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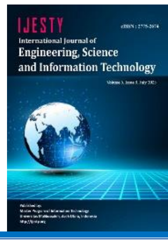

Data-Driven Decision-Making Use Case: Applying Big Data Analytics to Forecast Important Decisions

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Abstract

Due to decreased material and resource usage and other tooling needs, additive manufacturing (AM) has rapidly developed over the past 10 years. It has shown significant promise for energy-efficient and environmentally friendly production. As manufacturing technologies have advanced in the modern period, intelligent manufacturing has gained greater attention from academia and business to increase the sustainability and efficiency of their output. Few studies have examined the effects of big data analytics (BDA) in CSR activities on CSR performance, despite the growing number of businesses implementing BDA in CSR initiatives. As digital technology is incorporated into various processes, supply chain management is increasingly interested in Big Data Analytics (BDA). It efficiently makes the transfer of goods and information possible. Nevertheless, little research has been done on how much BDA can enhance supply chains' environmental sustainability, even though it offers several benefits. We provide a thorough understanding of "data science" in this paper, covering a range of sophisticated analytics techniques that may improve an application's intelligence and capabilities through astute decision-making in diverse contexts. In light of this, we conclude by outlining the difficulties and possible lines of inquiry within the parameters of our investigation. Our literature analysis indicates that an increasing number of data-driven decision-making methods have been developed specifically to benefit from the wealth of sensor-generated data in the context of Industry 4.0. This article aims to provide researchers, decision-makers, and application developers with a reference point on data science and advanced analytics, especially regarding data-driven solutions for real-world issues.

Keywords: *Data-Driven, Decision-Makers, Big Data Analytics, Data Science, Supply Chains.*

1. Introduction

The combination of deep learning and AI has transformed business analytics in recent years, significantly changing how businesses approach making decisions based on data algorithms for machine learning that are capable of processing and interpreting intricate data patterns. These are among the many technologies that fall under the umbrella of AI [1]. Neural network designs with deep learning is a form of artificial intelligence that uses many layers to model complex relationships in big datasets. Businesses may extract relevant insights from numerous sources of information by integrating such technologies into business analytics, which enables sophisticated predictive capabilities.

Forecasting, which is essential for predicting future trends, customer behavior, and operational efficiencies, has significantly improved as a result of the development of AI and deep learning. With the help of this cutting-edge technology, predictive analytics enables businesses to predict changes in the market, improve their marketing plans, and streamline processes with previously unheard-of precision. This capacity is especially important in the modern business environment, where quick technical breakthroughs and changing market conditions call for quick and well-informed decision-making. By allowing preemptive rather than reactive initiatives, the ability to leverage big data using AI-driven systems not only increases forecasting accuracy but also gives a competitive edge.

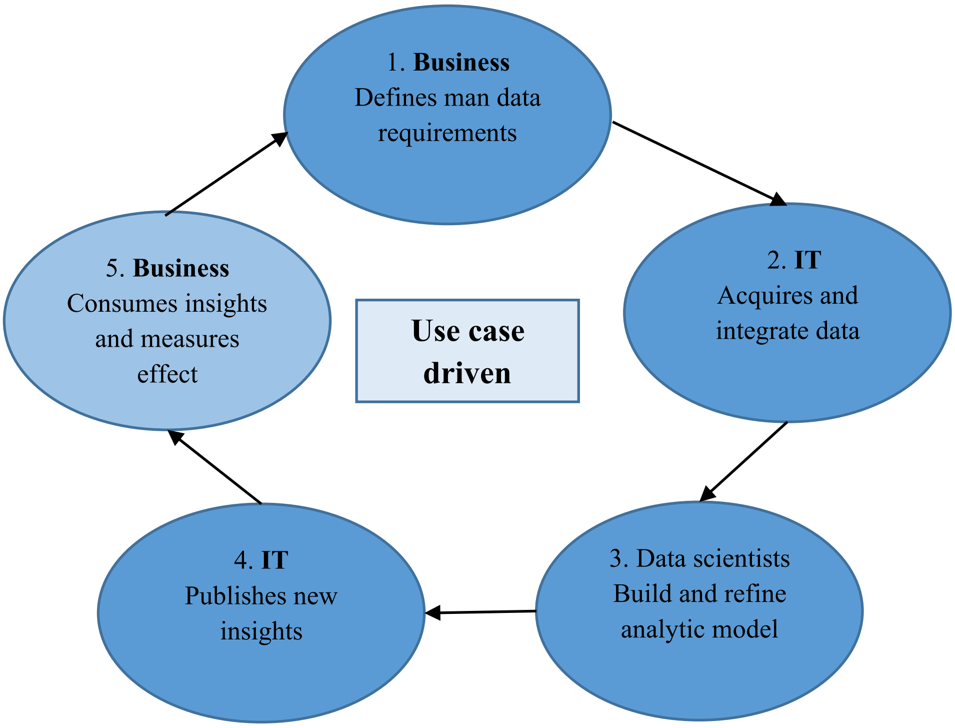

Fig 1. Big data analytic use cases

The foundation for every big data strategy is a use case shown Figure 1. This is not understood by most individuals. Those who are already in charge of marketing, business intelligence, or IT will typically be handed the big data charter.
These days, almost every part of our daily lives is digitally recorded as data in the age of "data mining and advanced analytics." The present electronic world is therefore full of various kinds of data, including as information security, social networking sites, business, monetary, healthcare, multimedia, and IoT data [3].The information may be semi-structured, unstructured, or structured, it is growing daily. To comprehend and examine the real data-related phenomena, data science is typically described as a "the idea that brings together the investigation of data, statistics, and related methods." The claims that "data science is the researchers of data" or "data research is the study of data" state that a data-driven output is a data product that is to be provided, or data-enabled or directed. This product can be a forecast, service, recommendation, comprehension of decision-making, contemplating, model, framework, tool, or system.
According to statistics gathered by Google Trends over the previous five years, "data science" is gaining popularity daily. Alongside data science, we have also shown the rising popularity trends of similar topics including "data analytics," "information mining," massive data," and "machine learning." Indicators of popularity for these data-driven areas, particularly "data science" and "ML," are rising everyday. This statistical data, along with the importance of data-driven intelligent choices in a range of real-world application sectors, motivates us to briefly study "Information science" and machine-learning-based "Advanced Training analytics" in this work.
This is how the rest of the document is organized. The background information, relevant literature, and study scope are defined in the next section. The principles offered in the section that discusses data science model for developing a data-driven solution. follows. Next, give a quick overview of smart computing and several advanced analytics techniques. The following section discusses and summarizes some real-world application areas. After highlighting and summarizing a number of research questions and possible avenues for future investigation, the final section brings this paper to a close.

2. Literature Review

The framework ought to incorporate the triptych associated with "data, details, and knowledge" together with go into greater detail about how learned information is used to real-world decision-making [4]. In order to assist in decision-making, it should make full application of data extraction methods rather than concentrating on just one or a small number of them. Furthermore, as planned, either preventative or remedial maintenance guarantees the appropriate and seamless power project operations, the O&M should be included in the framework phases. Accessibility is essential since all participating personnel, whatever their professional backdrop or degree of organization, should be able to use the suggested framework.
The demand for tools that evaluate data and make efficient and effective choices has led to the long-standing disciplines of analysis of data and business analysis seeing extraordinary growth in all fields of knowledge, but especially in organizations and enterprises [5]. As the amounts of data have grown, data analysis has changed as well. Business intelligence tools have combined online analytical processing (OLAP), reporting and querying, visualization, and—above all—data mining technologies with their well-established categories of text mining and web mining with cutting-edge social media data analysis that has depended on methods for examining sentiment and opinion mining, also known as opinion mining and sentiment.
Due to Industry 4.0, condition monitoring techniques have evolved over the past several years, shifting from visual inspections and human information processing to high-energy sensors that provide immediate big data information on a range of variables, including temperature, thermography, and vibrations [6]. On the basis of these data, advanced data analytics techniques can be applied to improve decision-making in a time-constrained manner and control the uncertainty brought on by the unpredictable degradation process and prognostic results. Predictive maintenance decision-making refers to the stage that is initiated by data-driven, (near) immediate

projections to produce proactive suggestions regarding plans and maintenance procedures that eliminate or lessen the consequences of the expected failure.

The process of examining, purifying, converting, and modeling data to obtain valuable details for recommendations and decision-making support is known as data analysis [7]. While "Big Data Analytics" refers to sophisticated analytic techniques that take into consideration large and diverse datasets to examine and retrieve data from large datasets, it has many aspects and gets closer, covering various methods under several names, across various business, science, and social science schemes. This is a sub-process for obtaining insights from big data.

Precisely a result of considering and comprehending related issues in a data-analytic manner, there has been a lot of excitement lately regarding the enormous potential made possible by new and larger avenues for urban data to better serve the objectives of sustainable development by better operating, managing, and developing cities [8]. Human perceptions of how communities can be planned are undoubtedly being enhanced and transformed by big data. Additionally, they are providing a wealth of new tools for informed decision-making and improved understanding of how to promote urban sustainability as quickly and effectively as possible.

Businesses must understand the substantial advantages that come with using blockchain and big data. Blockchain's decentralized blocks provide for transparency throughout supply chains, notwithstanding certain objections against its use in supply chain activities [9]. Customers may obtain precise cost information with blockchain, and the innovation can influence their behavior by enabling them to make well-informed decisions. As an alternative, customer reviews are entered into a database and made available to vendors, facilitating smooth system transactions.

Gathering and evaluating information that can give a stronger foundation for comprehending the causation of environmental factors across the supply chain can increase the effectiveness of supply chain management decision-making [10]. As a result, there is a notable need for advanced data-driven decision assistance in the logistics setting. This allows for effective and efficient decision-making across the supply chain. To do so, however, calls for relevant and precise data sets or information, which enables managers to forecast decision outcomes and their potential effects on the supply chain as a whole. This is frequently made feasible by modeling approaches.

3. Methods

3.1. Smart Cities and Big Data Analytics

A smart city made up of intelligent domains is called a SC. The ground breaking study identified six intelligence domains that define a SC's intelligence [11]. Figure 2 illustrates these as smart people, smart lifestyle, smart economy, smart government, smart transportation, and smart environment. Scholars disagree over how many and what kind of smart domains comprise an SC, but they all agree that a city can only be considered smart if it maintains cross-domain relationships and information sharing. This is intuitively possible with ICT-based solutions.

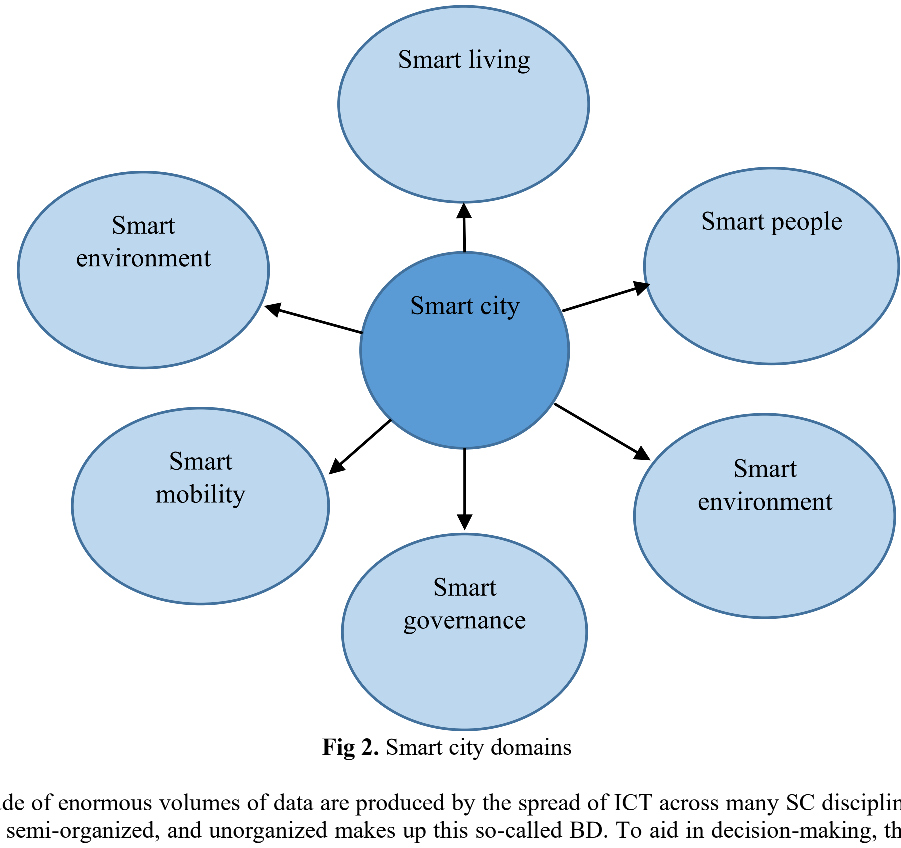

Fig 2. Smart city domains

In exchange, a multitude of enormous volumes of data are produced by the spread of ICT across many SC disciplines. A combination of data that is organized, semi-organized, and unorganized makes up this so-called BD. To aid in decision-making, the discipline of IS has been paying more and more attention to the analysis of BD, known as BDA, to uncover insights and hidden relationships. Several viewpoints in the literature have expressed interest in the applicability of SC and BDA. We can identify the volumes of the collected BD during these stages alongside the diversity of stakeholder demands because SC projects are dynamic and complex, and the stakeholders involved are diverse from the very beginning of planning to the very end of daily service management and oversight. Few articles have proposed developing domain-independent BDA structures that can meet the analytical needs of stakeholders at various stages of SC projects while also preserving and exchanging the extracted analytics, even though there are many articles discussing the uses of BDA in various SC domains.

3.2. Big Data Analytics and Data-Driven Decision-Making

One of the main facilitators of DDD is BDA. DDD, or information science in its broadest definition, is a modern trend that is drawing more and more attention in IS. DDD is making decisions based on information analysis as opposed to only gut feeling. The advantages of DDD and its beneficial effects on businesses' productivity were illustrated by the writers. SCs are not a break to this rule, as the intelligence of cities relies on the IS's provision of a multitude of varied digital data that forms the foundation for analytics-based decision-making. BDA makes use of several algorithms, such as deep learning, data mining, machine learning, and artificial intelligence.
These contemporary approaches to data analysis differ from classic statistical methods in that they deal with data that is structured as well as unstructured and extract both quantitative and qualitative characteristics. Unstructured data analysis is commonly exemplified by picture recognition and text analytics.

3.3. Decision-Making Levels

Decisions are made at three levels in a SC project, just like in a regular project: strategic, tactical, and practical. Major choices that impact all or major parts of a project or business are known as strategic decisions activity. High management makes these kinds of decisions. Strategic decisions have a direct impact on the achievement of the organization's common goals. Over time, they have an impact on the business enterprise. When defining the challenge, management must apply their assessment, intuition, and business judgment because strategic decisions are typically unstructured. Decisions in this situation are based on a combination of knowledge about environmental elements and cumulative partial experiences, which are dynamic and uncertain.
Tactical decisions are made at the intermediate stage of management. These decisions are related to implementing strategic choices. They concentrate on developing divisional plans, arranging procedures, establishing distribution channels, and acquiring resources such as staff, materials, funds, and other assets.
Decisions on operations are made by lower tiers of management. They have to do with the business's daily activities. Because they are produced often, they have a limited lifespan. Because these decisions are based on the facts of the case, they don't require a great deal of business judgment. IS must concentrate on managerial choices since managers want information to make logical, educated judgments.

3.4. Making decisions based 006Fn data—big information and data analytics

The existence of "big data," which includes data set attributes like size, rate of change, diversity, and variability, is what defines today's data-driven environment [12]. These data come from both new, frequently unstructured data sources (like social media data) and more established ones (like accounting system and point-of-sale data). In order to give businesses a competitive edge throughout all of their business operations, the data-driven evolution forces them to adapt their work procedures and calls for new competencies centered on creative data collection and analysis techniques.
In keeping with their business responsibilities, accountants and other middlemen should play significant roles in data-driven decision making processes, which include problem identification, alternative course of action consideration, and presentation of the outcomes of activities performed. "As their organizations transition from traditional, transaction-based accountancy to analytics, accounting professionals have the opportunity to play a key role in the introduction and execution of business analytics." Overall, it appears that by 2018, the US will see a shortage of more than 100,000 workers with advanced analytical abilities and 1.5 million management-level workers who can incorporate the results of data analysis into decision-making procedures. Accounting programs should therefore think about how to guarantee that their finance majors have the skills required for the information-driven decision-making environment.

3.5. Organization Decision-Making Use Cases

The following are the five use cases for Datameer and IBM big data:
1. Analytics for customers;
2. Data-driven goods and services, like technologies for customization;
3. Upgrading and optimization of enterprise data warehouses;
4. operational analytics and business operations monitoring; and
5. Identification of fraud, compliance, and security intelligence extensions. Not a single one of those use case categories calls for long-term, strategic choices.

New data sources can enhance operational decision-making and open doors for innovative data-oriented solutions. Senior managers must wish to employ computerized tools, believe that the data and analyses are relevant to the decision, and then implement the conclusions and suggestions. This is because electronic decision-support tools and analytics have the potential to assist people in making logical decisions that are more likely to result in goal attainment and positive outcomes.
The challenge of supporting decision-making is complicated, and it's likely that numerous new mechanisms must be developed in order to take use of new data streams. Decisions were categorized by Robert Anthony according to organizational levels (see Figure 3).

Fig 3. Three organization decision making general use cases

Currently, operational control, tactical, and operational decision-making are the main areas of attention for emerging data sources and analytics. For instance, operations staff use the findings from the examination of new data sources to make daily choices as part of continuing operational activities, while middle-level executives use fresh sources of data and analytics to track the caliber of goods and service. Increasing the speed and rationale of these repetitive, everyday decisions is the aim of analytics.

The use of predictive analytics and "big data" decision support tools by lower-level managers and operating staff is something that many senior executives desire. Additionally, some senior managers are interested in hiring managers who understand "big data" applications, data scientists, and data analysis professionals. Senior managers' desire or belief that "big data" and analysis can or will influence long-term operational decision-making is not well supported by the research.

However, salespeople promoting "big data" technology and software appear to believe that the potential for transforming businesses and the globe with "big data" is limitless. It is said that "big data" is causing a fundamental change in the way decisions are made.

More and improved measurement, record-keeping, and analysis are all facilitated by new data, but there is no assurance that the data will have a meaningful impact on important or strategic management choices. If the anticipated data revolution is to materialize, the utilization of data and quantitative decision support by senior managers requires motivation. More data does not necessarily equate to more pertinent, significant, or practical data. Furthermore, significant findings are not always guaranteed when data is analyzed using information mining and other technologies. Correlation-based analyses, for instance, are unable to prove causation.

Several publications describe the use of cameras by a fast-food chain to decide what should be shown on the drive-up menu display as an example of "big data" decision-making. Items that can be prepared quickly or those that might take longer will be shown on the menu screen based on the length of the waiting queue. Determining waiting line length and image recognition may be innovative data uses, but this application automates an operating-level choice that a human might make rapidly and then physically switch or toggle the digital information display.

4. Result and Discussion

We provide the synthesis and analysis of the evaluated papers in this part. The following stages were part of the procedure we used:

1. Table 1 displays the three areas of contribution we used to organize the literature on data-driven decision-making algorithms for maintenance applications. Every reviewed manuscript was also allocated to the appropriate area.
2. We also detailed the types of methodologies and evaluation applications for each area of contribution, and we conducted a comprehensive analysis and synthesis of the relevant publications.

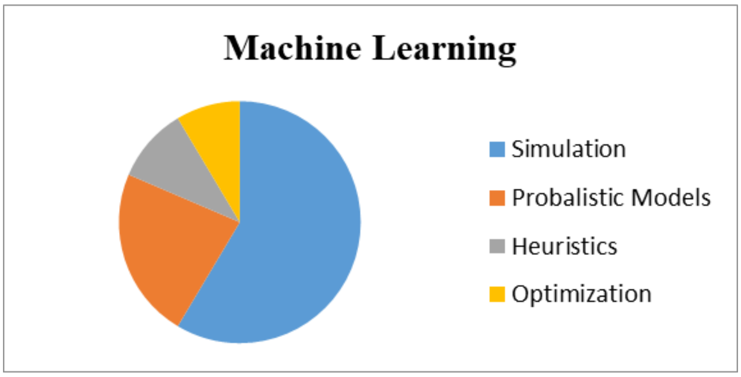

Fig 4. The kind of approaches used in each contributing area

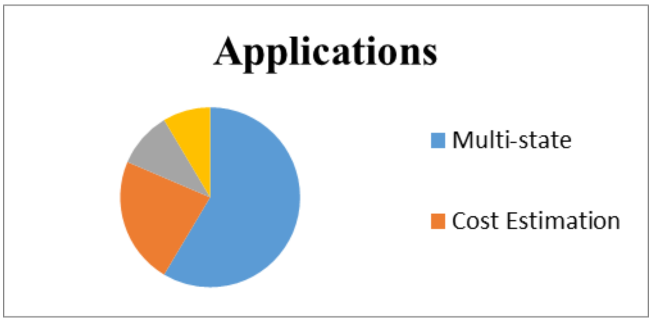

Fig 5. Applications for every contribution region

As seen in Figures 4 and 5, respectively, we classified the approaches taken in the examined publications and connected them to the areas where they could contribute and the applications that are offered. It should be mentioned that certain research projects combine different decision-making techniques; as a result, their references could fall under more than one approach category. Likewise, in certain instances, the suggested techniques are assessed in many applications. In this paper, we simply extracted and examined the decision-making algorithms because the majority moreover, a prediction system for gathering forecasting information is to be entered into the system.

Table 1. Applications of algorithms for decision-making in manufacturing repair

Area of contribution
Planning for maintenance and estimating costs
Cooperative organizing and arranging
Optimization of systems with several states and components

Table 2 provides a summary of this section's findings regarding the gaps in knowledge on algorithms that use data for decision-making. We list the primary gaps that the literature has not adequately addressed for each area of contribution.

Table 2. The gaps in knowledge for each area of contribution

Area of contribution	Research gaps
Preparation for servicing and estimating costs	1. Consider the state of degradation at the moment rather than forecasts. 2. Instead than using real-time information, process batches of data. 3. Not apply data-driven techniques that result in algorithms tailored to a particular situation.
Scheduling and preparing together	1. Analyze data in groups rather than in real time. 2. Not using data-driven techniques that result in algorithms tailored to a particular situation. 3. Dependence on the notion of flawless repair or maintenance, ignoring varying degrees of flawed maintenance efforts.
Optimization of systems with several states and components	1. Evaluate data in chunks rather than in real time. 2. Avoid using data-driven techniques that result in algorithms tailored to a particular situation. 3. Their intricacy makes it difficult to deploy in a data-driven production environment.

Table 3. Techniques for planning maintenance and estimating costs

Category of methods
Coding and efficiency in mathematics
Technology based on rules and heuristics
Models that use Markov and probability
Modeling
Intuition and logic that is fuzzy
Training with machines

While Table 4 lists the applications in which the suggested algorithms and approaches are assessed, Table 3 lists the techniques that are employed in the articles that fall under this area in which one can contribute. Table 3 illustrates the prevalence of mathematical programming/optimization techniques, However, there is also a great deal of study on heuristics, rule-based systems, and Stochastic models. Applications pertaining to energy and rotating machinery have attracted the greatest amount of research interest, as seen in Table 4.

Table 4. Evaluation of maintenance plans and cost estimation

Applications
Optical apparatus
Equipment that rotates
Manufacturing of semiconductors
Petroleum exploration
Vitality
Automobile

5. Conclusion

Senior managers make an effort to make well-considered decisions, but there isn't much evidence that "big data" can help with long-term, strategic choices.

The process of developing decision support is dictated by what works, which may be appropriate considering the pressure managers put on it to yield beneficial outcomes.

The volume of data generated by sophisticated, IoT-enabled machinery, automated manufacturing systems, and multiple sensors challenges established decision-making methods in the context of Industry 4.0 service applications. In this paper, we evaluated the literature on data-driven decision-making methods for manufacturing applications, with a focus on maintenance operations. Our analysis of the literature indicates that an increasing number of data-driven decision-making methods have been developed specifically to benefit from the wealth of sensor-generated data in the context of Industry 4.0. The emergence of cyber-physical systems and cloud services for data processing and storage will make next-generation maintenance decision-making more responsive and capable of supporting accurate and proactive judgments.

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