

The significance and application of data analytics models for strategic management



Muhammad Ramzan *

College of Computing and Informatics, Saudi Electronic University, Riyadh, Saudi Arabia

ARTICLE INFO

Article history:

Received 18 July 2023

Received in revised form

9 December 2023

Accepted 25 December 2023

Keywords:

Data analytics

Strategic decision-making

Competitive advantage

Data analysis techniques

Strategic management

ABSTRACT

In today's global landscape, the survival and success of organizations depend significantly on the effective use of their data assets for informed strategic decision-making. The exponential proliferation of data and its multiple uses present profound challenges and opportunities. Proficient management, processing, and use of this vast reservoir of data have emerged as a paramount concern in today's world. At the same time, the wise application of data analytics techniques and frameworks offers compelling strategic advantages. Identifying and deploying the most relevant data analytics methodologies within the realm of strategic management presents a formidable challenge for senior executives. This study examines the central role of data analytics in strategic decision-making and explores how organizations can leverage it to gain a competitive advantage. In addition, the research examines recent literature that sheds light on the various dimensions of integrating data analytics into strategic management. The study also provides selected illustrative use cases and instances of strategic management at the corporate, business, and functional levels. In particular, it presents a spectrum of both quantitative and qualitative data analysis techniques to underscore the availability of frameworks that facilitate the integration of data analysis into strategic management and decision-making processes.

© 2023 The Authors. Published by IASE. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

1. Introduction

Strategic management, which includes strategic planning and decision-making processes, is a key tool for creating a sustainable and protective environment for businesses in a highly competitive business world (Settembre-Blundo et al., 2021; Padash and Ghatari, 2020). It is used as a tool to promote healthy competition and improve business performance. Managers are increasingly using key performance indicators, insights, statistical analysis, and computer tools, including simulation, instead of their reports, perception, or intuition to make strategic decisions considering the insights that can be gained from mining big data (Silahtaroglu and Alayoglu, 2016). To this end, the mining and research of large data sets using business intelligence tools and information mining

methodologies are becoming an essential part of decision-making processes (Grover et al., 2018). therefore, businesses should learn how to leverage the power of big data analytics for their decision-making.

Djemaiel et al. (2014) described big data as large and complex sets of data that require fast capture, management, and analysis. Big data can appear in different forms, such as statistical data, partially defined information, or unorganized data. Wamba et al. (2015) offered a definition of big data using five key characteristics, known as the Five Vs. The Five Vs are as follows:

1. Volume stands for the size of the data.
2. Velocity stands for the rate of data erasure.
3. Variety stands for the data structure types, including structured databases, pictures, text, and so forth.
4. Value stands for any cost that could add value to the enterprise.
5. Veracity stands for the quality of the data.

Big data can be used to assess how well an organization is performing and to design improved organizational frameworks that enhance decision-

* Corresponding Author.

Email Address: m.ramzan@seu.edu.sa

<https://doi.org/10.21833/ijaas.2024.01.010>

Corresponding author's ORCID profile:

<https://orcid.org/0000-0002-2982-5052>

2313-626X/© 2023 The Authors. Published by IASE.

This is an open access article under the CC BY-NC-ND license

(<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

making effectiveness. One application of this is simulation, which involves creating models of advanced systems to enhance them or developing new systems to significantly boost business performance. Additionally, employing statistical methods and computer tools represents another approach to facilitating decision-making by providing deeper insights into organizational performance (Shabbir and Gardezi, 2020; Harrington and Tumay, 2000). It enables analysis of current systems, making it simpler to see flaws in existing structures, and provides solutions for issues that arise.

This paper will explore how big data analytics and simulation tools contribute to strategic management, enhancing business performance, and supporting environmental decision-making. The structure of the paper is as follows: Section 2 will discuss the role of strategic management and how analyzing data is crucial in making informed decisions. Section 3 will introduce various data

analytics methods and techniques that are pertinent to strategic management. Finally, Section 4 will offer a discussion and examination of the main findings from this study.

2. Strategic management

The sustainability and strategic direction of an organization significantly depend on effective decision-making at the strategic level. The core principles of strategic management involve evaluation, decision-making, and planning. This management level is concerned with analyzing the organization's objectives and both its internal and external environments (Choubey and Mishra, 2016). As depicted in Fig. 1, strategic management encompasses three primary stages: formulation, implementation, and evaluation. Each stage plays a supportive role to the others and contributes to making strategic decisions within its scope.



Fig. 1: Basic steps of strategic management

The strategic process also involves setting the organization's vision and goals, as well as analyzing its strengths, weaknesses, and opportunities. The next phase, implementation, is when these planned strategies are put into practice. This stage requires efficient allocation and use of staff and resources to successfully execute new strategies. Following this, the final phase evaluates the effectiveness of the strategies that have been implemented. This step is crucial for ensuring the strategic management process is effective and leverages data analysis to ensure accuracy. Fig. 2 illustrates key factors to consider in this context. Munive-Hernandez et al. (2004) and Grzybowska and Kovács (2017) have highlighted several strategic-level modeling techniques that are important for detailed planning and decision-making, including:

- IDEF0 (Integrated Definition Methods) is used to model the functions of an enterprise and its decision-making processes.
- Petri net, specifically place/transition net, is a mathematical modeling language used for the description of distributed systems.
- EPC (Event-Driven Process Chain) is a flowchart-based diagram that is used for business process modeling.

These methods are pivotal in structuring and analyzing the strategic steps an organization takes,

ensuring that every phase, from vision setting to strategy evaluation, is systematically approached and well-informed.

The Warnier/Orr Diagram is a tool used in strategic planning for outlining problems and gathering information. It employs a graphical method to simplify the process of determining requirements for strategy development and helps in the organization and design of system components. This approach, which is both top-down and bottom-up in its design considerations, facilitates a clear understanding of system specifications (Davis, 1983; Warnier, 1976).

In addition to the Warnier/Orr Diagram, simulation modeling is another technique that can be utilized during the strategy implementation phase. It allows for the examination of the potential outcomes of various alternatives without the need to make actual changes. This form of data analysis in strategic management aids in selecting the most advantageous option for real-world application (Shannon, 1975).

Furthermore, the Analytical Hierarchy Process (AHP) is extremely useful in evaluating plans. AHP provides a comprehensive perspective on the problem, aiming to fully understand its scope and intricacies. This method helps in breaking down complex decisions into a series of simpler, hierarchical steps, making it easier to assess and compare different strategies.

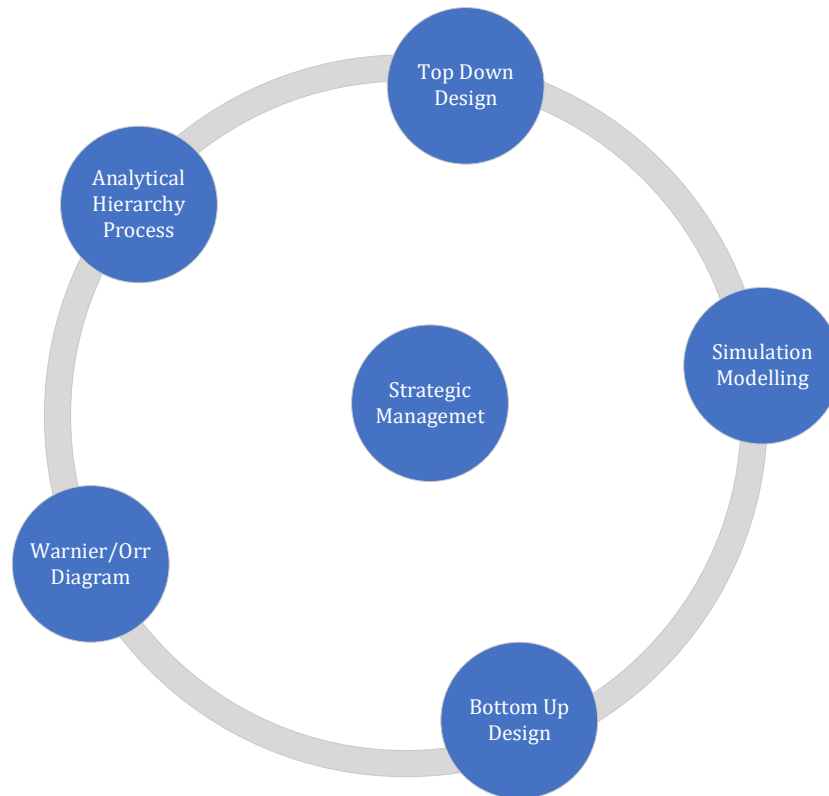


Fig. 2: System analysis and design techniques

Afonina (2015) outlined various strategic management tools that are essential for overseeing and guiding organizational strategy. These tools include SWOT analysis (evaluating strengths, weaknesses, opportunities, and threats), customer satisfaction and behavior analysis, employee satisfaction studies, segmentation of markets based on consumer needs and preferences, analysis of market share, profitability of customers, and assessment of service levels. Additionally, the study highlights the importance of leveraging insights, perceptions, or gut feelings to choose or refine strategies previously connected to these analyses.

Research by Papulova and Gazova (2016) explored different approaches to data modeling for strategic management, identifying three critical types of reasoning for effective organizational function: mechanical, intuitive, and strategic reasoning. Mechanical reasoning relies on logical judgment, intuitive reasoning is based on creativity and past experiences, and strategic reasoning involves making predictions and assessing the long-term impacts of planning and management decisions. This distinction underlines the value of combining analytical tools with human insight to navigate the complexities of strategic management effectively.

2.1. Strategic management and data analytics

As previously mentioned, the role of data analytics in strategic management is crucial. Technological advancements offer both new opportunities and challenges for businesses, influencing every aspect of operations. This is

particularly relevant in strategic management, which focuses on long-term organizational decisions. Through strategic decision-making, technology can lead to the creation of new markets and stronger competitive advantages. Innovations can affect an organization in various ways, including altering industry pricing strategies as well as shifting the values and expectations of employees, supervisors, and customers (David, 2011). Consequently, the use of modern data analysis technologies, big data sets, and analytical models is becoming increasingly vital for businesses. It's important for companies to stay updated with these advancements and incorporate them into their strategic planning.

A study examining the impact of statistical technology on decision-making found that combining information technology with traditional decision-making methods enhances outcomes (Provost and Fawcett, 2013). The research highlighted a significant link between improved business performance and the use of statistical data alongside information technology for decision-making. Data analysis technologies provide several advantages to organizations, notably by offering a unique strategic edge. This advantage stems from the technology's capacity to reveal new perspectives for decision support, characterized by the Five Vs: velocity, scale, cost, variety, and veracity. Moreover, it allows for the presentation of data in multiple formats. A key challenge for organizations at this point is to conduct a cost-benefit analysis of adopting these technologies and deploying the necessary infrastructure to maximize their impact.

Fig. 3 illustrates the Five Vs of data and the primary challenges associated with them. Hadi et al.

(2015) discuss how data analysis models that handle large amounts of data can generate knowledge, along with their strengths and weaknesses, due to these characteristics. The research indicates that while the Five Vs offer strong strategic motivations for using contemporary data analysis techniques in decision-making, effectively deploying and managing these in a rapidly changing and expansive data environment

poses significant challenges. Even though working with big data presents challenges, the advantages it offers for strategic planning and decision-making are vast. Big data provides deep insights into customer behavior, which can be leveraged for a competitive edge and to guide strategic management efforts more effectively.

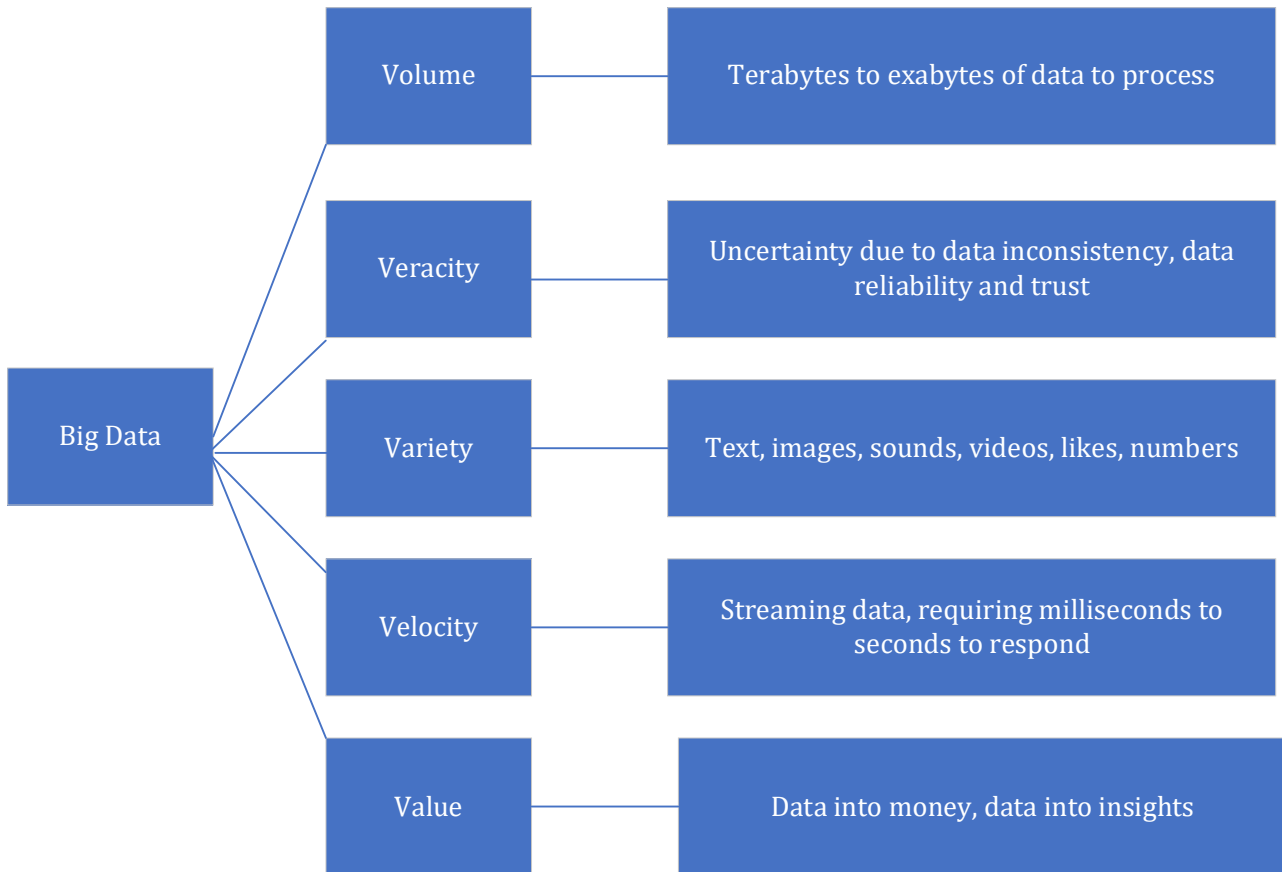


Fig. 3: Five Vs of big data

Evaluation and decision-making at strategic levels increase the effectiveness of deploying metrics used in decision-making and enable achieving several strategic benefits, such as optimization of supply chain and human resources (Bhimani, 2015; Bertei et al., 2015; Erevelles et al., 2016). In addition, successful business entities in the modern world use big data and data analysis frameworks to strengthen their competitive capabilities (Etzion and Aragon-Correa, 2016). In essence, a business entity will be more efficient if it pushes harder for effective utilization of its data assets using such data analysis techniques (Tambe, 2012). Organizations are increasingly feeling the pressure and necessity to utilize big data analytics to enhance their understanding and make more effective decisions. Research indicates that the current advancements in data analysis technology have significantly improved the ability to access, combine, present, and review all available data, reaching levels of effectiveness not seen before (Garmaki et al. 2016). As can be observed, the use of huge fact analysis makes it easier to work with large records. However, in order to implement large-scale data analytics,

organizations must have certain capabilities. It is essential to use advanced tools, adequate statistics, extensive records, analytical skills, and industry expertise to make informed decisions (Gupta and George, 2016; Ghasemaghaei et al., 2018; Davenport and Patil, 2012).

In the literature, there are several examples of big data analytics being applied to strategic management (Wills, 2014; Ward, 2014). For instance, companies have analyzed customer purchasing behaviors and predicted future trends. Some large organizations have even created customized programs using big data analytics to better understand and support customer buying habits. These efforts have provided valuable insights, showcasing how data analysis can significantly inform strategic decision-making processes.

3. Data analytics methods and techniques

In previous sections, we emphasized that to uncover valuable insights within statistics, including various metrics, data, and figures, it's essential to utilize data analysis methods. Research has indicated

that there are two highly effective approaches for data analysis, especially in the context of strategic management: Qualitative data analysis techniques and Quantitative data analysis techniques. These methods can significantly aid business decision-makers in extracting corporate insights from different types of data. These statistical analysis techniques can be used either separately or together with other methods to achieve the desired results.

3.1. Quantitative data analysis techniques

Each quantitative statistical analysis method has its own unique process for extracting knowledge from large data sets. For instance, the Monte Carlo simulation is a technique used in fields like finance, engineering, and technology to simulate and assess possible outcomes in situations where there is uncertainty. Similarly, a mobile telecommunications service provider might use this method to evaluate network performance under various scenarios to identify improvement opportunities. Other quantitative analysis methods include flow charts and trend analysis, which various organizations can apply in their specific settings to analyze data.

Two commonly used quantitative data analysis techniques are regression analysis and hypothesis testing. Regression analysis helps in understanding the relationship between dependent and independent variables, while hypothesis testing is used to confirm or refute a presumption made about a data set. These techniques provide structured approaches to analyzing quantitative data, allowing businesses to make informed decisions based on statistical evidence.

3.1.1. Regression analysis

Regression analysis is a statistical method used to find relationships between variables where one variable is dependent on another. In the field of finance, it's used by fund managers and financial analysts to evaluate assets and explore how different variables, like stock and commodity prices, relate to each other.

This analysis helps a quantitative data analyst to understand the impact of changes in variables by conducting experiments where independent variables (factors that can be changed) are adjusted. Think of it as understanding cause and effect; for example, the amount a person invests in the stock market (independent variable) might affect the total money they have at retirement (dependent variable).

There are two primary types of regression analysis: simple linear regression and multiple linear regression. Simple linear regression looks at the relationship between two variables, while multiple linear regression examines the relationship between one dependent variable and two or more independent variables.

For instance, a market researcher might use linear regression to study the link between a company's products and customer satisfaction. They

could assign numerical values to customer satisfaction levels on a scale from 1 to 10. With this data, the researcher can perform a regression analysis to discover how closely related product quality is to customer satisfaction.

3.1.2. Hypotheses analysis

Hypothesis testing is a method used in statistics to determine if there is enough evidence in a sample of data to infer that a certain condition is true for the entire population. This approach involves making an initial assumption, known as the hypothesis, and then determining whether the data supports this hypothesis or not. Essentially, the analyst proposes two hypotheses: the null hypothesis, which suggests no effect or no difference, and the alternative hypothesis, which suggests there is an effect or a difference. Through statistical analysis, the analyst can conclude whether to reject the null hypothesis and accept the alternative hypothesis or vice versa, based on the evidence from the data.

3.1.3. Null hypotheses

The null hypothesis is the initial theory. Between the two companies shown in the facts, null means there is no difference. For example, the null hypothesis would state that there is no difference in student satisfaction with their professors between students from high-income groups (group 1) and those from low-income areas (group 2). When conducting hypothesis testing, the goal of the researcher or analyst is to show that there is a difference between the firms under consideration, thereby rejecting the validity of the null hypothesis.

3.1.4. Alternative hypotheses

Usually, the null hypothesis is opposed to the alternative hypothesis. Let us imagine that a particular product experiences a 25% revenue boom once a year for 15 years. In this case, the null hypothesis is that the proposed product price increase will be 25%. Hypothesis analysis is used to determine whether the null hypothesis is always true. In this case, the analyst uses casual speculation to determine the accuracy of the predicted 25% boom price. The opportunity hypothesis is that the growth fee for the product is not 25%. In this case, a 5-year boom can serve as a random sample rather than a 15-year boom. When the test has come to an end, the trier of fact can only conclude based on the findings.

3.2. Qualitative data analysis techniques

Deductive and inductive qualitative data methodologies serve as the foundation for qualitative data analysis techniques.

Deductive process. Researchers and analysts who already have a principle, or a preset idea, of the

likely entry from a pattern population use this evaluation approach. The deductive technique aims to gather the information that could logically and properly support a concept or speculation.

Inductive approach. By using this technique, a researcher or analyst who has limited knowledge of the results of a sample population gathers the right amount of information on a topic of interest. The records are then examined to seek patterns. The objective is to create a principle that offers an explanation for the patterns found in the data.

Content assessment and discourse evaluation are the two main methods that statisticians employ to evaluate qualitative data. Another well-liked strategy is narrative assessment, which focuses on the tales and accounts told by participants in an examination. The descriptions and standard procedures for content evaluation and discourse evaluation are listed below.

3.2.1. Content analysis

Content analysis can be used by statisticians and researchers to identify trends in a wide range of written communication. In recorded conversations, styles that indicate the purpose, meanings, and effects of the content can be observed through content analysis.

The intention of content creators and their impact on target audiences can also be determined with the aid of content analysis. Considering the COVID-19 pandemic, for example, content analysis of political communications can offer qualitative insights concerning employment policy. An analyst could track the occurrences of the word "employment" in social media posts, news articles, and other media, as well as how it links to other pertinent terms like "finance system," "business," and "foremost avenue." The purpose of a political marketing campaign can thus be better identified with its messages by an analyst by looking at the connections between these terms.

The content evaluation approach includes a wide range of elements, including the following:

- **Pick out the advantages of the facts:** Choosing the type of content to be studied is the first stage in the content evaluation process. Resources range from written text found in books, newspapers, and social media posts to visual information found in photos and videos.
- **Establish records criteria:** This stage entails figuring out what will make a chosen text relevant to the examiner. "Does the text reference a certain subject or imply a circumstance related to the issue?" are some examples of questions to ask when evaluating factual criteria. Another such question is: "Does it fit into a particular chronological range or geographic region?"
- **Expanding the coding for the data is necessary** since qualitative statistics, which is not necessarily numerical, needs to be codified in coaching for size. To categorize the records, it is necessary to create a

set of fixed or systems of codes. As soon as the coding system is created, text can use the appropriate codes.

- **Analyze the outcomes:** The information exam system is the product of the work done in the earlier steps. To analyze results and draw conclusions, information analysts look for patterns and correlations in the data. They might include statistical methods for analyzing the records in order to gain more information from them.

3.2.2. Discourse analysis

Discourse analysis: Reading between the lines, or the capacity to identify hidden messages in communication, is essential because messages are not always what they seem to be. Even if spoken and written communications all have a subliminal or underlying message, it is possible for one organization to understand them one way while being utterly misunderstood by another, which would likely result in a breakdown in civil discourse.

Discourse analysis makes it possible to present data about the social and cultural background of written and spoken communication during the course of talks. Discourse analysis looks at how people use language to achieve their goals, including arousing emotion, sowing doubt, or forming beliefs. It also looks at the social environment of verbal interchange. Both verbal and nonverbal cues are examined in discourse analysis. For instance, the way a speaker pauses on a particular word or words can reveal information about the speaker's thinking or attitude toward that phrase.

Discourse analysis makes it easier to discern the underlying intent and purpose of a conversation and resolves miscommunications. For instance, to highlight the application, a review of discussion transcripts between a doctor and a patient can determine whether the patient truly understood a diagnosis. Through discourse analysis, an analyst can identify subtle subtexts in linguistic exchanges and determine if the information is a fact, fiction, or propaganda. Among the steps in discourse evaluation are:

- **Establishing the research question:** This step clarifies the purpose of the investigation and provides a clear justification. The analysis will be guided by the research question.
- **Choose the content types you want to employ for your research:** Speeches, news releases, speeches, social media text, and more are all acceptable.
- **Get the facts:** The content gathered for the evaluation often focuses on a message-delivery issue (such as a political leader or business) and its targeted target audience (residents and customers, for example).
- **Examine the content:** Words, phrases, sentences, and content structure can be used to track trends in a subject's attitudes and motivations as well as the message's effect on the intended audience.

This brief overview introduces new methods of both quantitative and qualitative analysis that are becoming essential for successful strategic management, including planning, forecasting, and decision-making. Using such technologies is now more of a requirement than a mere option available to organizations.

4. Conclusion

This paper explores the role of data analytics in strategic management, arguing that despite the challenges of implementing data analysis techniques, the benefits significantly outweigh these hurdles. It emphasizes the importance for modern organizations to employ data analysis and big data to gain a competitive edge. Data analysis is highlighted as a key tool for gaining market insights, aiding in planning, and optimizing assets. The paper also discusses how data analysis frameworks support the collection of knowledge for both tactical and strategic management purposes. Additionally, it explains how simulation modeling, powered by big data analysis, can produce valuable information for strategic planning by simulating systems and setting parameters for these simulations. Furthermore, the paper outlines various quantitative and qualitative data analysis methods that are effective for making strategic decisions.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

- Afonina A (2015). Strategic management tools and techniques and organizational performance: Findings from the Czech Republic. *Journal of Competitiveness*, 7(3): 19-36. <https://doi.org/10.7441/joc.2015.03.02>
- Bertei M, Marchi L, and Buoncristiani D (2015). Exploring qualitative data: The use of big data technology as support in strategic decision-making. *The International Journal of Digital Accounting Research*, 15(21): 99-126. https://doi.org/10.4192/1577-8517-v15_4
- Bhimani A (2015). Exploring big data's strategic consequences. *Journal of Information Technology*, 30(1): 66-69. <https://doi.org/10.1057/jit.2014.29>
- Choubey G and Mishra A (2016). Strategic management is essential for organisational growth: A case study of Havells. *International Journal of Science and Research*, 5(4): 374-377. <https://doi.org/10.21275/v5i4.NOV162536>
- Davenport TH and Patil DJ (2012). Data scientist. *Harvard Business Review*, 90(5): 70-76.
- David FR (2011). *Strategic management concepts and cases*. Pearson, London, UK.
- Davis WS (1983). *Systems analysis and design: A structured approach*. Addison-Wesley Longman Publishing, Boston, USA.
- Djemaiel Y, Essaddi N, and Boudriga N (2014). Optimizing big data management using conceptual graphs: A mark-based approach. In the 17th International Conference on Business Information Systems, Springer International Publishing, Larnaca, Cyprus: 1-12. https://doi.org/10.1007/978-3-319-06695-0_1
- Erevelles S, Fukawa N, and Swayne L (2016). Big data consumer analytics and the transformation of marketing. *Journal of Business Research*, 69(2): 897-904. <https://doi.org/10.1016/j.jbusres.2015.07.001>
- Etzion D and Aragon-Correa JA (2016). Big data, management, and sustainability: Strategic opportunities ahead. *Organization and Environment*, 29(2): 147-155. <https://doi.org/10.1177/10860266166650437>
- Garmaki M, Boughzala I, and Wamba SF (2016). The effect of big data analytics capability on firm performance. In the 20th Pacific Asia Conference on Information Systems, Chiayi, Taiwan.
- Ghasemaghahi M, Ebrahimi S, and Hassanein K (2018). Data analytics competency for improving firm decision making performance. *The Journal of Strategic Information Systems*, 27(1): 101-113. <https://doi.org/10.1016/j.jsis.2017.10.001>
- Grover V, Chiang RH, Liang TP, and Zhang D (2018). Creating strategic business value from big data analytics: A research framework. *Journal of Management Information Systems*, 35(2): 388-423. <https://doi.org/10.1080/07421222.2018.1451951>
- Grzybowska K and Kovács G (2017). The modelling and design process of coordination mechanisms in the supply chain. *Journal of Applied Logic*, 24: 25-38. <https://doi.org/10.1016/j.jal.2016.11.011>
- Gupta M and George JF (2016). Toward the development of a big data analytics capability. *Information and Management*, 53(8): 1049-1064. <https://doi.org/10.1016/j.im.2016.07.004>
- Hadi HJ, Shnain AH, Hadishaheed S, and Ahmad AH (2015). Big data and five V's characteristics. *International Journal of Advances in Electronics and Computer Science*, 2(1): 16-23.
- Harrington HJ and Tumay K (2000). *Simulation modeling methods*. Volume 8, McGraw Hill Professional, New York, USA.
- Munive-Hernandez EJ, Dewhurst FW, Pritchard MC, and Barber KD (2004). Modelling the strategy management process: An initial BPM approach. *Business Process Management Journal*, 10(6): 691-711. <https://doi.org/10.1108/14637150410567884>
- Padash A and Ghatari AR (2020). Toward an innovative green strategic formulation methodology: Empowerment of corporate social, health, safety and environment. *Journal of Cleaner Production*, 261: 121075. <https://doi.org/10.1016/j.jclepro.2020.121075>
- Papulova Z and Gazova A (2016). Role of strategic analysis in strategic decision-making. *Procedia Economics and Finance*, 39: 571-579. [https://doi.org/10.1016/S2212-5671\(16\)30301-X](https://doi.org/10.1016/S2212-5671(16)30301-X)
- Provost F and Fawcett T (2013). Data science and its relationship to big data and data-driven decision making. *Big Data*, 1(1): 51-59. <https://doi.org/10.1089/big.2013.1508> PMID:27447038
- Settembre-Blundo D, González-Sánchez R, Medina-Salgado S, and García-Muiña FE (2021). Flexibility and resilience in corporate decision making: A new sustainability-based risk management system in uncertain times. *Global Journal of Flexible Systems Management*, 22(Suppl 2): 107-132. <https://doi.org/10.1007/s40171-021-00277-7> PMID:PMC8329640
- Shabbir MQ and Gardezi SBW (2020). Application of big data analytics and organizational performance: The mediating role of knowledge management practices. *Journal of Big Data*, 7(1): 1-17. <https://doi.org/10.1186/s40537-020-00317-6>
- Shannon RE (1975). *Systems simulation: The art and science*. Prentice-Hall, Hoboken, USA.

- Silahtaroglu G and Alayoglu N (2016). Using or not using business intelligence and big data for strategic management: An empirical study based on interviews with executives in various sectors. *Procedia-Social and Behavioral Sciences*, 235: 208-215. <https://doi.org/10.1016/j.sbspro.2016.11.016>
- Tambe P (2012). Big data know-how and business value. Working Paper, NYU Stern School of Business, New York, USA.
- Wamba SF, Akter S, Edwards A, Chopin G, and Gnanzou D (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, 165: 234-246. <https://doi.org/10.1016/j.ijpe.2014.12.031>
- Ward DG (2014). A guide to the strategic use of big data. *Information Management Journal*, 48(6): 45-48.
- Warnier JD (1976). Logical construction of programs. Van Nostrand Reinhold Company, New York, USA.
- Wills MJ (2014). Decisions through data: Analytics in healthcare. *Journal of Healthcare Management*, 59(4): 254-262. <https://doi.org/10.1097/00115514-201407000-00005>
PMid:25154123