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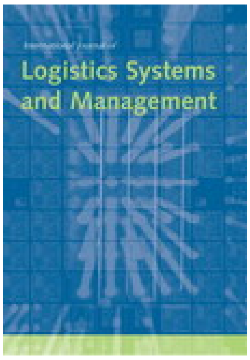

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A hybrid approach to examine the potential of additive manufacturing to cope with supply chain disruptions during COVID-19 pandemic

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Abstract: The COVID-19 pandemic has created lots of uncertainties, one of which is dealing with the ripple effect (supply chain disruptions) across multiple industries (like automotive, healthcare, aerospace, etc.). This work proposes a hybrid approach for identifying various enablers across three supply chain decision-making phases (strategic, tactical and operational) that aid in the organisation's implementation of additive manufacturing. The work is divided into three phases: first, the variables are identified through a literature review; second, the questionnaire's validity and reliability are checked; and third, the variables are prioritised using fuzzy entropy and fuzzy technique of order preference by similarity to ideal solution (TOPSIS) methods, which convert linguistic values (obtained via questionnaire survey) to crisp values for the research variable dimensions. The outcomes of this discussion assist managers in making more informed and effective decisions about how to implement additive manufacturing in their organisation in order to minimise supply chain disruptions.

Keywords: additive manufacturing; supply chain disruptions; fuzzy entropy; fuzzy TOPSIS; strategic; tactical; operational.

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1 Introduction

The COVID-19 epidemic has had an impact on the supply chain in several industries (such as automotive, aerospace, healthcare, consumer goods, and so on). The disruptions are caused by shortages of medical equipment such as test kits, personal protective equipment (PPE), nasal swabs, face shields, ventilator valves, and other items, as well as semiconductor chips, minerals and materials, batteries, and other items (Wen et al., 2021; Sharma et al., 2020). 3D printing is a technique that helps in minimising shortage-related disruptions. Traditionally, additive manufacturing has been utilised in numerous industries for prototyping purposes; however, due to a lack of expertise in the implementation phase of additive manufacturing, only a few companies are now using it to create end goods. By producing a direct physical product from a 3D CAD model using an additive manufacturing machine and only raw materials, additive manufacturing helps to reduce the various steps of the traditional manufacturing supply chain (Chaldoupis, 2018). In terms of supply chain decision phases (strategic, tactical, and operational), this paper gives a list of numerous criteria that aid in the deployment of additive manufacturing in a company.

1.1 Additive manufacturing

Additive manufacturing is a method for layer-by-layer fabrication of a wide range of 3D physical structures and complex geometries from a 3D CAD model. 'Charles Chuck Hull' invented stereo-lithography, the first marketed 3D printing equipment, in 1984 (Melchels, 2012). Since then, many developments in the field of 3D printing have occurred, such as powder bed fusion, sheet lamination, binder jetting, fused deposition modelling, and so on.

1.2 Supply chain driven by additive manufacturing

Currently, the 3D printing business gaining its application in many industries because it opens up great opportunities in accelerating innovations reduces the length of the supply chain, and reduces material and energy utilisation, and wastage. There are many studies in the literature that focuses on the potential disruptions of 3D printing in the global supply chain, transportation, inventory, and logistics. Durach et al. (2017) conclude that scenarios that involve an increase in decentralised manufacturing or the rise of additive manufacturing printing services have a strong potential to become true rather than mass customisation or a significant reduction in inventory. From an environmental perspective, Kellens et al. (2017) states that additive manufacturing can be a good alternative for producing customised parts or small production runs as well as complex part designs creating substantial functional advantages during the part use phase. Sirichakwal and Conner (2016) have concluded in their study is that reduction in holding cost has a great impact on reducing the stock-out probability where the average demand rate for spare parts is low. Additive manufacturing applications are mainly found in the aerospace, automotive, healthcare, and consumer goods industry. However, although a number of companies are already using additive manufacturing technologies, they are facing difficulties in the implementation process. Therefore, this study aims to form the additive manufacturing implementation framework on the basis of supply chain decision phases, namely, strategic, tactical, and operational.

Table 1 Additive manufacturing techniques

S. no.	*Additive manufacturing process*	*Description*
1	Stereolithography apparatus	UV light source is used to build the object from a vat of polymer by lowering the platform equal to the height of layer thickness (Neckers, 1990; Zakeri et al., 2020).
2	Selective laser sintering	The laser source is utilised to sinter the polymer powder particles and fuse them together to build the part layer by layer (Mokrane et al., 2018).
3	Fused deposition modeling	Fabrication is done by depositing the heated viscous thermoplastic material on the build plate or previous layer and then allowing it to solidify to obtain the 3D physical object (Stansbury and Idacavage, 2016; Tanikella et al., 2017).
4	Multi jet fusion	Fabrication of 3D printed parts is accomplished by sprinkling fusing and detailing agent particles as well as applying heat energy to the powdered particles layer by layer (Habib et al., 2018; Xu et al., 2019).
5	Inkjet printing	Printing of an object is done by ejecting the material from the tiny nozzle. As the print head vector glides across a surface, many layers are formed up, one by one (Derby, 2015).

1.3 Supply chain decision phases

The rapid shift in the market and demand pattern has significantly shortened the product life cycles and also high-quality products are made available at affordable prices. Consumer nowadays wants a variety of products. While talking about today's era, mass production is supplanted by low volume and high-value production. The existing literature evidence that the supply chain decision phases such as strategic, tactical, and operational (i.e., customisation, risk reduction, productivity and profitability, energy-efficient, reduced supplier's dependencies, etc.) help in the adoption of 3D printing. Furthermore, this adoption will benefit the manufacturer in reducing the time between the customer order and product final delivery. All these factors will give the organisation a competitive edge in marketing consumer goods and services.

1.3.1 Strategic factors

Strategic factors are substantial actions that influence the entire or a significant portion of a company enterprise and assist the organisation in developing goals, environment, ethics, and systems that improve performance and customer satisfaction (Balan et al., 2007). They provide a major contributor to the attainment of the enterprise's common aims. They have long-term consequences for the business enterprise, and strategic planning also supports the management in analysing the interaction with the other firm and defining a basic direction for the company. The strategic factors which have been identified through the literature and help in the implementation of additive manufacturing are productivity and profitability, eco-friendly manufacturing, risk reduction, top management commitment, and customer satisfaction.

1.3.2 Tactical factors

Tactical aspects are geared towards designing divisional strategies, organising operations, developing channels of distribution, and acquiring resources like workers, resources, and money (Talib and Rahman, 2010). These decisions are made at the management level in the middle and are related to plant layout, production planning, and quality assurance. The tactical factors which have been identified through the literature and help in the implementation of additive manufacturing are customisation, virtual inventory, product standardisation, reduced supplier's dependencies, and energy-efficient manufacturing.

1.3.3 Operational factors

Operational factors are concerned with the enterprise's day-to-day activities. They have a short time horizon since they are taken repeatedly. These decisions are based on facts about the occurrences and do not necessitate much business judgment. Lower levels of management make operational decisions and are related to inventory, quality control, and scheduling processes. The operational factors which have been identified through the literature and help in the implementation of additive manufacturing are design and manufacturing flexibility, reduced wastage, agility, meet safety regulations, and quality of the product.

2 Literature review

Notable existing literature portrays AM as being disruptive to businesses and their supply lines and also making those supply lines being resilient concerning the natural catastrophic events, whereas peer-reviewed academic literature takes a more balanced approach. For that matter, according to certain research, additive manufacturing can cause big and subtle modifications in a company's structure (Steenhuis and Pretorius, 2017). Some authors have identified the various additive manufacturing applications in Industry 4.0 for the various industries such as automotive, aerospace, healthcare, and consumer goods industry (Chaldoupis, 2018; Haleem and Javaid, 2019). By looking at the Indian manufacturing industry, Luthra and Mangla (2018) intend to identify key hurdles to Industry 4.0 activities and examine the identified main difficulties in order to prioritise them (by using EFA and AHP methods) for effective Industry 4.0 concepts for supply chain sustainability in emerging economies.

The Indian automotive industry is one of the world's largest and fastest expanding. Through a thorough literature review and discussions with experts from the Indian manufacturing industry (Luthra et al., 2015), critical success factors (CSFs) and performance measures for the green supply chain management (GSCM) have been identified. Factor analysis and IRP approach are used to examine the relationship between the CSFs and rank them with respect to performance measures. Sharma (2021) has used a novel approach to examine the structural dependencies among the various variables for perfect order fulfilment. In their research they have used an interpretive structural modelling approach to model the relationship among the various supply chain variables. Durach et al. (2017) has used a multistage survey (Delphi technique) to rank the various identified barriers to additive manufacturing adoption with respect to future scenarios. The results show that the powder bed fusion and material jetting were ranked at the top in their analysis. The qualitative and quantitative approaches were used to study the supply chain implications of 3D printing through a collection of case studies to identify the AM's capabilities in manufacturing final products in the industry and the potential consequences of different product life cycle phases, e.g., design, preparation, production, usage, etc. (Zanoni et al., 2019). A conceptual framework and literature study-based approach was used to know the disruptive impact of AM on the supply chain. For that, they have used the SCOR model to know the AM impact on the SC design (i.e., plan, source, make, deliver, return, and enable) and SC performance output (such as cost, assets, responsiveness, reliability, and flexibility) (Verboeket and Krikke, 2019). Another, Pandey and Sharma (2017) has developed a structural model to drive the relationship between various risks which may disrupt the automotive supply chain, for that they employed a ISM and MICMAC approach and found that poor planning, scheduling and hazards are the key risk variables (highest driving power) and can be considered as the root cause of the problem. Sonar et al. (2020) has identified the AM implementation factors using the integrated ISM and MICMAC approach with respect to the Indian manufacturing sector. All the above-mentioned articles evidence that researchers have tried to identify the AM implementation, however, they are predicted on either a single case or single entity, making it difficult to generalise and be successful in AM implementation. Furthermore, there is a gap in the literature concerning AM implementation factors by taking both academic and industry perspectives. Because of the interconnectedness of factors that drive Am implementation which can offer different industries and academic perspectives on AM implementation can provide a unique perspective. In order to contribute to both academics and industry, this article investigates the impact of AM on supply chain decision phases such as strategic, tactical, and operational.

Table 2 List of identified enablers

Code	*Identified enablers*	*Description*	*References from literature*
SF	*(Strategic factors)*		
SF1	Risk reduction	Reduces risk across all operations in a worldwide manufacturing organisation. New goods are made in less time and can be evaluated well before going into full manufacturing. In the healthcare field, implants made with this technique are useful for surgery planning and risk reduction.	Luthra et al. (2015), Ramola et al. (2019), Haleem et al. (2018) and Chadha et al. (2019)
SF2	Customer satisfaction	AM efficiently meets customer needs by developing an innovative/customised product. It offers the potential to meet consumer requirements in a significantly brief period of time. Personalised items are made in less time, which increases the product's market reputation and customer happiness.	Hofmann and Rüsch (2017), Theorin et al. (2017) and Eltayeb et al. (2011)
SF3	Productivity and profitability	Efficient in increasing productivity by transforming input into desired output through the use of suitable techniques. Reduce material, energy, and labour consumption to increase production. By properly utilising facilities, provides value-added activities to manufacturers and improves their profitability for both product and service.	Haleem and Javaid (2018), Qin et al. (2016), Prinz et al. (2016), Eltayeb et al. (2011) and Green et al. (2012)

Table 2 List of identified enablers (continued)

Code	*Identified enablers*	*Description*	*References from literature*
SF	*(Strategic factors)*		
SF4	Eco-friendly manufacturing	Additive manufacturing allows for eco-friendly goods, waste and scrap elimination at the end of the product life cycle, and resource-efficient material selection through recycling	Eltayeb et al. (2011) and Javaid et al. (2021)
SF5	Top management commitment	For AM successful implementation, it must have the support of top management, which works as a driving force for the organisation to incorporate AM into its operations.	Green et al. (2012) and Mudgal et al. (2009)
TF	*(Tactical factors)*		
TF1	Customisation	AM uses its various technologies to efficiently construct a bespoke and customised product. It is also feasible to replace bespoke parts in a shorter period and at a lower cost.	Lee et al. (2014) and Zawadzki and Żywicki (2016)
TF2	Virtual inventory	In a traditional production system, inventory control is a big issue that raises the product's final cost. A substantial spares stockpile protects against protracted machine downtime caused by crucial part shortages. Inventory, on the other hand, takes up space, ties up cash, and can decay or become obsolete. There's no need to keep stock in the storage if you can print parts on demand.	Yoo et al. (2016) and Schumacher et al. (2016)
TF3	Product standardisation	To lay the groundwork for trade-in additive manufacturing, standardisation is required. Standardisation enhances the industry's ability to collect data and trace the flow of 3D printed goods, leading to greater international coherence and visibility.	Monzón et al. (2015)
TF4	Energy efficient	With a focus on low-energy use during production hours, AM can be more responsive to demand management. The number of environmental consequences left by AM operations, as well as the energy consumed during the use phase, are critical elements in AM sustainability studies.	Eltayeb et al. (2011), Green et al. (2012) and Mudgal et al. (2009)
TF5	Reduced supplier dependencies	AM drastically decreases stock and eliminates the need for moulds. It also allows for localised production, which reduces reliance on suppliers and saves money on transportation and inventory.	Meyer et al. (2021)
OF	*(Operational factors)*		
OF1	Design and manufacturing flexibility	Because customer demand fluctuates, the AM system's ability to design and build a variety of items to fulfil customer needs is a vital aspect in maintaining competitiveness.	Long et al. (2016) and Zhong et al. (2017)

Table 2 List of identified enablers (continued)

Code	*Identified enablers*	*Description*	*References from literature*
OF	*(Operational factors)*		
OF2	Reduce wastage	Due to the recycling of input material, there is extremely low material waste in some additive manufacturing systems. The material handled in powder form is easily recycled. Because there is less waste of raw materials, the product's final cost is lower.	Eltayeb et al. (2011), Green et al. (2012) and Sanders et al. (2016)
OF3	Agility	Customised goods with the requisite strength are made in a shorter period of time. Also applicable to the creation of a conceptual model in order to expedite the research and development process. Printing speed can be increased by raising the layer thickness, but accuracy suffers as a result.	Schumacher et al. (2016), Zhong et al. (2017) and Schlechtendahl et al. (2015)
OF4	Quality	Objects are made in AM by layering material one at a time. This means that 3D printers aid in the creation of better items with greater dimensional accuracy and surface polish by reducing layer thickness.	Bordoni and Boschetto (2012)
OF5	Meet safety regulations	More thorough safety standards and regulatory frameworks are linked to the use of AM technology in industries like healthcare, which will naturally result from the growing use and understanding of AM for regulated products.	Parry and Banks (2020)

3 Methodology

The goal of this study is to identify and rank the various enablers that promote the implementation of additive manufacturing using the multi-criteria decision making (MCDM) technique, namely the fuzzy entropy and fuzzy technique of order preference by similarity to ideal solution (TOPSIS) methods. To do this, a questionnaire was created and distributed to experts with adequate expertise and understanding of additive manufacturing. Cronbach's alpha coefficient was obtained using SPSS software to assess the reliability of the questionnaire and to test research hypotheses, the one-sample two-tailed test was run with a confidence interval of 95%. The method seeks to solve the problem by following the stages illustrated in Figure 1, and it is then discussed with an actual example.

3.1 Basic steps of fuzzy entropy and fuzzy TOPSIS methodology

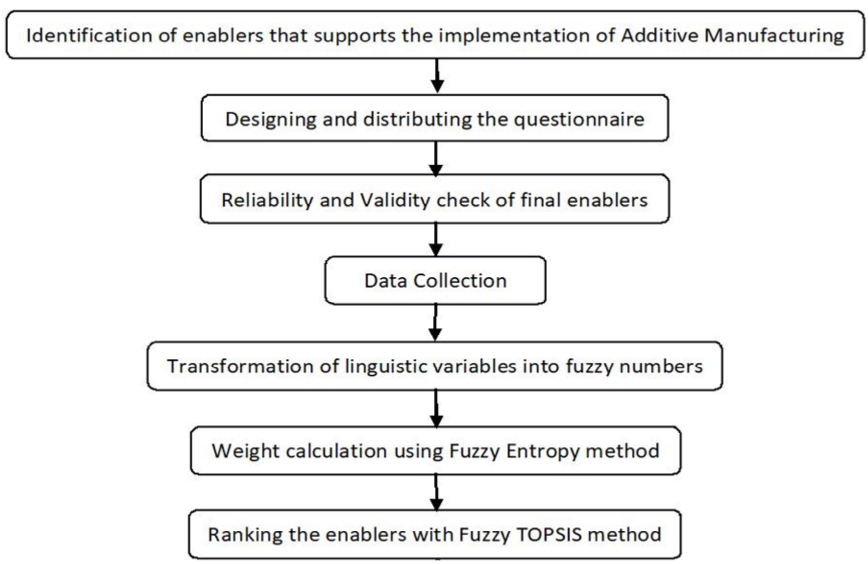
In 1965, 'Lotfali Asgarzadeh' Professor at the University of California at Berkeley, was the first to present the fuzzy sets and fuzzy numbers theory. Zadeh suggested a mathematical technique (fuzzy set theory in 1996) for decision-making based on fuzzy descriptions of some facts with the proposed methodology. It is a set that does not have clearly defined limits and can obtain items only to a certain degree (i.e., elements having a certain degree of membership) (Zadeh, 1996). Suppose the fuzzy set M is a subset of the universal set X. The fuzzy set M from the set of X is defined by the membership function $Q_M(x)$ which gets all the elements x in the set X of real numbers from the interval [0, 1]. The membership function $Q_M(x)$ is called the degree of membership of the element x of the fuzzy set M.

The membership function for the triangular fuzzy number n (r, s, t) is defined in equation (1):

$$Q_M(x) = \begin{cases} 0, & x < r \\ \dfrac{(x-r)}{(s-r)}, & r \le x \le s \\ \dfrac{(t-x)}{(t-s)}, & s \le x \le t \\ 0, & x > t \end{cases} \tag{1}$$

In this study, linguistic values will be used to assess consistency with a particular statement when measuring the dimensions of a survey ranging from strongly disagree to strongly agree using a five-point scale. The relationship between the membership function and the corresponding fuzzy number is shown in Table 3, which shows the conversion of linguistic variables to fuzzy numbers.

Figure 1 Research methodology



The weighted mean of the triangular fuzzy number n = (n_1, n_2, n_3) is defined by Z(n) in the equation (2). By the use of equation (2) the triangular fuzzy number gets defuzzified (i.e., transformed into crisp values).

$$Z(n) = \frac{(n_1 + 4n_2 + n_3)}{6} \tag{2}$$

Assume that X = (a_{ij}, i =1, 2, …, m; j = 1, 2, …, n) are the components of the decision matrix (DM) and that each entity of a_{ij} is produced by turning linguistic values a_{ij} = (r_{ij},

s_{ij}, t_{ij}) into fuzzy numbers. The fuzzy entropy approach is used to determine the weights for distinct criterion W = (w_1, w_2, …, w_j) using fuzzy numbers. The following expression represents the general initial DM:

$$DM = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \tag{3}$$

Table 3 Conversion of linguistic values to fuzzy numbers

Linguistic variables	*Fuzzy numbers*
Strongly disagree (SD)	(1, 1, 2)
Disagree (DA)	(2, 3, 4)
Undecided (UD)	(4, 5, 6)
Agree (AG)	(6, 7, 8)
Strongly agree (SA)	(8, 9, 9)

3.1.1 Fuzzy entropy method

For circumstances when the data is fuzzy or in an interval, Zadeh (1996) created Shannon entropy method (Momeni, 2006; Borzadaran, 2012). The following are the key fuzzy integrated Shannon's entropy weighting steps:

Step 1 Normalisation of defuzzified DM.

Let the DM be $(a_{ij})_{m*n}$, where m and n represent the number of alternatives and criteria available. The DM is normalised by the equation (4)

$$H_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}} \tag{4}$$

Step 2 Entropy calculation for each criteria.

The equation for the same is provided as

$$E_j = \left(\frac{-1}{Lnm}\right)\sum_{i=1}^{m} H_{ij} LnH_{ij},\ j = 1, 2, \ldots, n \tag{5}$$

Step 3 Degree of deviation calculation for each criteria.

$$D_j = 1 - E_j,\ j = 1, 2, \ldots, n \tag{6}$$

Step 4 Entropy weights calculation for each criteria.

$$W_j = \frac{D_j}{\sum_{i=1}^{n} D_j} \tag{7}$$

3.1.2 Fuzzy TOPSIS method

To solve the multi-criteria decision-making problem, Yoon and Hwang, (1995) and Hwang and Yoon (1981) introduced TOPSIS method with '*n*' criteria and '*m*' options. Fuzzy TOPSIS method is used in this study to rank the various options and the steps for the same are discussed below:

Step 1 Compute the enablers' aggregate fuzzy matrix.

If $X_{ij} = (r_{ij}, s_{ij}, t_{ij})$ is the fuzzy rating given by the k^{th} expert. Then, the aggregate fuzzy rating for each criteria is given as

$$r = \min\left[r_{ij}\right]_{m*n}, \; s = \frac{1}{k}\sum_{k=1}^{k} s_{ij}, \; t = \max\left[t_{ij}\right] \tag{8}$$

Step 2 Construct the normalised fuzzy matrix.

$$F = \left[f_{ij}\right]_{m*n}, \; i = 1, 2, \ldots, m; \; j = 1, 2, \ldots, n$$

where

- for maximisation (benefit criteria),

$$f_{ij}^{-} = \left(\frac{r_{ij}}{t_j^*}, \frac{s_{ij}}{t_j^*}, \frac{t_{ij}}{t_j^*}\right); \text{ where } t_j^* = \max t_{ij} \tag{9}$$

- for minimisation (cost criteria),

$$f_{ij}^{-} = \left(\frac{r_j^*}{r_{ij}}, \frac{r_j^*}{s_{ij}}, \frac{r_j^*}{t_{ij}}\right); \text{ where } r_j^* = \min t_{ij} \tag{10}$$

Step 3 Compute the weighted normalised matrix.

$$V^{-} = \left[v_{ij}^{-}\right]_{m*n}; \text{ where } v_{ij}^{-} = f_{ij}^{-} \cdot W_j; \; i = 1, 2, \ldots, m; \; j = 1, 2, \ldots, n \tag{11}$$

Step 4 Calculate the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) for each criteria as follow:

$$I^{+} = \left(v_1^{-+}, v_2^{-+}, \ldots, v_n^{-+}\right); \text{ where } v_j^{-+} = \left(t_j^{-+}, t_j^{-+}, t_j^{-+}\right) \text{ and } t_j^{-+} = \max\left[t_{ij}^{-}\right] \tag{12}$$

$$I^{-} = \left(v_1^{--}, v_2^{--}, \ldots, v_n^{--}\right); \text{where } v_j^{--} = \left(r_j^{--}, r_j^{--}, r_j^{--}\right) \text{ and } r_j^{--} = \max\left[r_{ij}^{-}\right] \tag{13}$$

Step 5 Calculate the distance (d_i^{+}, d_i^{-}) of each alternative from FPIS and FNIS respectively.

$$d_i^{+} = \sum_{j=1}^{n} d_v\left(v_{ij}^{-}, v_j^{-+}\right); \; i = 1, 2, \ldots, m \tag{14}$$

$$d_i^{-} = \sum_{j=1}^{n} d_v\left(v_{ij}^{-}, v_j^{--}\right); \; i = 1, 2, \ldots, m \tag{15}$$

where $(v_{ij}^{-}, v_{ij}^{-+})$ and $(v_{ij}^{-}, v_{ij}^{--})$ represents the distance between two fuzzy numbers. For example: if $l = (l_1, l_2, l_3)$ and $m = (m_1, m_2, m_3)$ are two triangular fuzzy numbers of fuzzy set M, then the distance between two fuzzy numbers can be expressed as:

$$d_v\left(l^-, m^-\right) = \sqrt{\frac{1}{3}\left[(l_1 - m_1)^2 + (l_2 - m_2)^2 + (l_3 - m_3)^2\right]} \tag{16}$$

Step 6 Determine the closeness coefficient CC_i of each alternative.

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{17}$$

3.2 Listing of identified variables through literature review

Table 4 Identification of enablers' details

Sr. no.	*Identified enablers*	*References*
E1	Customisation	Lee et al. (2014) and Zawadzki and Żywicki (2016)
E2	Design and manufacturing flexibility	Long et al. (2016) and Zhong et al. (2017)
E3	Virtual inventory	Yoo et al. (2016) and Schumacher et al. (2016)
E4	Reduce wastage	Eltayeb et al. (2011), Green et al. (2012) and Sanders et al. (2016)
E5	Agility	Schumacher et al. (2016), Zhong et al. (2017) and Schlechtendahl et al. (2015)
E6	Risk reduction	Luthra et al. (2015), Ramola et al. (2019), Haleem et al. (2018) and Chadha et al. (2019)
E7	Customer satisfaction	Hofmann and Rüsch (2017), Theorin et al. (2017) and Eltayeb et al. (2011)
E8	Quality	Bordoni and Boschetto (2012)
E9	Productivity and profitability	Haleem and Javaid (2018), Qin et al. (2016), Prinz et al. (2016), Eltayeb et al. (2011) and Green et al. (2012)
E10	Eco-friendly manufacturing	Eltayeb et al. (2011) and Javaid et al. (2021)
E11	Product standardisation	Monzón et al. (2015)
E12	Meet safety regulations	Parry and Banks (2020)
E13	Energy efficient	Eltayeb et al. (2011), Green et al. (2012) and Mudgal et al. (2009)
E14	Reduced suppliers dependencies	Meyer et al. (2021)
E15	Top management commitment	Green et al. (2012) and Mudgal et al. (2009)

3.3 Questionnaire survey

In this study, the fuzzy entropy and fuzzy TOPSIS method are used to rank all the identified enablers through literature review. To achieve this questionnaire was prepared and distributed to experts who have reasonable knowledge and understanding of additive manufacturing. The questionnaire of a five-point Likert scale was developed to identify the importance of each enabler. The respondents were asked to indicate the level of importance of each enabler based on the following scale: strongly agree, agree, undecided, disagree, and strongly disagree. Then these linguistic values are converted into fuzzy numbers by using Table 3. Upon designing the questionnaire, 19 valid replies from academic and industry professionals were received, which were then used to rank the enablers using fuzzy entropy and fuzzy TOPSIS methods, after ensuring the validity of the final enablers and the questionnaire's reliability.

3.4 Formulation of research hypothesis

The first stage in establishing a research hypothesis is to define the research objective. The purpose of this study is to evaluate and assess the impact of identified enablers on additive manufacturing implementation using a MCDM technique. Finally, 15 enablers in the three parts of the supply chain have been identified through literature (strategic, tactical, and operational). A research hypothesis (H_0: null hypothesis) is formed based on these final 15 enablers, as illustrated below:

H1 The implementation of AM is influenced by risk reduction as a strategic factor.

H2 The adoption of AM is influenced by customer satisfaction as a strategic factor.

H3 Productivity and profitability as strategic factor affect the implementation of AM.

H4 Eco-friendly manufacturing as a strategic factor affects the implementation of AM.

H5 The implementation of AM is influenced by top management as a strategic factor.

H6 Customisation as a tactical factor affects the implementation of AM.

H7 Virtual inventory as a tactical factor affects the implementation of AM.

H8 Product standardisation as a tactical factor affects the implementation of AM.

H9 Energy-efficient as a tactical factor influences AM adoption.

H10 Reduced supplier dependencies as a tactical factor influences AM adoption.

H11 The adoption of AM is influenced by design and manufacturing flexibility as an operational factor.

H12 Reduced wastages as an operational factor affects AM adoption.

H13 The adoption of AM is affected by agility as an operational factor.

H14 Quality of the product as an operational factor affects the adoption of AM.

H15 Meeting safety regulations as an operational factor influences AM adoption.

3.5 Reliability and validity check

Following the design and distribution of the questionnaire, the next stage is to formulate the study hypothesis, as stated in Subsection 3.4. Because of the tiny sample size, a one-sample two-tailed t-test is used to determine the validity of the enablers. For 19 replies, the t-critical (t_c) value is 2.101, with a 95% confidence interval and 18 degrees of freedom (df). Table 5 displays the results of a t-test for each hypothesis run in the SPSS software. Each individual hypothesis has a higher t_i value than the t_c values, indicating that all enablers have a beneficial impact on the implementation of additive manufacturing. Cronbach's alpha value is calculated in SPSS software to assess the questionnaire's reliability, and it comes out to be 0.821, indicating that the questionnaire's reliability test is acceptable.

Table 5 Results of hypothesis testing

H_0	t_i	*df*	*One-sided P-value*	*Two-sided P-value*	*Mean difference*	*Lower @ 95% CI*	*Upper @ 95% CI*	t_c	*Accept/ reject H_0*
H1	19.396	18	<0.001	<0.001	3.89474	3.4729	4.3166	2.101	Reject H_0
H2	21.726	18	<0.001	<0.001	4.15789	3.7558	4.5600	2.101	Reject H_0
H3	14.862	18	<0.001	<0.001	3.63158	3.1182	4.1450	2.101	Reject H_0
H4	16.977	18	<0.001	<0.001	3.68421	3.2283	4.1401	2.101	Reject H_0
H5	20.076	18	<0.001	<0.001	3.84211	3.4400	4.2442	2.101	Reject H_0
H6	16.918	18	<0.001	<0.001	3.78947	3.3189	4.2600	2.101	Reject H_0
H7	16.433	18	<0.001	<0.001	3.73684	3.2591	4.2146	2.101	Reject H_0
H8	13.565	18	<0.001	<0.001	3.21053	2.7133	3.7078	2.101	Reject H_0
H9	15.372	18	<0.001	<0.001	3.36842	2.9081	3.8288	2.101	Reject H_0
H10	17.450	18	<0.001	<0.001	3.73684	3.2869	4.1868	2.101	Reject H_0
H11	18.205	18	<0.001	<0.001	4.05263	3.5850	4.5203	2.101	Reject H_0
H12	13.112	18	<0.001	<0.001	3.52632	2.9613	4.0913	2.101	Reject H_0
H13	19.396	18	<0.001	<0.001	3.89474	3.4729	4.3166	2.101	Reject H_0
H14	17.685	18	<0.001	<0.001	3.63158	3.2002	4.0630	2.101	Reject H_0
H15	13.602	18	<0.001	<0.001	3.26316	2.7591	3.7672	2.101	Reject H_0

3.6 Application of fuzzy entropy and fuzzy TOPSIS method

The evaluation of enablers is presented in this section using fuzzy entropy and the fuzzy TOPSIS technique. The first step is to construct a fuzzy evaluation matrix based on expert input and the linguistic variables listed in Table 3. Table 4 provides the detail of Identified enablers through literature review, and Table 6 shows the resulting evaluation matrix.

Table 6 is provided by comparing all of the enablers in relation to the three components of supply chain decision stages, namely strategic, tactical, and operational, using responses from the Expert_1 questionnaire survey.

Table 6 Fuzzy evaluation matrix for identified enablers (Expert_1)

	Strategic factor (SF)			*Tactical factor (TF)*			*Operational factor (OF)*		
E1	6	7	8	2	3	4	4	5	6
E2	2	3	4	4	5	6	4	5	6
E3	6	7	8	2	3	4	6	7	8
E4	2	3	4	2	3	4	6	7	8
E5	6	7	8	2	3	4	6	7	8
E6	6	7	8	4	5	6	2	3	4
E7	6	7	8	2	3	4	6	7	8
E8	6	7	8	6	7	8	6	7	8
E9	6	7	8	6	7	8	2	3	4
E10	6	7	8	2	3	4	6	7	8
E11	6	7	8	2	3	4	6	7	8
E12	6	7	8	2	3	4	2	3	4
E13	6	7	8	2	3	4	6	7	8
E14	6	7	8	6	7	8	2	3	4
E15	6	7	8	6	7	8	2	3	4

3.6.1 Fuzzy entropy method

For assigning the weights to each criteria, i.e., strategic, tactical, and operational, the fuzzy entropy method is used in our study. The first step is to create the average fuzzy DM by getting the inputs from the experts through a questionnaire survey which is shown in Table 7.

Table 7 Average fuzzy DM

	Strategic factor (SF)			*Tactical factor (TF)*			*Operational factor (OF)*		
E1	5.894	6.894	7.526	5.578	6.578	7.368	5.789	6.789	7.473
E2	6.736	7.736	8.263	6	7	7.789	6.105	7.105	7.736
E3	5.684	6.684	7.578	5.526	6.473	7.315	5.368	6.368	7.263
E4	5	5.947	6.789	5.210	6.157	7	5.105	6.052	6.842
E5	5.894	6.894	7.631	5.789	6.789	7.631	5.789	6.789	7.578
E6	5.789	6.789	7.526	5.368	6.368	7.210	4.631	5.631	6.526
E7	6.315	7.315	7.947	4.947	5.947	6.789	4.631	5.631	6.578
E8	5.578	6.578	7.263	5.052	6.052	6.842	5.263	6.263	7.105
E9	5.263	6.263	7	5.052	6.052	6.842	4.157	5.105	6
E10	5.368	6.368	7.157	4.947	5.947	6.736	4.842	5.842	6.684
E11	4	5	5.947	4.631	5.631	6.526	4.526	5.526	6.473
E12	4.631	5.631	6.526	5.052	6.052	6.894	4.578	5.526	6.421
E13	4.947	5.947	6.789	4.631	5.631	6.526	5	5.947	6.789
E14	6.105	7.105	7.842	5.526	6.473	7.368	4.631	5.526	6.421
E15	5.684	6.684	7.473	5.684	6.684	7.421	5.052	6.052	6.894

The next step is to use equation (2) to turn the average fuzzy DM into a defuzzified DM, as illustrated in Table 8. The defuzzified DM is then normalised using equation (4), which is presented in Table 9 so that all of the elements of the matrix have the same dimensions.

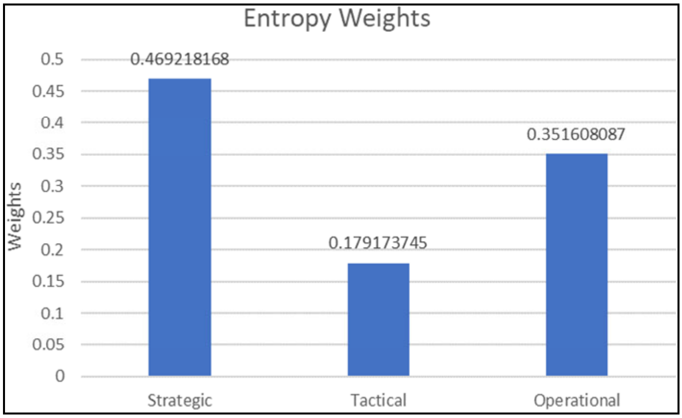
Table 8 Defuzzified DM

	Strategic factor (SF)	*Tactical factor (TF)*	*Operational factor (OF)*
E1	6.833	6.544	6.737
E2	7.658	6.965	7.044
E3	6.667	6.456	6.351
E4	5.930	6.140	6.026
E5	6.851	6.763	6.754
E6	6.746	6.342	5.614
E7	7.254	5.921	5.623
E8	6.526	6.018	6.237
E9	6.219	6.018	5.096
E10	6.333	5.912	5.816
E11	4.991	5.614	5.518
E12	5.614	6.026	5.518
E13	5.921	5.614	5.930
E14	7.061	6.465	5.526
E15	6.649	6.640	6.026

Table 9 Normalisation of defuzzified DM

	Strategic factor (SF)	*Tactical factor (TF)*	*Operational factor (OF)*
E1	0.070	0.070	0.075
E2	0.079	0.075	0.078
E3	0.069	0.069	0.071
E4	0.061	0.066	0.067
E5	0.070	0.072	0.075
E6	0.069	0.068	0.063
E7	0.075	0.063	0.063
E8	0.067	0.064	0.069
E9	0.064	0.064	0.057
E10	0.065	0.063	0.065
E11	0.051	0.060	0.061
E12	0.058	0.064	0.061
E13	0.061	0.060	0.066
E14	0.073	0.069	0.062
E15	0.068	0.071	0.067

Figure 2 Entropy weights for strategic, tactical, and operational factors (see online version for colours)



The entropy for each index is then calculated using equation (5) as a guide. The entropy for each index, namely strategic, tactical, and operational, is 0.9980, 0.9992, and 0.9985, respectively, after calculations. Now, using the entropy values, the degree of deviation for each criterion is determined using the formula in equation (6), yielding 0.0019, 0.0007, and 0.0014.

Finally, equation (7) calculates the entropy weights for each index which are displayed on Figure 2, based on the conducted analysis on the collected data through the questionnaire from the experts, the highest weight of the project success criteria belongs to the strategic variable and lowest weights of the project success criteria belongs to the tactical variable, obtaining 0.4692, 0.1791, and 0.3516, respectively.

Table 10 Aggregate fuzzy matrix

	Strategic factor (SF)			*Tactical factor (TF)*			*Operational factor (OF)*		
E1	2.000	6.895	9.000	2.000	6.579	9.000	2.000	6.789	9.000
E2	2.000	7.737	9.000	2.000	7.000	9.000	2.000	7.105	9.000
E3	2.000	6.684	9.000	1.000	6.474	9.000	2.000	6.368	9.000
E4	1.000	5.947	9.000	1.000	6.158	9.000	1.000	6.053	9.000
E5	2.000	6.895	9.000	2.000	6.789	9.000	2.000	6.789	9.000
E6	2.000	6.789	9.000	2.000	6.368	9.000	2.000	5.632	9.000
E7	2.000	7.316	9.000	2.000	5.947	9.000	2.000	5.632	9.000
E8	2.000	6.579	9.000	2.000	6.053	9.000	2.000	6.263	9.000
E9	2.000	6.263	9.000	2.000	6.053	9.000	1.000	5.105	9.000
E10	2.000	6.368	9.000	2.000	5.947	9.000	2.000	5.842	9.000
E11	2.000	5.000	9.000	2.000	5.632	9.000	2.000	5.526	9.000
E12	2.000	5.632	9.000	2.000	6.053	9.000	1.000	5.526	9.000
E13	2.000	5.947	9.000	2.000	5.632	9.000	1.000	5.947	9.000
E14	2.000	7.105	9.000	1.000	6.474	9.000	1.000	5.526	9.000
E15	2.000	6.684	9.000	2.000	6.684	9.000	2.000	6.053	9.000

3.6.2 Fuzzy TOPSIS method

Next step is to obtain the aggregate fuzzy matrix (Table 10) by taking the arithmetic mean of the responses obtained from the 19 experts by using the equation (8) shown in the step 1 of fuzzy TOPSIS method.

Table 11 Normalised fuzzy DM

	Strategic factor (SF)			*Tactical factor (TF)*			*Operational factor (OF)*		
E1	0.222	0.766	1.000	0.222	0.731	1.000	0.222	0.754	1.000
E2	0.222	0.860	1.000	0.222	0.778	1.000	0.222	0.789	1.000
E3	0.222	0.743	1.000	0.111	0.719	1.000	0.222	0.708	1.000
E4	0.111	0.661	1.000	0.111	0.684	1.000	0.111	0.673	1.000
E5	0.222	0.766	1.000	0.222	0.754	1.000	0.222	0.754	1.000
E6	0.222	0.754	1.000	0.222	0.708	1.000	0.222	0.626	1.000
E7	0.222	0.813	1.000	0.222	0.661	1.000	0.222	0.626	1.000
E8	0.222	0.731	1.000	0.222	0.673	1.000	0.222	0.696	1.000
E9	0.222	0.696	1.000	0.222	0.673	1.000	0.111	0.567	1.000
E10	0.222	0.708	1.000	0.222	0.661	1.000	0.222	0.649	1.000
E11	0.222	0.556	1.000	0.222	0.626	1.000	0.222	0.614	1.000
E12	0.222	0.626	1.000	0.222	0.673	1.000	0.111	0.614	1.000
E13	0.222	0.661	1.000	0.222	0.626	1.000	0.111	0.661	1.000
E14	0.222	0.789	1.000	0.111	0.719	1.000	0.111	0.614	1.000
E15	0.222	0.743	1.000	0.222	0.743	1.000	0.222	0.673	1.000

Table 12 Weighted normalised fuzzy DM

	Strategic factor (SF)			*Tactical factor (TF)*			*Operational factor (OF)*		
E1	0.104	0.359	0.469	0.040	0.131	0.179	0.078	0.265	0.352
E2	0.104	0.403	0.469	0.040	0.139	0.179	0.078	0.278	0.352
E3	0.104	0.348	0.469	0.020	0.129	0.179	0.078	0.249	0.352
E4	0.052	0.310	0.469	0.020	0.123	0.179	0.039	0.236	0.352
E5	0.104	0.359	0.469	0.040	0.135	0.179	0.078	0.265	0.352
E6	0.104	0.354	0.469	0.040	0.127	0.179	0.078	0.220	0.352
E7	0.104	0.381	0.469	0.040	0.118	0.179	0.078	0.220	0.352
E8	0.104	0.343	0.469	0.040	0.120	0.179	0.078	0.245	0.352
E9	0.104	0.327	0.469	0.040	0.120	0.179	0.039	0.199	0.352
E10	0.104	0.332	0.469	0.040	0.118	0.179	0.078	0.228	0.352
E11	0.104	0.261	0.469	0.040	0.112	0.179	0.078	0.216	0.352
E12	0.104	0.294	0.469	0.040	0.120	0.179	0.039	0.216	0.352
E13	0.104	0.310	0.469	0.040	0.112	0.179	0.039	0.232	0.352
E14	0.104	0.370	0.469	0.020	0.129	0.179	0.039	0.216	0.352
E15	0.104	0.348	0.469	0.040	0.133	0.179	0.078	0.236	0.352

As the aim of our study is to maximise the criteria i.e., strategic, tactical and operational factors, therefore the enablers are to considered as benefit criteria. Hence by the using the equation (9), the values of aggregate DM are converted to normalised DM. The same, i.e., normalised DM, is presented in Table 11. The weights obtained by fuzzy entropy are used to create a weighted matrix in the next stage, which is done using equation (11). Table 12 depicts this matrix.

Enablers are the benefit criterion in this project. After generating the weighted normalised DM, use equations (12) and (13) to determine the FPIS and FNIS for each of the criteria. The FPIS is one that maximises the benefits while minimising the costs. It is the highest possible value based on the criteria. In the same way, a FNIS maximises the cost criteria while minimising the benefit criteria. It is the worst valve possible based on the criteria (Dehdasht et al., 2020). Using equation (14) and (15), determine the distance (d_i^+, d_i^-) of each criteria from FPIS and FNIS, respectively. The value of the proximity coefficient CC_i for each enabler is determined using these distances (d_i^+, d_i^-) and the equation (17). The distance (d_i^+, d_i^-) and closeness coefficient CC_i for each enabler are shown in Table 13. All enablers are sorted in descending order based on their closeness coefficient CC_i.

Table 13 Ranking of the enablers based on closeness coefficient (CC_i)

S. no.	*Enablers*	d_i^+	d_i^-	CC_i	*Rank*
E1	Customisation	0.037	0.098	0.724	3
E2	Design and manufacturing flexibility	0.000	0.127	1	1
E3	Virtual inventory	0.061	0.077	0.557	6
E4	Reduce wastages	0.109	0.021	0.163	15
E5	Agility	0.035	0.099	0.739	2
E6	Risk reduction	0.069	0.077	0.525	8
E7	Customer satisfaction	0.058	0.088	0.603	4
E8	Quality	0.065	0.082	0.557	7
E9	Productivity and profitability	0.106	0.043	0.289	14
E10	Eco-friendly manufacturing	0.082	0.072	0.469	9
E11	Product standardisation	0.134	0.079	0.371	12
E12	Meet safety regulation	0.116	0.053	0.311	13
E13	Energy efficient	0.104	0.062	0.373	11
E14	Reduced supplier dependencies	0.074	0.059	0.443	10
E15	Top management commitment	0.059	0.081	0.579	5

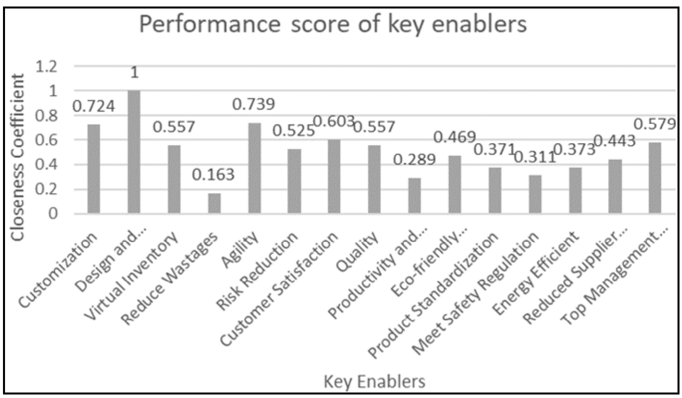
Figure 3 shows a bar chart that depicts the primary enablers of additive manufacturing. The final ranking of enablers and selection of important drivers was based on an average of each enabler's effect on three supply chain characteristics, as shown in Figure 3 (strategic, tactical, and operational). In the operational dimension, the closeness coefficient index for 'design and manufacturing flexibility' is the highest which is one and the lowest value of closeness coefficient is 0.163 for 'reduce wastage' which also comes under the operational dimension. The findings of this study revealed that the fuzzy entropy and fuzzy TOPSIS techniques can provide decision-makers and managers with two types of information:

1 a ranking of enablers

2 a list of essential enablers for the deployment of additive manufacturing.

The recommended fuzzy entropy and fuzzy TOPSIS methods help improve the process of identifying key factors while facilitating the successful implementation of layered modelling. The fuzzy entropy and fuzzy TOPSIS methods also help in prioritising the enablers, allowing managers and decision-makers to focus on the key enablers mentioned. The methodology proposed in this study is effective for evaluating and evaluating what enables the implementation of additive manufacturing within the three aspects of the supply chain decision-making phase (strategic, tactical, and operational).

Figure 3 Ranking of key enablers for successful additive manufacturing implementation



4 Conclusions

Overall, the multiple advantages of additive manufacturing over traditional manufacturing have convinced enterprises to use additive manufacturing as a decentralised way of production to satisfy changing client demand. However, although the existing research focuses on the barriers to additive manufacturing adoption in industries, there is currently no examination of enablers accountable for additive manufacturing implementation throughout supply chain decision phases (strategic, tactical, and operational). Enablers of additive manufacturing implementation can motivate the managers to adapt and successfully implement additive manufacturing effectively. As a result, this paper offered a methodology for identifying and classifying enablers based on the three criteria of supply chain decision stages using fuzzy entropy and fuzzy TOPSIS techniques (strategic, tactical, and operational). It was discovered that using the fuzzy entropy method to weight the criteria and fuzzy TOPSIS to select the significant enablers based on the closeness coefficient (CC_i) was a helpful approach. From the study, we found that the highest weight of the project success criteria belongs to the strategic factors followed by operational and tactical factors, obtaining 0.4692,0.1791, and 0.3516 weights, respectively. This analysis, for example, demonstrates that 'design and manufacturing flexibility (E2)' is the most important factor with a high closeness coefficient (CC_i = 1), which amplifies the effects of other factors. The findings of this research revealed the following:

1 Identification of '15' enablers that assist the adoption of additive manufacturing across three supply chain decision phases (strategic, tactical, and operational).

2 The enablers were ranked according to their closeness coefficient (CC_i), which was determined using fuzzy entropy and the fuzzy TOPSIS algorithm. Because of its high (CC_i), the enabler 'design and manufacturing flexibility (E2)' is ranked first.

3 A multi-criteria decision-making model to evaluate the essential enablers for the adoption of additive manufacturing is proposed.

4 The proposed methodology employing fuzzy entropy and fuzzy TOPSIS was a reasonable and practical approach for identifying key enablers of additive manufacturing implementation.

The findings of this study can assist managers and officials in improving decision-making by identifying significant and critical parameters for the successful implementation of additive manufacturing. Using multi-criteria decision-making techniques such as Decision-Making Trial and Evaluation Laboratory (DEMATEL) or interpretive structure modelling (ISM), further studies can examine and analyse the interrelation and interaction between the identified key enablers in this study. The methodology used is novel, and it may be used to a variety of situations in which data for dimensions of research variables are collected through statements to which participants reply in the form of linguistic values.

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