LEVERAGING DATA SCIENCE FOR EFFECTIVE OPERATIONS MANAGEMENT: TRENDS AND APPLICATION IN MANUFACTURING

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ABSTRACT

Data science has become an inevitable vertical in almost all sectors now. However, it plays a vital role in operation management for an effective manufacturing process. The manufacturing sector has always had complex issues since it handles raw material, production units, manpower, recent technology and modern equipment for the production of finished goods. Looking at this process, the data generation will be massive at each end. Data science would help in many ways to know where to look for further optimisation to provide a competitive product to the market. This paper aims to look at recent trends and the application of data science in operation management for an effective management process. Further, the paper addresses the current gaps existing in the manufacturing process that differ from company to company. A simple random sampling method has been deployed for this study with 110 respondents. The data has been collected through offline mode in Madras Export Processing Zone and various industrial estates in Tamil Nadu mainly on Chennai, Coimbatore, Salem and Madurai area). This study intended to know how data science applied in industry to improvise the industrial operations and process management. No data science models or methods deployed in this study. It studies where it has been applied and used to provide more productivity in manufacturing processes. This paper provides useful insights from the research analysis and interprets the results that arrived based on this research. The research gap addressed in this research shows how effective data science helps to optimise day-to-day operations and how it could be improved further to improve the competitiveness of the finished goods from a manufacturing industry's perspective. The research reveals that there is a strong correlation between data science and improving the efficiency of day-to-day operations of the manufacturing industry. This research also suggests that there is a huge scope for implementing data science that enables models in MSME industries to help to improve their profitability and growth of the firms. However, the research results are limited to the study region only and may differ from region to region or country to country.

Key Words: Operations, Efficiency, Data Science, Profitability, Optimization, Management

1. INTRODUCTION & BACKGROUND

In this fast-moving world, manufacturing is playing a vital role, and it needs more focus factory concerned operations. Therefore, it requires effective operation management. To improve the day-to-day operation & challenges in manufacturing process, data is essential. There data science helps to mitigate the challenges with effective solutions especially in following areas: Data science algorithms in Operations Management, Data science & Industry 4.0 in Operations Management, SMART Factories Industrial Automation, Real-time tracking and Effective inventory control.

Regarding the duties and techniques of data mining and how they are used in production scheduling and planning. Four categories of data mining systems has been examined, based on the types of databases that are mined, the knowledge that is sought, the methods employed, and the applications that have been modified. Another study examines production scheduling and planning with an emphasis on either long-term or short- to mid-term planning. Process planning, strategic capacity planning, aggregate planning, master scheduling, material needs planning, and order scheduling are just a few of the many planning techniques used in production planning. Due to variations in manufacturing time, product, and environment, these operations give rise to a variety of issues (Ismail, R., Othman, Z., & Bakar, A. A., 2009).

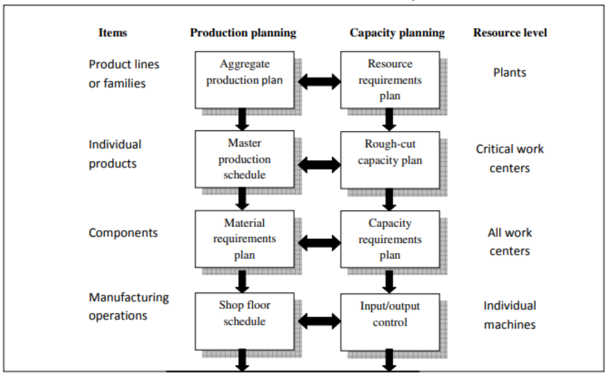


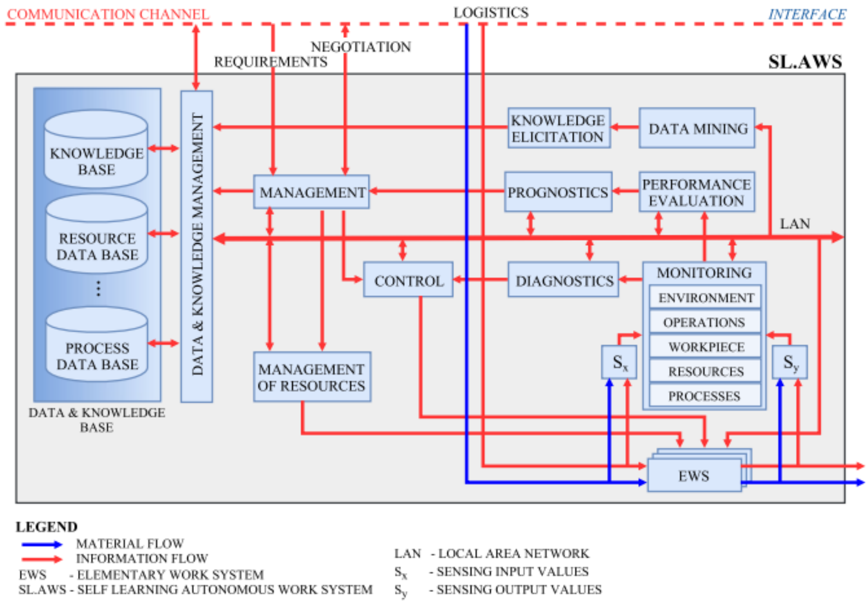
Figure 1. Operation management – Production & Capacity planning
(*Source*: Data Mining, Ismail, R., et al.2009)

Two efficient techniques were put forth by researchers to rank operations management controls according to operational risk. The techniques rely on combining a good statistical approach with a scorecard reporting style that is simple to understand. The first approach creates an easy-to-read ranking of operations performance by employing the concept of a "Gini rating" to summarise the information found in operational self-assessment surveys. The second approach presents a straightforward non-parametric Bayesian model that can incorporate data from surveys and actual loss data to provide a combined risk estimate that may be used as the foundation for capital coverage (Giudici, P.,2015). The core of the UK's industrial capacity is the precision engineering industry. Businesses in this sector provide assistance to key economic drivers like nuclear, off-highway equipment, aircraft, military, racing, oil & gas, and unconventional energy. This sector is primarily made up of small and medium-sized businesses (SMEs). Successful precision engineering companies must be adept at supply chain solutions and process innovation. In these kinds of companies, implementing creative, cooperative solutions has become a crucial tactic for boosting SME decision-making skills and overall business competitiveness. Through online cooperation, mentoring, and assistance for SME businesses, better collaborative alliances may be formed, and SMEs can benefit from precise engineering and improve their performance (Hernández, J. E., Lyons, A. C., & Stamatopoulos, K.,2016). This study intended to know how data science applied in industry to improvise the industrial operations and process management. No data science models or methods deployed in this study. It studies where it has been applied and used to provide more productivity in manufacturing processes.

2. LITERATURE REVIEW

2.1 Data science algorithms in Operations Management

Simulation has been used by large industries to assist in design and production decision-making. But as technology has developed and big data has emerged, simulation may be used to assist and carry out data analytics for related performance improvements. This calls for extensive data collecting and analysis efforts in addition to a great deal of model construction experience. Manufacturing simulation models are used as data analytics apps in and of themselves, as well as to assist other data analytics applications by acting as validation tools and data producers. The idea of a virtual factory is introduced as a means of simulating and modelling production. By including multi-resolution modelling capabilities, virtual factories surpass conventional factory simulation models and enable study at several levels of detail (Jain, S., Shao, G., & Shin, S. J., 2017).



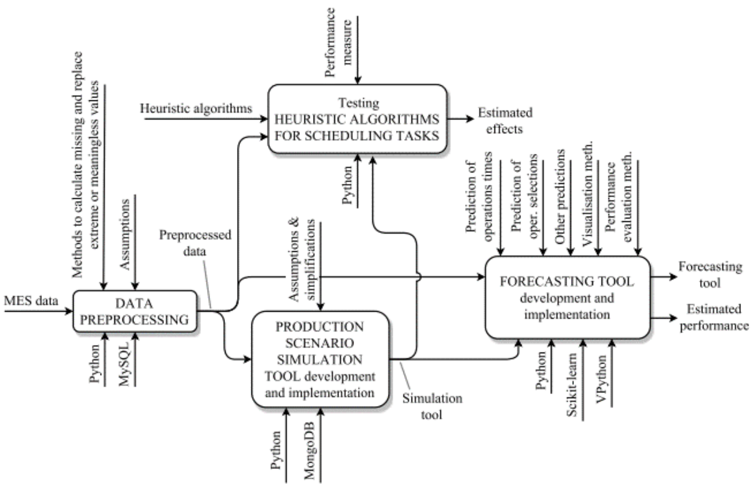


Figure 2. Data science algorithms in Operations Management

(*Source*: Kozjek, D., et al., 2018)

There is a lot of promise in using manufacturing data to enhance manufacturing operations management. An approach to data analytics in engineer-to-order manufacturing systems, where product quality and reliability of deadlines are crucial factors in management decision-making, is covered in another study. The goal of the study is to provide tools that facilitate operation scheduling and examine manufacturing data that is gathered by a manufacturing execution system when an engineer-to-order business is operating. Production simulation and resource overload prediction are two applications for the created technologies (Kozjek, D., Rihtaršič, B., & Butala, P., 2018).

For operational ease, daily tasks are completed using enterprise resource planning systems like SAP and Oracle. Big data was created and recorded by all of these operations, and managers and strategic decision-makers mostly rely on it when making decisions. Using lean concepts to manage this kind of large data for a manufacturing organisation is a difficult undertaking. In general, big data refers to datasets that may be captured and subjected to computational analysis in order to produce patterns and trends. In the current period of development, it is true that these data amounts need a lot of room and are expensive.Big data may assist manufacturing units enhance the quality of their products and provide clarity in their work procedures. It can also help them unravel uncertainties, such as inconsistent equipment availability and assembly shop performance. Predictive manufacturing as an application strategy and desired openness needed a lot of data, as well as sophisticated prediction tools to turn this vast data into knowledge that could be used. The lean concept may be used to reduce the waste that results from gathering large amounts of data. Applying lean concepts to the management of manufacturing process big data is analogous to minimising trash in, garbage out in order to lower data costs and shorten the time needed to process data for managers' decision-making.Big data may assist manufacturing units enhance the quality of their products and provide clarity in their work procedures. It can also help them unravel uncertainties, such as inconsistent equipment availability and assembly shop performance. Predictive manufacturing as an application strategy and desired openness needed a lot of data, as well as sophisticated prediction tools to turn this vast data into knowledge that could be used. The lean concept may be used to reduce the waste that results from gathering large amounts of data. Applying lean concepts to the management of manufacturing process big data is analogous to minimising trash in, garbage out in order to lower data costs and shorten the time needed to process data for managers' decision-making (Majiwala, H., Parmar, D., & Gandhi, P.,2018).

2.2. Data science & Industry 4.0 in Operations Management

Data-enabled decision-making and the growth of information and communication technology may make smart manufacturing a crucial part of sustainable development. The semiconductor business is one of the few global sectors seeing development in the smart world age, owing to demand from all around the world. In wafer manufacturing, the integration or combination of virtual versions of real equipment, Cyber-Physical Systems, and regionalised or decentralised decision-making into a smart factory offers great prospects to save costs, increase productivity, and enhance quality. The flow of information from sensors, robotics, and cyber-physical systems can help to make production more intelligent. As a result, modelling, optimisation, and simulation would be more necessary to deliver value from production data (Khakifirooz, M., Fathi, M., Chien, C. F., & Pardalos, P. M., 2019).Manufacturing businesses throughout the world are undergoing significant change as a result of the fourth industrial revolution; they require more productivity, competence, and efficiency. Sensors are being added to an increasing number of industrial equipment, and these sensors generate enormous amounts of data. The majority of businesses are unaware of the importance of data or how to capitalise on it. The businesses lack the methods and resources necessary to gather, store, process, and evaluate data. Another paper's goal is to provide data analytics methods for examining industrial data. Descriptive & predictive analysis will be provided by the analytical methods. Additionally, the research incorporates data from the business's ERP system. The methods will assist the businesses in achieving competitive advantages and increasing operational efficiency (Iftikhar, N., Baattrup-Andersen, T., Nordbjerg, F. E., Bobolea, E., & Radu, P. B., 2019).

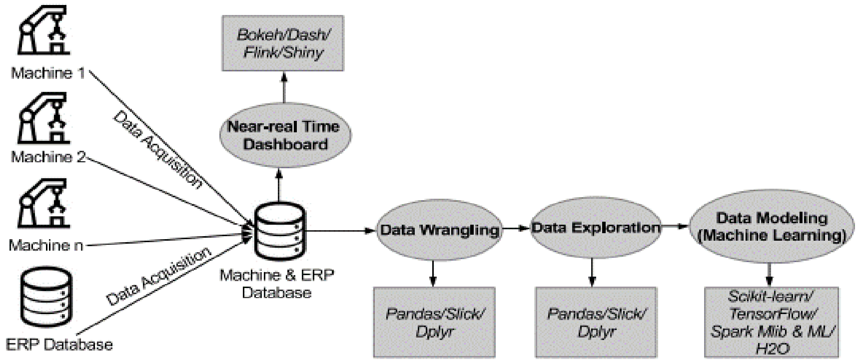


Figure 3. Data science & Industry 4.0 in Operations Management
(*Source*: Iftikhar, N., Baattrup-Andersen, et al., 2019)

Smart factories aim to increase productivity and lower production costs, but achieving manufacturing competitiveness through improvements in product quality and yield is more important. As product functions become more sophisticated and processing becomes more miniaturised, micro-manufacturing process yields have become a crucial management factor that determines a product's production cost and quality. Since micro-manufacturing processes typically go through multiple stages to produce a product, it is challenging to identify the process or part of apparatus where a fault has occurred, making it difficult to realistically ensure high yields. Additionally, it provides plans for gathering the data required for big data analysis of a manufacturing site and system construction (Sim, H. S., 2019).

2.3 SMART Factories Industrial Automation

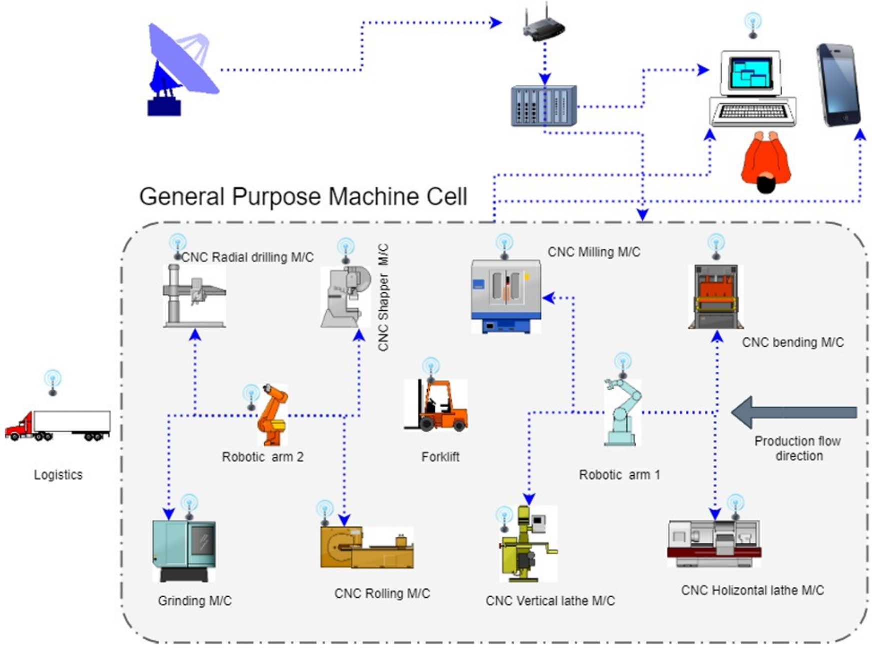


Figure 4. Automation & Industry 4.0 in Operations Management
(*Source*: Kocsi, B., Matonya, M. M., et al.,2020)

By implementing competitive advantages like cost reduction, speedy delivery, and distinctive, high-quality items, several organisations are attempting to increase their earnings. To achieve these competitive advantages, several businesses employ efficient production-scheduling strategies. Due to the constant changes in part and process parameters, scheduling strategies are still difficult to implement in high-mix, low-volume manufacturing businesses, particularly in Industry 4.0 contexts. These issues in HMLV Industry 4.0 manufacturing led to the development of a novel, highly efficient real-time manufacturing-planning decision-support system model (Kocsi, B., Matonya, M. M., Pusztai, L. P., & Budai, I., 2020).

One of the key technologies in modernising the management styles and production procedures of conventional companies is industrial intelligence. To view and evaluate industrial production and logistical operations, the framework makes use of data analytics. It also exhibits the cleverness of scheduling, planning, operation optimisation, and optimum control. To overcome some of the major problems that manufacturing, resources and materials, energy, and logistics systems frequently face, such as high energy consumption, high costs, low energy efficiency, low resource utilisation, and significant environmental pollution, data analytics and system optimisation technologies are used in the four-level framework. By combining data analytics with optimisation, businesses may increase their ability to foresee and govern unknown regions and uncover hidden knowledge to make better decisions (Tang, L., & Meng, Y.,2021).Contributions from leaders in a number of key data analytics application areas in operations management to highlight recent advancements, talk about recurring themes, pinpoint current trends, and make predictions about the future. Data analytics has undoubtedly benefited from significant theoretical advancements by researchers in the field as well as several significant contributions in a variety of application ranges that are either straight or circuitously connected to the discipline. The most common uses of data analytics are described in another research that just focusses on the element of data mixing in operational decision-making(Feng, Q., & Shanthikumar, J. G., 2022).

Uncertain behaviour that follows an unknown probability distribution is one of the primary challenges in decision-making systems, and big data offers novel ways to address this issue. Conventional data-driven methods typically involve two phases. Using data to forecast or estimate the uncertainty behaviour is the first step. Finding choices that maximise an objective function that is dependent on the results of the first step is then necessary for the second phase. This course looks at data-driven solutions that combine the traditional two-step predict-then-optimize/estimate-then-optimize process. One crucial method for reaching integrated data-driven solutions is the use of machine learning techniques. Furthermore, several integrated data-driven approaches have proven useful in a variety of real-world decision-making scenarios, such as power system operations, supply chain management, and portfolio optimisation (Qi, M., & Shen, Z. J., 2022).

2.4 Data Analytics scope, modelling in Operations Management

A new digital environment with distinct characteristics and behaviours that mimic and impact the actions and processes of actual entities has been produced by the metaverse and Web 3.0. Our understanding of how supply chain and operations management will be impacted by the metaverse is the focus of another study. Novel metaverse processes and decision-making areas including digital inventory allocation in the metaverse, joint demand forecasting for metaverse and physical products, integrated production planning for the metaverse and physical worlds, pricing and contracting for digital products, and new performance metrics like virtual customer experience level, digital product availability, and digital resilience and sustainability can all lead to new research areas (Dolgui, A., & Ivanov, D.,2023).

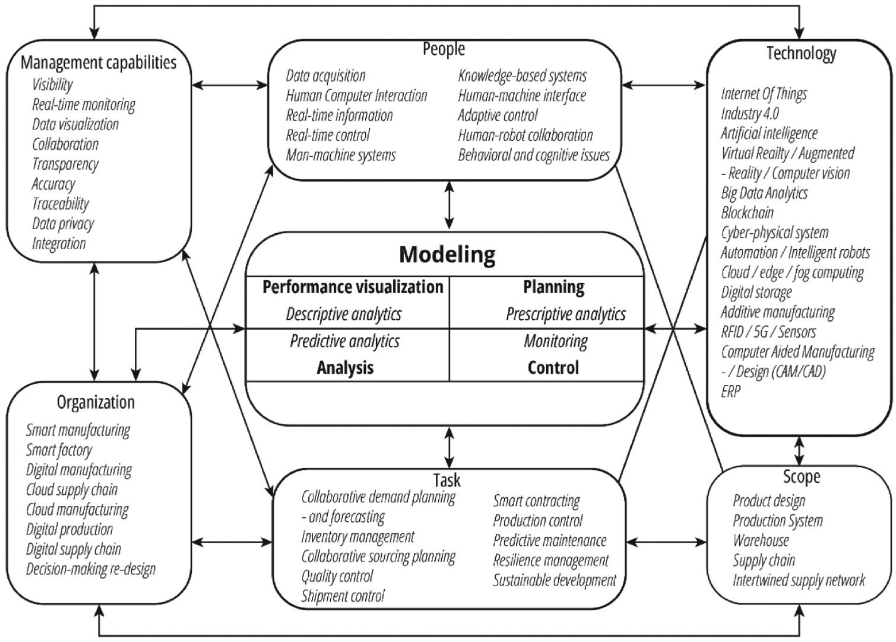


Figure 5. Data Analytics scope, modelling in Operations Management
(*Source*: Dolgui, A., & Ivanov, D.,2023)

Traditional paradigms in a variety of sectors have been altered by artificial intelligence (AI), which has emerged as a revolutionary force in operational management. With an emphasis on the effects on efficiency, strategic planning, and decision-making, this study explores the complex relationship between artificial intelligence and operational management. AI helps businesses to maximise resource allocation, optimise workflows, and boost productivity by utilising sophisticated algorithms and machine learning approaches. Furthermore, managers may make proactive decisions and reduce risk by using AI-driven predictive analytics, which gives them insightful knowledge about future trends and patterns. AI is a creative engine in operational management that propels automation and value chain optimisation. Integration of AI-powered tools and systems may help firms increase operational precision, dependability, and scalability. operational needs and market circumstances (Sharma, T., Rathore, A., Lehri, B. P. S., Tiwari, M., Vadar, P. S., & Garg, B., 2024).

Despite having machinery, these businesses are sometimes regarded as low- and medium-low tech since they lack digital technology and still rely on manual labour and conventional methods. A different study's results offer important information that may be utilised to create practical solutions that help small and medium-sized businesses adopt data-driven methods to enhance their operations. The study also emphasises how the results may affect further investigation and real-world uses. The finished framework may be transformed into a system that can be modified and upgraded on a regular basis to meet particular requirements (Harno, S., Chan, H. K., & Guo, M.,2024).The use of AI by operational management represents a significant shift in the organisation, affecting efficiency, competitive dynamics across industries, and decision-making procedures. AI enhances efficiency and decreases mistakes by automating manual operations. AI chatbots for customer service and optimisation algorithms are two examples of this. One of the most often used artificial intelligence (AI) techniques, demand prediction, is the subject of another study that analyses several machine learning algorithms. To forecast the supply chain's long-term demand, the present study combines artificial neural networks and support vector machines with more traditional time series prediction techniques like moving average and exponential smoothing (Kumar, K. S., Gupta, V., Patil, Y., Jindal, G., Cheepurupalli, N. R., & Bhanushali, M. M., 2025).

2.5 Real-time tracking and Effective inventory control

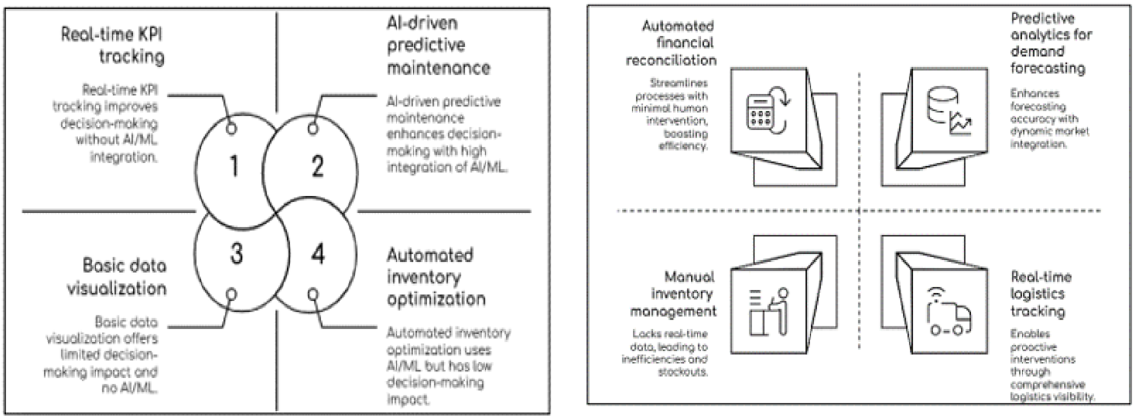


Figure 6. Real-time monitoring and effctive inventory management
(*source*:Rahman, M. A., Alam, M. S., & Mrida, M. S. H.,2025)

Interactive dashboards are essential for improving management decision-making in today's data-driven corporate environment because they offer real-time analytics, performance tracking, and predictive insights. Nevertheless, dashboards' intricacy, usability, and acceptance issues sometimes compromise their usefulness in corporate decision-making procedures. According to the study, too complicated dashboards cause cognitive overload and decrease decision efficiency, whereas simple, easy-to-use dashboards greatly increase decision-making accuracy and speed. According to the study, proactive decisionmaking is enhanced by automated alerts and AI-generated recommendations, but poor alert management might result in alert fatigue and decision paralysis. Additionally, businesses with strong governance frameworks—which include encryption protocols, data validation procedures, and role-based access control—reported better decision consistency and increased trust in dashboard-generated information (Rahman, M. A., Alam, M. S., & Mrida, M. S. H., 2025).

3. RESEARCH OBJECTIVES & METHODOLOGY

This paper aims to look at recent trends and the application of data science in operation management for an effective management process. Further the paper addresses the current gaps existing in the manufacturing process differ between the companies to company. A simple random sampling method has been deployed for this study with 110 respondents. The data has been collected through offline mode in Madras Export Processing Zone and various industrial estates in Tamil Nadu mainly on Chennai, Coimbatore, Salem and Madurai area). Percentage analysis to find respondent opines and facts, ANOVA, correlation and simple regression analysis carried out to interpret the results.

4. RESULTS SUMMARY

4.1 INSIGHT OUT ANALYSIS:

Key Findings base on Factual & Opine Survey:

Figure 7 indicates the factual analysis in graphical view and interference of the information as follows:

- *Gender profile:*
  - gender profile of the respondents 84.5% of respondents were male and 15.5% of respondents are female.

- *Role of respondents:*
  - 8.2% of respondents were delivery manager, 3.6% were Line manager and production manager respectively, 13.6% of respondents were production head whereas 12.7% of Chief executive officers, 6.4% were Business owners, 17.3% of respondents were production in charge whereas 16.4% of respondents were quality technicians, 9.1% of respondents were factory supervisors and inspectors.

- *Age of Respondents*
  - 23.6% of respondent's falls under the age of 18 to 25 years, 31.8% of respondents fall under the age of 25-45 years, 35.5% of respondents fall under the age of 45-55 years and 9.1% of respondents are above the age of 55 years.

Figure 8 indicates the factual analysis in graphical view and interference of the information as follows:

- *Educational profile:*
  - 23.6% of respondents holds Master degree whereas 31.8% of respondent hold Undergraduate degree level, 35.5% of respondent holds Industrial Diploma course whereas 9.1% respondents hold Management degree/diploma.

- *Business profile*
  - 30.0% of respondents working in Tool manufacturing, 19.1% of respondents working in Plastic products, 11.8% of respondents working in Chemical products whereas 11.8% of respondents Metal & machinery manufacturers, 9.1%, of respondents are from electronics Manufacturers, 6.4% from Service providers and 11.8% respondents are working under packaging products.

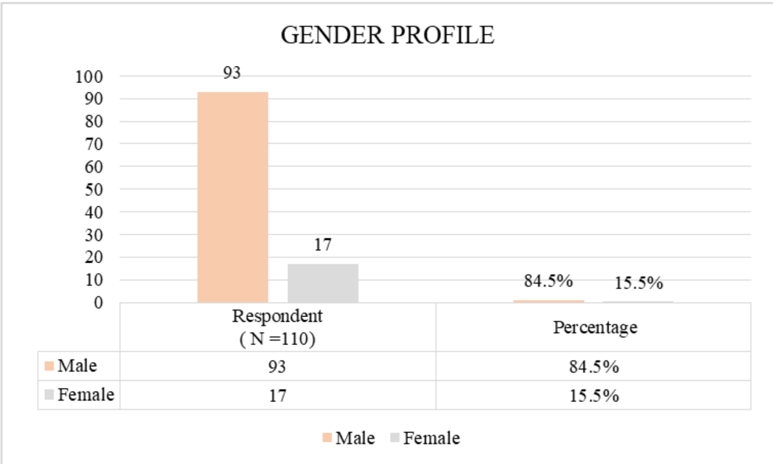
- *Data science-based software's and application for Betterment of operation management*
  - 41.8% of respondent opine that their organization willing to use Very Often on data science models, 21.8% of respondent opine rarely, 23.6% of respondent opine Occasionally their firm uses Data science model , 12.7% of respondents opines Not at all using data science models due to cost overheads.

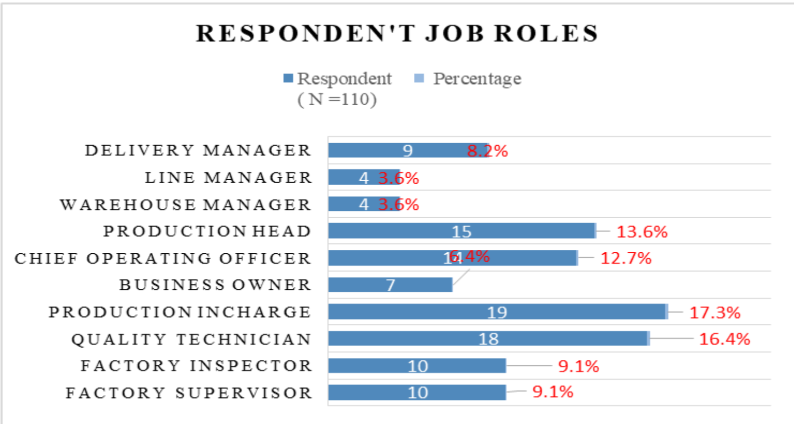
- *Industrial application using data science models*

- 29.1% of respondents opined that it will use to Raw material selection and rejection, 13.6% opined on deduct defect similarity & it's reduction, 0.9% opines Automatic report generation & process simplification, whereas 40.9% opines Automation and Plant monitoring system, however 15.5% opines production monitoring and failure reporting dashboards system.

Table - 1 indicates the Demographic profile of respondents. Table 2 indicates Facts & opines of respondents participated in the survey. Table 3 indicates what respondent expects data science models that will improve the effectiveness of the current manufacturing process and their opines has been indicated in detail.

Figure 7. Factual Analysis





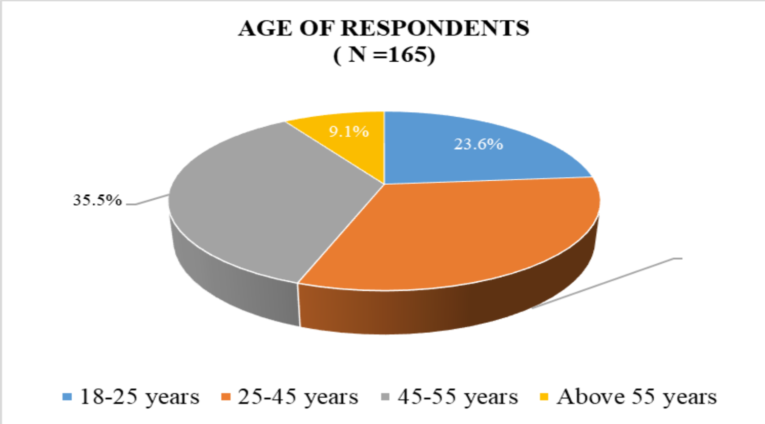
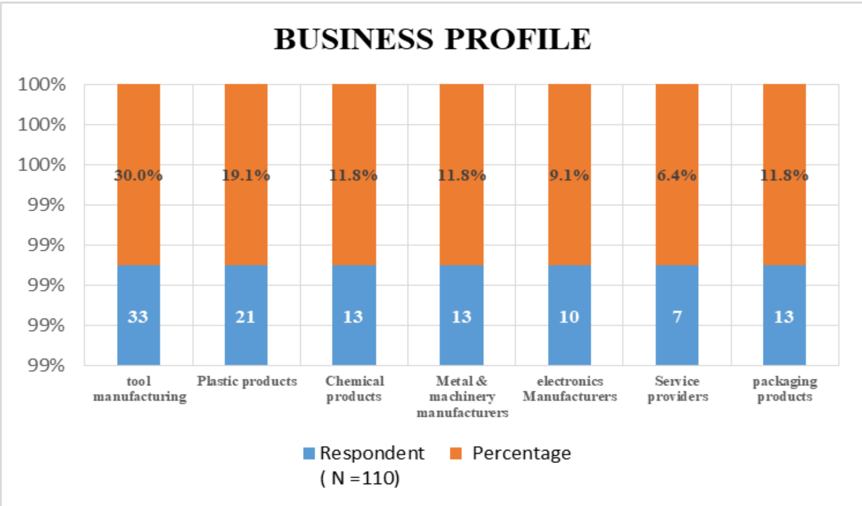
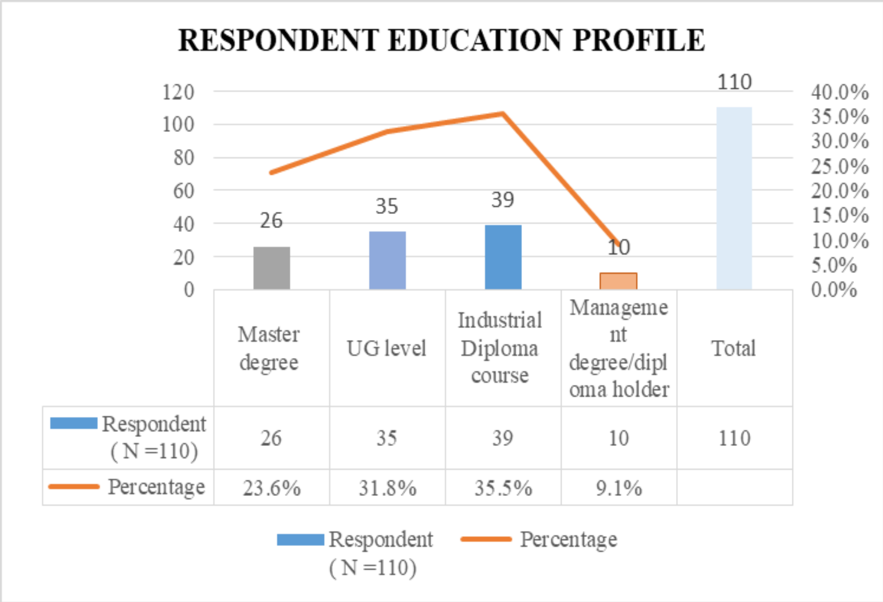


Figure 8. Factual & Opinion Analysis





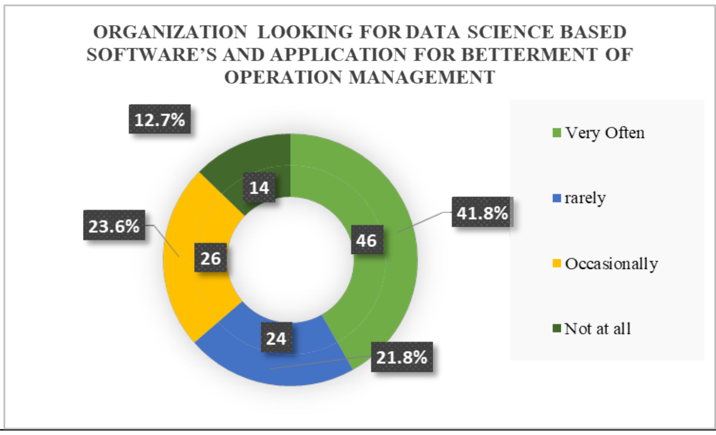
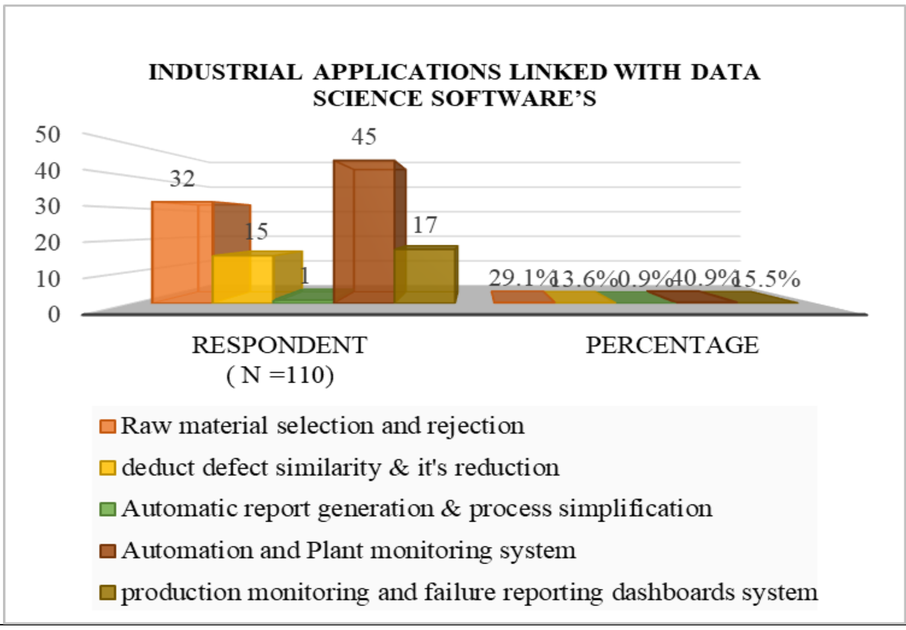


Figure 9. Factual & Opinion Analysis



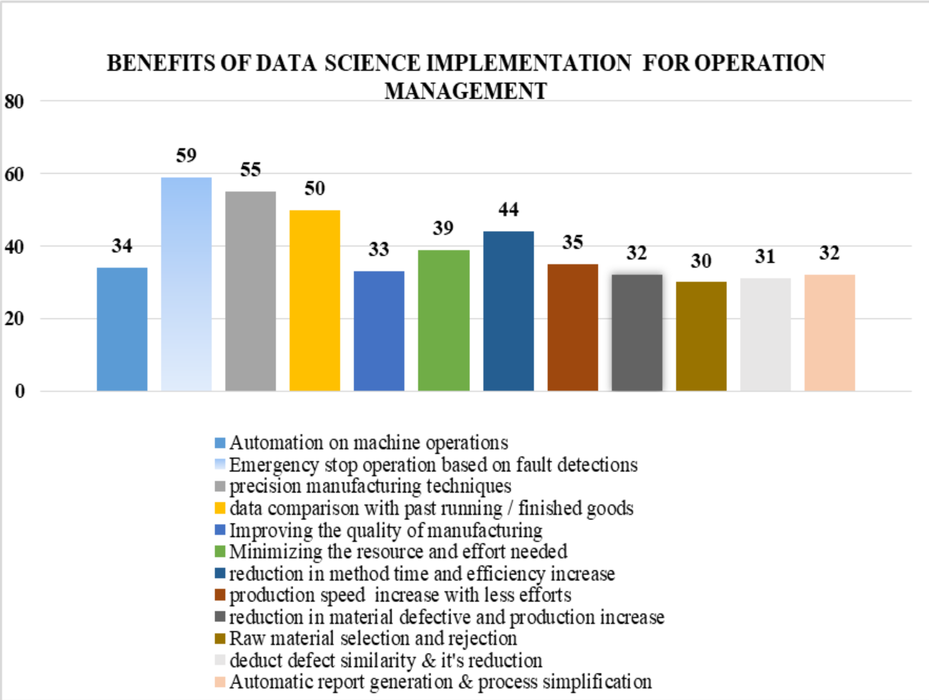


Table – 1: Demographic Profile of Respondents

Gender Profile	Respondents (N = 110)	Percentage
Male	93	84.5%
Female	17	15.5%
Total	110	100.0%
Job Role	**Respondents (N = 110)**	**Percentage**
factory supervisor	10	9.1%
Factory inspector	10	9.1%
Quality technician	18	16.4%
Production in charge	19	17.3%
Business owner	7	6.4%
Chief Operating Officer	14	12.7%
Production head	15	13.6%
Warehouse manager	4	3.6%
Line Manager	4	3.6%
Delivery manager	9	8.2%
Total	110	100.0%
Educational Profile	**Respondents (N = 110)**	**Percentage**
Master degree	26	23.6%
UG level	35	31.8%
Industrial Diploma course	39	35.5%

Management degree/diploma holder	10	9.1%
Total	110	100.0%
Age Group	**Respondents (N = 110)**	**Percentage**
18-25 years	26	23.6%
25-45 years	35	31.8%
45-55 years	39	35.5%
Above 55 years	10	9.1%
Total	110	100.0%

Table – 2: Factual Data based on Respondent Opinions

Company Profile / Business Focus Area	Respondents (N = 110)	Percentage
Tool manufacturing	33	30.0%
Plastic products	21	19.1%
Chemical products	13	11.8%
Metal & machinery manufacturers	13	11.8%
Electronics Manufacturers	10	9.1%
Service providers	7	6.4%
Packaging products	13	11.8%
Total	110	100.0%
Organization Looking for Data Science based Software's and Application for Betterment of Operation Management	**Respondents (N = 110)**	**Percentage**
Very Often	46	41.8%
Rarely	24	21.8%
Occasionally	26	23.6%
Not at all	14	12.7%
Total	110	100.0%
Industrial Applications Linked with Data Science Software's	**Respondents (N = 110)**	**Percentage**
Raw material selection and rejection	32	29.1%

Deduct defect similarity & it's reduction	15	13.6%
Automatic report generation & process simplification	1	0.9%
Automation and Plant monitoring system	45	40.9%
Production monitoring and failure reporting dashboards system	17	15.5%
Total	110	100.0%

Table – 3: Factual Data based on Respondent opinions

Benefits of Data Science Implementation for Operations Management	**Respondents (N = 110)**	**Percentage**
Automation on machine operations	34	30.9%
Emergency stop operation based on fault detections	59	53.6%
Precision manufacturing techniques	55	50.0%
Data comparison with past running / finished goods	50	45.5%
Improving the quality of manufacturing	33	30.0%
Minimising the resources and effort needed	39	35.5%
Reduction in method time and efficiency increase	44	40.0%
Production speed increases with less effort	35	31.8%
Reduction in material defective and production increase	32	29.1%
Raw material selection and rejection	30	27.3%
Deduct defect similarity & it's reduction	31	28.2%
Automatic report generation & process simplification	32	29.1%

4.2 REGRESSION ANOVA ANALYSIS & INTERPRETATION

Regression line equation -$\hat{Y} = 0.7652 + 0.9944X$, Data science-based applications will improve organisation operation management, predicted data-driven operation management will improve the company's performance, R2 = .99, F (1,112) = 20338.76, $p < .001$. $\beta = .99$, $p < .001$, $\alpha = 0.77$, $p = .013$.

Table – 4: Regression ANOVA Results

Source	DF	Sum of Square	Mean Square	F Statistic (df_1, df_2)	P-Value
Regression (between $\hat{y}_i$ and $\bar{y}$)	1	198590.4015	198590.4015	20338.759 (1,112)	0.00034
Residual (between y_i and $\hat{y}_i$)	112	1093.5832	9.7641		
Total (between y_i and $\bar{y}$)	113	199683.9846	1767.1149		

Table 4 indicates Regression and ANOVA results and below are the detailed interpretations.

- Data-driven operation management will improve company's performance and data science-based applications will improve your organization operation management relationship R-Squared (R2) equals 0.9945.

- This means that 99.5% of the variability of data driven operation management will improve company's performance is explained by data science-based applications will improve your organization operation management. Correlation (R) equals 0.9973.
- This means that there is an appropriate robust direct connection between data science-based applications will improve your organization operation management and data driven operation management will improve company's performance. The Standard deviation of the residuals (Sres) equals 3.1248.
- The slope: b=0.9944 CI[0.9806, 1.0082] means that when you increase data science-based applications will improve your organization operation management by 1, the value of data driven operation management will improve company's performance increases by 0.9944.The y-intercept: b=0.7652 CI[0.1645, 1.3659] means that when data science-based applications will improve your organization operation management equals 0, the prediction of data driven operation management will improve company's performance's value is 0.7652.The x-intercept equals -0.7695.
- Goodness of fit: Overall regression: right-tailed, F (1,112) = 20338.759, p-value = 0.00034 since p-value < α (0.05), we reject H0.
- The linear regression model, Y = b0+ b1X + ε, provides a better fit than the model without the independent variable resulting in Y = b0 + ε.
- The slope (b): two-tailed, T (112) =142.614, p-value = 0. For one predictor it is the same as the p-value for the overall model. The y-intercept (b): two-tailed, T (112) = 2.524, p-value = 0.013. Hence, b is significantly different from zero.

5. DISCUSSION

As a result of the manufacturing industry's rapid advancement and use of information and communication technology, vast volumes of diverse data are currently being produced, collected, and stored. Since several new approaches, methods, strategies, and tools for data analytics create new opportunities for data exploitation by turning them into meaningful information and/or knowledge, handling vast volumes of complicated data—often referred to as big data—presents a problem. In contrast to other industries like marketing, healthcare, and business, the use of sophisticated data analytics in manufacturing is less widespread and diverse, which means that the data that is accessible is frequently left unused (Kozjek, D., Vrabič, R., Rihtaršič, B., Lavrač, N., & Butala, P., 2020). In data-driven manufacturing, which seeks to increase operational effectiveness and product quality while lowering costs and risks, data science now offers enormous prospects by transforming raw data into industrial information. Manufacturing companies, however, struggle to manage their data science initiatives in order to realise these possible advantages. Maturity models are designed to help organisations by offering a comprehensive road map for certain areas of progress. In an attempt to solve this issue, a different paper suggests a theoretically based Data Science Maturity Model for manufacturing companies to evaluate their current advantages and disadvantages, conduct a gap analysis, and create a roadmap for ongoing advancements in their transition to data-driven manufacturing (Gökalp, M. O., Gökalp, E., Kayabay, K., Koçyiğit, A., & Eren, P. E., 2021). Operations management research has both possibilities and problems as a result of the previously unheard-of availability of data and the expanding range of software programs available to visualise it. Usually employ data to explain situations, forecast events, or prescribe solutions based on whether they are developing, evaluating, or putting ideas into practice. When applied properly, visualisation may enhance, support, and supplement the researcher's comprehension at many phases of the research process (theory development, testing, or translating and communicating results). However, visualisation might provide false and misleading statements if it is used improperly or without enough thought. Research provides recommendations on how researchers should utilise visual data representations, especially on how to avoid misrepresentation, which may occur when visualisation is used incorrectly (Basole, R., Bendoly, E., Chandrasekaran, A., & Linderman, K., 2022).With the help of information management, organisations may analyse both historical and current data, providing them with all the information they want to make wise strategic decisions. Using data to make timely, credible, and relevant decisions has become essential for most modern businesses to succeed (Ragazou, K., Passas, I., Garefalakis, A., Galariotis, E., & Zopounidis, C. 2023). Data science has become a key factor in changing how businesses operate in a variety of sectors by promoting innovation, operational effectiveness, and strategic decision-making. The physical and intangible advantages of data science, such as cost savings, better customer satisfaction, and increased productivity, are further examined in another article. These advantages add up to a competitive advantage in the marketplace. also considers new developments that may influence data-driven corporate operations in the future, such as blockchain and IoT integration, ethical data practices, AI, and machine learning. It makes suggestions on how companies might get ready for this changing environment, stressing the value of cooperation, a data-centric culture, and strong infrastructure. Another paper's conclusion emphasises how important data science is to long-term company performance in a world that is becoming more and more data-driven (Adeniran, I. A., Efunniyi, C. P., Osundare, O. S., Abhulimen, A. O., & OneAdvanced, U. K., 2024).Nowadays, services account for the majority of economic activity. Research approaches that enable businesses to address issues pertaining to service operations while promoting the development of new artefacts to support the complex reality that services embody are necessary. Action research is a technique that has been successful in organisations by resolving actual issues. Other methodologies that offer workable and applicable answers can be added to this one. Design Science Action Research is a methodology that supports the creation of new objects operating in the actual setting of companies. It combines AR with Design Service Research and investigates its applicability for Operation Management research (Castro, V. D., Martín-Peña, M. L., Martínez, E. M., & Salgado, M., 2025).

6. MANAGERIAL IMPLICATIONS

Data models brings more benefit in the operations mainly on manufacturing in various areas such as follows: Automation on machine operations, Emergency stop operation based on fault detections, precision manufacturing techniques, data comparison with past running / finished goods, Improving the quality of manufacturing, Minimising the resources and effort needed, reduction in method time and efficiency increase, production speed increases with less effort, reduction in material defective and production increase, Raw material selection and rejection, deduct defect similarity & it's reduction, Automatic report generation & process simplification which will improve precise and improve accuracy in manufacturing goods and process. This kind of data models will help MSME industries to improve the competitiveness of their manufacturing products by reducing the process cost etc.

7. CONCLUSION

From this standpoint, data science has become an inevitable vertical in almost all sectors now. However, it plays a vital role in operation management for an effective manufacturing process. The manufacturing sector has always had complex issues since it handles raw material, production units, manpower, recent technology and modern equipment for the production of finished goods. Looking at this process, the data generation will be massive at each end. Data science would help in many ways to know where to look for further optimisation to provide a competitive product to the market. This paper provides useful insights from the research analysis and interprets the results that arrived based on this research. The research gap addressed in this research shows how effective data science helps to optimise day-to-day operations and how it could be improved further to improve the competitiveness of the finished goods from a manufacturing industry's perspective. The research reveals that there is a strong correlation between data science and improving the efficiency of day-to-day operations of the manufacturing industry. This research also suggests that there is a huge scope for implementing data science that enables models in MSME industries to help to improve their profitability and growth of the firms. However, the research results are limited to the study region only and may differ from region to region or country to country.

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