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Research Article

Unlocking Manufacturing Potential: The Impact Of Big Data And Predictive Analytics

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ABSTRACT

Combine Big Data and Predictive Analytics for manufacturing performance metrics and control: New efficiency question and answers for operations. With data becoming one of the core strategic resources in the recent past, manufacturers are tapping large amount of data from sources including sensors, machines, and supply chains to improve efficiency and reduce costs. Big Data analytics is the capability to analyse large volumes of data to discover new patterns and relationships in the data. While Decision Support Systems employs this information in the determination of solutions to current or existing issues, Predictive Analytics on the other hand applies the same in the anticipation and probable prevention of the same in the future. Using AI, equipment take time to breakdown, time of maintenance to be made and quality control enhances to be achieved. Much the same manner, this transfer of decision-making to data analytics improves the practicality of business operations and cultivates adaptability in quarterbacking innovation that meets the market's needs. Also, the use of such technologies is useful in cutting unnecessary time, avoiding wastage, and in the proper use of the available resources. Nevertheless, the use of Big Data and Predictive Analytics in manufacturing involves the following issues, such as security, integration, and qualified personnel. Nevertheless, the advantages that stem from the application of these technologies cannot be overlooked, therefore incorporating these technologies is crucial for the evaluation of manufacturing performance. The aim of this paper is to understand several examples of industry that has employed Big Data and/or Predictive Analytics in manufacturing performance to discuss on how they have influenced efficiency, cost, and strategic improvement.

Keywords: Big Data, Predictive Analytics, Manufacturing Performance, Data-Driven Decision-Making, Operational Efficiency.

1. INTRODUCTION

The manufacturing industry is currently in the process of evolution mainly because of the introduction of Big Data and Predictive Analytics. These cutting-edge innovations are now altering the ways, in which manufacturers are assessing and improving the performance, providing higher degrees of understanding and effectiveness. This first section describes the key aspects and use of these technologies prior to extending the focus on their influence specifically within manufacture.

Lately, Big Data and Predictive Analytics have emerged as a revolution in manufacturing by which great volumes of data produced from production processes, supply chain, and customers' interaction can be utilized by manufacturing companies. Combined with these technologies, the manufacturers can shift from managing problems as they occur to having preventive measures in anticipation of the problems. It also cuts time down and costs, and in the same breadth, increases product quality and shortens the time of delivery in the market. Real-time decision-making based on data is finding its way to becoming a competitive advantage as smarter manufacturing operations emerges as he key to countering increased competition in the industry.

1.1 The Role of Big Data in Manufacturing

Big Data is now an asset for manufacturing industry as the purpose of analyzing big amount of data from different sources is crucial. Every manufacturing equipment, the supply chain, and sensors generate a massive volume of data whereby, if analyzed properly, offers probable patterns. Another section explains how by use of

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Big Data the manufacturers are in a better position in assessing their environment for enhanced decision making and planning.

Manufacturing is not only concerned with the collection of data but with the collection, processing and use of information from the acquisition of data through to the generation of information and its use for decision making. The real time further processing of data means that the general status of the factory equipment, performance and even problems can be viewed as they are collecting data to attempt to quantify the production line. This real time analysis is useful in product quality assurance, certain segments of the supply chain, legal requirement, and to compliance to set industry standards. In addition it is possible to predict patterns of failure of the equipments so that systems which exhibit such patterns are not allowed to fail through Big Data. With a much more extensive implementation of Industry 4. 0 and IoT in the manufacturing sector, the application of Big Data analytics is even more critical for enhancing the current processes and, at the same time, developing the organisational progress and performance in the international environment. Global market for Big Data analytics in 2020 and the compounded average growth rate for the year 2021 to 2028 The analysis done by Emergen research indicates that the Big Data analytics market had a value of US Dollar 1. 11 Billion and market is estimated to be expanding at CAGR of 33.1 per cent of the years between 2021-2028, as seen in the figure 1 below;

Figure 1: Big data analytics in manufacturing market: Application dynamics (USD Billion)

1.2 Understanding Predictive Analytics

In addition to Big Data, Predictive Analytics uses past events to determine what 'is likely', or 'what will happen' in business strategy. The most significant of these is the aspect of a SWOT analysis in making intended manufacturers to make anticipative decisions. Using of technical algorithms and machine learning, Predictive Analytics can be useful to know equipment failure, exact time for maintenance and, most important, efficiency. Supply chain also has great benefits of the use of Predictive Analytics for the following reasons: It helps the manufactures to predict the future demand of the products, controlling of stocks, and threat of interrupting the supply chain . Analyzing the tendencies which are observable from the aggregated historical information, one can predict the difficulties which may appear in manufacturing, and therefore the related strategies may be adjusted beforehand. It also assists in the process of increasing the flexibility of the operations, due to the increase in the proactivity and responsiveness of the supply chain, customers satisfaction is enhanced and operating cost is minimized. Predictive Analytics as a business process is process oriented and is done in six major steps as it will be discuss in the following figure 2.

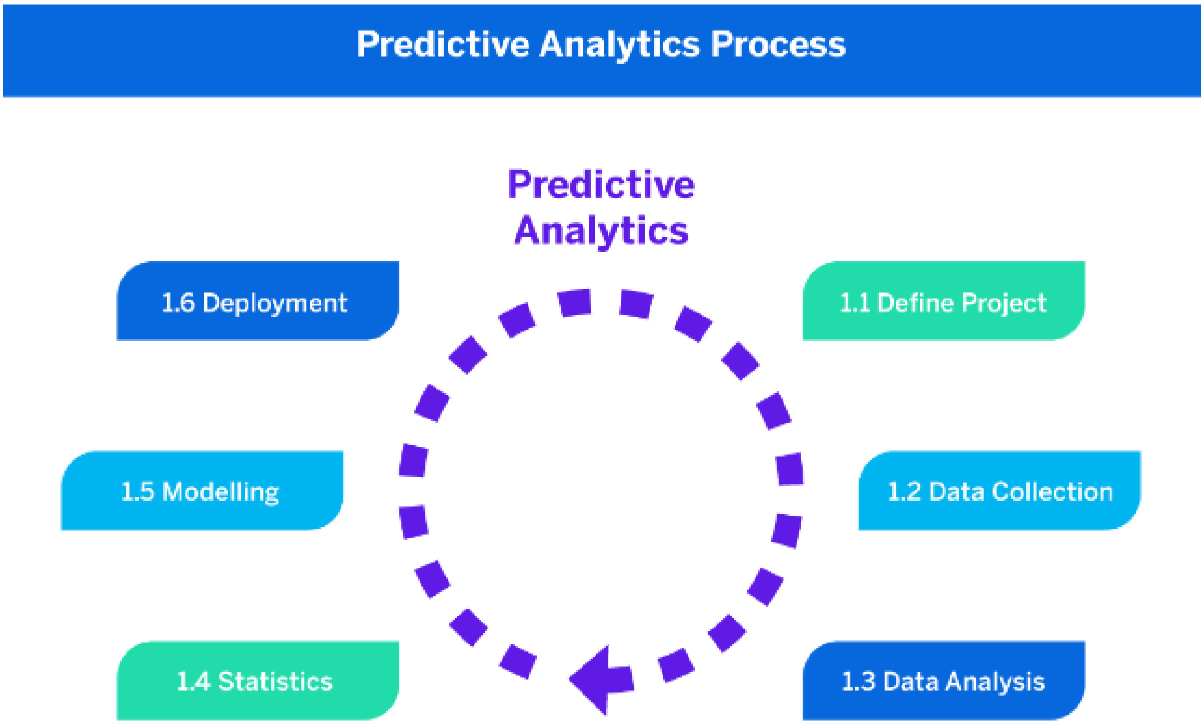

Figure 2: Step by step process of Predictive Analytics

1.3 Impact on Operational Efficiency

The revelation of Big Data and Predictive Analytics in manufacturing also has dramatic effects on the operation. These technologies in essence perform data analysis and give real time analytics cutting on time spent, on wastage and misuse of resources. This section discusses how manufacturers can raise productivity and cost functions by using more data-driven approaches.

Big Data and Predictive Analytics are useful in production by providing information on the problems within the supply chain processes with a view of solving them. state-of-the-art analytical tools such as data mining can reveal complicated and subtle trends and opportunities in raw data which, in turn can mean finer tuning of timetables depending on production, equipment parameters as well as distribution of the workforce. Such detailed information is essential in optimising resource allocation, the management of production cycles or, in general, the overall throughput of the operations. Manufacturers are therefore in a position to reduce their costs immensely and thereby improving their competitiveness by offering higher quality products more frequently and within a shorter time.

1.4 Challenges in Implementation

All as they are, Big Data and Predictive Analytics are not without issues in a given business. Some of the main issues could include the following; being vulnerable to data security issues; the complexity of integration; and the need to hire highly skilled staff. Besides, the problem of data protection rises in importance as the manufacturers obtain a vast amount of information. This information therefore has to be protected from cyber criminals and other Illicit players therefore the need for high measures of security and vigilance all the time. The manufactures must insist on high level encryption technique in the systems they develop, strict access control and often change the sensitiveness of their security measures in order to counter any specific attack that might occur in future. These are real security threats to any organization and it becomes important to address them if the organization is to maintain its customer loyalty coupled with respect for laid down standard.

The third issue is the integration complexity was found to be a function of the system architecture, and hence complicates the implementation of new technology that is different from the existing systems. Manufacturers are challenged to align end-to-end of the organizations concerning data and processes. Integration is best kept under tight control and thus needs to be planned well Middle wear solutions have to be robust Basic systems tend to need improvement. In order to counter these issues, certain preconditions in systems' design must be solved Proper attention to integration and communication between the It departments together with the operational teams for information and data sharing.

Adequate manpower to dissect result from big data analysis as well as assist with the prediction from analytic of business intelligence. Job demand for data scientists, analysts and engineers who are conversant with these

technologies is high and at times talent is very hard to come by. Manufacturers need either to acquire or learn relevant skills either through training and development programmes or hire skilled human resource either from within the company or the market. It covers the challenge of the lack of qualified employees, according to which the use of big data approaches in daily productive operations is crucial for the long-term sustainability of production.
With the new changes in the manufacturing environment, the use of Big Data and Predictive Analytics has been seen to progress. Future trends of this field and development in technology will dictate the performance evaluation of manufactures. One of the possible further developments of Big Data and PA is the combination with AI and machine learning. One can model the predictive models with the help of AI algorithms that in turn learn from large quantities of data and make more accurate predictions in the process. This advancement shall enhance even more effective and precise manufacture approximate breakdowns of specific equipment, improved flow of production as well as customization that will correspond to consumers' needs. However, as AI technology will progress the overall production performance assessment rises to a new level of sophistication due to the capability of AI to offer more profound analysis and automation of complicated decision-making.
Another important trend is the development and application of Internet of Things (IoT) in contexts of manufacturing. Machinery, production lines, ecosystems, and the supply chain consist of IoT devices and sensors that gather real-time data for the analysis. When together with Big Data and Predictive Analytics, data from IoT can be used to increase the level of understanding of the performance in operation and identify a problem before it becomes acute. Such integrated way of thinking will lead to the emergence of more adaptable manufacturing infrastructures, which could adapt to certain conditions and thereby enhance the performance at the same time.The emergence of digital twins is one of the extraordinary breakthroughs in manufacturing performance analysis. A digital twin is therefore a digital model of physical assets, processes or systems, by which a manufacturer can monitor and virtually test several possibilities. Digital twins when integrated with Big Data and Predictive Analytics allows manufacturers to run simulations, try out changes on the virtual model without having to do it in the actual facility, improve performance in a test environment. This innovation will help organisations to improve prediction, efficiency and ongoing advancement in manufacture performance.

2. REVIEW OF WORKS

This innovation has significantly altered the evaluation and optimization of the performance of manufacturing with the help of Big Data and Predictive Analytics. It is thus possible to understand how these consequences occur and to solve problems associated with such revolutionary technologies that industries are gradually injecting. This review include the synthesis of several studies with an intention of coming up with a synthesis in light of manufacturing revolution Inkermans et al (2014) hold that Big Data and Predictive Analytics. Hence, the review of the theoretical framework and practical application and concern address the gap in the current state and the future trend of the manufacturing performance evaluation.

2.1 Structural Equation Modeling and Big Data Analytics

In their paper that critically reviewed advanced analytic techniques that are very essential in developing measurement models, Anderson and Gerbing (1988) noted SEM as one of the advanced techniques. SEM does assist to identify complex interrelation of data and is even more useful while analyzing Big Data. Likewise, Chen et al. (2015) also deploy similar modelling techniques to the one applied here to look in detail, at how Big Data analytics assists the supply chain, through identification of complex relationships in extremely large data sets. This kind of modeling makes it possible for the manufacturing factors' interaction to be examined comprehensively, hence a proper assessment of the processes' performance.

Further, Henseler et al. (2014) discussed dynamics of SEM application in analysis of relationships between Big Data variables. In their study, they discovered that, the use of SEM in Big Data environment helps in defining the forecasting models for decisions making and organisational processes improvement. Through the application of the SEM, the manufacturers are well positioned to interpret the effects of several factors on performance and hence achieve the right strategic positioning for the firm.

Regarding the development of the reliable performance measurement systems, the same can serve enhancement of the SEM application in Big Data analysis. For example, Dubey et al. (2017) wrote about utilisation of SEM techniques to enhance the supply chains' PM system for sustainability benchmarking. It in turn enhances the ability to analyze quantitative indicator and to predict the corresponding tendency with regard to manufacturing improvement.

2.2 Big Data Analytics and Supply Chain Management

Discussions on big data and its applicability particularly in the supply chain have been presented by Chen, Preston and Swink in their paper published in 2015. They demonstrated how such data can be used to create value, more exactly in supply chains' management. This capability will be relevant in matters concerning inventory management and reduction in lead times and in fact boosting on the supply chain performance. Akter et al. (2016) also notes how Big Data analytics enhance the extent of strategic fit of the firm for better performance and supply chain optimisation.

Several authors such as Bhakoo and Choi (2013) have carried out empirical studies on the institutional pressures and supply chain practices and in these studies, Big Data have been proved to be very useful. Looking at the outcomes of the studies it is evident that Big Data can help manufacturers confronting outside factors and enhancing supply chains' performances. When organizations are using analytics in the supply chain planning, the chances are covered for all future interruption and hence the supply chain strategies of manufacturers get even stronger and powerful.In addition, Järvinen and Karhu (2018) enlighten how the capabilities of Big Data analytics are contingent for SC management. In the authors' view, there is a wealth of information that confirms the fact that big data solutions must be aligned with strategic development plans. It can therefore be concluded that the application of analytics that is in consonance with the SC objectives can contribute to the enhancement of developmental capabilities that can enhance the performance of manufacturers and also enhance the SC competitive edges at the same time.

2.3 Organizational Culture and Big Data Adoption

In the record of Big Data analytics, the organisational tradition still turn out to be an important element in the integration proposition of Allaire and Firsirotu (1984). From their work, they established that there was a huge gap in terms of culture that could enhance the adoption of new technologies like Big data. After that Toh and Wong (2017) further expanded the discussion of the impact of organisational culture on the level and way Big Data analytics improved the organisations' operation performance. Referring to their work, they have suggested that by opening up the role of analytical insights, organizations que are most likely to adopt and use analytics.

Liu et al. 2010 carried out a quantitative research on the effects of institutional pressures and culture on internet-based supply chain management systems. As highlighted in their work, this is a clear pointer to the fact that some cultural issues are highly influential in the embrace of Big Data technologies. Considering the given guidelines, it will be desirable to emphasize that it is possible to state that establishing the necessary culture for using Big Data effectively, the organizations will be able to raise the number of positive results and enhance the productivity considerably.

In similar to this development, Jackson and Schuler (1995) also described the commitment of human resource management with organisation culture. According to Olson, et al. (2015), which has been discussed earlier in this paper, it is feasible to encourage the application of analytics and support Big Data endeavours by means of appropriate configuration of the HR practices. This alignment results of formation of culture with acceptance to measurement and adoption of big data analytics solutions.

2.4 Big Data Analytics Capability and Business Strategy

Akter et al. (2016) concluded that the capability of Big Data analytics must be aligned to business strategy to enhance the performance of the firm. According to their research, it is equally clear that alignment is key to making big data work. This view is seconded by George et al. (2014), who talked about how big data and management have to integrate with organizational objectives if they have to deliver value and innovation.

Similarly, working on the idea of Big Data application in management, McAfee et al. (2012) stressed that Big Data is most effective when it is used in support of business strategies. Jang and Song's work has determined that Big Data as a tool support strategic decisions and enhances performance outcomes when it is integrated with strategic planning among manufacturers. This alignment proves useful in tackling certain issues that confront and/or opportunities that presents itself in the manufacturing industry.

Wu and Chapman (2014) explained that big data analytics involves analytical techniques in supervision to meet the goals and objectives of the business in its provision of services. From their study, they offer recommendations that state strategic alignment of Big Data initiatives is critical to success and innovation. In this way, the vision of data analytics can help manufacturers improve their performance and stay relevant on the market.

Dubey et al. (2017) carried out a systematic review of Big Data and analytics and managed to capture majority of the challenges facing data analytics of which include security of data and its integration. In their study, these scholars underscore the need to overcome these challenges in the interests of correct use of analytics in manufacturing. To these, Boyd and Crawford advanced the definition of Big Data in 2012 to include other questions important to Big Data's enactment including questions such as privacy.

Aydiner et al. (2019) analyzed the samples in terms of business analytics and firm performance with a view on business process performance as a mediator. Cross-sectional studies entirely dismiss the value of Big Data analytics as a result of the various barriers to implementation. By so doing, it is possible for manufactures to gain big returns and at the same time promote the development of better products.

Regaring future research, Liang et al., (2007) identified two issues: the role of enterprise systems and external pressure for the diffusion of technology. In this respect, their results pointed to the imperative of furthering future directions in Big Data analytics as a process which remains under a continuous process of development of technology as well as methods. Aloud to these developments and reaction to emergent issues will be crucial to perpetuate competitive superiority and further Big Data in manufacture performance appraisal.

3. PROPOSED METHODOLOGY

Therefore, to assess Big Data and Predictive Analytics on the manufacturing performance, the study will use the case study analysis approach. This would require developing of samples or histories of organizations in the manufacturing industry which have adopted these technologies. More concretely, the evaluation is focused on the element of Big Data and Predictive Analytics and the problems encountered, as well as variations in the organisation's performance in terms of efficiency of operation, cost, and standard of the product. Therefore, this approach provides clear and practical suggestions to the ways in which these technologies may be employed and the advantages of enhancing the manufacturing work.

4. RESULTS AND DISCUSSION

Case Study:
Company: General Electric (GE)

Background: General Electric has embraced fully the Big Data and Predictive Analytics in its operations in a multinational manufacturing giant particularly in aviation and energy. GE used data from the industrial equipment and the operation in utilizing the Predix platform GA manufacturing operations cloud based analytics solution.

Implementation: The GE employed the big data for purposes of estimating the time of failure of their equipment in the jet engines and turbines through the use of the predictant maintenance algorithms. It also used Big Data analytics in the production of schedules as well as supply. Operations were improved by using superior watch and elaborate dissecting in real time, to improve quality and productivity.

4.1 Operational Efficiency

Increased Production Efficiency: Big Data and Predictive Analytics held an increase in operation efficiency by 10-15%. With the help of predictive maintenance, they got only 20 % of time they previously lost per each step of the production for unpredictable breakdowns thus increasing the reliability of the time line of production.

Consistent Operations: This was done as a way of achieving less down time in order to boost the production cycle of GE so as to meet the market needs of the widely demanded products with higher service levels and availability of the products.

4.2 Cost Reduction

Maintenance Savings: The controls of predictive maintenance cut the maintenance expenses by 15% for avoiding unscheduled repairs and enhancing equipment's longevity. This made the flow of work seamless, reduced interrupts and the overall expenses were cut.

Optimized Inventory: Optimisation of the supply chain through insights of Big Data reduced the holding cost by 12%. Improved stock management improved on the reserve stock whilst increasing on overall efficiency in the supply chain.

4.3 Quality Control

Enhanced Quality: Real-time analytics increased product quality to an extent of 10% by the identification of potential defects at the early stages to allow for alteration. It mean that we had the proactive quality control that allowed minimising the defect rates and maintained the high level of products.

Consistency: Early defects improved product quality and higher standards, they met and frequently surpassed customer expectations and reasserted the company's reliability – GE.

4.4 Strategic Decision-Making

Improved Forecasting: With help of data-driven insights, GE improved its methods of forecasting and planning and, thus made the prognosis more exact and the decisions more effective.

Agility: Such features allowed GE to achieve market responsiveness and effective immediate and long-term responses to the observed market conditions and organizational functioning.

5. CONCLUSION

The adoption of Big Data together with the use of Predictive Analytics has revolutionized the manufacturing at General Electric bringing new improvements in several areas of performance. In this way, the application of Big Data tools made it possible for GE to increase its operational efficiency by cutting the number of cases when the production line was out of order, and by achieving a smoother production rhythm. This efficiency not only improved manufacturing line but also improved reliability of meeting customer need. Another essential advantage of using the technologies was, therefore, cost reduction. With the help of the predictive analysis, GE made successful interventions to reduce the maintenance costs by 15 %and due to the enhanced supply chain facility inventory holding costs decreased by 12%. This map of financial savings shows how important it is for companies to unleash data analytics for cost optimization and overall expenses' control.

As much as the quality assurance was concerned, it was noted that real time analysis was very instrumental in enhancing the quality of the product. Noting that CQM enabled GE to identify the quality problems before they escalated to something even worse, showed how it was possible to improve the quality by per cent as well as ensure that clients received the best products possible. The output that the company could provided also became stabilized and at a good quality that made the company well rooted in the industry. Successful usage of Big Data and Predictive Analytics represent the change for manufacturing. The changes in efficiency, costs, quality and choice improvements prove how increased technology can bring improvements to a range of aspects and how it can present a significant competitive advantage to the different organisations in the industry.

Towards achievement of advanced manufacturing technologies, GE should incorporate other advancements such as, AI, the industrial internet (IoT) to its reported Big data & analytic solution. By incorporating better algorithms AI can solve better predictive models from the large data set; IoT can provide better quality of real-time data from connected devices. Becoming integrated with present analytics advancements also may improve operation, cost, and quality in addition. However, for optimising the benefit out of Big Data phenomenon, one has to search for the ways and means to get more data for GE. The improvement of the usage data concerning suppliers' activity, the market trends and customers' feedback can add value to the context of manufacturing setting. The broader database would provide a better filter of the environment and the performance of the organisation in a manner that would allow better strategy decisions and modifications of the organisational responses to new events in a particular market. Moreover, more understanding of the data in supply chain should be able to provide clearer concepts of how to synchronize and collaborate with other organization.

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