Adoption of Artificial Intelligence for Manufacturing Companies

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Abstract Artificial intelligence is gaining popularity in every aspect of business and development of organizations. In manufacturing sector, application of this technology is constantly evolving. However, application of artificial intelligence technology in the manufacturing sector is in the various sectors of manufacturing such as the supply chain management, production testing, quality assurance and engineering. The present study is undertaken to understand the areas of application of artificial intelligence in the manufacturing sector by considering the areas of quality assurance, product design and development, purchase, order-level management, maintenance, logistics and supply chain management. The results of the study show areas of application of artificial intelligence and future directions for enhancing this technology in the manufacturing sector.

Keywords Emerging technology · Manufacturing · Artificial intelligence · Production management

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1 Introduction

Manufacturing process is in the process of drastic change with innovation and change in the higher application of digital devices such as additive manufacturing, internet-of-things (IoT), cyber security and augmented reality [1]. Further, there is an advancement in the manufacturing due to application of robots and automaton in the process of manufacturing; this has led to digitalization of the manufacturing and challenges manufacturing enterprises to reconsider, reexamine, and reevaluate their present operations and future strategic directions in the new era known as Smart Manufacturing and Industry 4.0 [2].

These developments in the domain of manufacturing sector indicate that there would change in the ecosystem of the manufacturing process in the organizations; these changes motivate the research and become the central theme of this study, to be more focused towards the study, and the study examines application of artificial intelligence in manufacturing sector and provides direction in realizing how artificial intelligence technology would support in the improving the process of manufacturing.

The present literature on application of artificial intelligence in manufacturing has indicated on the progress in the manufacturing due to this technology. Further, the literature studies also have indicated development in the computational hardware such as the sensor technology, which has the capability to collect large data has supported in the growth of this technology in the manufacturing. In the same vein, review on the studies has indicated challenges of implementation of this technology with regard to productivity, quality, flexibility and cost.

However, there are other domains of the manufacturing which require deeper understanding such as procurement, quality assurance, product design and development and supply chain management. Such knowledge and understanding are of great benefit to the practical implementation of AI in today's highly complex industrial environments that each has its own individual requirements and context.

Therefore, considering the above discussion the purpose of the current research is to understand the application of artificial intelligence in the manufacturing organizations. The purpose of the study is addressed by considering the following research objectives (RO).

- RO.1: Determining the areas of application of artificial intelligence in the manufacturing organizations.
- RO.2: Evaluate the relative importance of area of application of artificial intelligence concerning the manufacturing.

In step 1, the first research objective (RO1) is addressed by applying for a systematic literature review and Step 2 consists of applying the fuzzy Delphi method (FDM) to fulfil the second objective (RO2).

2 Literature Review

In section of the study, literature review is presented and following aspects are included in this section (a) Introduction to artificial intelligence and (b) Growth of application of artificial intelligence in manufacturing.

2.1 (a) Introduction to Artificial Intelligence

The concept of artificial intelligence is reflected in the 1950s with the introduction of perceptron which is a part of neural network which is developed to simulate a human neural system by applying the weighed sum as input.

Even though the concept of has the foundation with regard to human learning and cognitive artificial intelligence, there was a reduction in the interest in this technology and many studies indicated that more information is needed from the experts for application of this technology is real world challenges.

Later in the development of the technology and introduction of the deep learning along with the advancement in sensing and computational with the combination of machine learning and deep learning lead to more application in the real-life situations of the organization.

The upgraded artificial intelligence technology with machine learning and deep learning was able to provide meaning that can infer and describe the behaviour of the human. Further, the application of this technology gained popularity, where the productivity of the human is enhanced in the organization and added value to the work process of the employees.

Hence, the technology of artificial intelligence which is the branch of computer science has become the part of development of the human and organization. In the present context, this technology dominates in various organization and play an important role in the development of the organization.

However, the biggest challenges that revolves around this technology is that due to rapid advancement in this technology organization need to learn to handle change brought by this technology and take the advantage of this technology for growth and development of the organization.

2.2 (b) Application of Artificial Intelligence in Manufacturing

The manufacturing operations includes production of higher-quality products with lower cost of production and also to provide safe working ecosystem for the employees at the shop floor of the factory.

However, matching these operational demands of manufacturing process has been challenge due to changing demand pattern of the customers and higher level of competition in the market, hence application of technology is a befitting direction for managing these manufacturing challenges in the organization.

Technology of artificial intelligence provides a road-map for meeting these challenges, as artificial intelligence is grounded on the concept of root causes analysis and then classifying based on the multivariate and nonlinear patterns in operational. This technology is based on the concept of data, and hence, large data is developed and generated, which is can be applied in the tool of artificial intelligence.

In the context of manufacturing process data is generated for artificial intelligence in four areas, namely environmental data, process data, production operation data and measurement data. In the context of environmental data includes information related to humidity at the shop floor, level of noise, etc. while process data in the manufacturing includes machining and grinding coolant temperatures, power, and heat treat temperature/energy.

Data related to production includes timestamps or elapsed time of each part in each operation station, machine downtime, starvation/blockage, idle time, and shift scheduling. Measurement data in the manufacturing includes product diameter, form, and balance.

Hence, artificial intelligence with the application of big data has the capability to improve the manufacturing process and also to solve complex manufacturing process, which also improves the quality and process of the manufacturing. Therefore, application of artificial intelligence in manufacturing would support in the making smart factories.

3 Proposed Artificial Intelligence Potential in the Manufacturing

Manufacturing process includes various aspects and with the digitalization manufacturing systems consist of machines, robots, conveyors, and supporting activities such as maintenance and material handling arranged to produce the desired product.

In this study, seven areas of manufacturing are selected for application of artificial intelligence they are (1) quality assurance, (2) product development, (3) procurement, (4) order management, (5) maintenance, (6) logistics, and (7) supply chain management.

Table 1 shows the list of criteria and sub-criteria related to the study on application of artificial intelligence in the manufacturing.

Table 1 Application of artificial intelligence in the manufacturing (criteria and sub-criteria)

Criteria	Sub-criteria
Quality assurance (**1**)	Early identification of quality defects (**1.1**)
	Root cause diagnosis of quality issues (**1.2**)
	Reduced time of testing and reporting of quality (**1.3**)
	Support predictive analysis (**1.4**)
	Lack of skilled workforce (**1.5**)
Product development (**2**)	Faster design development (**2.1**)
	Match customer expectation on product design (**2.2**)
	Reduced cost of product design and development (**2.3**)
	Better product prototypes (**2.4**)
	Better management of product life cycle (**2.5**)
Procurement (**3**)	Better classification of material at shop floor (**3.1**)
	Better invoice data extraction (**3.2**)
	Automated compliance in procurement (**3.3**)
	Effective contract extraction and management (**3.4**)
	Effective contract lifecycle management (**3.5**)
Order management (**4**)	Effortless demand forecasting (**4.1**)
	Better vendor management (**4.2**)
	Smart warehouse management (**4.3**)
	Reduced downtime (**4.4**)
	Automated material procurement (**4.5**)
Maintenance (**5**)	Information about overall equipment effectiveness (**5.1**)
	Intelligent detection of error in the machines (**5.2**)
	Identify optimal material management and production process (**5.3**)
	Ability to identify machine readiness in manufacturing (**5.4**)
	Reduced cost in maintenance (**5.5**)
Logistics (**6**)	Better connection with logistics partners (**6.1**)
	Effective logistics predictive analytics (**6.2**)
	Better transportation forecasting (**6.3**)
	Strategic asset positioning (**6.4**)
	Effective streamline of logistics operation (**6.5**)
Supply chain management (**7**)	Reduced operations cost (**7.1**)
	On-time delivery management (**7.2**)
	Intelligent decision making (**7.3**)
	Boost operational efficiencies (**7.4**)
	Effective fleet management in SCM (**7.5**)

Table 2 Profile of the respondents

Years of establishment	*N*	%	Founders experience	*N*	%
0–1 years	81	71.1	5 to 10 years	91	79.8
1–3 years	15	13.2	10 years to 15 years	14	12.3
3–5 years	18	15.8	15 Years and above	9	7.9
Total	114	100.0	Total	114	100.0
Customer category	N	%	Designation of respondents	N	%
Technology services	105	92.1	Founders	93	81.6
Predictive services	9	7.9	Venture capitalist	21	18.4
Total	114	100.0		114	100.0

4 Research Methodology

The planned approach, i.e., fuzzy AHP and TOPSIS grey, is useful to apprehend the application of artificial intelligence in manufacturing sector. The respondents designated for the study include 25 production managers and 15 factory managers. The research included 40 experts to allocate weights to various criteria and sub-criteria and score each sub-criterion. The profile of the respondents' is indicated in Table 2.

The suggested criteria for understanding the application of artificial intelligence are analysed using the fuzzy. TOPSIS has been used to assess and highlight the significant factor to act as an opportunity for effective implementation of this technology in the manufacturing sector.

5 Fuzzy AHP Method

AHP method was proposed by Saaty proposed for multicriteria decision making. This method has grown towards more erudite options. Fuzzy-based AHP smears to build a pairwise matrix of decision-makers' preference by means of TFNs. The fuzzy scale applied in this research is given in Table 3.

The fuzzy AHP is adopted in the subsequent stages:

Table 3 Triangular fuzzy numbers (TFNs) scale

Linguistic preference	TFN's
Equally	(1,1,1)
Moderately	(2/3,1,3/2)
Strongly	(3/2,2,5/2)
Very strongly	(5/2,3,7/2)
Extremely	(7/2,4,9/2)

Stage 1: Construct of Pairwise matrix.
Stage 2: Define the fuzzy

$$Y = \sum_{j=1}^{m} T_{gi}^{j} \times \left[\sum\nolimits_{i=1}^{n} \sum_{j=1}^{m} T_{gi}^{j} \right]^{-1} \tag{1}$$

$$\left[\sum_{i=1}^{m} \sum_{j=1}^{m} T_{gi}^{j} \right] = \left(\frac{1}{\sum_{n}^{i=1} \sum_{m}^{j=1} b3ij}, \frac{1}{\sum_{n}^{i=1} \sum_{m}^{j=1} b2ij}, \frac{1}{\sum_{n}^{i=1} \sum_{m}^{j=1} b1ij} \right)$$

$$\left(SY_j \geq SY_i\right) = (d) = \left\{ \begin{array}{c} 1, incase\, of\, b2_j \geq b2_i \\ 0, incase\, of\, b1_i \geq b3_j \\ \frac{b1_i - b3_j}{(b2_j - b3_j) - (b2_i - b1_i)}, \text{otherwise} \end{array} \right\} \tag{2}$$

Stage 4: Calculate minimum possibility degree using equation

$$V(SY \geq SY_1, SY_2, SY_3, SY_4, SY_5 \ldots\ldots\ldots, SY_k),$$

for (i = 1,2,3,4,5,6,7,.........,k)

$$V[(SY \geq SY_1), (SY \geq SY_2), and \ldots (SY \geq SY_k)] = minV(SY \geq SY_i) \tag{3}$$

for (i = 1,2,3,4,5,6,7,.........,k)
Stage 5: Let's assume weight vector

$$d'(A_i) = \min V(SY \geq SY_i); \text{for}(i = 1, 2, 3, 4, 5, 6, 7, \ldots\ldots\ldots, k)$$

Then weight vector can be defined as

$$W' = \left(d'(A_1), d'(A_2), d'(A_3), d'(A_4), d'(A_5), \ldots\ldots\ldots .d'(A_n)\right)^T \tag{4}$$

Finally, the weight vector can be normalized using equation

$$W = (d(A_1), d(A_2), d(A_3), d(A_4), d(A_5), \ldots\ldots\ldots .d(A_n))^T \tag{5}$$

where W represents a non-fuzzy number,

6 TOPSIS

TOPSIS is generally used for deciphering complex decision problems. The TOPSIS method is adopted using the subsequent seven stages:
Stage 1: Build H Matrix

$$[\text{labelsep} = 2.8\text{mm}]H = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix} \tag{6}$$

Stage 2: H matrix normalization

$$g_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}}, (j = 1, 2, \ldots.., m), (i = 1, 2, \ldots.., n) \tag{7}$$

Stage 3: Weighted matrix development

$$q_{ij} = w_j g_{ij}, (j = 1, 2, \ldots\ldots, m), (i = 1, 2, \ldots.., n) \tag{8}$$

Stage 4: Use Eq. 9 and 10 to get positive and negative solution

$$A^+ = \left\{ \max_i q_{ij} \,|j \; \in J), \left(\min_i q_{ij} \,\middle|j \in J' \middle| i \in n \right) \right\} = \left[q_1^+,\; q_2^+,\; \ldots\ldots.,\; q_m^+\right]z \tag{9}$$

$$A^- = \left\{ \underset{i}{minq_{ij}} \,|j \; \in J), \left(\underset{i}{maxq_{ij}} \,\middle|j \in J' \middle| i \in n \right) \right\} = \left[q_1^-,\; q_2^-,\; \ldots\ldots.,\; q_m^-\right] \tag{10}$$

Stage 5:

$$d_i^+ = \left[\sum_{i=1}^{m} (q_{ij} - q_j^+)^2\right]^{1/2}, (i = 1, 2, \ldots., n) \tag{11}$$

$$d_i^- = \left[\sum_{j=1}^{m} (q_{ij} - q_j^-)^2\right]^{1/2}, (i = 1, 2, \ldots., n) \tag{12}$$

Stage 6:

$$C_i^+ = \frac{d_i^-}{d_i^+ + d_i^-}, (i = 1, 2, \ldots\ldots, n) \tag{13}$$

Stage 7: Rank the alternatives on the basis of Ci in stage 6.

6.1 Grey System Theory

Prof. Deng proposed the grey system theory on the basis grey set concept.

The theory uses a grey no. to minimize uncertainty in the data.

$$\otimes a + \otimes b = \left[\underline{a} + \underline{b}; \overline{a} + \overline{b}\right] \tag{14}$$

$$\otimes a - \otimes b = \left[\underline{a} - \underline{b}; \overline{a} - \overline{b}\right] \tag{15}$$

$$\otimes a \times \otimes b = \left[\min(\underline{ab}, \overline{ab}, \overline{a}\underline{b}, \underline{a}\overline{b}); \max\left(\underline{ab}, \overline{ab}, \overline{a}\underline{b}, \underline{a}\overline{b}\right)\right] \tag{16}$$

$$\otimes a : \otimes b = \otimes a \times \left[\frac{1}{\overline{b}}, \frac{1}{\underline{b}}\right]; 0 \notin \otimes b \tag{17}$$

TFNs can be converted into grey numbers using $\tilde{a} = (a1, a2, a3)$, and $\tilde{b} = (b1, b2, b3)$ into grey numbers $\otimes a = [a1, a2]$, and $\otimes b = [b1, b2]$ using Euclidean distance between $\otimes a$ and $\otimes b$ as given in the equation below:

$$d(\otimes a, \otimes b) = \sqrt{\frac{1}{2}\left[\left(\underline{a} - \underline{b}\right)^2 + \left(\overline{a} - \overline{b}\right)^2\right]} \tag{18}$$

7 Results and Analysis

The results are indicated in two stages. In the first stage, fuzzy AHP results are presented, wherein results with regard to weights for the main criteria and sub-criteria are presented. In the second stage, TOPSIS grey results are indicated with ranking indicating the alternatives for the challenges for implementation of AI and ML in foundry units.

8 Fuzzy AHP Results

The analysis with fuzzy AHP has four levels, firstly development of hierarchical structures, secondly, main criteria weights, thirdly, sub-criteria weights and fourth, final weights sub-criteria.

The first level is hierarchical structures developed based on the four parts, namely goals, criteria, sub-criteria and alternatives. The details hierarchical structure are presented in Fig. 1.

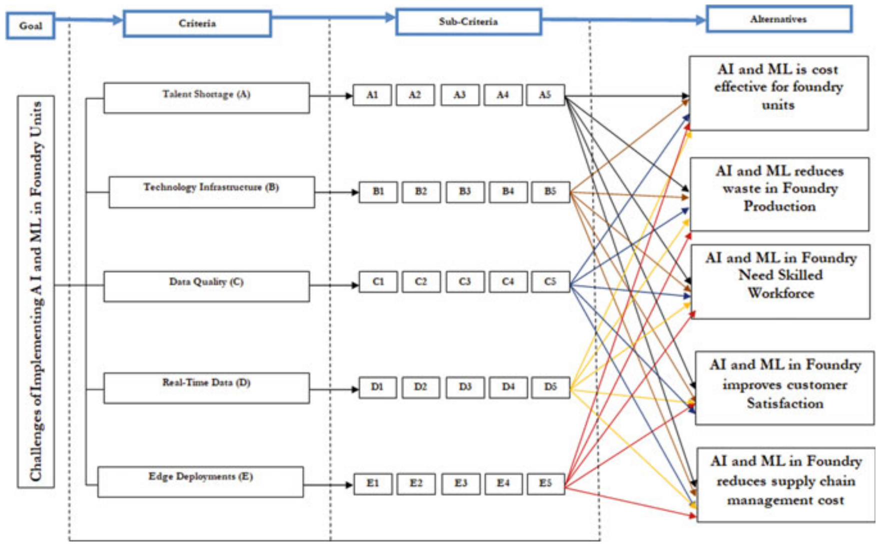

Fig. 1 Hierarchical structure

The results from main criteria weights indicated in Table 4 shows that the challenge with regard to technology infrastructure (B), 0.221 ranked a highest challenge in foundry units for implementation of AI and ML in foundry. Further, the second ranked weight is 0.216 Data Quality (C) which indicates second challenge with regard to implementation of this technology in foundry units in the study units of foundry. The third weight age is 0.21, real-time data (D) collection challenge for analysing the information for AI and ML technology in foundry units. Talent shortage (A) is ranked fourth with 0.205 weights in the ranking of the weight age and fifth ranking of weight is edge deployment (E) 0.149 as weight age.

After the application of fuzzy AHP in the sub-criteria weights shows that in the rank of in the range of 1 to 5 shows in the global weight is ranked higher, with regard to complexity of foundry technology, and its working environment to implement sensors is ranked first with 0.1285, while manufacturing complexity due to technology infrastructure is ranked second with 0.1136. Third is ranked with regard to complexity due to batch production method applied in the foundry, this influences the AI and ML implementation in foundry. Fourth is ranked after difficulty in production, planning, and control method in foundry units and fifth is ranked after difficulty in connections of sensors and computers for collection of data for application of AI and ML in foundry. The detailed results from the other weight age are information is presented in Table 4.

Table 4 Results with regard to main criteria, sub-criteria, and ranking of the criteria on challenges of implementation of AI and ML in foundry

Criteria	Main criteria weight	Sub-criteria code	Sub-criteria weight	Global weight	Rank
Talent shortage (A)	0.205	A1	0.225	0.0461	12
		A2	0.2	0.0410	16
		A3	0.17	0.0349	20
		A4	0.24	0.0492	11
		A5	0.165	0.0338	21
Technology infrastructure (B)	0.221	B1	0.276	0.0610	7
		B2	0.173	0.0382	17
		B3	0.165	0.0365	18
		B4	0.232	0.0513	10
		B5	0.154	0.0340	20
Data quality (C)	0.216	C1	0.201	0.0434	13
		C2	0.199	0.0430	14
		C3	0.167	0.0361	19
		C4	0.239	0.0516	9
		C5	0.194	0.0419	15
Real-time data (D)	0.210	D1	0.301	0.0632	4
		D2	0.291	0.0611	6
		D3	0.541	0.1136	2
		D4	0.612	0.1285	1
		D5	0.356	0.0748	3
Edge deployments (E)	0.149	E1	0.231	0.0344	21
		E2	0.33	0.0492	11
		E3	0.415	0.0618	5
		E4	0.122	0.0182	22
		E5	0.356	0.0530	8

8.1 Ranking of Alternatives Using TOPSIS Grey

The developed TOPSIS grey integrated methodology has been used to assess and prioritise the alternatives of ranking for opportunities for implementation of AI and ML in foundry units. The results show that AI and ML provide an opportunity for improving customer satisfaction of foundry industry (0.482326). This, technology also provides opportunity to reduce the supply chain cost of foundry industry (0.436217), and this is ranked second in results analysis. This technology reduces overall cost of production (0.411854). The detailed information with TOPSIS grey result analysis is provided in Table 5.

Table 5 Ranking of opportunity for implementation of AI and ML in foundry units through TOPSIS grey

Alternatives	D +	D-	C +	Ranking
AI and ML is reduces cost in overall production of foundry	9.66908	6.77085	0.4118	3
AI and ML reduces wastage	9.59228	6.24699	0.3943	4
AI and ML need skill development	10.0157	5.76561	0.3653	5
AI and ML improves customer satisfaction	8.35958	7.78878	0.4823	1
AI and ML reduces supply chain cost	9.03350	6.98951	0.4362	2

9 Discussions

The result analysis indicates that technology infrastructure is ranked among the key factor of challenge for implementation of AI and ML in the foundry units. The technology infrastructure development is influenced by the factors associated with data collection of analysis through AI and ML such as influence of heat, dust and batch method of production process of foundry.

The study findings has given an new directions in the study of challenges with regard to AI and ML implementation in foundry, as previous studies have indicated that talent shortage is the key factor and challenge for implementation of this technology in foundry units. Further, studies have also indicated that edge technology as a factor of challenge of implementation. This technology is related to networking and advanced computing for implementation of this technology in foundry. However, there is an opportunity of implementation of this technology in foundry units, and the results analysis indicated that this technology supports the foundry units with improved customer satisfaction and reduced cost in the supply chain management.

The above discussion provides a direction for practical implications for improving implementation of AI and ML in foundry units. Firstly, foundry units need to invest in technology especially related to sensor and cloud computing for data capturing and analysis, this improves the efficiency in real-time data analysis. Secondly, foundry units need to invest in this technology as this technology supports in cost reduction in supply chain management and other manufacturing cost as this technology collect real-time data and based on this data faster decision-making can be taken by the managers of foundry. Thirdly, foundry units need to train employees to using this technology in the foundry units.

10 Conclusion and Future Research

The overall results indicated that this technology is effective in foundry industry as this technology supports in customer satisfaction and reducing cost of production. However, there are challenges with regard to technology development for collecting real-time data due to foundry manufacturing ecosystem. Further studies can be undertaken other foundry cluster of other states of India, and also studies can be carried out and compared with developed and underdeveloped countries foundries. Finally, the study results indicate that AI and ML is a powerful tool for foundry industry for improving production efficiency and enhancing customer satisfaction.

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