerial capabilities needed to make effective use of the available data.

In light of the results, we can conclude that the study successfully achieved its objectives of highlighting the importance of human, technical, and managerial dimensions in Big Data analysis. The results underline the importance of fostering a holistic approach to data-driven decision-making, taking into account both technical expertise and the development of analytical skills.

Overall, this study highlights the need for organizations to prioritize the development of analytical capabilities and adopt a holistic approach to effectively harnessing Big Data. The findings contribute to the existing body of knowledge on Big Data analytics and provide practical implications for companies looking to harness the potential of data-driven decision-making in the Moroccan market.

6.1 Limitations and future research

This work does not explore the concepts of 'information quality' and 'organizational capability in depth to measure their impact on firm decision-making. Therefore, future research can exploit the profound relationship between quality dynamics, organizational capabilities, and decision-making.

As our hypothetical model is limited to the Moroccan context, further research is needed to test the ability of the implications of this work to be generalized to other regions and groups of senior managers.

Based on a quantitative study, the results of this work need to be further investigated at the level of each sector to understand better how a Big Data information processing capability functions as a capability/dynamic and its role in business strategy and decision making.

In addition, the qualitative study with case studies would allow for an in-depth analysis of data integration mechanisms within the firm. The principle of triangulation would enable the perception of executive managers and functional teams of data and its contribution to the achievement of their objectives to be identified. Similarly, the qualitative study could target industrial firms, thus enabling an in-depth analysis of Big Data integration at either the production or supply chain level.

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