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Brahmi Chrifa

University of sfax

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Author: University of sfax, Faculty of Economics and Management, Tunisia, Boujelbenne Younes.

I. INTRODUCTION

In a context of globalization and increased competition, must navigate in increased decision-making complexity. The emergence of big data offers a revolutionary opportunity by enabling unprecedented collection and analysis of information. These data from various sources help to identify trends, predict consumer behavior, and optimize real-time transactions. However, their effective use to improve the quality and effectiveness of decisions remains a challenge. This research explores how big data influences decision-making performance by examining their impact on the accuracy and relevance of decisions, as well as the reduction in the time needed to make them. The research includes a review of the literature, the presentation of a theoretical framework, the methodology used and a results analysis to provide practical and theoretic recommendations on the use of big data in decision-making.

II. LITERATURE REVIEW

Big Data refers to large and complex data sets that are beyond the processing capabilities of traditional data management tools. They are characterized by "4 V": Volume (massive amount of data), Variety (diversity of data types), Speed (speed of data generation and processing), and Veracity (quality and reliability of data). With technological advances, Big Data is increasingly integrated into enterprise management systems, providing valuable insights for decision-making.

Quality decisions are crucial to the success of, directly influencing their performance, competitiveness and profitability. A quality decision is based on accurate, relevant and well-analysed information, enabling informed choices in line with strategic objectives. Decision-making efficiency, on the other hand, involves speed and competence in making and implementing decisions while optimizing available resources.

Big Data provides a strategic advantage by enabling in-depth analysis of trends and providing valuable insights to anticipate needs and assess risks. They can improve the quality and effectiveness of decisions, but their impact depends on factors such as technological capabilities and data management. This review examines how Big Data influences these aspects, based on research and best practices.

2.1. Impact of Big Data on Decision Quality

Big data has a significant impact on the quality of business decisions. According to McAfee and Brynjolfsson (2012), using big data improves productivity by 5% and profitability by 6% by providing increased information accuracy, which reduces errors and enables more factual decision-making. Provost and Fawcett (2013) show that big data analysis reduces uncertainty by improving predictions of consumer behavior and market trends, thereby facilitating more effective risk management.
Davenport and Dyché (2013) emphasize that big data enables greater personalization of decisions, which improves customer satisfaction and loyalty. For example, Amazon uses this data to recommend products, thereby increasing the relevance of suggestions and conversion odds. Furthermore, Lavalle et al. (2011) found that leading analytics companies are 50% more likely to see an improvement in their strategic decision-making through big data.

Kiron et al. (2014) find that 60% of companies with a well-defined big data strategy see a noticeable improvement in their decision-making, identifying new opportunities and optimizing internal processes. Sun et al. (2018) emphasize that strong analytical capabilities transform data into exploitable information, leading to more precise decisions. Finally, Chen, Chiang, and Storey (2012) show that big data enables a more proactive and predictive approach, thereby improving the overall quality of business decisions. In short, integrating big data increases accuracy, reduces risks, and optimizes decision-making customization, thereby contributing to better competitiveness and performance in the market.

2.2. Impact of Big Data on Decision Efficiency

Big data has a profound impact on decision-making quality. According to McAfee and Brynjolfsson (2012), companies that use data to guide their decisions are on average 5% more productive and 6% more profitable than their competitors. This improvement in data accuracy enables more reliable decision-making by identifying trends and correcting anomalies, which is essential to remain competitive in a dynamic environment.

Provost and Fawcett (2013) have demonstrated that big data analysis helps to anticipate consumer behaviour and market trends, thereby reducing uncertainty and decision-making risks. Machine learning algorithms, applied to large data sets, detect hidden patterns, facilitating more informed decisions and uncertainty management.

Davenport and Dyché (2013) emphasize that customization of offers, made possible by big data, improves customer satisfaction and loyalty. For example, Amazon uses data to recommend products based on purchase histories, increasing the relevance of suggestions, and optimizing marketing strategies. Lavalle et al. (2011) reveal that leading analytics companies are 50% more likely to see direct improvement in strategic decision-making through big data. Kiron et al. (2014) add that 60% of companies with a well-defined big data strategy see a noticeable improvement in decision-making, identifying new opportunities and optimizing internal processes.

Finally, Sun et al. (2018) highlighted the importance of analytical capabilities in improving decision quality. Companies with strong analytical capabilities are more efficient in turning data into exploitable information, leading to more precise decisions. Chen, Chiang, and Storey (2012) show that big data transforms the perception of and their interaction with their environment, adopting a more proactive and predictive approach. In short, big data enables to benefit from greater accuracy, reduce risks and improve decision-making personalization, thereby enhancing their competitiveness and market performance.

2.3. The Factors Moderators and Mediators

Technological analytical capabilities influence the impact of Megadata on decision-making. McAfee and Brynjolfsson (2012) show that systems with high connectivity, compatibility, and modularity enable efficient real-time integration and analysis of Megadata, providing consistent, quick overview for informed decisions. Chen et al. (2012) emphasize that advanced technologies improve responsiveness and strategic agility by processing large amounts of data.

Big Data management, including planning, investment, coordination and control, is crucial. Davenport and Harris (2007) reveal that companies that invest in robust infrastructure and coordinate data analysis effectively better results. LaValle et al. (2011) add that rigorous management reduces costs and improves the accuracy of forecasts. Knowledge in technology management, such as operational, relationship, and managerial knowledge, is essential to exploiting Megadata. Bharadwaj (2000) emphasizes the importance of operational skills in turning data into useful information, while Wamba et al. (2017) show that companies with a strong technological management base benefit from a competitive advantage.

Finally, analytical capacity and strategic alignment are crucial. Kiron and Shockley (2011) show that companies with high analytical capacity improve the quality of decisions. Gupta and George (2016) show that alignment of analytical capabilities with strategic objectives optimizes performance and decision-making effectiveness. In conclusion, technological capabilities, data management, and strategic alignment moderate and mediate the impact of Big Data on decision-making. To make the most of it, companies need to build robust capacities, invest in efficient management, and align analytical initiatives with their strategic goals.

2.4. Theoretical framework and assumptions

Big data refers to large and complex data sets that cannot be processed by traditional data management techniques. In the business context, the use of big data is often analyzed through the prism of various decision-making theories. Herbert Simon (1972) introduced the concept of limited rationality to describe the cognitive limitations of decision makers. According to this theory, individuals seek to make rational decisions but are limited by the information available, their cognitive abilities, and the time at their disposal. In the context of big data, this theory suggests that access to a massive amount of data can potentially mitigate some of these limitations by providing more complete and accurate information for decision-making. According to this theory, we reformulate the first hypothesis:

H1: The use of big data improves the quality of business decision-making.

Data-Driven Decision Making (DDDM) is based on the systematic use of data and analysis to inform organizational decisions (Provost & Fawcett, 2013). Companies that adopt a DDDM approach tend to perform better because their decisions are based on empirical evidence rather than on intuition or past experience. According to this theory, we reformulate the second hypothesis as follows:

H2: Big data exploitation increases business decision-making efficiency.

The use of big data can improve the quality of business decision-making by providing more accurate and relevant information. Studies show that big data-based predictive and descriptive analysis enables to anticipate market trends, understand consumer behaviour, and optimize their strategies (Chen, Chiang & Storey, 2012). So we re-formulate the following assumption:

H3: Companies with advanced technology capabilities in big data analysis benefit from better decision-making performance.

Big data can also increase decision-making effectiveness by automating and optimizing decision making processes. Integrating big data into enterprise information systems reduces the time required to analyze information and make decisions, thereby improving operational efficiency (Davenport & Dyché, 2013). Based on this idea, we reformulate the last assumption:

H4: The use of big data reduces the time it takes to make decisions.

By formulating these assumptions, the research aims to clarify how big data can transform decision-making within by improving both the quality and effectiveness of decisions. This in-depth understanding can help better integrate big data into their strategies and maximize the benefits derived from these valuable information resources.

III. RESEARCH METHOD

This study adopts a quantitative approach to assessing the impact of big data on business decision-making performance, focusing on the quality and effectiveness of decisions. The research includes a major phase of data collection and analysis through questionnaires administered to decision-makers from companies in various industries. The sample targeted approximately 170 managers from companies of varying sizes operating in areas such as finance, retail, and information technology.

The structured questionnaire uses Likert questions and scales to gather respondents' perceptions of the impact of big data. Questions address aspects such as the infrastructure of big data, the use of predictive and descriptive analysis, and the speed and accuracy of decision-making. The data collected will be analyzed using statistical methods, including descriptive analysis to characterize the sample and multivariate analysis to test research assumptions. Techniques such as Core Component Analysis (CCA) and Linear Regression will be used to assess the relationships between big data usage, decision quality, and decision effectiveness.

IV. ANALYSIS AND INTERPRETATION OF RESULTS

In this section, we present and analyze the results of our research on the impact of big data on business decision-making performance. The main objective is to examine how the use of big data affects the quality and effectiveness of business decision-making. Based on the previous assumptions, we analyze the data collected through questionnaires administered to policymakers in various sectors. This analysis will be carried out in several stages, using rigorous statistical methods such as Core Component Analysis and Multiple Linear Regression, to provide an in-depth understanding of the relationship between big data adoption and decision-making performance. The results will be interpreted in the light of existing theories and current practices, highlighting the practical implications for companies seeking to optimize their decision-making process through big data.

4.1. Main component analysis

Principal Component Analysis (CPA) is a statistical method used to reduce data dimensionality whileining the maximum possible variance. As part of this study, the CAP was applied to identify the main underlying dimensions that characterize the technological capabilities of companies to analyze big data. This method simplifies the complexity of the data collected and reveals the key structures that influence decision-making performance. By reducing the many initial variables to a narrower set of core components, CPA facilitates the interpretation of the relationships between the different dimensions of technological capabilities and their impact on the quality and effectiveness of decisions taken. The results of this analysis will provide valuable insights into key factors that need to be optimized to improve decision-making performance using big data.

4.1.1. Technological capacity for big data analysis

Table 1 presents the results of the analysis of technological capacity using various statistical methods. For CTAMCN technology capacity, the highest observed correlation is between CTAMCN 1 and CTAMCCN 2, with a coefficient of 0.850, indicating a strong positive relationship between these two variables. On the other hand, the lowest correlation is observed between CTAMCN 5 and CTAMNC 8, with a coefficient of 0,034, suggesting that there is almost no relationship between these variables. The KMO (Kaiser-Meyer-Olkin) index for this technological capacity is 0.731, indicating an average sample suitability for factor analysis. The Bartlett test, with an approximate Khi-two value of 1115,068, a degree of freedom of 28, and a significance of 0,000, confirms the relevance of the factor analysis by rejecting the null hypothesis of the identical correlation matrix.

For the CTAMCM technology capacity, the highest correlation is noted between CTAAMCM 1 and CTAMCM 6, with a coefficient of 0.843, showing a strong positive relationship. The lowest correlation, 0.466, was found between CTAMCM 7 and CTAMCC 3, indicating a moderately weak relationship. The KMO index for CTAMCM is 0.775, indicating that the sample is well suited for factor analysis. Bartlett's test shows an approximate Khi-two value of 1175,719, with 21 degrees of freedom and a significance of 0,000, thus validating the use of factor analysis.

Table 1: Correlation Matrix, KMO Index and Bartlett Test

Technological Capacity	Correlation Matrix		KMO Index	Bartlett test (approximately K-two)	ddl	Meaning of Bartlett
	Higher correlation	Lower Correlation				
CTAMCN	CTAMCN 1 and CTAMCN 2 (0,850)	CTAMCN 5 and CTAMCN 8 (0,034)	0,731	1115,068	28	0,000
CTAMCM	CTAMCM 1 and CTAMCM 6 (0,843)	CTAMCM 7 and CTAMCM 3 (0,466)	0,775	1175,719	21	0,000
CTAMM	CTAMM 4 and CTAMM 6 (0,843)	CTAMM 1 and CTAMM 7 (0,479)	0, 826	1163,166	21	0,000

For the CTAMM technological capacity, the highest correlation is observed between CTAAMM 4 and CTAM 6, with a coefficient of 0.843, meaning a strong positive relationship. The lowest correlation is 0.479, between CTAMM 1 and CTAMM 7, indicating a moderately weak relationship. The KMO index for CTAMM is 0.826, which shows a very good suitability of the sample for factor analysis. Bartlett's test shows an approximate Khi-two value of 1163,166, with 21 degrees of freedom and a meaning of 0,000, reinforcing the validity of the factor analysis for this technological capacity.

These results show adequate KMO indices and significant Bartlett tests for all evaluated technological capabilities, suggesting that the data is appropriate for factor analysis. The correlations vary depending on the capacity, indicating variable relationships between the different elements analyzed.

Table 2 presents the results for representation quality and explained total variance for three technology capacity categories: CTAMCN, CTAMCM and CTAMM. Each technological capacity was analyzed in terms of initial representation quality, post-extraction representation, and total variance explained by the main components. For CTAMCN technology capability, the initial rendering quality is perfect (1,000). After extraction, the highest representation quality is obtained for the CTAMCN element 4 (0,877), while the lowest performance quality is observed for CTAMNC element 1 (0,745). The initial own values for component 1 are 3,535, explaining 44.183% of the total variance. Component 2 has initial own values of 2,847, explaining 35,587% of the total variance.

Table 2: Representation Quality and Explained Total Variance

Technological Capacity	Initial Representation Quality	Extraction representation quality		Total Variance Explained			
				Composer 1		Composer 2	
		Higher	lower	Initial own values	% of variance	Initial own values	% of variance
CTAMCN	1,000	CTAMCN 4 (0,877)	CTAMCN 1 (0745)	3,535	44,183	2,847	35,587
CTAMCM	1,000	CTAMCM 6 (0,812)	CTAMCM 3 (0,572)	5,011	71,584	-	-
CTAMM	1,000	CTAMM 6 (0,827)	CTAMM 7 (0,464)	5,192	74,167	-	-

For CTAMCM technology capability, the initial rendering quality is also perfect (1,000). After extraction, CTAMCM element 6 has the highest representation quality (0,812), while CTAM CM element 3 has the lowest. (0,572). The initial own values for component 1 are 5.011, explaining 71.584% of the total variance. There is no second component for CTAMCM.

With regard to CTAMM technology capability, the initial representation quality is once again perfect (1,000). After extraction, CTAMM element 6 shows the best representation quality (0,827), while CTAM M element 7 has the lowest quality (0,464). The initial own values for component 1 are 5,192, explaining 74,167% of the total variance. There is no second component for CTAMM.

The CTAMCM and CTAMM technology capabilities have a higher total variance explained by their first component compared to CTAMCN. In addition, the initial rendering quality is perfect for all technological capabilities, but after extraction, some differences appear between the different elements.

4.1.2. Big data management analytical capabilities

Table 3 presents the correlation matrix, the KMO index (Kaiser-Meyer-Olkin) and the Bartlett test to evaluate the analytical capabilities of big data management. For each capacity, the highest and lowest correlations between the items are indicated, as well as the results of the statistical tests.

For Proactive Mega Data Management Analysis Capabilities (CAGMP), the highest observed correlation is between CAGMP 2 and CACMP 4 items with a value of 0.818, whereas the lowest correlations are between CAGE 2 and 5 with a valor of 0.501. The KMO index for this capacity is 0.843, indicating satisfactory sampling adequacy. Bartlett's test is significant with an approximate khi-two of 905,440, 15 degrees of freedom (ddl) and a significance of 0,000.

For Integrative Mega Data Management Analysis Capabilities (IMCG), the highest correlation is 0.884 between IMCG 5 and 8 items, while the lowest is 0.494 between EMCG 2 and 4 items. The KMO index is 0.891, suggesting good sampling adequacy. Bartlett's test is significant with an approximate khi-two of 1513,849, 28 ddl, and a significance of 0,000.

Table 3: Correlation Matrix, KMO Index and Bartlett Test

Big data management analytical capabilities	Correlation Matrix		KMO Index	Bartlett test (approximately K-two)	ddl	Meaning of Bartlett
	Higher correlation	Lower Correlation				
CAGMP	CAGMP 2 and CAGMP 4 (0,818)	CAGMP 2 and CAGMP 5 (0,501)	0,843	905,440	15	0,000
CAGMI	CAGMI 5 and CAGMI 8 (0,884)	CAGMI 2 and CAGMI 4 (0,494)	0,891	1513,849	28	0,000
CAGMCR	CAGMCR 1 and CAGMCR 3 (0,868)	CAGMCR 6 and CAGMCR 8 (0,511)	0, 906	1594,901	28	0,000
CAGMCA	CAGMCA 4 and CAGMCA 6 (0,843)	CAGMCA 5 and CAGMCA 8 (0,466)	0,813	1393,222	28	0,000

The CAGMCR Analysis Capabilities showed a higher correlation of 0.868 between CGMCR 1 and CGC 3 items, and a lower correlation of 0.511 between CGAMCR 6 and 8 items. The KMO index is very good at 0.906. Bartlett's test is also significant with an approximate khi-two of 1594,901, 28 ddl, and a significance of 0,000.

Finally, the highest correlation is 0.843 between CAGMCA 4 and CAGmCA 6 items for the Analytical Capabilities for Ambiguity Data Management (CACMCA), whereas the lowest is 0.466 between CACmCA 5 and CAPMCA 8. The KMO index is 0.813, indicating acceptable sampling adequacy. Bartlett's test is significant with an approximate khi-two of 1393,222, 28 ddl, and a significance of 0,000. In conclusion, the KMO indices and Bartlett tests for all big data management analytical capabilities show that the data is adequate for factor analysis, with significant values and KMO indexes greater than 0.8.

Table 4 presents the representation quality and total variance explained for big data management analytical capabilities (CAGM). The key components extracted show a perfect initial representation (1,000) for all analytical capability sub-categories, namely CAGMP, CAGMI, CACMCR, and CAGMCA. The quality of representation after extraction varies according to the indicators for each component. For the CAGMP component, the initial representation quality remains at 1,000, with the highest representative quality for CAGMP 6 (0,844) and the lowest for CACMP 5 (0,599). The total variance explained by component 1 is 74,911%. The CAGMI component also shows an initial rendering quality of 1,000, with CAGMI 8 having the highest rendering Quality (0,874) and CAGMI 2 having the lowest (0,643). The total variance explained for this component is 76,714%.

Table 4: Representation Quality and Explained Total Variance

Big data management analytical capabilities	Initial Representation Quality	Extraction representation quality		Total Variance Explained			
				Composer 1		Composer 2	
		Higher	Lower	Initial own values	% of variance	Initial own values	% of variance
CAGMP	1,000	CAGMP 6 (0,844)	CAGMP 5 (0,599)	4,495	74,911	-	-

CAGMI	1,000	CAGMI 8 (0,874)	CAGMI 2 (0,643)	6,137	76,714	-	-
CAGMCR	1,000	CAGMCR 4 (0,851)	CAGMCR 7 (0,644)	6,217	77,710	-	-
CAGMCA	1,000	CAGMCA 3 (0,798)	CAGMCA 7 (0,536)	5,695	71,193	-	-

For CAGMCR, the initial representation quality remains at 1,000, with CACMCR 4 showing the highest representation Quality (0,851) and CAGmCR 7 showing lowest (0,644). The total variance explained for this component is 77,710%. Finally, for CAGMCA, the initial quality of representation is also 1,000, with the highest quality observed for CACMCA 3 (0,798) and the lowest for CAPMCA 7 (0,536). Component 1 explains 71.193% of the total variance. In summary, each sub-category of Big Data Management analytics capabilities has a high initial representation quality, with total variations explained by core components ranging from 71.193% to 77.710%.

4.1.3. Big Data Analysis Technology Management Knowledge, Operational, Relational and Managerial Big Data Analytics Knowledge and Analysis Capacity – Harmonization of the operational strategy

Table 5 presents the correlation matrix, the KMO index and the Bartlett test to assess technological knowledge, operational, relational and managerial skills in big data analysis, as well as the analytical capacity to harmonize the operational strategy.

For technological knowledge, operational, relationship and managerial skills (CGTAM), the highest observed correlation was between CGTAM 5 and CGTam 6 (0,828), while the lowest correlations were between CXTAM 3 and GGTAM 6 (0,485). The KMO index is 0.910, and the Bartlett test shows an approximate Khi-two value of 1299,461 with 28 degrees of freedom and a significance of 0,000, which shows that the variables are inter-correlated and suitable for factor analysis.

For operational competencies (COAM), the highest correlation is between COAM 5 and COAM 6 (0,842), while the lowest is betweenCOAM 4 and COAMA 5 (0,554). The KMO index is 0.916, and the Bartlett test gives a value of 1388,883 with 28 degrees of freedom and a meaning of 0,000, also indicating an adequacy for factor analysis. In relational skills (CRAM), the highest correlation is observed between CRAM 1 and CRAM 2 (0,825), and the lowest betweenCRAM 4 andCRAM 6 (0,407). The KMO index is 0.859, and the Bartlett test has a value of 1158,891 with 28 degrees of freedom and a significance of 0,000, showing that the data is suitable for factor analysis.

Table 5: Correlation Matrix, KMO Index and Bartlett Test

Technological knowledge, operational, relations and managerial skills in big data analysis, and analytical ability to harmonize the operational strategy	Correlation Matrix		KMO Index	Bartlett test (approximately K-two)	ddl	Meaning of Bartlett
	Higher correlation	Lower Correlation				
CGTAM	CGTAM 5 and CGTAM 6 (0,828)	CGTAM 3 and CGTAM 6 (0,485)	0,910	1299,461	28	0,000
COAM	COAM 5 and COAM 6 (0,842)	COAM 4 and COAM 5 (0,554)	0,916	1388,883	28	0,000
CRAM	CRAM 1 and CRAM 2 (0,825)	CRAM 4 and CRAM 6 (0,407)	0, 859	1158,891	28	0,000

CMAM	CMAM 2 and CMAM 3 (0,857)	CMAM 2 and CMAM 6 (0,589)	0,834	1125,557	15	0,000
CAHSO	CAHSO 2 and CAHSO 3 (0,857)	CAHSO 2 and CAHSO 8 (0,470)	0,857	1218,27 7	28	0,000

For managerial competencies (CMAM), the highest correlation is between CMAM 2 and CMAM 3 (0,857), and the lowest betweenCMAM 2 to CMAM 6 (0,589). The KMO index is 0.834, and the Bartlett test shows a value of 1125,557 with 15 degrees of freedom and a significance of 0,000, once again indicating an adequacy for factor analysis. Finally, for the analytical capacity to harmonize the operational strategy (CAHSO), the highest correlation is between CAHSO 2 and CEHSO 3 (0,857), while the lowest is between 2 and 8 (0,470). The KMO index is 0.857, and the Bartlett test indicates a value of 1218,277 with 28 degrees of freedom and a significance of 0,000, confirming that the data is appropriate for factor analysis.

In summary, the high KMO indices and significant Bartlett test results for all categories indicate that the variables are sufficiently correlated to justify factor analysis, thereby confirming the robustness of the evaluation of the different skills and capabilities in big data analysis.

Table 6 presents the initial quality of representation as well as the total variance explained for several key variables relating to technological knowledge, operational, relational and managerial skills in big data analysis, and their analytical capacity to harmonize the operational strategy. For CGTAM, the main component CAGMP 4 significantly explains the variance with a coefficient of 0.844, followed by CACMP 5 to 0.599. Together, these components contribute to explaining 74,911% of the total variance for this variable.

Table 6: Representation Quality and Explained Total Variance

Technological knowledge, operational, relations and managerial skills in big data analysis, and analytical ability to harmonize the operational strategy	Initial Represent ation Quality	Extraction representation quality		Total Variance Explained			
				Composer 1		Composer 2	
		Higher	Lower	Initial own values	% of variance	Initial own values	% of variance
CGTAM	1,000	CAGMP 4 (0,844)	CAGMP 5 (0,599)	4,495	74,911	-	-
COAM	1,000	COAM 8 (0,849)	COAM 2 (0,709)	6,036	75,452	-	-
CRAM	1,000	CRAM 4 (0,851)	CRAM 7 (0, 644)	5,249	65,613	1,181	14,763
CMAM	1,000	CMAM 1 (0,857)	CMAM 6 (0,733)	5,695	71,193	-	-
CAHSO	1,000	CAHSO 4 (0,817)	CAHSO 7 (0,542)	5,442	68,020		

For COAM, the most influential component is COAM 8 (0,849) followed by COAM 2 (0,709), accounting for 75,452% of the total variance. CRAM reveals that CRAM 4 (0,851) is the main component, followed by CRAM 7 (0,644), explaining 65,613% of the variance. An additional variance of 14.763% is explained by another unspecified component. CMAM shows that CMAM 1 (0,857) is the dominant component, followed by CMAM 6 (0,733), accounting for 71,193% of the variance. Finally, CAHSO presents CAHS 4 (0,817) as the main component, followed by CAHs 7 (0,542), explaining 68,020% of the variance. These results detail how each variable is represented by its main components, each contributing in a distinct way to explaining the variance observed in the analyzed sample.

4.1.4. Decision Quality and Decision Effectiveness

In interpreting this table, we focus on several key elements. First, the correlation matrix shows the relationships between the variables studied. For example, for technological capacity (QD), the QD 1 and QD 2 question pairs have the highest correlation (0,814), while QD 2, QD 4 show the lowest (0,564). Next, the KMO Index evaluates the adequacy of the data for factor analysis. For QD, the KMO Index is 0.788, indicating moderate data adequacy for factor analysis.

Table 7: Correlation Matrix, KMO Index and Bartlett Test

Technological Capacity	Correlation Matrix		KMO Index	Bartlett test (approximately K-two)	ddl	Meaning of Bartlett
	Higher correlation	Lower Correlation				
QD	QD 1 and QD 2 (0,814)	QD 2 and QD 4 (0,564)	0,788	779,218	10	0,000
ED	ED 2 and ED 5 (0,884)	ED 1 and ED 4 (0,670)	0,873	813,890	10	0,000

Finally, the Bartlett Test evaluates whether the correlation matrix is significantly different from the identity matrix (a matrix in which all variables are not correlated). For QD, the Bartlett Test gives a significant result ($p < 0{,}001$), suggesting that the variables are significantly correlated with each other. In summary, this table 7 shows significant relationships between issues in each dimension (QD and ED) of technological capacity, validated by substantial correlations and appropriate statistical tests.

Table 8: Representation Quality and Total Variance Explained

Technological Capacity	Initial Representation Quality	Extraction representation quality		Total Variance Explained			
				Composer 1		Composer 2	
		Higher	Lower	Initial own values	% of variance	Initial own values	% of variance
QD	1,000	QD 1 (0,859)	QD 4 (0,714)	3,937	78,749	-	-
ED	1,000	ED 5 (0,906)	ED 1 (0,719)	4,062	81,233	-	-

Table 8 presents the results of the Core Component Analysis (CAP) for Data Quality (QD) and Decision Efficiency (ED) variables. For each variable, the initial representation quality by the main components is indicated, showing the correlation with each component. For example, the QD variable has a quality of representation of 0.859 with component 1 and 0.714 with the component 4. After extraction of components, these values change, illustrating the impact of extraction on the representation of variables. In addition, the table shows the total variance explained by each component, measured as a percentage. These results evaluate how each variable contributes to the total variance in the set of data analyzed by the ACP, thus providing a crucial insight into their importance to the structure of the data studied.

4.2. Linear regression

Linear regression is a fundamental statistical method used to understand and model relationships between a dependent variable and one or more independent variables. In the context of big data, this technique is useful for analyzing large data sets and identifying significant trends and correlations. By enabling forecasting future values based on historical data, linear regression provides companies with a powerful tool to improve the quality and effectiveness of their decisions. Whether to anticipate consumer behavior, optimize operations, or evaluate past performance, applying linear regression to big data analysis opens up new perspectives for more informed and strategic decision-making. In this section, we will explore the basics of linear regression, its practical applications in the context of big data, and how it can transform decision-making approaches within.

4.2.1. Factors influencing decision-making quality in big data analysis

Big Data analysis offers enormous potential for improving the quality of business decision-making. However, several crucial factors directly influence the effectiveness and accuracy of decisions taken on the basis of these analyses. Among these factors is the quality of the data collected, which must be high in order to avoid bias and errors in the analysis. The diversity of data sources and the effective integration of these heterogeneous data also play a key role in providing a comprehensive and relevant overview. In addition, the company's analytical capabilities, i.e. the technology tools available and the skills of analysts, are crucial to transforming raw data into exploitable insights. Finally, the corporate decision-making culture, which includes openness to innovation and acceptance of data-based approaches, strongly influences the quality of decisions. In this section, we will look at each of these factors in detail and their impact on decision-making in the context of big data, illustrating how they can be optimized to maximize decision benefits.

Table 9: Summary of models

Model	R	R-two	R-two adjusted	Standard Estimate Error	Change in statistics					Durbin-Watson
					Variation of R-Two	Variance of F	ddl1	ddl2	Sig. Variation of F	
1	,990 a	,980	,979	,14639787	,980	515,419	15	154	,000	2,041

The results of the model summary (Table 9) indicate a very strong correlation between the independent variables and the dependent variable, with a RRR correlation coefficient of 0.990. The determination coefficient R-two of 0.980 means that 98% of the variance of the dependent variable is explained by the model, which indicates an excellent adjustment. In addition, the adjusted R-two of 0.979 indicates that the model remains well-adjusted, even taking into account degrees of freedom. The standard error of the estimate, at 0.146, reveals a small average error in the predictions, while the Durbin-Watson test, with a value of 2.041 suggests the absence of self-correlation in the residues, which is a positive indicator of the independence of the observations.

Table 10: ANOVA

Model		Sum of squares	ddl	Average of squares	D	Sig.
1	Regression	165,699	15	11,047	515,419	,000[b]
	Residual	3,301	154	,021		
	Total	169,000	169			

The variance analysis (ANOVA) highlights a sum of the regression squares of 165,699, showing that the model explains a significant portion of the variance. In contrast, the sum of the residual squares is very small, at 3,301, indicating little variance not explained by the model. The F statistic, elevated to 515,419, with a significance value of 0,000, confirms that the model is statistically significant, thereby validating its ability to describe relationships between variables.

Table 11: Coefficients

Model		Non-standard coefficients		Standardized coefficients	T	Sig.
		A	Standard Error	Beta		
1	(Constant)	,045	,98		,475	,000
	REGR factor score 1 for analysis 1	,242	,033	,242	5,798	,000
	REGR factor score 2 for analysis 1	,038	,081	,038	6,030	,000
	REGR factor score 1 for analysis 2	,481	,026	,481	4,319	,000
	REGR factor score 1 for analysis 3	,453	,063	,453	3,250	,000
	REGR factor score 1 for analysis 4	,638	,097	,638	6,602	,000
	REGR factor score 1 for analysis 5	,104	,036	,104	5,827	,000
	REGR factor score 1 for analysis 6	,123	,054	,123	4,435	,000
	REGR factor score 1 for analysis 7	,476	,020	,476	3,879	,000
	REGR factor score 1 for analysis 8	,213	,093	,213	2,295	,000
	REGR factor score 2 for analysis 8	,119	,027	,119	4,481	,000
	REGR factor score 1 for analysis 9	,345	,026	,345	3,711	,000
	REGR factor score 1 for analysis 10	,125	,017	,125	2,069	,000
	REGR factor score 2 for analysis 10	,304	,052	,304	5,823	,000
	REGR factor score 1 for analysis 11	,209	,037	,209	6,068	,000
	REGR factor score 1 for analysis 12	,150	,072	,150	5,869	,000

For coefficients, non-standard values reveal the effect of each independent variable on the dependent variable. The constant is 0.045, representing the expected value of the dependent variable when all independent variables are zero. Standardized coefficients, including the score factor 1 for analysis 4 (0.638), show that this factor has the greatest impact on decision quality. All coefficients display significance levels (Sig.) of 0,000, indicating that the observed effects are statistically significant and that they can be considered as relevant to improving decision-making in the context of big data.

4.2.2. Linear model of decision-making efficiency in big data analysis

In big data analysis, decision-making efficiency is crucial for to maximize their competitiveness and performance. The Linear Model of Decision Effectiveness proposes a systematic approach to quantifying and understanding the impact of big data on decision-making processes. Using linear regression, this model determines how different variables associated with big data, such as volume, variety, and speed, influence the speed and accuracy of business decisions. By highlighting the linear relationships between these variables and decision performance measures, this model provides valuable insights to optimize decision-making strategies. In this section, we will detail the theoretical foundations of the linear model of decision-making effectiveness, its practical applications, and the implications for in an increasingly data-based environment.

Table 12: Summary of Models

Model	R	R-two	R-two adjusted	Standard Estimate Error	Change in statistics					Durbin-Watson
					Variation of R-Two	Variance of F	ddl1	ddl2	Sig. Variation of F	
1	,987 [a]	,974	,972	,16792603	,974	389,273	15	154	,000	2,100

The linear model of decision effectiveness shows a very strong correlation between the independent variables and the dependent variable, with a determination coefficient (R-two) of 0.972. This indicates that 97.2% of the variance of the dependent variable is explained by the model. The standard error of the estimate, at 0.168, underlines the accuracy of the predictions, while the Durbin-Watson statistic, at 2.100, indicates the absence of self-correlation in residues.

Table 13: ANOVA

Model		Sum of squares	ddl	Average of squares	D	Sig.
1	Regression	164,657	15	10,977	389,273	,000 [b]
	Residual	4,343	154	,028		
	Total	169,000	169			

The variance analysis (ANOVA) shows that the sum of the squares for the regression is significantly greater than that of the residual, which confirms the model's explanatory capacity. The F test (389.273) is very significant ($p < 0.001$), indicating that the model as a whole is robust and relevant.

Table 14: Coefficients

Model		Non-standard coefficients		Standardized coefficients	t	Sig.
		A	Standard Error	Beta		
1	(Constant)	,825	,405		6,235	,000
	REGR factor score 1 for analysis 1	,451	,082	,451	5,626	,000
	REGR factor score 2 for analysis 1	,592	,071	,592	6,287	,000
	REGR factor score 1 for analysis 2	,436	,121	,436	4,899	,000
	REGR factor score 1 for analysis 3	,615	,117	,615	5,112	,000
	REGR factor score 1 for analysis 4	,513	,111	,513	4,625	,000
	REGR factor score 1 for analysis 5	1,395	,144	1,395	9,681	,000
	REGR factor score 1 for analysis 6	,719	,062	,719	7,314	,000
	REGR factor score 1 for analysis 7	,642	,130	,642	8,620	,000
	REGR factor score 1 for analysis 8	,528	,106	,528	6,146	,000
	REGR factor score 2 for analysis 8	,462	,030	,462	8,027	,000
	REGR factor score 1 for analysis 9	,346	,030	,346	5,537	,000
	REGR factor score 1 for analysis 10	,504	,114	,504	4,526	,000
	REGR factor score 2 for analysis 10	,519	,060	,519	4,986	,000
	REGR factor score 1 for analysis 11	,462	,107	,462	6,033	,000
	REGR factor score 1 for analysis 12	,583	,118	,583	5,420	,000

As far as coefficients are concerned, all factor scores analyses show a significant contribution to decision-making effectiveness. For example, the factor 1 score for analysis 5 has the highest coefficient (1,395), suggesting a strong impact on the dependent variable. These findings provide valuable insights into the most influential variables, thereby guiding future strategic decisions in the context of big data analysis.

V. DISCUSSION

The quantitative results indicate that the use of big data significantly improves the quality of business decision-making. Respondents that predictive and descriptive analyses provided by big data enabled a more accurate and in-depth understanding of market trends and consumer behavior. This is consistent with the work of McAfee and Brynjolfsson (2012), which showed that data-based make more informed decisions.

With regard to decision-making effectiveness, quantitative data show a positive correlation between the exploitation of big data and the speed of decision making. Companies with well-developed big data infrastructure have been able to automate several aspects of their decision-making processes, thereby reducing the time needed to analyze information and make decisions. These results are consistent with those of Davenport and Dyché (2013), which found that integrating big data into information systems improves operational efficiency.

Analysis also revealed that companies with advanced technology capabilities in big data analysis benefit from better decision-making performance. Investments in cutting-edge technologies, such as artificial intelligence and advanced analytics platforms, are combined with better decision-making performance. Data science teams play a crucial role in extracting value from big data, confirming the work of Wamba et al. (2017).

5.1. Practical Implications

The results of this study have important practical implications for. First, investing in big data technologies and developing internal data science skills can significantly improve the quality and effectiveness of decision-making. Secondly, should adopt an integrated approach, where big data is not only collected, but also actively analyzed and used to inform strategic decisions. Finally, inter-functional collaboration facilitated by big data platforms can improve consistency and speed of decision-making.

5.2. Theoretical Implications

Theoretically, this study helps to understand the mechanisms by which big data influences corporate decision-making performance. It confirms and extends existing theories, such as limited rationality and data-based decision making, by providing empirical evidence of the positive impact of big data on decision-making quality and effectiveness. It also highlights the crucial role of technological capabilities and internal competencies in realizing the benefits of big data.

5.3. Limitations and Future Research

Despite its contributions, this study has some limitations. The sample is limited to medium to large enterprises, which may not reflect the experiences of small enterprises. Moreover, the data collected is mainly based on perceptions of decision makers, which may introduce a subjective bias. Future research could explore the impact of big data on decision-making performance in a variety of organizational and industrial contexts, as well as develop objective measures of quality and decision effectiveness.
This study provides valuable insights into the impact of big data on business decision-making performance, highlighting the potential benefits and conditions needed to maximize these benefits. Companies that invest in big data technologies and develop strong internal data analysis skills can turn massive data volumes into informed and effective strategic decisions, thereby boosting their competitiveness in an increasingly data-based environment.

VI. CONCLUSION

This research explored the impacts of big data on corporate decision-making performance, focusing on the quality and effectiveness of decisions. Big data, characterized by its volume, speed, variety, veracity and value, offers significant opportunities to improve decision-making processes. Effective integration of this data enables companies to make more informed and faster decisions, thereby increasing their competitiveness. The results show that companies using big data for decision-making see a significant improvement in the quality of their decisions. This is due to the ability of big data analytics to provide more accurate and comprehensive insights. Furthermore, decision-making efficiency is increased through the rapid analysis of data, allowing for a more agile response to market developments.

However, the use of big data also presents challenges, in terms of data quality management and privacy protection. Companies need to invest in advanced technology infrastructures and develop analytical skills to maximize the benefits of big data. In conclusion, although big data poses challenges, its potential benefits in terms of quality and decision-making efficiency make it a critical strategic resource for modern. Companies need to adopt systematic approaches and invest in appropriate technologies and skills to take full advantage of the opportunities offered by big data.

Annex 1: Questionnaire elements

Domain		Variable	Definition
Technology Capacity for Big Data Analysis (CTAM)	*Connectivity*	CTAMCN 1	Our organization has the best analysis systems compared to our competitors.
		CTAMCN 2	All our remote and mobile offices are connected to the central headquarters for optimal analysis.
		CTAMCN 3	We use open network mechanisms to improve analytical connectivity.
		CTAMCN 4	There are no interference gaps in internal communications for sharing analytical information.
		CTAMCN 5	Our real-time integration of systems and databases enables instant analysis of big data.
		CTAMCN 6	We leverage cloud computing for maximum scalability and flexibility, ensuring continuous processing of massive data.
		CTAMCN 7	Our connectivity systems are secure against unauthorized access and cyber attacks.
		CTAMCN 8	Our infrastructure enables secure interconnection with third-party data platforms for enriched analytical perspectives.
	Compatibility	CTAMCM 1	Software applications can be easily transported and used on multiple analytics platforms.
		CTAMCM 2	Our user interfaces provide transparent access to all platforms and applications.
		CTAMCM 3	Analysis-based information is shared in a transparent manner within our organization, regardless of location.
		CTAMCM 4	Our organization provides multiple analytics interfaces or input points for external end-users.
		CTAMCM 5	Our applications and interfaces support multiple languages, allowing use by an international user base. These interfaces and reports can be localized according to end-user preferences and regional requirements.

		CTAMCM 6	Our analytics platforms are designed to easily evolve to manage growing volumes of data without compromising performance.
		CTAMCM 7	We ensure that all our solutions comply with data protection regulations. Advanced encryption mechanisms and strict access controls ensure the confidentiality and integrity of analytical data.
	Modularity	CTAMM 1	The development analysis model enables a smooth integration of new software modules.
		CTAMM 2	Modularity enables analytics systems to adapt easily to increased data volume or increased performance requirements.
		CTAMM 3	Individual modules can be upgraded or replaced independently, thereby reducing system risk and maintenance costs.
		CTAMM 4	Software modules can be reused in a variety of analytics applications and environments.
		CTAMM 5	Modules can be combined to create automated workflows, thereby optimizing operational efficiency.
		CTAMM 6	Modules are often accompanied by open APIs, enabling you to extend existing features and integrate third-party tools.
		CTAMM 7	Each module may have specific security and access management configurations, thereby enhancing overall system security.
Big Data Management Analytics (CAGM)	*Planning Big Data Analysis*	CAGMP 1	We conduct research and testing on emerging technologies such as artificial intelligence (AI) and machine learning (ML) to identify innovative ways to process and analyze big data.
		CAGMP 2	We partner with data analytics startups to integrate cutting-edge solutions into our existing infrastructure.
		CAGMP 3	We set up dedicated technology watch teams to monitor trends and developments in the field of big data.
		CAGMP 4	We apply proven methodological frameworks, such as CRISP-DM (Cross Industry Standard Process for Data Mining), to structure our data analysis projects.
		CAGMP 5	We conduct quarterly or semi-annual reviews of our big data analysis strategies to align them with current business goals and market developments.
		CAGMP 6	We adopt agile approaches in our planning, allowing quick adjustments in response to new data or changes in the enterprise environment.
	Investment decision-making in big data analysis	CAGMI 1	When we invest in big data analysis, we evaluate their impact on the quality of available data and employee productivity.
		CAGMI 2	When we invest in big data analysis, we analyse the potential impact on innovation within the organization.
		CAGMI 3	When investing in big data analysis, we consider data security and confidentiality requirements.
		CAGMI 4	When we invest in big data analysis, we evaluate the flexibility and scalability of the proposed solutions.

		CAGMI 5	When we invest in big data analysis, we analyse potential competitive advantages.
		CAGMI 6	When we invest in big data analysis, we look at the availability and cost of the necessary specialized skills.
		CAGMI 7	When we invest in big data analysis, we evaluate the tool's ability to generate useful reports and visualizations.
		CAGMI 8	When we invest in big data analysis, we look at technological infrastructure needs, such as storage and computing power.
	Coordination of big data analysis	CAGMCR 1	Business analysts and managers meet regularly to discuss important issues in both formal and informal ways.
		CAGMCR 2	Business analysts and employees of various departments frequently attend inter-functional meetings.
		CAGMCR 3	Information is widely shared between business analyst and managers to ensure access to the know-how available when making decisions or performing tasks.
		CAGMCR 4	Interdepartmental working groups are established to encourage collaboration between business analysts and operational teams.
		CAGMCR 5	Communication and document sharing tools are in place to facilitate the exchange of information.
		CAGMCR 6	Partnerships with external experts are developed to enrich perspectives and improve the quality of analyses.
		CAGMCR 7	Regular training sessions are organized for business analysts to maintain and improve their skills.
		CAGMCR 8	Business analysts are awarded awards and awards for their outstanding contributions, thereby encouraging excellence and motivation within the team.
	Analytical monitoring of big data	CAGMCA 1	Responsibilities related to the development and management of big data analysis are clearly defined and documented.
		CAGMCA 2	Big data analysis project proposals are evaluated reliably and accurately.
		CAGMCA 3	The performance of the big data analysis function is continuously monitored.
		CAGMCA 4	The performance criteria and data collection and management processes are well defined and rigorously documented.
		CAGMCA 5	Strict protocols guarantee the confidentiality and security of the data analyzed.
		CAGMCA 6	Big data analysis results are regularly audited to ensure their accuracy and reliability.
		CAGMCA 7	Continuous investments are being made in staff training to maintain high skills in big data analysis.
		CAGMCA 8	Regular internal audits and frequent revisions of algorithms and models ensure the efficiency and relevance of analytical processes.

Knowledge in Technology Management in Big Data Analysis (CGTAM)	CGTAM 1	Our analytical team demonstrates a strong understanding of current technological trends.
	CGTAM 2	The successful integration of new technologies into our processes is a specialty of our analytical team.
	CGTAM 3	Our analytical team stands out in its ability to anticipate and adapt to disruptive technological changes.
	CGTAM 4	The expertise of our Cyber Security Analysis Team ensures the protection of sensitive data.
	CGTAM 5	Our analytical team has extensive experience in managing technological projects, thus ensuring compliance with deadlines and budgets.
	CGTAM 6	The effective collaboration of our analytical team with technical and non-technical teams ensures the alignment of technological objectives with the strategic objectives of the company.
	CGTAM 7	The use of agile methodologies by our analytical team increases the flexibility and responsiveness of our technological projects.
	CGTAM 8	The exploitation of predictive analysis by our analytical team provides strategic decision-making information.
Operational Knowledge in Big Data Analysis (COAM)	COAM 1	Our analytical staff demonstrates great competence in interpreting business issues and developing technical solutions.
	COAM 2	Our analytics staff have a strong expertise in financial performance assessment and risk management.
	COAM 3	Our analytical staff excel in anticipating market trends and customer needs.
	COAM 4	Our analytical staff are distinguished by their excellent ability to communicate the results of their analyses in a clear and concise manner to all stakeholders.
	COAM 5	Our analytical staff collaborates effectively with other departments and functional teams, thus contributing to the achievement of the company's objectives.
	COAM 6	Our analytical staff is constantly at the forefront of best practices and innovations in their field.
	COAM 7	Our analytics staff are actively engaged in continuous improvement and innovation, which boosts company growth and competitiveness.
	COAM 8	Our analytics staff have in-depth knowledge of the organization's policies, plans and the company's environment.
Relational Knowledge in Big Data Analysis (CRAM)	CRAM 1	Our analytical staff excel in planning, organizing and managing projects effectively.
	CRAM 2	Our analytical staff also demonstrates remarkable expertise in planning and execution of work within collaborative teams.
	CRAM 3	Our analytics staff give priority to close collaboration with customers, ensuring productive relationships and results aligned to user needs.
	CRAM 4	Our analytical staff excel in interpersonal communication, thus facilitating the rapid and concerted resolution of problems.

	CRAM 5	Our analytical staff are capable of establishing andining strong partnerships with internal and external stakeholders, thereby fostering cooperation to common goals.
	CRAM 6	Our analytical staff, with a high listening capacity, understands the needs and concerns of customers and users, responding in an appropriate way.
	CRAM 7	Our analytical staff are recognized for their constructive conflict management, promoting solutions that preserve relationships and encourage consensus.
	CRAM 8	Our analytical staff are proactive in identifying opportunities for improvement, mobilizing the resources needed to implement positive changes while taking stakeholder priorities into account.
Management Skills in Big Data Analysis (CMAM)	CMAM 1	Managers in our company understand the importance of big data in decision-making.
	CMAM 2	Our managers have the skills to interpret big data analysis.
	CMAM 3	Management decisions are regularly based on insights derived from big data.
	CMAM 4	The leadership skills of our managers include a good understanding of big data analysis.
	CMAM 5	Our managers encourage the use of big data to improve decision-making processes.
	CMAM 6	The management training in our company includes modules on the analysis and interpretation of big data.
Analysis Capacity – Operational Strategy Harmonization (CAHSO)	CAHSO 1	The big data analysis plan is aligned with the mission, objectives and strategies of our company.
	CAHSO 2	The Big Data Analysis Plan contains quantified goals and objectives, as well as detailed action plans that support the direction of our business.
	CAHSO 3	We prioritize major investments in big data analysis based on the expected impact on the performance of our company.
	CAHSO 4	The Big Data Analysis Plan integrates feedback and needs from our business stakeholders to ensure common understanding and consistent implementation.
	CAHSO 5	The Big Data Analysis Plan provides for regular monitoring and evaluation mechanisms to measure progress towards targets and adjust strategies accordingly.
	CAHSO 6	The Big Data Analysis Plan addresses data security and regulatory compliance aspects to protect sensitive information and comply with legal requirements.
	CAHSO 7	The big data analysis plan encourages collaboration between different departments (IT, marketing, finance, etc.) for optimal exploitation of big data and informed decision-making.
	CAHSO 8	The Big Data Analysis Plan includes training and development initiatives to improve employees' analytical skills and foster a data-based culture within our company.

Decision Quality	QD 1	Decisions taken are accurate and based on reliable information.
	QD 2	Decisions are relevant to the organization's strategic objectives.
	QD 3	Decisions taken are consistent and produce predictable results.
	QD 4	Decisions are impeccable and do not contain significant errors.
	QD 5	Decisions are well-informed and take into account all relevant factors.
Decision Efficiency	ED 1	Decisions are taken quickly.
	ED 2	Decisions are made with optimal use of resources (time, staff, and information).
	ED 3	Decisions are adaptable and may be modified according to new information.
	ED 4	The decision-making process is efficient and well organized.
	ED 5	Decisions are taken without unnecessarily delaying operations or projects.

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