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Big Data and Impact in DDMRP

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Abstract: ***The integration of Big Data into Demand - Driven Material Requirements Planning (DDMRP) has emerged as a transformative force in supply chain management. This research explores the profound impact of Big Data in the context of DDMRP. Big Data, sourced from a variety of channels including online transactions, sensor data, social interactions, and more, has the potential to revolutionize demand forecasting, inventory management, and overall supply chain optimization. By enabling real - time data analysis and predictive modelling, organizations can make informed, agile decisions that drive cost reduction, inventory optimization, and improved customer service. However, the adoption of Big Data in DDMRP is not without 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 harness its potential. The findings of this study underscore the significance of Big Data in reshaping supply chain strategies and enhancing the responsiveness of modern businesses in a dynamic market environment.***

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 the realm of 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 (*Eaton et. al., 2012 and Schneider, 2012*). 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".

Big data is characterized by its three main components: "Variety, Velocity and Volume" (*Gerhardt et. al., 2012 and Intel IT Center, 2012)*

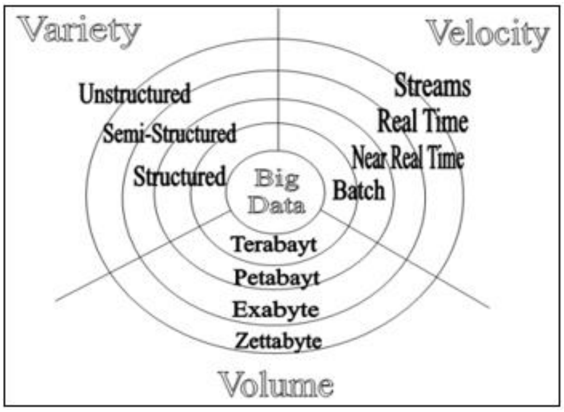

Figure 1.1: The 3Vs of Big data
Source: *Gerhardt et. al. (2012) and Intel IT Centre, (2012)*

1.1 Demand - Driven Material Requirements Planning (DDMRP)

DDMRP specifically pertains to the material planning and scheduling aspect of this comprehensive system. 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

DDMRP builds upon the fundamental principles of MRP, but it incorporates adjustments inspired by both 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 places its focus on safeguarding critical components—those key elements that are buffered. In a manner similar to 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. Additionally, the stock buffer levels are 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 bidirectional, 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, so aiding schedulers in improving the overall quality of the schedules produced. It is imperative to acknowledge that the following exposition provides a condensed and simplified depiction of the DDMRP methodology. (*Gothak and Albrt, 2013*).

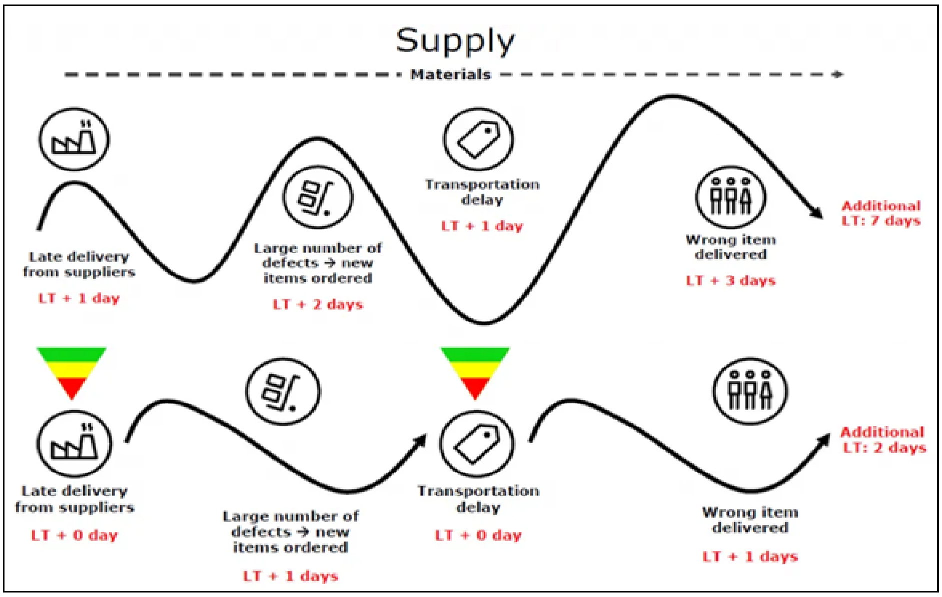

Figure 1.2: Supply and Demand of MRP

Source: *Srinivas, K. (2009)*

This paper is designed objective of advancing our understanding of the influence of Big Data in the realm of DDMRP. By uncovering the drivers behind the integration of Big Data and assessing the viewpoints of stakeholders, this study seeks to provide valuable insights for supply chain professionals, regulatory bodies, policy - makers, and the research community. This research endeavours 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 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 implementation of Big data in DDMRP?
3) What is the impact of big data on DDMRP in manufacturing sector?

Section 2 provides a comprehensive review of the existing literature, while 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 results. Section 5 conclude the study with contribution 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 (Dutton et. al., 2010) from various sources, each with a distinct data structure (Yager, 2004). To facilitate the integration of data from multiple sources into manufacturing processes, Dhu et. al., (2011) introduced a big data analytics framework for smart tool condition monitoring (TCM). The present framework employs a technique for integrating data from many sources in order 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 the presence of varying operational circumstances. Zhang (2010) 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. vaol et. al., (2012) 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 a wide array of data sources and vast volumes of data. Finally, Zhang et. al., (2011) 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 (Smith et. al., 2010). 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" (Smith et. al., 2007). 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 (kei et. al., 2010). Recognizing the multidimensional nature of manufacturing data, Liu et. al., (2014) introduced an innovative approach that combines process planning and control by utilizing intelligent software agents and incorporating features spanning multiple dimensions. In a similar vein, Luo et. al., (2012) 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 factors like 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, Lee et al. (2011) a systematic data - driven approach was implemented to effectively handle missing values and utilize random sampling for the purpose of defect detection in semiconductor wafers. In order to address the influence of noisy data, Zhao et al. (2009) 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 the diagnosis of 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, a concept that gained significant recognition in the publication "The Fourth Paradigm: Data - Intensive Scientific Discovery. " In their study, Et al. (2009) made an observation on 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 analysing 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.

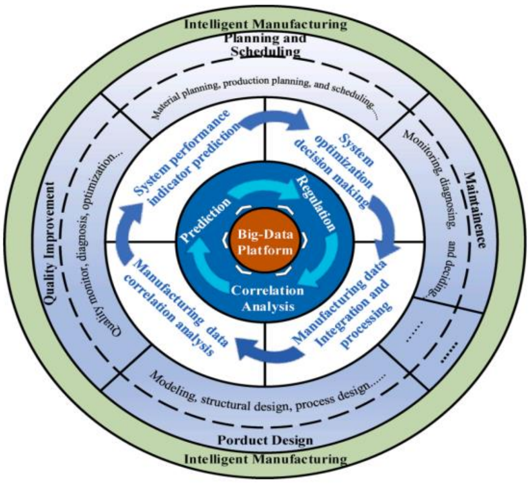

Figure 1.3: The framework of big data driven intelligent manufacturing
Source: Zhang J. (2010)

In the data science paradigm for manufacturing systems, the operational framework evolves into a "correlation + prediction + regulation" model. This model involves key 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, the optimization of 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 modelling 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 that have implemented 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 of application and challenges in regards to big data in DDMRP and also present the responses of experts involved in application of 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:

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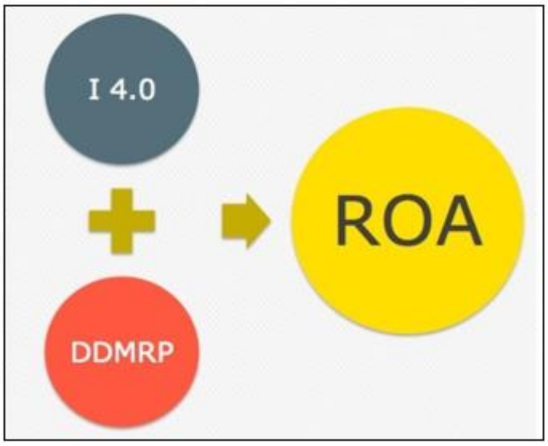

Figure 1.3: DDMRP in big data analytics
Source: *cmgconsultores, n. d*

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, 2010*), offers real - time adjustment of buffer sizes in response to demand signals, optimizing 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., 2012*), 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 serves as the foundation for data - driven decision - making in material preparation. Through analytics, DDMRP optimizes production, procurement, and distribution decisions, ultimately saving time and costs.

4.2 Challenges in implementation of big data in DDMRP

The integration of Big Data into DDMRP offers significant benefits but also presents several challenges which 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. It is imperative for businesses to invest in data quality standards and robust integration mechanisms to ensure the harmonization of data originating from diverse sources.
2) Securing sensitive information when handling extensive datasets is an absolute necessity for any DDMRP implementation. Compliance with data privacy regulations and safeguarding sensitive supply chain data should be paramount (*Orue et al., 2013*). 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, both in terms of processing capabilities and storage capacity. The scalability of big data operations hinges on having both 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. To rationalize these expenditures and ensure that the benefits of employing big data in DDMRP outweigh the costs, businesses should undertake a comprehensive ROI analysis.
5) The adoption of DDMRP powered by big data signifies a significant shift in the way materials are planned (*Xu et al., 2013*). 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 (*Mohammad et al., 2012*). To ensure the success of their big data initiatives, businesses must thoroughly assess the capabilities, flexibility, and support services offered by potential suppliers.

4.3 Impact of Big Data on DDMRP

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

Table 1.1: Response for Big data impact on DDMRP

S. No.	Statement	Response				
		Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	Big Data Analytics is implemented in our organization to support in 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 process	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

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 are effective in enhancing 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 led to a reduction in excess inventory levels. This is a positive sign of inventory optimization also indicates that manufacturing companies are successfully leveraging Big Data to optimize their inventory, reducing carrying costs and minimizing the risk of overstocking.
4) Enhanced Responsiveness: A majority of 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 improved operational efficiency and optimization contributes 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 is indicative of 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 are tracking and measuring their Big Data initiatives, and emphasizing the importance of data - driven performance metrics.
10) Strategic Influence: A majority of 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, in shaping the direction and future planning of manufacturing companies.

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 important to acknowledge that there are likely variations across different organizations and industries.

5. Conclusions

This paper starts from Big data in DDMRP and applied the method of Both Review of literature to improve the understanding of big data in DDMRP with reference to manufacturing sector and carried Survey/ questionnaire 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. Zhu et al. introduced a big data analytics framework for tool condition monitoring, allowing real - time monitoring. Zhang proposed a pixel - level fusion method for multi - source data. Tao developed a flexible framework for product lifecycle management in the big data environment. Zhang introduced a comprehensive architecture for multi - source lifecycle big data in product lifecycles.

Manufacturing systems face a multidimensional challenge in predicting and controlling performance parameters due to various influencing factors. Notable theoretical contributions include addressing semiconductor wafer manufacturing complexities, health monitoring of machinery, and innovative approaches to process planning and control, 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 handle 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, a majority of 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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