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RESEARCH ARTICLE

Effects of Analytics Large Data Set on Decision-Making and Organizational Performance: A Study on Chinese Manufacture Sector

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Abstract: In today's data-driven environment, Big Data Analytics (BDA) plays a vital role in enhancing decision-making quality and organizational performance. However, limited empirical research exists on how the five characteristics of big data (5Vs: Volume, Velocity, Variety, Veracity, and Value) influence decision-making effectiveness in China's industrial sector. Addressing this gap, the present study builds on Simon's decision-making theory and the information processing perspective to develop and test a research model linking BDA to decision-making and performance outcomes. Using a self-designed structured survey, data were collected from 312 managers across medium and large-sized manufacturing firms in China. Structural equation modeling (SEM) was employed to examine the relationships among constructs. The results show that all five BDA characteristics significantly enhance the quality and efficiency of decision-making, which in turn positively impacts organizational performance. Furthermore, multi-group analysis revealed no significant difference in the BDA–decision-making relationship between medium and large enterprises. This study contributes theoretically by integrating BDA with decision-making theory and practically by offering managers evidence-based insights on how to leverage big data for more informed and effective decision-making across industrial operations.

Keywords: big data analytics; china; decision-making; organizational performance

I. INTRODUCTION

Big Data is a term used to describe very large data sets that may be analyzed computationally to reveal patterns, trends, and correlations, often referring to human behavior and interaction [1]. The term "Big Data Analytics" (BDA) has recently exploded in use across a wide variety of practitioner and academic venues, including conferences, journals, and books. Ancestry, in this context, alludes to the fact that the amount, variety, and velocity of data being generated and made available today are all quite big [2]. The term "Big Data" has become increasingly popular ever since the definition statement's introduction characterized Big Data as "high-volume, high-velocity, high-variety, high-veracity, and high-value information assets that require efficient, innovative forms of information dissemination for improved insight and decision making" [3].

Not only have there been no large-scale experimental demonstration of net benefits thus far, but there are also huge costs and other challenges connected with Big data (project) that many businesses cannot afford, despite their being compelling BDA success stories [4]. The issue this paper seeks to answer is whether or if, by data-driven analysis and action, China's manufacturing sector may achieve higher levels of productivity and, ultimately, a competitive edge [5]. On addition, stories of corporate success usually include a series of ingenious and creative decision-making processes grounded in solid evidence.

Great-quality data, which may improve a company's efficiency and effectiveness, is in high demand in the manufacturing sector to meet the industry's competitive needs [6]. Organizational decision systems transform raw data into actionable insights, which, depending on the accuracy of the underlying data, may then be transformed into knowledge to aid in making data-driven choices. Unfortunately, in order to forecast future behaviors, reveal bias, or find new possibilities, conventional DSS and business intelligence procedures depend heavily on basic archive data and simple analysis tools [7]. Each person generates 1.7 GB of digital data each second in 2019, and the BDA market is projected to grow to $103 billion by 2023 [8]. Big Data provides a Big Opportunity for big and medium-sized organizations despite the terrible condition of the economy, but at a huge "Big Cost." Intelligent business choices result in an imaginative and proactive approach to problem resolution and converting obstacles into opportunities.

Businesses increasingly rely on big data (BD) systems. Accessing large, dynamic, and complex streams of information has the potential to dramatically improve organizational decision-making. We use the term "big data" to describe data sets that are not only massive in size but also highly variable and difficult to handle with

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traditional tools and techniques [9]. Today, every business that wants to succeed must have the ability to effectively use the information at its disposal. Merging enormous data sets acquired from many, sometimes incompatible, data sources is required to extract value from data [10]. BDA is essential for turning massive amounts of data into useful information BDA [11].

Social media users and Internet of Things (IoT) devices are only two examples of information sources from the outside the organization (IoT). In actual life, there is frequently a lengthy chain of events that must occur, with many different individuals playing key roles [12]. Companies and departments often need to collaborate in order to build a streamlined process due to the large number of data sources, the need of merging them, and the widespread use of BDA. Organizational silos are preventing big data from being used for decision-making [13]. There is no one department or office in charge of collecting, processing, and using all of the information that is generated. Instead, information is gathered from a wide variety of other sources, and businesses may join together to share resources and train employees in BD analysis. Applying BD to the decision-making process is famously difficult because of all the different people and processes involved [14].

Better decision-making is generally where the usefulness of BD begins [15]. It is not only the data itself that determines quality, but also how it is acquired and analyzed. In order to investigate the uncharted connections between various forms of data, BD and BDA often need the participation of several actors from a wide range of professions and fields of practice [16]. Many individuals, each with their own set of talents and resources, might be responsible for carrying out the various tasks. There is a flow or chain of operations that might be called the "big data chain" because of the participation of many different types of companies. The first link in the BD chain is the collection of data from its origins, and the last link is the adoption of a decision based on that data.

The steps in a huge data chain may be separated out analytically [17]. As a matter of fact, there is a plethora of data sources, flow variations, and decision-making options to consider. Over the course of such a series, numerous people work to boost both the volume and quality of the material that is made public. Eliminating noise, making chosen data sets machine-readable and linked, and including meta-data are all examples [18]. The effectiveness of using BD in decision-making may be impacted by several actions. The chain approach is seldom considered an analytical way to study BD. When you combine the search terms "big data" with "chain," you get a scant few results [19]. With the proliferation of mobile devices, social media platforms, websites, and other passive and active data sources, businesses have access to a wealth of information. Big data's efficient collection, analysis, and interpretation processes lead to better real-time customer relations, more effective corporate operations, and more productivity with less additional expenditure. The manufacturing industry in China contributes roughly 27.44% to the country's GDP. About 30% of goods exports and approximately 58% of the employed labor force in China are directly or indirectly related to the production of cotton textiles and the manufacture of garments.

Volume, velocity, variety, veracity, and value—the five core characteristics of big data—establish a foundational causal relationship with intelligent and information-driven decision-making. This study investigates the relationship between the "5Vs" of big data and decision-making within the manufacturing industry of China, aiming to explore the extent to which these characteristics influence organizational performance. While the importance of high volume of data for integrated and optimized decision-making is well acknowledged, it is the effective handling of the other four characteristics—velocity, variety, veracity, and value—that determines the true strategic advantage of big data usage. For instance, velocity, or the speed at which data is generated and processed, is particularly critical in industries such as finance, where real-time fraud detection and algorithmic trading require immediate response and processing capabilities. In contrast, in e-commerce and retail sectors, understanding customer buying behavior and enabling data-driven marketing initiatives demands a focus on variety and veracity. These organizations must manage and integrate diverse data types—from transaction logs and browsing patterns to social media sentiment—while ensuring the accuracy and trustworthiness of such information.

In the manufacturing sector, where this study is situated, the relevance of veracity and value becomes paramount. Ensuring data accuracy from various sources such as IoT sensors, supply chain systems, and production lines directly impacts quality control, predictive maintenance, and operational efficiency. Furthermore, deriving value from these vast data sets supports strategic decisions related to production optimization, inventory management, and supplier selection. By contextualizing each of the 5Vs within relevant industrial domains, this study emphasizes that different sectors place different emphases on specific characteristics of big data depending on their operational needs and strategic goals. This nuanced understanding allows for more targeted implementation of BDA to enhance decision-making and ultimately, organizational performance. The purpose of this study is to improve the industrial performance in China. A rise in the value of the US dollar relative to the Chinese currency has made it more difficult for the economy as a whole to function and for the government to subsidize businesses. In the industrial industry, BDA is not a luxury but a need. Chinese business leaders may now make more informed and effective judgments to support economy [20].

II. LITERATURE REVIEW

Building data management and BDA competence is essential for a successful BD chain [21]. BDA can perform a wide range of tasks, from the purely descriptive and exploratory to the inferential, predictive, causal, and mechanistic. In order to do this, several techniques are used, including natural language processing, text mining, linguistic computing, machine learning, search and sort algorithms, and syntax and lexical analysis, and so on. Predictive analytics, a subfield of business intelligence, uses past data to make predictions about the future by looking for trends, patterns, and correlations [22]. The capacity of an organization to process information has been shown to have an effect on its performance in previous studies on data processing [23]. The caliber of decisions is probably affected by the actions taken to process BD and BDA skills.

The results of BDA should be understandable to decision-makers, who should not be swayed by flashy visuals [24]. Knowledge of the interrelationships between the various issue factors was shown to increase the quality of decisions by [25]. However, if the decision-maker lacks an appreciation for the inter-dependencies, the quality of their decisions may suffer. Better choices are made after interacting with the people responsible for collecting and analyzing the data [26]. This may also be true for BD, implying that collaboration improves the quality of decisions made by all parties. Decision quality, as defined by [27], is the degree to which one consistently makes wise choices [28]. The quality of decisions may rise or fall depending on the state of information quality and processing [29]. It is becoming more difficult for people to read and make sense of an unfamiliar environment as data becomes bigger, more complicated, and less easily explained. It is possible that in BD, nobody knows what the data represents or why it is being gathered. The quality of decisions is impacted by a lack of understanding of BD sources.

When dealing with a larger data collection, complexity increases [30]. The term "big data" is used to describe databases that have grown so vast that conventional database management systems are cumbersome to operate; moreover, the volume of big data exceeds the capacity of standard methods of data storage and analysis. The three main characteristics of big data are its volume, velocity, and variety [31], where volume refers to the size of the data, velocity to the rate at which the data is changing, and variety to the different formats and types of data which are important for making decisions in an organization. In addition, IBM introduced the concept of "veracity" as the fourth V [32], and other academics believe the value of data to be the fifth V in terms of its importance in decision-making [33].

The term "big data analytics" refers to the practice of applying sophisticated analytics methods to massive data troves. There are more problems and difficulties when dealing with larger data sets [34]. High-quality analytics may aid in making more informed choices, lessening potential negative outcomes, and gaining new and useful insights. Management judgment has been studied extensively throughout the years because of its significance. The four steps of Simon's decision-making process—intelligence, design, choice, and implementation—are widely embraced by decision-makers across disciplines [35]. As a result, each stage of the BDA pipeline has its own set of difficulties and decisions to make [32]. Questions like "how to obtain data," "which data to acquire," "how to represent data in proper way for analysis after extraction," and "how to make judgments on acquired information" all fall under this category of decision-making. adds that adopting a data-driven decision-making approach results in changes in management practices including those related to company culture, leadership, and Human Resource Management.

Synthesis of literature concludes that theoretical and practical approach of data refinement and data assembling is different in some studies whereas some present same approaches. Information-driven decision-making has become need of every corporation for which BDA provide the insights and techniques to improve on the manual data mining and decision-making algorithms

A. FRAMEWORK AND HYPOTHESES

Simon set out to investigate the idea that the "Universal Choice Maker." The interplay between an organization's culture and its leaders' personalities and practices can have an impact on the quality of decisions they're tasked with making [36]. Reference [37] made important contributions to our knowledge of the decision-making process. To be more accurate, he was a pioneer in the use of computational tools to crucial decision-making. Reference [38] and his later work with [39] proposed the idea that decision-making occurs in stages. The idea of the human brain as a computer capable of making choices was first proposed by him. His approach to making decisions involves three stages: deliberation, preparation, and selection. The most current discoveries in data-driven decision-making and information-based decisions feed all three stages of the Simon decision-making paradigm.

Intelligence is concerned with issue identification and data collection. Design focuses on potential answers to issues, whereas selection centers on deciding how to best approach challenges and turn them into opportunities [40]. The ability of humans to process such a massive data set and turn it into well-informed, well-considered choices is now outstripped. Philosophers have evolved through a number of phases of decision-making, all of which need a strategic, proactive approach based on expertise and honed information. In order to facilitate data-driven decision-making, BDA afforded us the luxury of understanding information [41].

Decision-making is categorized as intelligence phase; internal and external sources are used to collect information purely for identifying problems and opportunities. This phase mainly deals with diversity of data and volume of data from different sources used for BDA [42]. Such Big Data needs care and cautious dealing as sources, some are not identified [43]. Once data sources are defined and authenticated, the acquisition and storage of data remain critical challenges. Platforms such as Big Data Pipeline, Oracle, and the .NET framework are commonly employed to securely store data, ensuring its availability for generating alternative solutions to problems and identifying new opportunities.

Hadoop, MapReduce, and in-memory database management are used for data processing, which transforms data into knowledge. SQL, HIV, Pig, and R are only some of the languages that may be used for statistical analysis of bid data, which in turn can be utilized for process computing and management of presented alternatives. Vendors like Vertica, Greenplum, and IBM's Nateza all use somewhat different approaches to solution management. The next step is the Design Phase, which comprises three primary components: planning, analytics, and analysis. Designing the solution is performed with the aid of Rapid Miner and WEKA for best-fit decisions [44].

Several tiers of AI deployment were examined using Multi-Criteria Decision Making techniques in this study. Findings from the research illuminate the complexity of implementation challenges and provide policymakers direction for going ahead. The studies reveal that there are major challenges to the implementation at the tactical, operational, and strategic levels. The results shed light on the various obstacles to AI integration in the areas of governance, scalability, and privacy and provide policymakers recommendations for overcoming them [45].

The study expands on Simon's decision-making framework by using BDA to analyze the influence of data characteristics like volume, velocity, variety, honesty, and value on conclusions drawn from the collected information. The outcomes of sustained focus and innovative thought, necessary for issue solving or finding a viable strategy to deal with a critical situation, may have positive or negative consequences for businesses [46]. In the last stage, we go back over all of the offered solutions and judge them using the Knowledge Discovery in Databases (KDD) approach and integration module once again.

The stock market's volatility, the lack of consistency in data, and the influence of external factors may all work against the success of an Input-Process-Output (IPO). Several researchers have presented AI-based strategies for IPO success prediction throughout the years; they are discussed in [47]. The translation of decisions into action may be represented in either graphical or textual form. Organizational success is determined by the extent to which administrative supervision is exercised through the visible and controlled implementation of decisions that contribute to this success. Therefore, the quality and reliability of information are essential. [48].

B. RESEARCH HYPOTHESES

On the basis of conceptual framework and related theories of BDA and decision-making model, study designed following null hypotheses:

$H_0$1: As far as China's manufacturing sector is concerned, there is no correlation between BDA and internal business decisions.

Despite the variety of human brilliance and the limitations of intuition in picking remedies to situations, the abundance of digital data has made it easier for managers and executives to construct alternate solution data sets [49]. Big Data's context, velocity, and value necessitate the usage of business intelligence for prompt response to problems and opportunities. This research uses decision-making, which is affected by Big Data's "5Vs," as a dependent variable to probe the connection between decision-making and organizational efficacy and efficiency. In addition, Classification (Decision tree, Foresting, Support Vector Machine, etc.), Clustering (Boosting, XGboost), and Regression are often used methods (Simple, Linear, and Logistic) [50]. Applying this MLL (Machine Learning Language) analytic criteria, we may examine the most favorable occurrences. Raw data and potential outcomes from the predictive analysis are given in this step so that a choice may be put into action. The BDA's decision-making modules enter the Choice Phase in the third stage. During the selection process, the effects of potential solutions on the decision and the managed implementation are assessed.

Traditional database management systems (DBMS; SQL, MPP, Cassandra, and EDWs) and the digital world's distributed file system Hadoop Distributed File System are both suitable for acquiring and storing such a large volume of data [51]. Alternatives to Hadoop for managing Big Data's storage include HBase and Couch Db. KDD kernel-based integration's third phase, the processing of data, begins with the lifespan and transformation phase after the second phase, information storage and acquisition, is over. The integrator is accountable for the setup, preparation, and processing of solutions derived from sets of issues and opportunities. Module integration and DBMS processing tools may be substituted for ETL/ELT high-speed internet-based networking [52].

$H_0$2: Organizational effectiveness is correlated with decision-making in China's manufacturing sector.

The purpose of decision-making in today's era of big data is to streamline complicated problems into manageable ones that can be put into action. But there are significant challenges that must be overcome before this objective can be realized [49]. According to [53], companies are starting to place more value on data analytics, which has led to the rise of data-driven decision-making (DDD), or making judgments based on the results of an analysis of data rather than gut instinct. There are new avenues to explore when decisions and worldviews are based on evidence rather than intuition. Reference [54] demonstrates how cognitive perspectives, such Simon's model from 1977, have influenced the development of organizational decision-making procedures. A company's competitiveness might improve as a result of these changes, which could lead to better interactions with customers, lower management risks, and more operational efficiency. It is becoming clear that big data is a strategic management asset for businesses, essential to their growth and survival [55]. It has to be built in a manner that increases organizational performance and delivers long-term value, as well as helping with decision-making [56]. As a corollary, the choices need adjusting the process to influence the outcome [57].

The necessity for massive amounts of trustworthy data has grown as the speed at which enterprises in China's industrial sector may burn through cash has accelerated [54]. Making business choices like whether to produce or purchase, downsize or maintain, close or stay open, and so on requires a high level of intellectual acumen. In China's industry, which is seeing a contributor in revenue, investing in costly Big Data is a monumental choice. Intelligent decision-making systems have an empirical need to change impediments into opportunities, and it takes a lot of time and literature to persuade business systems that the opportunity cost is worth it since the benefits are greater and more efficient [42].

III. RESEARCH METHODOLOGY

Using a statistical survey design and a custom-made 5-point Likert scale questionnaire, we assessed the influence of the "5Vs" (independent variables) on final decisions (dependent variable). Since they have the means to put in place and manage BDA, 10 of the most notable companies in China's manufacturing sector have been selected. Paper and pencil were used in the survey's administration. CEOs, VPs, and GMs are in charge of this study. This study took precautions to safeguard the primary data by addressing ethical concerns such as obtaining valid permission and keeping personal information secure. As a resource-based technology, decision-making in the R&D department is the sole responsibility of the Board of Directors, and the Board's inability to make decisions in the past due to a lack of information and time usage has led to problems that have been mitigated by the use of BDA.

The industrial industry in Europe has enhanced their goods' timeliness after using BDA [58]. Executive-level strategies are a reflection of directions based on Boards of Directors, with the strategic level following the transformation of the tactical level's decision-making process; using the BDA improves supply chain management issues in the tactical sector of decisions; and using the BDA to predict and cluster natural disasters, such as the Tsunami in Indonesia, has aided companies like Ford and Mercedes-Benz in managing logistics [24]. Executive-level strategies are a reflection of directions based on BODs, with the strategic level following the transformation of the tactical level's decision-making process; using the BDA improves supply chain management issues in the tactical sector of decisions; and using the BDA to predict and cluster natural disasters, such as the Tsunami in Indonesia, has aided companies like Ford and Mercedes-Benz in managing logistics.

Sample size was calculated using Slovin's algorithm, and 139 people were selected at random from the whole population (whose size was already known). After the sample size was determined, participants were drawn at random from among Chinese manufacturing firms. The goals of the research and the use of the questionnaire were explained to participants. Participants were given a 5-point Likert scale questionnaire, ranging from "strongly disagree" (on the extreme) to "strongly agree" (on the extreme).

IV. RELIABILITY ANALYSIS

Prior to collecting all of the data from the (139) participants, a reliability test was conducted on the questionnaire. Twenty people from the pilot test sample filled out the questionnaire, and all five sections got "Cronbach's Alpha" scores above .70, the minimum acceptable level. Cronbach's alpha values for speed, variety, sincerity, and value are shown in Table I; these values all surpassed

Table I. Reliability of data

S/no.	Variables	No.	Cronbach's alpha	%
1	Volume	20	.85	84.31%
2	Velocity	20	.79	78.95%
3	Variety	20	.91	91.32%
4	Veracity	20	.90	90.41%
5	Value	20	.88	87.22%
6	Overall	20	.911	90.11%

Table II. Hypotheses testing

S/no.	Factors	Numbers	*t*-Test statistic	*P*-value
1	Volume	6	3.41	.011
2	Velocity	7	2.39	.000
3	Variety	7	2.67	.012
4	Veracity	5	1.99	.021
5	Value	6	2.34	.000

Table III. Normality test

S/no.	Factors	Z value	Error	Z value/ error	Kurtosis range
1	Volume	2.567	.387	6.6330	> +1.9
2	Velocity	1.897	.387	4.9018	>+1.9
3	Variety	12.786	.387	33.038	>+1.9
1	Veracity	2.431	.387	6.2816	> +1.9
2	Value	6.781	.387	17.521	> +1.9

the threshold for statistical significance, indicating that the questionnaire is reliable for analysis.

A. HYPOTHESES TESTING

T- and *p*-value tests were used to determine whether or not to reject the null hypotheses and accept the research hypotheses. In Table II, we utilized the independent sample test (2-tailed) to reject the null hypothesis. The research's null assumptions were shown to be correct by the use of the second Kurtosis test. Tvolume = 3.4081, tvelocity = 2.39, tvariety = 2.67, tveracity = 1.99, and tvalue = 2.34, all shown in Table II, are bigger than the *t*-table values for degree of freedom @ 138. Table II shows that the research rejects all of the null hypotheses and accepts all of the alternative hypotheses. Based on the results in Table II, it seems that the model is substantially different and suitable for prediction since all of the *p*-values are less than .50.

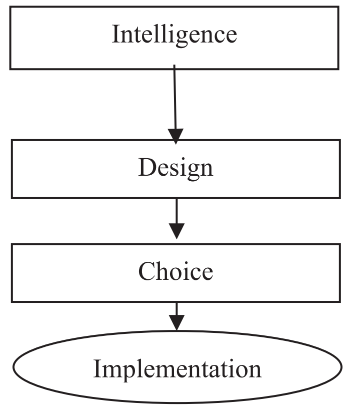

Fig. 1. Simon's decision-making model 1977.

Despite the fact that the impact of some characteristics of BDA is high and others are low, the results of the independent sample test (2-tailed) establish the argument that the model is fit and the null hypotheses of the study are rejected; the qualitative expression for this narration is that the "5Vs" of BDA affect the decision-making in the manufacturing industry of China (see Fig. 2). The Kurtosis test values used to verify the *t*-value and *p*-value statistics are shown in Table III.

All of the skewness-Kurtosis values in Table III are larger than +1.96, indicating that the data is normally distributed and that the null hypotheses may be rejected. For normalized data, the skewness is set to 0 (see Fig. 3).

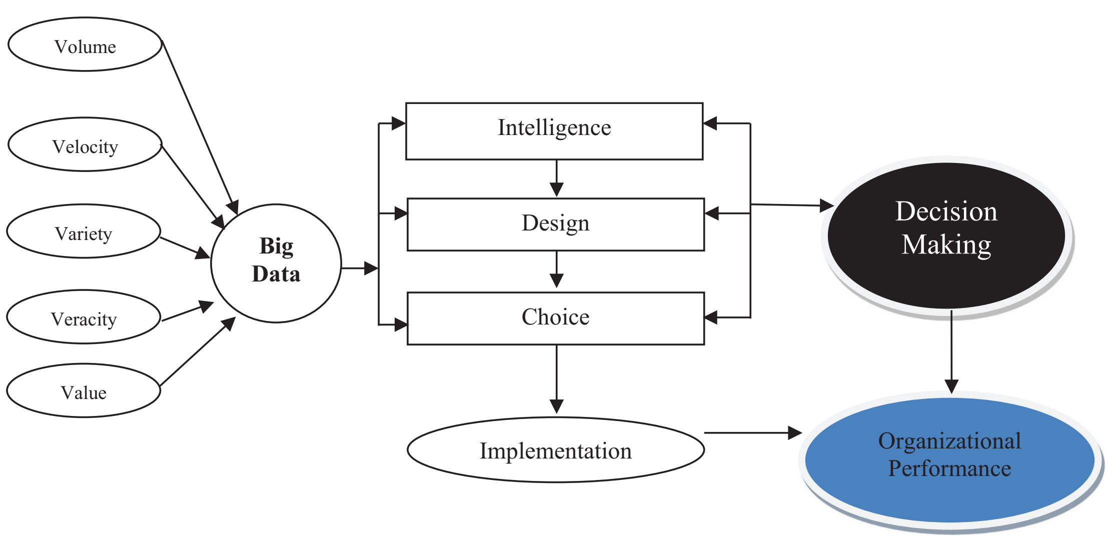

Fig. 2. Design principles derived on Herbert Simon's model of deliberation.

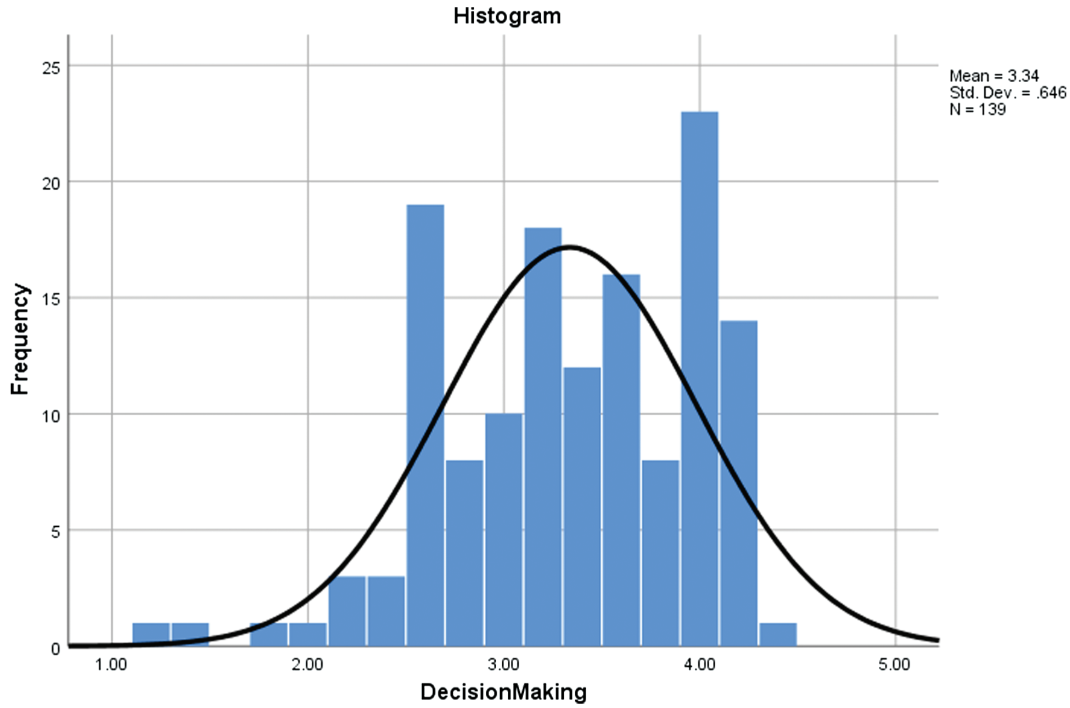

Fig. 3. Histogram for normally distributed data.

B. DESCRIPTIVE STATISTICS

The descriptive statistics portion of this article explains how to make sense of the mean evaluations of the summary given by the study's participants (Executives, Directors, and Managers). The participants' judgments, based on their own experiences, were recorded using a 5-point Likert scale. Data volume, data velocity, data diversity, data authenticity, and data value are all crucial for making data-driven choices in the modern day. Problems always come with possibilities, and there is a certain skill required to turn those possibilities into actual gains. Unfortunately, even the most competent "Decision Makers" often make "Big Mistakes" because of carelessness or a lack of understanding of the problem's context (see Fig. 1). Here, the wisdom of BDA steps in to help save time and gather accurate context about the challenges at hand.

Executives, directors, and managers' (participants) average assessments of the volume, velocity, variety, truthfulness, and value of BDA, as well as the effects of these five features of BDA on decision-making in China's manufacturing sector. All of the values indicate that the respondents either agreed or strongly agreed with the questionnaire's claims. Any company is only as good as its executives, board of directors, and managers, who occupy the highest decision-making positions. Insights from BDA may come at a hefty price, but they are a valuable resource for enterprises over the long term, according to those who provided qualitative responses on the manufacturing sector in China [59]. The quality control and research and development departments, as well as the finance and information departments, may all benefit from choices that are informed by data.

Subheadings of typical judgments in the manufacturing business are distinct from those in the service industries in that they need prompt, efficient action. In the study conducted by [60], it was determined that the decision-making processes of the service sector and the manufacturing sector are distinct. In the manufacturing sector, a more thoughtful and analytical approach to tackling problems is required.

C. REGRESSION ANALYSIS

The purpose of the linear regression is to determine how one or more independent variables affect a dependent variable [61]. To be more precise, the outcome of a linear regression analysis yields a single intercept and a single slope (based on the mean) that characterize the optimal fit between variable X and variable Y. Using this equation, we can get the slope of the regression line [62]. The research treats the decision-making process as a dependent variable and the features of BDA as independent variables (volume, velocity, variety, veracity, and value).

The model's adjusted R square is .9; it means that a shift of only one unit in a Big Data characteristic will result in a 99 percent shift in the way choices are made (see Table IV). As a corollary, this means the dependent variable may be predicted with great accuracy using the model. R-squared for this predictor is stable at 99%. Volume, velocity, variety, veracity, and Value all contribute to a 9.9 percent improvement in the effectiveness and efficiency of a corporation's decision-making ability. Thus, under a linear model, decisions are data-driven and more efficient.

It can be predicted that the model is significant and will bring changes in the decision-making efficiency of the corporation for sure with the changes in all the independent variables, as shown in Table V for R-Change, which is the same as what was shown in the

Table IV. Regression model summary

Model	R	R square	Adjusted R square	Std. error of the estimate
1	.999[a]	.9	.99	.033

Table V. Change statistics of model

R square change	F – change	Sig. F change
.9	278.2	.000

summary model Table VI for f (2, 137) = 27779.207, p = .000. That means a 10 percent shift in the volume, velocity, variety, veracity, and value of available information will result in a 5 percent shift in the effectiveness with which business decisions are made.

Analysis of model variance is implied in Table VI. Model 1 of ANOVA is substantially fit to predict values and explain variation in variables, with the mean difference square of projected D.V. and I.V. being (Y1-Y) 2 = 60.750 and f (2, 137) = 27779.207, p = .012. Organizations in Chinese manufacturing sector might expect changes to their data-driven decisions across a number of dimensions, including volume, velocity, variety, veracity, and value, according to a qualitative representation of this variation.

Model is fit and significant to predict influence of independent variable on dependent variable at p = .013, .000, .000, .012, .000, and .234. Using coefficients for volume, velocity, variety, credibility, and value of 1.362, .430, 2.341, 1.123, and 1.999, respectively, a linear model of regression can predict the extent to which a change in the independent variable would affect the efficacy of the decisions made (see Table VII). The results shown by the linear model suggest that the study assumptions are correct and that the features of BDA have an effect on the ability of organizations to make data-driven decisions:

$$Dc\_mkg = \alpha + \beta(V1) + \beta(V2) + \beta(V3) + \beta(V4) + \beta(V5) + e$$

A linear decision-making function exists, with a constant change unit of .111 in both decision-making capacity and efficiency. The volume, pace, diversity, validity, and utility of BDA will determine whether or not the change will be favorable. Decision control implementations determine the degree of system transformation. The idea that choices are based on habits and gut feelings was first put out by Simon (1977). Managers educated in proactive cognition make manufacturing industry decisions. The decision-making model is linear; thus, it may be used with either a pragmatic approach or a choice based on knowledge. Knowledge-based activities, such as analyzing the problem and its context, developing potential solutions, and selecting the best one at the right time with adequate means for putting them into action and keeping them under control, are at the heart of all three of Simon's (1966) stages of decision-making. Poor decision control is the same as failure for businesses.

D. SUMMARY OF FINDINGS

All the null hypotheses are rejected, and study hypotheses are accepted as exhibited in Table VII. T-values of volume, velocity, variety, veracity, and value are greater than t-table value. There is a significant relationship between volume, velocity, variety, veracity, and value and decision-making of corporation. Skewness and Kurtosis exhibited in Table V implies that data is normally distributed and rejection of null hypotheses is justified. Descriptive statistics of the study exhibited in Table VI implies that summary of mean ratings characteristics of BDA influence information-driven decision-making of manufacturing industry of China. Regression analysis and change statistic exhibit that model is fit for prediction and significantly different with p-values less than .50.

Table VII. Regression analysis

Model		Unstandardized coefficient				
		B	Std. error	Mean square	F	Sig.
1	(Constant)	.111	.044		2.536	.013
	Volume	1.362	.006	1.037	233.516	.000
	Velocity	.403	.010	.172	38.731	.000
	Variety	2.341	.013	.232	56.345	.012
	Veracity	1.123	.002	1.234	32.124	.000
	Value	1.999	.234	2.345	1.223	.234

Each of the "5Vs" has a linear and consistent impact on the decision-making function. Data ratings are near to highly agree with the study's assumptions, as shown in the scatter plot of these ratings in Fig. 4. Manufacturing industry decision-making and organizational performance are correlated in this study.

V. DISCUSSION

In today's rapidly evolving data-driven environment, business executives face unprecedented uncertainty and complexity. To navigate this, they require a dual perspective: identifying high-risk, high-reward opportunities such as market diversification or digital transformation, and embedding data analytics into day-to-day operational and strategic decisions. This study sheds light on how BDA enables such a dual strategy, particularly within China's manufacturing sector—a critical yet vulnerable industry that has been significantly impacted by the disruptions of COVID-19. Our findings are deeply embedded in Herbert Simon's three-phase decision-making model: intelligence, design, and choice. In the intelligence phase, organizations scan and collect information from internal systems and external markets. Here, volume and variety of data were found to play a dominant role in enhancing managerial awareness and strategic sensing. Access to large data sets from diverse sources—such as supply chains, customer feedback, and market reports—enables firms to understand evolving demand patterns, anticipate disruptions, and identify new growth opportunities.

In the design phase, which involves developing and analyzing alternatives, the role of velocity and veracity becomes prominent. Managers require accurate, real-time data to model different scenarios, evaluate trade-offs, and simulate decision consequences.

Table VI. Factor analysis as a tool for manufacturing sector decision-making

Model		Sum of squares	Df	Mean square	F	Sig.
1	Regression	60.644	2	30.322	27779.207	.012[b]
	Residual	.106	137	.001		
	Total	60.750	139			

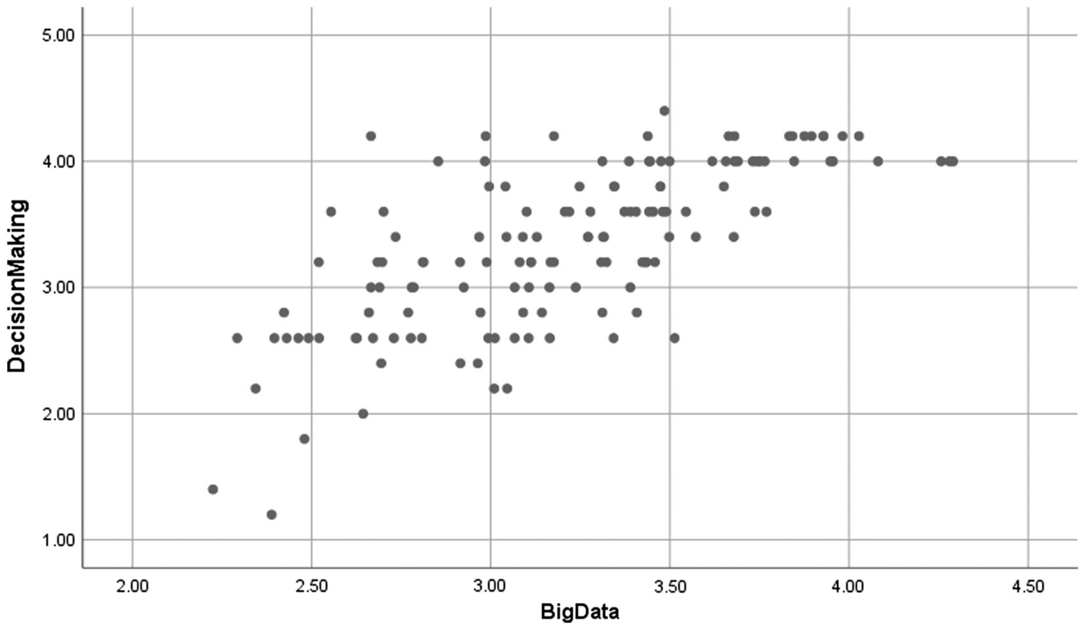

Fig. 4. Decision-making as a linear function of scatter plot.

Our findings suggest that Chinese manufacturing firms value data timeliness and reliability as essential inputs for improving operational responsiveness and quality assurance—aligning with previous work by [6], yet providing new insight into how data trustworthiness (Veracity) is more highly emphasized in emerging markets where data inconsistency is a known challenge. In the choice phase, where a decision is selected and implemented, the role of Value becomes critical. The study shows that decision-makers in manufacturing prioritize actionable insights that lead to measurable outcomes—such as cost reduction, process efficiency, and improved delivery times. This reflects the shift from data-driven hype to value-driven execution, consistent with the findings of [63] but diverging from some Western literature that places more emphasis on exploratory analytics rather than operational efficiency.

Comparative analysis with existing literature reveals that while volume and velocity have traditionally received more attention, our study found Veracity and Value to be more influential in shaping high-quality decisions within China's manufacturing firms. This difference may be attributed to the structural characteristics of Chinese Small and Medium Enterprises and large manufacturers [64], which often face greater risks of data inconsistency and resource constraints, making data relevance and usability more important than raw data volume. From a practical perspective, the findings have significant implications for business leaders and policymakers. Manufacturing firms should prioritize investment not only in data infrastructure but also in governance frameworks that ensure data quality, security, and contextual relevance. Managers should be trained to interpret and act on analytics outputs, moving beyond intuition-based practices to evidence-driven decision-making. By embedding BDA capabilities across departments, firms can enable predictive maintenance, optimize inventory, minimize waste, and improve customer responsiveness.

Moreover, in the post-COVID environment where digital transformation is no longer optional, BDA provides a foundation for organizational resilience and agility. Companies that adopt BDA holistically—from operational processes to boardroom strategy—will be better positioned to cope with volatility and adapt to changing global dynamics. Finally, this research contributes to theory by offering an integrated view of how each of the 5Vs aligns with Simon's decision-making stages, and to practice by illustrating how BDA can support smarter, faster, and more reliable decisions in one of the world's most important industrial economies.

VI. CONCLUSION

Based on IBM SPSS statistical analysis, the study indicates that BDA is a cutting-edge tool for absorbing vast amounts of information in the modern era of digital commerce. The opportunity cost of using BDA is greater, according to the research. Executives, Directors, and Managers in Chinese industrial sector are under enormous pressure, so it is difficult for them to make difficult choices under time constraints. Background setting knowledge on challenges and opportunities is necessary for operational, strategic, R&D, market, downsizing, and other types of choices.

BDA rely on large amounts of information from trustworthy sources, making the rapid pace of technological progress a valuable asset. The decision-making phases of Simon (1966)—Intelligence, Design, and Choice—and the relationships between volume, velocity, variety, veracity, and values are all positively correlated with one another and the success of the decision-making process. In a linear model, the characteristics of big data have an immediate impact on the decision-making function:

$$Dc\_mkg = \alpha + \beta(V1) + \beta(V2) + \beta(V3) + \beta(V4) + \beta(V5) + e$$

The study concludes that there is a causal link between decision-making and the success of industrial companies, and that this finding may be extrapolated to the service and finance industries. The quality of the decisions made by management may have a dramatic impact on the effectiveness and efficiency with which a company operates, ultimately leading to increased production. Making decisions based on data requires persistence, stability of thought, and the result is a step-by-step improvement in results.

VII. LIMITATION AND FUTURE DIRECTIONS

This study contributes to the growing body of knowledge on BDA by empirically examining how the five key characteristics of big data (volume, velocity, variety, veracity, and value) influence decision-making effectiveness and organizational performance in China's manufacturing sector. Drawing upon Simon's decision-making model, the findings demonstrate that BDA plays a pivotal role in enhancing the intelligence, design, and choice phases of decision-making, with Veracity and Value emerging as particularly influential factors in this industry context. Despite these valuable insights, the study has several limitations that must be acknowledged. First, the research was conducted within the manufacturing sector only, which, although significant in China's economy, may not represent other dynamic sectors such as finance, healthcare, or services. Sector-specific factors, operational structures, and data maturity levels may yield different outcomes. Second, the study employed a cross-sectional design, capturing perceptions and performance at a single point in time. This design limits our ability to observe how BDA adoption and its impact on decision-making evolve across different phases of technological integration. Third, the research focused solely on Chinese firms, meaning the findings are culturally and economically contextualized and may not be universally applicable to firms in other countries with different digital maturity levels or organizational cultures.

To address these limitations, future research should adopt more diverse and expansive sampling strategies, including firms from multiple sectors and regions. Conducting cross-industry comparative studies would allow for the identification of sector-specific drivers and barriers to BDA adoption. Moreover, longitudinal research designs should be implemented to assess how the relationship between BDA and decision-making evolves over time, especially in response to external disruptions such as technological change, pandemics, or supply chain crises. Further research can also expand the current model by incorporating moderating and mediating variables, such as digital leadership, employee data literacy, organizational agility, and technological infrastructure. Additionally, integrating constructs like environmental sustainability, employee psychological well-being, and organizational resilience can provide a richer and more holistic understanding of BDA's broader organizational impact. For instance, future studies could explore how BDA and AI are being used to address issues of workplace stress, job satisfaction, and employee empowerment in data-driven environments. Moreover, in light of the post-COVID-19 digital shift, future studies should investigate how BDA and AI are enabling the transformation toward virtual operations and environmentally responsible supply chains. There is a growing need to understand how data analytics supports green decision-making, inter-organizational trust, and eco-efficiency, especially as firms adopt circular economy principles and sustainability-focused Key Performance Indicators.

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CONFLICT OF INTEREST STATEMENT

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