# Big Data and its Impact on Demand-Driven Material Requirements Planning

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**Received** Feb 24, 2024, **Revised:** Apr 09, 2024, **Accepted:** Apr 20, 2024, **Published Online:** Apr 30, 2024
**Reviewers**: Anonymous Peer Review
**Citation:** Mukherjee, A., 2024. Big Data and its Impact on Demand-Driven Material Requirements Planning. *International Journal of Supply Chain Management, 13*(2), 1-9, https://doi.org/10.59160/ijscm.v13i2.6233

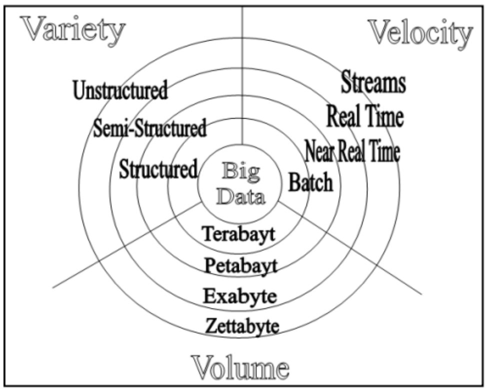
*Abstract*— **Integrating Big Data into Demand-Driven Material Requirements Planning (DDMRP) has become a game-changer in supply chain management. This study explores Big Data's significant impact in the context of DDMRP. Big Data, sourced from various channels such as online transactions, sensor data, social interactions, and more, can transform demand forecasting, inventory management, and overall supply chain optimization. By allowing real-time data analysis and predictive modeling, organizations can make informed and agile decisions that drive cost reduction, inventory optimization, and improved customer service. However, implementing Big Data in DDMRP has its challenges, including data security and the need for advanced analytics capabilities. This research delves into the application, benefits, challenges, and impact of Big Data implementation in DDMRP. The study provides valuable insights for organizations seeking to leverage their potential. The findings underscore the significance of Big Data in reshaping supply chain strategies and enhancing the responsiveness of modern businesses in a dynamic market environment. The uniqueness of this paper lies in examining how Big Data, sourced from various channels, can revolutionize demand forecasting, inventory management, and overall supply chain optimization. The research also highlights the challenges of Big Data adoption in DDMRP, including data security and the need for advanced analytics capabilities.**

***Keywords*** *- Big Data, Transformative force, Supply chain management, predictive modelling, inventory optimization.*

## 1. Introduction

The focal point of contemporary science and business operations revolves around big data and its analysis. This data is derived from a multitude of sources, encompassing online transactions, emails, multimedia content (videos, audio, and images), clickstream data, logs, social media posts, search queries, healthcare records, interactions on social networking platforms, scientific data, information from sensors, and mobile phone usage and associated applications [2], [14]. These vast datasets are amassed within databases on a massive scale, making them increasingly challenging to effectively "capture, structure, store, handle, share, analyse, and visualize using conventional database software tools." [[1]]

***Figure:1.1 The 3Vs of big data***




***Source: [1]***

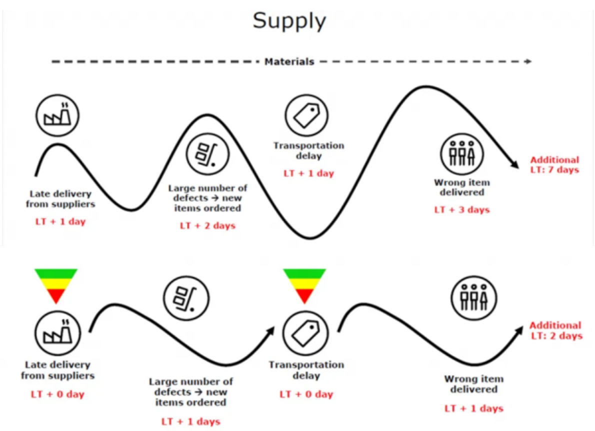
### *1.1 Demand-Driven Material Requirements Planning (DDMRP)*

DDMRP pertains explicitly to this comprehensive system's material planning and scheduling aspect. It plays a pivotal role within a 'demand-driven operational framework,' or a manufacturing strategy focused on significantly reducing lead times and aligning operations with market requirements. This encompasses the meticulous coordination of planning, scheduling, and execution with actual consumption [[13]].

DDMRP builds upon the fundamental principles of MRP, but it incorporates adjustments inspired by the Theory of Constraints (TOC) and Lean methodologies. Drawing from TOC, DDMRP introduces the notion of critical items and the strategic positioning and safeguarding of inventory. Specifically, DDMRP focuses on safeguarding critical components—those buffered elements. Like the TOC perspective, the primary aim is to preserve and facilitate the smooth flow of materials. To achieve this, two mechanisms come into play: stock buffers (distinct from safety stock) and lead times. The stock buffer levels are also dynamic, adjusting in response to various influencing factors. This dynamic buffer adjustment ensures the constant integrity of buffer protection over time.

Moreover, these buffers serve a crucial role, informed by Lean principles, by mitigating the impacts of variances bidirectionally, meaning they address variations from both the supply and demand sides. As a result, this contributes to a decrease in the degree of variability within the execution system, aiding schedulers in improving the overall quality of the schedules produced. Acknowledging that the following exposition provides a condensed and simplified depiction of the DDMRP methodology is imperative. [[13]]

***Figure 1.2: Supply and Demand of MRP***




***Source: [Error! Reference source not found.]***

This paper is designed with the objective of advancing our understanding of the influence of Big Data in the realm of DDMRP. This study seeks to provide valuable insights for supply chain professionals, regulatory bodies, policymakers, and the research community by uncovering the drivers behind integrating Big Data and assessing stakeholders' viewpoints. This research endeavors to deliver a comprehensive analysis that contributes to the ongoing dialogue regarding the pivotal role of Big Data in shaping the future of the DDMRP framework and its impact on the broader landscape of supply chain management. The present paper is carried out to answer the following Questions:

1. What are the applications and benefits of implementing Big data in DDMRP?
2. What are the Challenges encountered in implementing Big data in DDMRP?
3. How does big data impact DDMRP in the manufacturing sector?

Section 2 provides a comprehensive review of the existing literature. In contrast, Section 3 presents a detailed overview of the research methodology, encompassing the methodologies employed, research design, sources of data collecting, and instruments used for analysis. Section 4 presents the discussion and analysis of the results. Section 5 concludes the study with contributions and implications for future research.

## 2. Literature Review

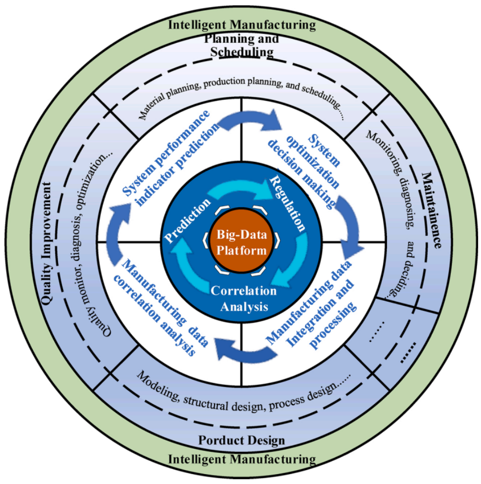
### *2.1 Big Data in Manufacturing Workshops*

In conjunction with the increasing prevalence of IoT technologies and a growing number of sensors in manufacturing environments, data from manufacturing processes is being captured and stored in information systems [[3]] from various sources, each with a distinct data structure [[21]] To facilitate the integration of data from multiple sources into manufacturing processes, [[22]] introduced a big data analytics framework for smart tool condition monitoring (TCM). The present framework employs a technique for integrating data from many sources to analyse "picture data, 3D point cloud data, and frequency signal data". This technology facilitates the continuous monitoring and dynamic management of machining processes, even in varying operational circumstances. [[23]]introduced a methodology for pixel-level fusion, which involves integrating raw data from multiple sources to provide a cohesive dataset with enhanced resolution. This approach highlights the potential for broader utilization of multi-source data fusion techniques. [[16]]delved into the data dependency within product lifecycle management in the context of big data and introduced a conceptual framework known for its flexibility, accuracy, and computational efficiency. This framework is designed to handle many data sources and vast volumes of data. Finally, [[24]]introduced a comprehensive architecture for multi-source lifecycle big data in product lifecycles (BDA-PL), aiming to enhance “product lifecycle management (PLM) and facilitate cleaner production (CP) decision-making within manufacturing processes”. In manufacturing systems, the performance parameters are impacted by various factors, leading to a multidimensional challenge in prediction and control [[17]]. Current approaches to tackling multidimensional problems can be categorized into several types. For instance, “in semiconductor wafer manufacturing systems, the cycle time of wafer products is influenced by over a thousand factors, including factors like the processing time for each operation, queue sizes for each machine, and machine utilization” [[18]]When it comes to monitoring the health condition of machinery, comprehensive condition monitoring systems collect real-time data from multiple sensors following extended periods of operation [[7]]Recognizing the multidimensional nature of manufacturing data, [[8]]introduced an innovative approach that combines process planning and control by utilizing intelligent software agents and incorporating features spanning multiple dimensions. Similarly, [[9]]proposed a cloud manufacturing (CMfg) architecture designed to handle multidimensional data, enabling on-demand utilization, dynamic collaboration, and the seamless sharing of manufacturing resources. In industrial big data, multi-noise is a significant challenge due to electromagnetic interference and harsh environmental conditions. For instance, when working with a dataset for predicting wafer cycle times, around 5,000 records have missing values and approximately 1,500 records show abnormal values within every 8 million records. To tackle data affected by multi-noise, [[6]]implemented a systematic data-driven approach to effectively handle missing values and utilize random sampling for defect detection in semiconductor wafers. In order to address the influence of noisy data, [[25]]proposed the utilization of “deep residual networks with dynamically weighted wavelet coefficients (DRN + DWWC)”. This approach aims to efficiently eliminate various types of noise, leading to enhanced accuracy in diagnosing gearbox faults.

### *2.2 Big data for intelligent Manufacturing*

The primary scientific paradigm underlying Big Data Analytics in Industrial Manufacturing Systems (BDAIMS) is data science. This concept was recognized in the publication "The Fourth Paradigm: Data-Intensive Scientific Discovery." In their study, [[5]]observed a paradigm change in scientific research. The proposition was made that data-intensive science has the potential to emerge as the “prevailing paradigm, surpassing experimental science, theoretical derivation, and simulation-based methodologies.” In contrast to traditional scientific research paradigms, which rely on constructing intricate mathematical models to approximate real systems through experimentation, derivation, and simulation and subsequently analyzing and optimizing these systems, the realm of complex, large-scale dynamic systems poses challenges in building such comprehensive models. On the contrary, the essence of Big Data lies in extracting knowledge by uncovering correlations within datasets, providing deeper insights, advanced analysis, and enhanced decision-making capabilities.

***Figure:1.3 The framework of big data driven intelligent manufacturing***




***Source:*** *[[26]]*

The operational framework evolves into a "correlation + prediction + regulation" model in the data science paradigm for manufacturing systems. This model involves vital steps: first, correlational analysis to understand relationships among various factors based on data; second, predictive modelling using machine learning to forecast system performance indicators; and third, optimizing controllable variables for improved system performance. The Big Data

Analytics in Industrial Manufacturing Systems (BDAIMS) process comprises four stages: data integration and pre-processing, correlational analysis to identify performance factors, predictive modeling using diverse machine learning models, and implementing decision-making methods for improved system performance. This can lead to better product design, enhanced manufacturing efficiency, improved product yield, and a more robust system through intelligent maintenance with health management.

## 3. Research Methodology

This study utilized a "mixed-methods approach, combining qualitative and quantitative methods. Qualitative data was gathered through surveys and questionnaire responses", while quantitative data analysis was employed. Random sampling was used to select five manufacturing companies and 10 respondents from each company, resulting in a total sample size of 50 respondents.

Data was collected from both primary and secondary sources. Primary data was obtained from manufacturing organizations implementing Big Data in DDMRP. Secondary data was sourced from relevant literature and industry reports. Qualitative data underwent thematic analysis to transcribe questionnaire responses and identify drivers for Big Data implementation in DDMRP. Quantitative data analysis involved tabulation and percentage methods for data presentation and analysis.

## 4. Result And Discussion

This section will highlight the information on the application and challenges of big data in DDMRP and present the responses of experts involved in applying big data and DDMRP in organizations.

### *4.1 Applications and Benefits of Big Data in DDMRP*

Leveraging Big Data in DDMRP offers a multitude of applications and benefits, providing businesses with a competitive advantage and enhancing material planning in several ways, which are as follows:

***Figure:1.3 DDMRP in big data analytics***


***Source:*** *[[28]]*

1. Big data analytics enable more accurate demand predictions, refining demand estimation in DDMRP by analysing historical data, market trends, and external factors, thereby reducing forecasting errors and excess inventory.
2. DDMRP, driven by big data (*Santos, 2020*), offers real-time buffer size adjustment in response to demand signals. This optimizes storage costs without compromising service quality, as safety stocks always align with current demand.
3. Leveraging big data analytics, DDMRP enhances inventory management throughout the supply chain, leading to substantial savings through measures like reducing buffer stocks, minimizing surplus inventory, and increasing inventory turnover.
4. DDMRP, equipped with real-time data analytics (*El Marzougui et al., 2020*), swiftly adapts to market shifts, changing customer preferences, and supply chain issues, enhancing businesses' agility and responsiveness to customer needs.
5. DDMRP, empowered by big data, results in greater customer satisfaction by facilitating precise order fulfilment, consistent deliveries, shorter lead times, and accurate orders, enhancing the customer experience.
6. Big data is the foundation for data-driven decision-making in material preparation. DDMRP optimizes production, procurement, and distribution decisions through analytics, ultimately saving time and costs.

### *4.2 Challenges in the implementation of Big data in DDMRP*

The integration of Big Data into DDMRP offers significant benefits but also presents several challenges that are necessary to address and are as follows:

1. Integrating data from multiple sources while upholding its integrity represents a complex undertaking. Inaccurate or incomplete data can lead to erroneous predictions and suboptimal planning. Businesses must invest in data quality standards and robust integration mechanisms to harmonize data from diverse sources.
2. Securing sensitive information when handling extensive datasets is necessary for any DDMRP implementation. Compliance with data privacy regulations and safeguarding sensitive supply chain data should be paramount [[12]]. Employing measures such as encryption, access controls, and data anonymization is indispensable for businesses.
3. Organizations must guarantee the scalability of their technology infrastructure to accommodate the increasing volumes of data in processing capabilities and storage capacity. The scalability of big data operations hinges on having the requisite technical infrastructure and skilled personnel to manage it.
4. Implementing big data solutions often necessitates investments in technology, software, and human resources, which can impact the return on investment. Businesses should undertake a comprehensive ROI analysis to rationalize these expenditures and ensure that the benefits of employing big data in DDMRP outweigh the costs.
5. Adopting DDMRP powered by big data signifies a significant shift in how materials are planned [[19]]Staff members may require guidance and support during this transition, emphasizing the importance of effective change management strategies for a smooth transition.
6. Navigating the complex landscape of varied privacy and data protection laws across different sectors and regions is essential for businesses to avoid legal complications and safeguard their reputation.
7. Selecting the right suppliers and partners is critical when it comes to big data technologies [[10]]To ensure the success of their big data initiatives, businesses must thoroughly assess the capabilities, flexibility, and support services offered by potential suppliers.

| S.no | Statement | Response | | | | |
|---|---|---|---|---|---|---|
| | | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
| 1. | Big Data analytics is implemented in our organization to support DDMRP. | 5 | 10 | 15 | 12 | 8 |
| 2. | Big Data analytics has improved demand forecasting accuracy in our organization. | 2 | 7 | 10 | 18 | 13 |
| 3. | Big Data in DDMRP has led to a reduction in excess inventory levels. | 4 | 9 | 11 | 15 | 11 |
| 4. | Big Data analytics has improved our organization's ability to respond to changes in demand. | 3 | 6 | 12 | 16 | 13 |
| 5. | Big Data in DDMRP has optimized our production scheduling and inventory management. | 2 | 5 | 9 | 18 | 16 |
| 6. | Big Data has reduced lead times in our manufacturing processes. | 4 | 8 | 11 | 15 | 12 |
| 7. | Big Data on DDMRP has resulted in cost savings for our organization. | 3 | 7 | 10 | 17 | 13 |
| 8. | Big Data integration into DDMRP has improved collaboration among different departments of our organization. | 5 | 9 | 12 | 14 | 10 |
| 9. | Big Data on DDMRP can be clearly quantified and attributed to improvements. | 6 | 7 | 8 | 15 | 14 |
| 10. | Big Data analytics has influenced strategic decision-making in our organization. | 4 | 6 | 11 | 16 | 13 |

Table : Impact of big data implementation in DDMRP in the manufacturing sector

### *4.3 Impact of Big Data on DDMRP*

This section will present the responses of professionals working in manufacturing organizations with knowledge and awareness of Big data in DDMRP.

***Table:1.1 Response for Big data impact on DDMRP***

***Source:*** *Created by researcher from responses in questionnaire*

The table 1.1 shows the responses on impact of big data implementation in DDMRP in manufacturing sector.

The responses are analysed and interpreted as follows:

1. Positive Adoption of Big Data: A majority of respondents (60%) agree (Agree or Strongly Agree) that Big Data analytics is implemented in their organization to support DDMRP. The

responses indicate a notable adoption of Big Data analytics in the manufacturing sector for DDMRP. The majority of respondents agree that their organizations have implemented Big Data to support DDMRP. This suggests that many manufacturing companies recognize the potential benefits of leveraging Big Data in their supply chain processes.

2. Improved Demand Forecasting: A significant proportion of respondents (62%) agree (Agree or Strongly Agree) that Big Data analytics has improved demand forecasting accuracy in their organization. This suggests that Big Data plays a positive role in enhancing demand forecasting. This finding implies that Big Data analytics tools and methodologies effectively enhance the precision of demand predictions, which is critical for inventory management and supply chain planning.
3. Inventory Optimization: A considerable number of respondents (57%) agree (Agree or Strongly Agree) that Big Data in DDMRP has reduced excess inventory levels. This is a positive sign of inventory optimization and indicates that manufacturing companies successfully leverage Big Data to optimize their inventory, reducing carrying costs and minimizing the risk of overstocking.
4. Enhanced Responsiveness: Most respondents (62%) agree (Agree or Strongly Agree) that Big Data analytics has improved their organization's ability to respond to changes in demand. This reflects the agility, responsiveness that Big Data can bring to supply chain management to adapt quickly to market fluctuations.
5. Operational Efficiency: A significant proportion of respondents (68%) agree (Agree or Strongly Agree) that Big Data in DDMRP has optimized their production scheduling and inventory management. This indicates that improved operational efficiency and optimization contribute to operational efficiency and resource utilization.
6. Lead Time Reduction: A significant number of respondents (62%) agree (Agree or Strongly Agree) that Big Data has reduced lead times in their manufacturing processes. This indicates improved speed and responsiveness and can lead to quicker response times and more streamlined production cycles.
7. Cost Savings: A majority of respondents (60%) agree (Agree or Strongly Agree) that Big Data on DDMRP has resulted in cost savings for their organization. This highlights the potential for cost reduction, resource allocation, and inventory management through Big Data.
8. Improved Collaboration: A significant portion of respondents (48%) agree (Agree or Strongly Agree) that Big Data integration has improved collaboration among different departments. Improved collaboration can lead to more effective decision-making.
9. Measurable Impact: A notable number of respondents (58%) agree (Agree or Strongly Agree) that the impact of Big Data on DDMRP can be quantified and attributed to improvements. This suggests that organizations track and measure their Big Data initiatives and emphasize the importance of data-driven performance metrics.
10. Strategic Influence: Most respondents (62%) agree (Agree or Strongly Agree) that Big Data analytics has influenced strategic decision-making in their organization. This indicates the strategic significance of big data in decision-making and shaping manufacturing companies' direction and future planning.

In summary, the responses suggest that Big Data is perceived as having a positive and tangible impact on DDMRP in the manufacturing sector. While the majority of respondents report positive outcomes, it's essential to acknowledge that there are likely variations across different organizations and industries.

## 5. Conclusions

This paper starts with big data in DDMRP. It applies the method of both literature reviews to improve the understanding of big data in DDMRP with reference to the manufacturing sector. It also carried out surveys/questionnaires to highlight the impact of big data on DDMRP.

### *5.1 Theoretical Contribution*

This paper reveals the importance of big data in the context of the increasing use of IoT and sensors in manufacturing; data comes from diverse sources with distinct structures. Significant theoretical contributions have been made to handle this data. [[22]]introduced a big data analytics framework for tool condition monitoring, allowing real-time monitoring. [[23]] proposed a pixel-level fusion method for multi-source data. [[16]] developed a flexible framework for product lifecycle management in the big data environment. [[26]] introduced a comprehensive architecture for multi-source lifecycle big data in product lifecycles.

Due to various influencing factors, manufacturing systems face a multidimensional challenge in predicting and controlling performance parameters. Notable theoretical contributions include addressing semiconductor wafer manufacturing complexities, machinery health monitoring, and innovative process planning and control approaches, including cloud manufacturing architecture.

In industrial big data, multi-noise from factors like electromagnetic interference and challenging conditions impacts data quality. Noteworthy theoretical contributions include systematic approaches to handling missing and noisy data, improving defect detection, and enhancing gearbox fault diagnosis.

Big Data Analytics in Industrial Manufacturing Systems (BDAIMS) is the shift to a data science paradigm, emphasizing data-intensive approaches over traditional mathematical modelling. This transformation introduces a new operational framework for manufacturing systems, focusing on "correlation + prediction + regulation." The process involves correlational analysis, predictive modelling with machine learning, and the optimization of variables for improved system performance. BDAIMS integrates theoretical principles with practical manufacturing applications, making it a valuable addition to the manufacturing sector.

### *5.2 Practical Implications*

The analysis of responses on the impact of Big Data implementation in DDMRP within the manufacturing sector reveals several significant practical implications. Firstly, most respondents show a substantial adoption of Big Data for supporting DDMRP, indicating a growing awareness of the potential benefits of leveraging Big Data in supply chain processes. Moreover, a significant proportion recognizes that Big Data has improved demand forecasting accuracy, highlighting its efficacy in enhancing demand prediction—a crucial factor in inventory management and supply chain planning.

Additionally, the data underscores the successful use of Big Data for inventory optimization, leading to reduced carrying costs and a decreased risk of overstocking. Furthermore, Big Data's role in enhancing responsiveness to changing demand is evident, with a majority reporting improved agility and adaptability in supply chain management. Also, respondents acknowledge improved operational efficiency, lead time reduction, cost savings, improved collaboration among departments, quantifiable impact, and strategic influence all of which underscore the comprehensive and strategic role that Big Data plays in shaping the future of manufacturing companies.

### *5.3 Limitations and future research directions*

The paper carries research on the impact of Big Data on DDMRP which had limited availability of real-world data and challenges related to generalizability. Acquiring real-world data from manufacturing companies that have implemented Big Data in DDMRP can be problematic due to concerns regarding the sensitivity of operational data. However, this limitation can hinder the ability to create a diverse and comprehensive dataset for analysis. Further research can explore and develop methods for quantifying the economic impact of Big Data implementation in DDMRP and can assess how it affects key performance indicators like return on investment, cost reduction, and revenue growth.

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