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The Significance of Machine Learning in the Manufacturing Sector: An ISM Approach

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Abstract: *Background:* Our day-to-day commodities truly depend on the industrial sector, which is expanding at a rapid rate along with the growing population. The production of goods needs to be accurate and rapid. Thus, for the present research, we have incorporated machine-learning (ML) technology in the manufacturing sector (MS). *Methods:* Through an inclusive study, we identify 11 factors within the research background that could be seen as holding significance for machine learning in the manufacturing sector. An interpretive structural modeling (ISM) method is used, and inputs from experts are applied to establish the relationships. *Results:* The findings from the ISM model show the 'order fulfillment factor as the long-term focus and the 'market demand' factor as the short-term focus. The results indicate the critical factors that impact the development of machine learning in the manufacturing sector. *Conclusions:* Our research contributes to the manufacturing sector which aims to incorporate machine learning. Using the ISM model, industries can directly point out their oddities and improve on them for better performance.

Keywords: machine learning; Industry 4.0; manufacturing industry; smart manufacturing; interpretive structural modeling (ISM)

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1. Introduction

In the world, at present, what makes a company or an industry more engaging and recognized is the volume of production and its ability to perform despite the challenges of the market. Several methods have been proposed through the years to measure or check the productivity of companies. Parameters, such as the volume of products produced, supplies in different states, and the resilient behavior of the company, have been considered when defining the prosperity or the popularity of the company among consumers [1]. Amini and Chang [2] stated that the most efficient item that industries need to date is an automatic machining system, which helps control the system's processes and manages the overall monitoring system to handle any situation. These can be achieved through the collaborative work of machine learning and system improvements in the manufacturing sector.

Machine learning (ML) is a subset of artificial intelligence and a branch of computer science that focuses on the use of data and algorithms to imitate the way a human being learns. Through this technology, computer programs and algorithms have been developed to perform specific tasks without the need for explicit instructions [3]. Machine learning is one of the most advanced technologies at present that is being implemented in industries, where it is used in different work processes, especially in the manufacturing sector. The implementation of ML has helped improve the monitoring and execution of various processes by reading and analyzing previously collected data and performing simple instructions. The data collected are also used for predicting future forecasts, which can help to detect any defects or mishaps and thus completely avoid them or at least reduce their impact on the industry [4]. ML in the MS also has the ability to accommodate smart sensors, devices, and machines to perform tasks, such as quality improvement, process optimization, task scheduling, continuous inspection, and predictive maintenance [5]. To date, it is one of the most efficient technologies that people want to use in their everyday life to make things work easier, including forecasting, training machines, and robots, performing daily household work. ML has started playing a significant role in field of technology as well as in our everyday lives. In different scenarios, it can be introduced through different model structures to fit the working environment of an industry. This will not only help in the above-mentioned areas, but will also work through the problems of strategic distribution and labor utility within the industry.

The manufacturing sector (MS) is essentially engaged in the production of products from raw materials or commodities. There are several steps involved, starting from the initial stage of collecting the raw materials to the preparation of the finished goods [6]. Manufacturing includes different industries, such as pharmaceuticals, software, welding, heavy manufacturing, and others [7]. For instance, ML can be used by drug manufacturers [8] for accurate measurements or determining the right amount of the mixture for each drug; furthermore, systems can be designed to easily recommend the treatments that would be advisable for certain symptoms. ML can also be used in the 3D-printing industry [9], where goods can be produced through instructions given to the software, and the hardware of the system can then complete the product. One of the major concerns that comes with the implementation of ML is the security of the machine [10], the dependability of the data's structure, the reliability of the machine's performance [11], and fault diagnosis [3,10]. ML has also helped with the sales of a product [12]. Since the operations of ML revolve around the application of data, there may be cases where the data are unavailable or the existing data have been misinterpreted, which may lead to unwanted results at the end of the operation. For supply and demand activities, once a firm has been fed with the data of the consumers, the tasks can be automated and the demand and supply can be monitored and managed through the system. This type of advanced technique has helped the even faster arrival of Industry 4.0. Through process automation, the process of segregating faulty manufactured products has become extremely easy after the integration of the data [13,14]. This process extensively decreases or completely removes the monitoring or labor involved.

Any MS at present has several steps to follow, where the thorough inspection and timely production of goods can satisfy well-developed supply chain management techniques [15]. The processes range from the collection of raw material through to the supply of the final products to the consumers, and the monitoring techniques involved in these processes can be easily applied through the implementation of machine learning to the existing system [2]. The demand for certain goods to be produced at a certain time and what the demand of the market will be can be easily predicted [16] through the implementation of ML. Logistics and demand forecasting can also be predicted to produce quality products for the customers' satisfaction through this technique. The best part of ML is that the machines become smart enough to work by themselves once trained [2], while also providing proper statistics on the production, planning, and control of the environment [6,17]. These machines, once set up through the algorithms, are then able to gather prior information on their own accord and perform the desired task as per the requirements [18]. The messages sent from the industry to the suppliers or consumers can be filtered through text mining [19], which is a part of ML. With this, the true text and valid information can be presented to genuinely address the problem. By integrating ML in the MS, we aim to achieve a high-quality product for a minimum cost and with the maximum accuracy to satisfy the customers' demands [20]. Since the time required for the existing products is reduced, ML provides opportunities to the industry for product diversification.

Given the importance of ML in the MS, the authors conduct research on how and what is affecting the development of ML in the MS the most. After a collective analysis, the authors were able to highlight 11 factors responsible for the integration of ML into the industry. Since the idea of ML is fairly new, little work is available on its practical implementation in the MS. After a thorough review of the framework of the subject, we are able to identify the objective through examining the gaps in the research.

RQ 1: Identification of significant factors seen as impacting machine learning in the manufacturing sector.

RQ 2: Analysis of the identified factors through ISM and MICMAC analysis to understand the level of effectiveness of machine learning in the manufacturing sector.

Less work has been conducted on the digital side of the manufacturing sector. Though some authors have mentioned machine learning in the manufacturing sector, there is no prioritization of the factors involved. Since no recent, comprehensive work based on the general understanding of the significance of machine learning in the manufacturing sector using ISM has been published, this paper is a step ahead in that direction. This paper is an attempt to rank the different factors involved. In this research, ISM followed by MICMAC analysis is used to develop a structural relationship between the factors. Interpretive structural modeling (ISM) is a multi-criteria decision-making technique that is incorporated to develop a relationship between the factors. ISM has helped in describing complex situations in simpler forms through structural analysis. The MICMAC analysis incorporates the driving and dependence power of the factors to develop a graphical classification. It also validates the interpretive structural model factors to produce their results and conclusions. The paper is organized in the following format: Section 1 contains an introduction to the topic of machine learning in the manufacturing sector; the significance of machine learning in the manufacturing sector from the literature review is presented in Section 2; Section 3 describes the method implemented for the analysis of the recognized factors for ML in the MS; this is followed by Section 4, which presents the results of the discussion; and lastly, Section 5 presents the conclusion to the study.

2. Literature Review

Since the world to, date, is significantly progressing towards the use of online services and digital machines, every industry is competing to improve their production and performance. With the expanding businesses, these engineering and manufacturing problems are data-rich with little understanding of the area. Here, ML has provided us with tools to improve this understanding of the field and improvise the utilization of the available data [21]. The world heavily depending on online services and the increasing use of digital gadgets has led to increased data generation with every passing second. These generated data are often mined and used by industries to present their scope for future performances. The data are also helpful for training machines in performing specific tasks through the development of predictive models [22]. High quantities of data generated through physical methods from MS cause a heavy data load. Additionally, the traditional method of data extraction is not structured enough to efficiently process this data. At times, the storage of these data to be processed further becomes a challenge for the industry [21]. However, the use of the data-mining process under ML has made significant changes in the ways the data are processed, making it more efficient [23]. Choi et al. [24] mentioned that with the introduction of ML, the industry has to remodel itself to accommodate new changes. The authors also determined that the efficiency was greatly improved and the added effort from man and machine resources made way for product diversification. With the progress of industries into the season of 4.0, the usage of smart devices and machines has loaded the factories with enormous quantities of data [5], ML techniques have shown to be effective in managing these data and constructing a workable environment through it, producing better forecasting capabilities for future work. Locating the relevant data for use can be difficult. Andrei et al. [25] said the task of locating the existing data can be challenging work, especially if larger organizations are involved in it. Finding the relevant data leads to the understanding of their structure [26]. The data are then used to model algorithms that are used by the industries to simplify any working process. One major disadvantage is the absence of relevant data; it may be possible that some data are present in the form of logs and are not stored or cannot be rephrased to build a data set. Such disruptions are obstacles to application development as they fail to produce a clear idea of whether the data are available or not. Even after data recognition occurs, a major question arises with the selection of an appropriate algorithm. With multiple options available, industries may find it challenging to settle on a specific algorithm [2,22]. The purpose of the algorithm is not only to solve the problem, but also to ensure minimum expenses, thus helping in better decision making. Sharp et al. [27] stated that ML in the MS helps with certain operations, such as decision management. The most important decision faced by industries is the current status of a product [28,29]. This is highly impacted, whether the product has been ordered or not, if the product is available, or whether the product is sitting idle in the inventory. Here, ML has helped in accessing real-time data and effective order fulfillment [12]. Having skilled employees with an understanding of ML has also helped estimate accurate propositions for a project. Determining the financial viability of or product feasibility for a company is also easily determined through the use of ML. Factors, such as process and tool cost, lot size, and outsourcing, can be an included function for the ML.

Andrews et al. [30], in their study, proposed algorithms through ML to study order fulfillment in an e-commerce company. The company considered had 18,000 consumer orders on regular days and 100,000 consumer orders on its peak days. The algorithm devised recorded the inputs from all the consumers. Additionally, it was found that the use of an algorithm optimized the order-fulfillment decisions and also assisted in reducing the shipping costs. Zhang et al. [31] performed a similar algorithm development where they tried to achieve an optimal order-fulfillment performance and to reduce the time between the order received and the product delivered. The results of Wuest et al.'s [32] work revealed that the implementation of ML in the MS not only helped to satisfy the demand for high-quality products in an organized manner, but also saw rapid-paced developments with favorable results. The association of ML to the industry under AI technology has helped with the understanding of the health status of industrial equipment [33]. Without the use of advanced technologies, it was difficult to track the exact placement and length of the disruption created. However, with the integration of digital transformation and the use of information techniques, computerized control, and the communication network, the ML was able to provide techniques to improvise the working situation. Peres et al. [34] and Carvalho et al. [35], through their work, showed that the inclusion of ML presented a reduction in the maintenance and repair costs. Additionally, improving the machine-cost and inventory reductions lead to the overall improvisation of operator safety.

Some research has mentioned that the inadequacy of resources led to the acceptance of machine learning by the industry, which later proved effective in reducing time, energy, and waste [6,17,31]. There were instances when industries had been ignorant about the usage of machine learning in their industry. The non-utilization of this advanced technology put industries on the back foot [32]. Weichert et al. [36] focused on the time frame between 2008–2018 and showed that ML was helpful in optimizing product quality and process involvement in the manufacturing industry. Suma and Shavige [37] concluded from their analysis that using data-mining techniques is a very important aspect of ML. This can be applied to predict the demand of the market. It can be used to analyze the real-time data set and can be efficiently manipulated to develop algorithms for better and more accurate predictions to satisfy product demand in the market. With the rapid development of ML, a considerable impact is felt regarding the ergonomics of the industry [38]. ML techniques have been used in auto-code injury causation developments, which helped prevent numerous industry-related accidents [39]. The use of wearable sensors and inertial measurement units to capture human action has led to the further improvisation of the work-safety protocol in the industry [40].

Graessley et al. [41] used different models under machine learning to survey and analyze data for evaluating revenue, cost, and efficiency gains. Additionally, they found that the use of ML provided better accuracy and efficiency for tackling these aspects. Similar to this, an electricity manufacturing company used a formulation based on the IoT (Internet of Things) and ML to help calculate the accurate quantity of electricity consumed by the customer to benefit both the manufacturer and consumer [42]. Zheng et al. [43], in their paper, mentioned the study of an industrial rubber mixer that used sensors for just-in-time semi-supervised machines, which integrated ML. When a test sample was tested, it collected datum and improvised on it according to the desired algorithm predicting model selection to provide better accuracy. Angelopoulos et al. [44] determined that the implementation of ML in the MS improved the outcome of the MS through process automation. With developmental enhancement through wireless connectivity and real-time-data collection and processing, it was possible to monitor fault detection, prediction, and prevention with better accuracy. With all the possibilities of incorporating machine learning in the manufacturing sector, one has to keep in mind whether the industry is capable of adopting changes or not [32]. The incorporation of new technology requires changes in the existing machines. Therefore, industries need to take into account their needs and existing facilities for efficient cooperation. Table 1 summarizes the eleven factors after considerable work was conducted on the literature review.

Table 1. Factors with their references.

Factors	Explanation	References
Significance of machine learning	The impact of machine learning on the industry has been considerable. It has significantly helped improve the working strategy, at present, and has also helped in the development of accurate, future predictions.	[1,2,21]
Unawareness of people	Many industries are still unaware of the effectiveness of machine learning. The lack of a proper understanding of the requirement of the system and how it is guided often leads people to not integrate it into their system.	[25,26]
Skilled labor	The combination of machine learning and skilled labor needs of time. It not only pacifies the workload, but also contributes to efficient working.	[24,27]
Process automation	Machine learning in the industry results in the rapid development of work processes. There has been a shift from traditional methods of process involvement to the automation of processes, resulting in much faster and efficient working methods.	[38–40,44]
Lack of manmade-machine and manpower	Since industries faces a lack of manpower, the technology helps to fill the gap.	[33–35]
Unavailability of historical data	The developmental working of machine learning relies on the knowledge and availability of data. Though this, there is accessibility to a large amount of data; there is always a possibility that we do not have access to what is required. Additionally, this lack of availability of data leads to the inefficiency of the work.	[21–23]
Diversified product generation	Machine learning when implemented does not only help with the product development, but can simultaneously be used for other processes in the system. Here, since product-development time is greatly reduced, space is created for product diversification.	[20,24]
Revenue of industry	The introduction of technology to the industry has progressed its working environment. Better machinery results in better product delivery, generating more revenue for the industry.	[5,11,18,24]
Just-in-time product generation	The just-in-time production system has become more efficient. Since process development has become faster, industries are very well adapted to the just-in-time production system.	[15,16,43]
Order fulfillment	Since machine learning acts on the available data, generating a forecast for order fulfillment becomes very easy. With prompt input, industries can fulfil order requirements on time.	[12,28–31]
Demand of the market	Machine learning has helped in fulfilling the demand for delivering quality products on time with better forecasting.	[32,36,37]

3. Methodology

Firstly, an extensive literature review was conducted to identify the factors that discussed the idea of the significance of machine learning in the manufacturing industry. The authors explored different databases with keywords, such as machine learning, Industry 4.0, process automation, smart manufacturing, data mining, and manufacturing industry. A conference was conducted at KIIT University consisting of academicians and industrial experts from the manufacturing sector, where an open discussion was conducted to point out the significant factors affecting ML in the MS. Through a brain-storming session, a list of fifteen factors was established. These were further ranked by the experts, which concluded eleven critical factors. The eleven factors received a score from 8 to 4 in the ranking procedure. Other factors from the short-listed factors, such as the data storing capacity of the industry, selection of algorithms, flexibility of industrial capability, and ignorance of the technology, scored very low (Score = 1) and were not included in the final list. Table 1 shows the list of eleven factors that were found to be crucial for the significance of machine learning in the manufacturing industry. The authors consulted eight experts from the manufacturing sector who were associated with the session, each with a minimum experience of ten years in the manufacturing sector. The authors then, with the inputs from the experts, constructed the structure self-interaction matrix (SSIM). The number of experts considered, the literature review, and the methodology used for the research were fairly sufficient, as ISM did not limit the sample size of the experts. In addition, similar examples have been set by previous researchers. Charan et al. [45] identified fourteen factors with inputs from seven experts for their work in supply chain management. Similarly, Dahooie et al. [46] identified seventeen factors with the combined input from the researched data and expert's opinion in the healthcare industry. Singh and Rathi [47] stated sixteen factors through a questionnaire survey of industrial experts and academicians on six sigma barriers in small- and medium-sized industries. Similarly, Marinelli et al. [48] used the questionnaire method to obtain the input from academicians and construction professionals to develop a relationship between the ten factors with regard to off-site construction.

3.1. Interpretive Structural Modeling (ISM)

Interpretive structural modeling (ISM) is a multi-criteria decision-making (MCDM) technique, a methodology used for establishing a relationships among the key factors of any given objective. It is a technique that builds relationships and showcases the structural development of the factors of a complex system [49]. Since ISM does not provide any direction for constructing the expert's size, it becomes easier to define results with fewer experts. Even still, ISM exhibits certain limitations. Though this method establishes a structural relationship between the factors, it fails to specify the intensity of the impact of the factors on the others. Moreover, the inputs obtained from the experts may be influenced by their biased decisions. Nonetheless, this method has been extensively used by researchers in the past in various fields. These include supply chain risks and management [50,51], the automobile industry [52], logistics [53], risk assessments [54], construction projects [55], supplier selection [56], and many more. The steps involved in ISM modeling are (1) identification of critical factors; (2) construction of structure self-interaction matrix (SSIM); (3) construction of reachability matrix; (4) development of level partition; (5) depicting the relationship between the factors as developed through the reachability matrix and level partition; and (6) constructing the ISM model. A diagrammatic description of the steps involved in the methodology is presented in Figure 1.

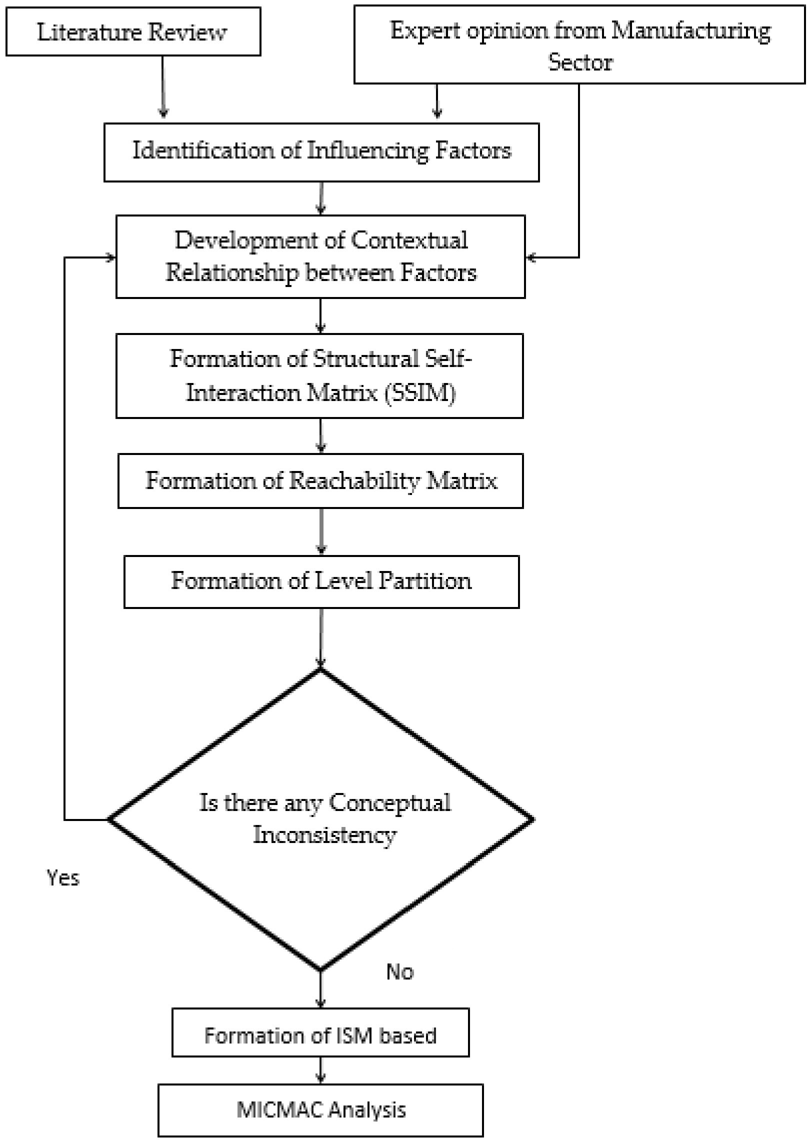

Figure 1. Solution methodology.

3.1.1. Structural self-interaction matrix (SSIM)

A total of eight experts from the manufacturing sector were involved to finalize the eleven factors. They were consulted to develop a contextual relationship between the eleven factors. The relationships between the factors are described using four symbols: V, A, X, and O (Table 2). If i and j are two factors that need the description of their relation, this can be described as follows:

V: i will impact j;
A: j will impact I;
X: both i and j will impact each other;
O: I and j are independent.

Table 2. SSIM matrix.

Factors	Notation	SML	UOP	SL	PA	LMMM	UHD	DPG	RI	JIT PG	OF	DTM
Significance of machine learning	SML	1	A	A	X	A	A	X	A	X	V	A
Unawareness of people	UOP		1	A	V	A	O	V	A	V	V	A
Skilled labor	SL			1	V	O	V	V	O	V	V	A
Process automation	PA				1	A	A	X	A	X	V	A
Lack of manmade-machine and manpower	LMMM					1	V	V	O	V	V	A
Unavailability of historical data	UHD						1	V	A	V	V	A
Diversified product generation	DPG							1	A	X	V	A
Revenue of industry	RI								1	V	V	A
Just-in-time product generation	JIT PG									1	V	A
Order fulfillment	OF										1	A
Demand of the market	DTM											1

3.1.2. Reachability Matrix

The reachability matrix (Table 3) is created from the SSIM matrix (Table 2). Here, the symbols V, A, X, and O are replaced by the numerical values of 1 and 0 to create the reachability matrix. The following rules are followed for the replacement of the symbols: (1) if the (I, j) position in SSIM is V, then (i, j) in the reachability matrix becomes 1 and (j, i) becomes 0; (2) if the (i, j) position in SSIM is A, then (i, j) in the reachability matrix becomes 0 and (j, i) becomes 1; (3) if the (i, j) position in SSIM is X, then (i, j) in the reachability matrix becomes 1 and (j, i) becomes 1; and (4) if the (i, j) position in SSIM is O, then (i, j) in the reachability matrix becomes 0 and (j, i) becomes 0.

Table 3. Reachability matrix.

j i	SML	UOP	SL	PA	LMMM	UHD	DPG	RI	JITPG	OF	DTM	DRIVING POWER
SML	1	0	0	1	0	0	1	0	1	1	0	5
UOP	1	1	0	1	0	0	1	0	1	1	0	6
SL	1	1	1	1	0	1	1	0	1	1	0	8
PA	1	0	0	1	0	0	1	0	1	1	0	5
LMMM	1	1	0	1	1	1	1	0	1	1	0	8
UHD	1	0	0	1	0	1	1	0	1	1	0	6
DPG	1	0	0	1	0	0	1	0	1	1	0	5
RI	1	1	0	1	0	1	1	1	1	1	0	8
JITPG	1	0	0	1	0	0	1	0	1	1	0	5
OF	0	0	0	0	0	0	0	0	0	1	0	1
DTM	1	1	1	1	1	1	1	1	1	1	1	11
DEPENDENCE POWER	10	5	2	10	2	5	10	2	10	11	1	

3.1.3. Level Partition

The reachability and antecedent sets were developed from the reachability matrix (Table 3) based on the driving and dependence power of the factors. The reachability set consists of the factor itself and other factors that are influenced by it. The antecedent set consists of the factor itself and other factors that influence it. An intersection set was also constructed. It presents the common factors between the reachability and antecedent sets. The factor that shares a common value between the reachability and intersection sets is placed on level I (see Table 4). Then, that factor was excluded from the other factors for the following level iteration. The process was repeated until all the factors were included in the level iteration.

Table 4. Level-partition table.

Factor	Notation	Reachability Set	Antecedent Set	Intersection Set	Level
F1	SML	1, 4, 7, 9, 10	1, 2, 3, 4, 5, 6, 7, 8, 9, 11	1, 4, 7, 9	II
F2	UOP	1, 2, 4, 7, 9, 10	2, 3, 5, 8, 11	2	III
F3	SL	1, 2, 3, 4, 6, 7, 9, 10	3, 11	3	IV
F4	PA	1, 4, 7, 9, 10	1, 2, 3, 4, 5, 6, 7, 8, 9, 11	1, 4, 7, 9	II
F5	LMMM	1, 2, 4, 5, 6, 7, 9, 10	5, 11	5	IV
F6	UHD	1, 4, 6, 7, 9, 10	3, 5, 6, 8, 11	6	III
F7	DPG	1, 4, 7, 9, 10	1, 2, 3, 4, 5, 6, 7, 8, 9, 11	1, 4, 7, 9	II
F8	RI	1, 2, 4, 6, 7, 8, 9, 10	8, 11	8	IV
F9	JIT PG	1, 4, 7, 9, 10	1, 2, 3, 4, 5, 6, 7, 8, 9, 11	1, 4, 7	II
F10	OF	10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11	10	I
F11	DTM	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11	11	11	V

3.1.4. ISM Model

After determining the level partition from the reachability matrix, a diagram (Figure 2) was developed based on the factors on different levels. The diagram also indicated the interrelationship between the factors through nodes.

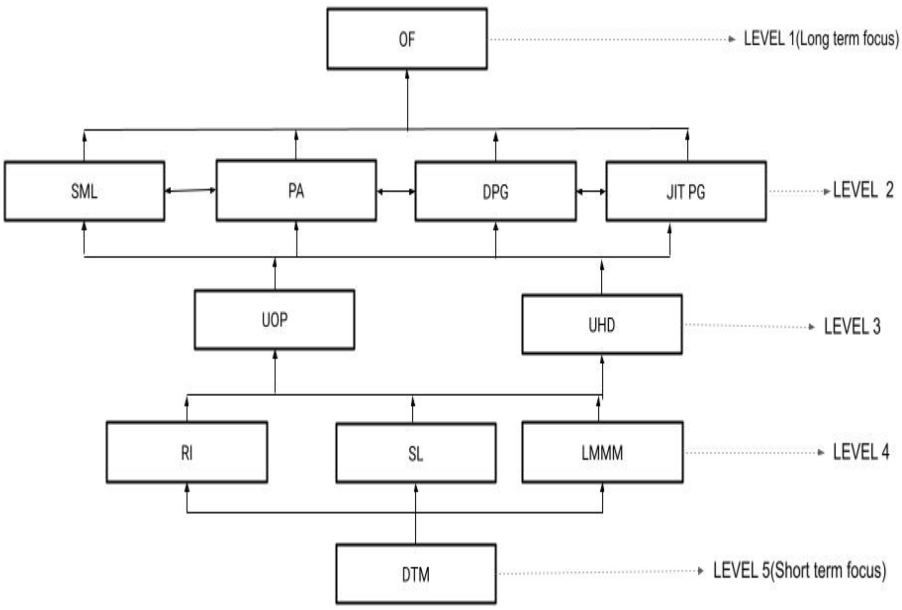

Figure 2. Interpretive structural model.

3.2. MICMAC Analysis

The MICMAC or the matrice d'impacts croisés multiplication appliquée á un classment is a structural analysis used to study the indirect relation between factors [57]. The driving power (DRP) and dependence power (DEP) of the factors were used as inputs for this analysis (Figure 3). This analysis categorized the factors into four divisions: (1) autonomous division sites: factors having low DRP and DEP values; (2) dependence division sites: factor having low DRP but high DEP values; (3) driver division sites: factors with high DRP but low DEP values; and (4) linkage division sites: factors having high DRP and DEP values.

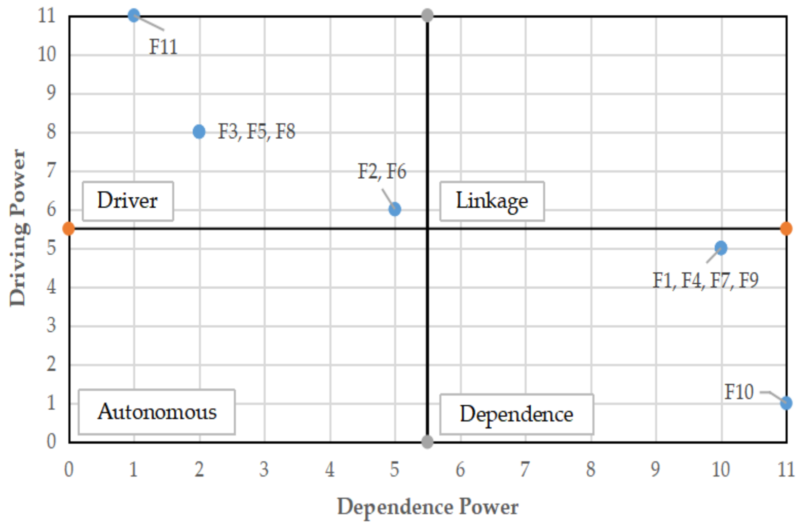

Figure 3. MICMAC analysis.

4. Results and Discussions

4.1. Interpretive Structural Modeling

This study aimed to identify critical factors and develop a structural relationship that influenced the significance of machine learning in the manufacturing sector through the ISM methodology. Furthermore, the study also segregated the driving and dependence powers through MICMAC analysis. This research identified eleven factors that were observed to be critical in influencing the significance of machine learning in the manufacturing sector, as presented in Table 1. The factors were finalized by experts, and their inputs were used to develop the SSIM matrix (Table 2). The representation of the relation was presented in the symbols V, A, X and O (see Section 3.1.1). In Table 2, the relation between skilled labor and process automation is described as 'V'. It indicates that the skilled labor factor impacts the process automation factor. The skilled labor factor impacts the unawareness factor of people and is represented by 'A'. Similarly, the relationship between the significance of machine learning and diversified product generation is symbolized by 'X', meaning both factors impact each other. The unavailability of historical data and unawareness of people are independent factors represented by 'O'.

After the SSIM matrix was developed, the reachability matrix was constructed by converting the symbols (V, A, X, and O) to 1 and 0 (see Section 3.1.2). Table 3 presents the reachability matrix developed from the SSIM matrix mentioned above. It can be observed from Table 3 that the DTM (demand of the market) factor has the highest driving power. Additionally, the OF (order fulfillment) factor has the highest dependence power.

Subsequently, the level partition table (Table 4) was constructed. First, the respective columns of the reachability and antecedent sets were constructed. From Table 3, it can be observed that the factor itself and factors influenced by it move in the horizontal direction and are grouped under the reachability set. Additionally, the factor itself and the factors that influence it move in the vertical direction and are grouped under the antecedent set. An intersection set was created to group the common factors among the reachability and antecedent sets. The reachability and intersection sets were compared to place the factors at different levels. From Table 4, we can see that the OF (F10) factor has a common value in the reachability set similar to that of the intersection set, and hence it is placed at 'level I'. Continuing with the same process, all the factors were placed at different levels. A total of five iterations were made to place the factors in five levels. The level-I factor suggests that it is the most dependable and all the other factors influence it. The factor at level V suggests it is the most reliable driver and can influence all the other factors. As we move from levels I to V, the dependency on the factors decreases and the driving nature increases. Then, the ISM model was created based on the level partition (Figure 2).

In the ISM model (Figure 2), factor F11 (demand of the market) is observed on level V. It is the strongest driver and influences all the other factors. It is defined as the short-term factor, suggesting factors at this level should be of immediate concern to the industry. The working of all the other factors starts from this level. Level IV contains F8 (revenue of the industry), F3 (skilled labor), and F5 (lack of manmade-machine and manpower). These factors are of an independent nature, but have the same level of importance and equally influence the factors of level III in the model. F2 (unawareness of people) and F6 (unavailability of historical data) are present on level III. These factors are also of an independent nature, but of equal importance. They are influenced by factors on level IV and they influence level-II factors. Level II has four factors: F1 (significance of machine learning), F4 (process automation), F7 (diversified product generation), and F9 (just-in-time product generation). The factors on this level are interdependent. F1 and F4 influence each other in a manner similar to that of F7 and F9, whereas F7 is equally influenced by F1 and F4. Similarly, F7 is influenced by F4 and F9. These factors, along with all the other factors on different levels, collectively influence level I. Level I contains factor F10 (order fulfillment). It is the most dependable factor and in a position where the work ends. Level I denotes the long-term factor, which the industry must aim to achieve for the successful involvement of machine learning in the manufacturing sector.

4.2. MICMAC Analysis: Classification of Factors

The MICMAC analysis compares the relationship between the driving and dependence powers (see Table 3). The result was examined among four divisions. The classification of the factors is presented in Figure 3.

The four divisions of significant factors are:

- Division I: Autonomous Factors

The autonomous factors consist of those factors that have weak driving and dependence powers. This research model does not exhibit any factors in this division.

- Division II: Dependence Factors

Division II represents the dependence factors and consists of five critical factors. The factors in this division have a low driving power and high dependence power. The dependence factors in this division are F1 (significance of machine learning), F4 (process automation), F7 (diversified product generation), F9 (just-in-time product generation), and F10 (order fulfillment).

- Division III: Linkage Factors

The factors in this division have high dependence and driving powers. No factors fall under this division.

- Division IV: Driving Factors

Division IV consists of factors having high dependence and driving powers. There are six factors in this division. They are F2 (unawareness of people), F3 (skilled labor), F5 (lack of manmade-machine and manpower), F6 (unavailability of historical data), F8 (revenue of industry), and F11 (demand of the market).

Researchers in the past have analyzed the significance of machine learning in manufacturing industries. Additionally, since then, critical factors were highlighted which showed its effect on the growth of the industry. Paturi and Cheruku [58] in their work recorded the development of machine learning in the manufacturing sector, which showcased that it has been the most useful in the optimization of work processes because of its ability to predict situations with accuracy. Since the data have been the main basis of operation for machine learning, Huo and Chaudhry [59] noted that the use of the algorithm was critical. Their work focused on recognizing profit-making factors for a Chinese manufacturing company. In contrast, this research identified factors that would help improve the significance of machine learning in the manufacturing sector. A contextual interrelationship was developed between the factors through the ISM technique. The results reveal that the demand of the market, revenue of the industry, skilled labor, and lack of manmade-machine and manpower are the most determining factors, which implies that customer demand and industrial capacity needs an in-depth understanding before the application of technology. The results further emphasize that order fulfillment, significance of machine learning, process automation, diversified product generation, and just-in-time product generation are dependent factors. It suggests that these factors are objectives that the industry should aim to achieve. The work provides a structural development that will help industries make step-by-step evaluations of their work, helping policy formulation to direct the need to fill the gap where required. Thus, this research contributes a distinctive analysis through the relationship developed between the factors that would help industries focus on their limitations to improve the situation of machine learning. Mohapatra et al. [60] used ISM methodology to study the prioritizing factors in the industry by integrating machine learning, and determined revenue generation as the highest priority. Solke et al. [61] mentioned the flexibility of working machines as a high priority using the ISM methodology.

5. Conclusions

Machine learning in the industry is a fairly a new concept. However, the constructive effects it has on the industry has motivated researchers and industrialists to acquire more of this technology in their systems. With this technology, we not only enhanced the industry's performance, but also fulfilled the rigorous demands of the consumers. Since we are still in the phase of exploring this technology, it is extremely crucial to identify the major factors that are responsible for its growth in the manufacturing industry. This research identified eleven factors that were observed to be important for the growth of machine learning in the manufacturing sector. These were settled on through an extensive review of the literature, brain-storming sessions, and expert opinions from the industries. The eleven factors were structured into five levels through the ISM technique. The factor at level I (order fulfillment) was influenced by all other factors. It is a factor that the industry needs to fulfill as its end objective, whereas the factor at level V (demand of the market) was the most relevant driver and it influenced all the other factors. This was the stage where the initiation of the processes occurred. Additionally, MICMAC analysis was performed to determine the driving and dependent factors. The result show six factors, F2, F3, F5, F6, F8, and F11, as the driving factors. These are the factors that the industry must focus on for improving the machine-learning environment in the manufacturing industry, and five other factors, F1, F4, F7, F9, and F10, as the dependent factors. There were no factors present either as linkage or autonomous factors.

This research showcased eleven critical factors that were found to influence machine learning in the manufacturing sector, with the results showing order fulfillment as the long-term focus and demand of the market as the short-term focus. However, the manufacturing industry is diverse. This work only specified the factors when the study was conducted on the overall manufacturing sector. Manufacturing exists for every other product, and when the manufacturing method is product-specific, the need for the technology differs. When the study is product-specific, their dependence and driver factors may differ from our results, as the study was limited to only eleven factors. The extension of the research to product-specific manufacturing will help to provide a better and more elaborate understanding of the industry. The integration of the fuzzy technique will further enhance the validity of the work. Nonetheless, the research exhibits constructive supervision to improve and promote the significance of machine learning in the manufacturing industry.

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