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International Journal of Process Management and Benchmarking

ISSN online: 1741-816X - ISSN print: 1460-6739
https://www.inderscience.com/ijpmb

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DOI: 10.1504/IJPMB.2022.10051451

Article History:

Received:	17 June 2022
Accepted:	17 September 2022
Published online:	04 January 2024

Technological competencies attributes analysis using qualitative techniques in Indian manufacturing industry

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Abstract: Technological competencies require significant attributes for their beneficial impact on the manufacturing organisations. The paper is focused on selection of best attributes through multiple MCDM methods for the successful implementation of technological competencies' factors which act as foundation for improving and enhancing the performance of manufacturing firms. Data was collected through a questionnaire survey, and various factors were analysed for further research. The factors that have a substantial impact on the company's performance and competitiveness were identified as a result of the investigation. Several sources of a firm's technology competences are identified in order of their efficacy by utilising several MCDM approaches.

Keywords: TOPSIS; VIKOR; MOORA; ENTROPY; competencies.

Reference to this paper should be made as follows: Sharma, H., Singh, C.D. and Singh, K. (2024) 'Technological competencies attributes analysis using qualitative techniques in Indian manufacturing industry', *Int. J. Process Management and Benchmarking*, Vol. 16, No. 1, pp.91–110.

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1 Introduction

In the present day scenario, the companies are finding it difficult to flourish and sustain themselves due to the market competition. At present, customers can opt from so much choice from vast field of competitors. The numbers of companies providing similar services are many and therefore the companies are always in process of devising strategies that will let them to be at the top of the rest in the competitive marketplace (Mariani and Wamba, 2020). As a result, firms are identifying and integrating new technology into their systems to produce goods more quickly and of greater quality (Yadav and Jayswal, 2021a). The technological competencies play a major role in clarifying why firms vary from each other, how they transform over time, and whether or not they have the potential of remaining competitive (Björkdahl, 2020).

Technology was chosen as a competency area because it has shaped humanity's history for centuries. Technology, in conjunction with the right application of that knowledge, allows for higher-quality and faster product (Kim et al., 2020). For the growth of new product in the market, one should keep on upgrading the existing technologies gradually which can result in a unique concept of making a new product (Jobin et al., 2022). The manufacturing firms which use latest technology tend to deploy new strategies to innovate superior product designs to gain an advantage over others in the market (Sehgal et al., 2021). Technology, on the other hand, is not always developed enough to be employed effectively and efficiently in manufacturing operations. Due to this, most of the time, firms cannot take profit as they can by utilising technology in an efficient manner (Li et al., 2019). Technologies, in particular, may require additional development before they can be integrated into the existing manufacturing system (Azhar and Subramanian, 2022). As a result, the function of technological competence in allowing firm performance is an essential topic that requires further research.

For a company's technology competency to grow, it is also necessary to have a diverse set of technological resources and capabilities. Firms with valuable, difficult-to-copy resources can achieve and keep a competitive advantage over time (Soloducho-Pelc and Sulich, 2020). Because replicating the best resources is costly, competitors will find it difficult to duplicate the exact manufacturing method (Qiu et al., 2020). A technological competency, defined as a collection of technology resources, can, for example, deliver a variety of services (Baert et al., 2016). Many scholars have researched the topic of technological competence, but it does not appear to be a conventional instrument for measuring because various organisations have varying levels of technological adoption. Thus, multiple methods should be employed to assess technological competence (Al-Henzab et al., 2018).

The paper's framework is divided into six sections: the basic concept and introduction to the topic are presented in Section 1. There is literature content in Section 2. The research approach for the study is presented in Section 3. Multiple criteria decision making (MCDM) methods are employed in the analysis in Section 4. The results obtained by this study are discussed in Section 5. The paper is concluded with recommendations for further study in Section 6.

2 Literature review

Competency is a significant and critical issue in industry today, where competency is comprehended as the ability to make practical use of knowledge and skills in various contexts (Martín-Rojas et al., 2011; Vu and Nwachukwu, 2021). Competency encompasses comprehension, critical thinking and judgement, all together and considers the social elements of the tasks to be performed (Caratozzolo et al., 2019). The purpose of the review is to gain an insight towards the origin of technological competencies and its strategic impact on manufacturing performance of firms.

Technology is an ever-changing and ever-growing world. It is critical for businesses to stay up with technological changes because, let us face it, technology is unavoidable (Khanagha et al., 2018). Technological competence development, according to the researchers, is one of a firm's most essential dynamic capacities, involving new knowledge acquisition, identifying opportunities. The research and development (R and D) structure offers the opportunity for a firm's dynamic improvement and innovation. However, relying entirely on internal R and D will prevent firms from staying current with all necessary technological knowledge. Generally, the firms begin out with a certain level of technological competency, which they further develop by making varied amounts of investments in R and D activities. By doing this, the firm can compete in more competitive environment, which in turn improve its innovativeness (Ritala and Stefan, 2021). The growth of technological competence is aided by the formation of the proper environment. According to a study using data from 111 firms, using project portfolio management, aligning technology with new product development, and creating a favourable environment for innovation all led to the growth of technological competence (Kandemir and Acur, 2022). Technical elements including technological skills, and technological infrastructure (TI) enhance the technological distinctive competencies. Managers should encourage technical advancements that prevent rival businesses from competing on a worldwide scale by efficiently attracting technological capital within the organisation and sharing knowledge there. They need to have a sense that enables them to alter perspective of manufacturing with evolution of technology and how the firms will operate its business using technology in the future (Nafchi et al., 2021).

The technologically superior products and services are in demand in the current era (Ghobakhloo and Fathi, 2019). Firms that can quickly adapt to new technology and implement changes can gain a competitive advantage over slower and less informed competitors. Furthermore, because organisations are cautious to investigate new technologies, it is vital for them to comprehend the competitive advantage that the new technology provides in comparison to existing technologies (Gärtner et al., 2021). If a firm is technologically proficient, it will feel comfortable adopting new technologies. It has been noted that firms and governments are shifting their investments into new and emerging technology in order to provide circumstances for the advancement of local innovation to increase their global competitiveness and ensure their survival (Chattopadhyay and Bhawsar, 2017). Government policy should be concentrating on the development of ICT infrastructure, encouraging SMEs' technical externalities within the industry, to help SMEs perform better. Manufacturing firms which adopt technological oriented strategy increase better turnovers and make it harder for competitors to copy them because they have to face different types of challenges to adopt these technologies in the firm (Reiman et al., 2021). The present day competencies related to workforce are getting redundant with arrival of latest technologies so the technological competencies are necessary to grapple with the intricate situations (Virmani and Salve, 2022). A firm's technological proficiency also includes the technical competency of its workers and their training and development in new technology adoption (TAD) (Sidhu et al., 2022). Technical competencies are recognised as valuable assets needed to design and manufacture a physical product by adding value with specific features (Ahmed and Shepherd, 2010). That is mainly due to the fact that, organisation's technological competencies incorporate practical and theoretical knowhow, methods, experience and equipment for developing new products (Wang et al., 2004). Technological diversity has a major role in the organisation which provides better arrangements to the industry or organisation to compete in the market with others. For organisations to properly manage and leverage technological diversification for growth, technology competency is required (Kim et al., 2016).

The review of the aforementioned literature on competencies reveals that, when applied effectively, competences have positive effects on firms or organisations. But, technological competencies can do better for the manufacturing firms to survive in the present competitive scenario. Furthermore, it was noted that no study had been identified that prioritised the relative significance of technological competencies. Therefore, it is imperative to conduct this research in order to prioritise the factors related to technological competencies that might aid system engineers, decision-makers, and managers in selecting the optimal course of action for improved organisational performance. The selection of technological competency factors in this study is based on several MCDM methods. In many situations, finding solutions for a given set of alternatives is the main emphasis of solving multi-criteria decision-making problems. The issue arises when the values of one or more decisional variation's qualities change (Guru and Mahalik, 2021).

The analytic hierarchy process (AHP) was used to enhance the work on technological competence. By using this different attributes were identified which were related to uniqueness and collectiveness. Likewise for assessing the organisational competitiveness obtained through sustainable manufacturing, analytical hierarchal process was proposed. Top management is considered as most influential in the firm when it comes to understand the various connections between sustainable manufacturing and organisational competitiveness (Hichem et al., 2021). A method was developed for proactively choosing the best manufacturing system among cellular manufacturing, lean manufacturing and traditional manufacturing systems. Hence, AHP technique has been employed for alternative prioritisation in a comparative evaluation of multi criteria decision-making systems (Kumar et al., 2020).

From a sustainability standpoint, choosing the right suppliers is a difficult process for successful supplier engagement in new product development. In order to assess supplier collaboration, a multi-criteria decision-making system based on fuzzy Delphi, ENTROPY weight, and grey relational analysis was presented (Sumrit, 2022). Flexible manufacturing systems are becoming more prevalent in Indian manufacturing. The improvements in the flexible manufacturing system are influenced by a number of elements when FMS is implemented. To analyse their inter-relationships and to prioritise the effect, DEMATEL technique has been implemented (Jain and Ajmera, 2020). By comparing decision-making approaches that incorporate Shannon ENTROPY and the weighted aggregated sum product assessment method, the industry's challenge of selecting the operating parameters for flexible production systems was resolved (Yadav and Jayswal, 2021b). The technique for order preference by similarity to ideal solution (TOPSIS) approach and AHP method are combined to find out the competencies preference that which type of competencies show better results and hence can be chosen in healthy way by using multi-criteria decision making techniques (Zaki et al., 2021).

Therefore, to comprehend experience in building a broad variety of engineering applications and attribute selection, it is required to apply the range of MCDM methods (Lode et al., 2021). When an organisation uses these techniques to analyse their various competencies then it becomes easy for them to select the better ones. This is done while ranking and priorities are given to the factors which affect the competencies. In this paper, various MCDM techniques have been used like TOPSIS, VIKOR, ENTROPY, multi-objective optimisation on the basis of ration analysis (MOORA), evaluation based on distance from average solution (EDAS), etc. which were carefully selected according to the need of the study.

3 Research methodology

This section provides a thorough explanation of the steps that were taken to conduct a comparative research based on ranking different technological competency variables using MCDM methodologies. This study looked at how the competency criteria affected the success of firms at manufacturing facilities in the country's North region.

There are multiple steps involved, and they are as follows:

- Gathering data and defining the objectives

It is the first and most important stage in any MCDM approach. Survey of various organisations has been conducted through a specially prepared questionnaire for understanding and determining factors related to technological competencies of Indian manufacturing firms. The questionnaire is based on four-point Likert scale. The work's primary goal is to use the five well-known qualitative approaches based on their popularity and superlative results for selection of best technological competency factors and arranging them in order to facilitate decision-making.

- The development of alternatives and the choice of criteria

  In this step, the decision-maker primarily selects the various criteria based on the requirements of the study.

- Assigning criteria weights

  To assess the relative weights of different criteria and ascertain the importance of each and every criterion, AHP is used.

- Ranking alternatives

  Five different MCDM techniques have been used in this stage to rank different technological competency variables. These techniques include TOPSIS, VIKOR, ENTROPY, MOORA, and EDAS among others.

- Making the decisions

  To help with decision-making, a final ranking order based on multiple MCDM techniques has been developed.

4 MCDM techniques analysis

The following are descriptions of the various MCDM techniques that were used in this study.

4.1 Decision making with TOPSIS method

The TOPSIS was developed by Hwang and Yoon (1981), for solving MCDM problems. This method is based on the inputs that are related to the weights. Equal weights, centroid weights and weights obtained using regression are the main types of weight criteria used in this technique. It is a way for comparing the performance of different options to the optimum solution. The alternative that is the furthest away from the negative ideal solution and the closest to the positive ideal solution should be chosen (Kumar et al., 2021).

Procedure

Step 1 Generate decision matrix by using the responses collected for attributes identified from the data collected using questionnaire. Table 1 shows the decision matrix.

Table 1 Decision matrix for TOPSIS

	TI	*TA*	*TC*	*TAD*	*TMS*	*IT*
TI	1	3	0.5	0.33	1	2
TA	0.33	1	1	0.5	0.2	2
TC	2	1	1	1	1	3
TAD	3	2	1	1	0.5	3
TMS	1	5	1	2	1	4
IT	0.5	0.5	0.33	0.33	0.25	1

Step 2 Construct normalised decision matrix by applying the following relationship:

$$r_{ij} = X_{ij} \Big/ \left(\sum X_{ij}^2 \right) \text{ for } i = 1, 2, 3, \ldots, m; \ j = 1, 2, 3, \ldots, n \tag{1}$$

Step 3 Construct the weighted normalised decision matrix by applying the following relationship. Table 2 represents weighted normalised decision matrix.

Weight normalisation = normalise score × weight

$$v_{ij} = r_{ij} w_j \tag{2}$$

Table 2 Weighted normalised matrix for TOPSIS

	TI	*TA*	*TC*	*TAD*	*TMS*	*IT*
TI	0.0391932	0.048043	0.047466	0.02747	0.149428	0.018605
TA	0.0129338	0.016014	0.094933	0.041621	0.029886	0.018605
TC	0.0783865	0.016014	0.094933	0.083242	0.149428	0.027907
TAD	0.1175797	0.032029	0.094933	0.083242	0.074714	0.027907
TMS	0.0391932	0.080072	0.094933	0.166484	0.149428	0.03721
IT	0.0195966	0.008007	0.031328	0.02747	0.037357	0.009302

Step 4 Determine the Euclidean distance from each alternative.

The Euclidean distance from the positive ideal alternative is:

$$S_i^* = \left[\sum \left(v_j^* - v_{ij} \right)^2 \right]^{1/2} \tag{3}$$

Similarly, the Euclidean distance from the negative ideal alternative is:

$$S_i' = \left[\sum \left(v_j' - v_{ij} \right)^2 \right]^{1/2} \tag{4}$$

Step 5 Calculate the closeness coefficient CC_i^* of each alternative

$$CC_i^* = S_i' \big/ \left(S_i^* + S_i' \right), 0 < CC_i^* < 1 \tag{5}$$

Step 5 Then, on the basis of the performance, score ranking of the factors has been done in which top management support (TMS) has been given the first rank as this attribute has the highest influence on the performance of the manufacturing industries and the last rank is given to information technology (IT) as shown in Table 3.

Table 3 Ranking of significant factors from TOPSIS

	S_i^*	S_i'	$S_i^* + S_i'$	$CC_i^* = S_i' / (S_i^* + S_i')$	*Rank*
TI	0.170570831	0.413002	0.583573	0.707712973	4
TA	0.212794342	0.461296	0.674091	0.684323878	5
TC	0.112495579	0.335404	0.447899	0.741062131	3
TAD	0.122090507	0.349415	0.471505	0.748837277	2
TMS	0.078386479	0.279976	0.358362	0.781264738	1
IT	0.226943255	0.476386	0.703329	0.677329818	6

4.2 Decision making with VIKOR method

The VIKOR methodology has been identified as an important method to be used in MCDM. In the presence of competing criteria, it focuses on ranking and selecting from a group of choices. A viable choice that gets close to the ideal answer is a compromise solution. A compromise, on the other hand, is a mutually agreed-upon arrangement (Singla et al., 2018).

The procedure of VIKOR for ranking alternatives is as follows:

Step 1 Generate decision matrix by using the responses collected for attributes identified from the data collected using questionnaire. Table 4 displays the decision matrix.

Table 4 Decision matrix for VIKOR

	TI	*TA*	*TC*	*TAD*	*TMS*	*IT*
TI	1	3	0.5	0.33	1	2
TA	0.33	1	1	0.5	0.2	2
TC	2	1	1	1	1	3
TAD	3	2	1	1	0.5	3
TMS	1	5	1	2	1	4
IT	0.5	0.5	0.33	0.33	0.25	1

Step 2 Calculation of normalised value of decision matrix by applying the following relationship. Table 5 represents weighted normalised decision matrix.

$$X_{ij}' = \left[\left(X_{ij} - X_j^-\right) / \left(X_J^* - X_j^-\right)\right] \tag{6}$$

where

X_J^* best (maximum) value from column of decision matrix

X_j worst (minimum) value from column of decision matrix

X_{ij} initial values in the cells of decision matrix.

Table 5 Normalised decision matrix for VIKOR

	TI	*TA*	*TC*	*TAD*	*TMS*	*IT*
TI	1	3	0.5	0.33	1	2
TA	0.33	1	1	0.5	0.2	2
TC	2	1	1	1	1	3
TAD	3	2	1	1	0.5	3
TMS	1	5	1	2	1	4
IT	0.5	0.5	0.33	0.33	0.25	1
Min(X_j^-)	0.33	0.5	0.33	0.33	0.2	1
Max(X_j^*)	3	5	1	1	1	4
Range	2.67	4.5	0.67	0.67	0.8	3

Step 3 Determine the weights of attributes.

$$X'_{ij} = \left[\left(X_{ij} - \min X_{ij}\right) / \left(\max X_{ij} - \min X_{ij}\right)\right] \tag{7}$$

The standard deviation (σ_j) was calculated separately for each criterion

$$\sigma_j = \sqrt{1/m \sum \left(X'_{ij} - X'_j\right)^2} \tag{8}$$

where X_j' is the mean of the values of the j^{th} criterion after normalisation and $j = 1, 2, \ldots, n$.

The (CV) of the criterion (σ_j) will be as displayed after computing (j) for all criteria.

$$CV_j = \sigma_j / X'_j \tag{9}$$

The weight (W_j) of the criterion (j) can be defined as

$$W_j = CV_j / \sum CV_j \tag{10}$$

Step 4 Compute the S_i (the maximum utility) and R_i (the minimum regret)

$$S_i = \sum W_j^* \left(X_j^* - X_{ij}\right) / \left(X_j - X_j^-\right) \tag{11}$$

$$R_i = \max\left[\sum W_j^* \left(X_j^* - X_{ij}\right) / \left(X_j - X_j^-\right)\right] \tag{12}$$

Table 6 Distance of alternatives from the ideal solution

	TI	*TA*	*TC*	*TAD*	*TMS*	*IT*	*S_i*	*R_i*
TI	0.14168	0.08606	0.08768	0.21867	0	0.0847784	0.618862247	0.218665326
TA	0.18915	0.17212	0	0.16318	0.1539	0.0847784	0.763126977	0.189145061
TC	0.07084	0.17212	0	0	0	0.0423892	0.285350733	0.172120687
TAD	0	0.12909	0	0	0.09619	0.0423892	0.267667059	0.129090515
TMS	0.14168	0	0	–0.3264	0	0	–0.184684464	0.141681694
IT	0.1771	0.19364	0.11749	0.21867	0.14428	0.1271676	0.978338322	0.218665326

Step 5 In this last step, we find the value of performance score which is given by q_i. To find the value, we use the following equation and then ranking is done as depicted in Table 7:

$$q_i = \{v(S_i - S^*)/(S^- - S^*)\} + \{(1-v)(R_i - R^*)/(R^- - R^*)\} \quad (13)$$

where S^* = minimum value among S_i, S^- = maximum value among S_i, R^* = min. value among R_i, R^- = max. value among R_i and v is the introduced weight of the strategy of S_i and R_i.

Table 7 Ranking of alternatives

Attributes	S_i	R_i	q_i	*Rank*
TI	0.6189	0.2187	0.442266	4
TA	0.7631	0.1891	0.194472	5
TC	0.2854	0.1721	0.742698	3
TAD	0.2677	0.1291	0.845456	2
TMS	–0.1847	0.1417	1	1
IT	0.9783	0.2187	0.070283	6

Step 6 Ranking the alternatives, by sorting in decreasing order the *S*, *R* and *Q* values.

4.3 Decision making with ENTROPY method

One of the most difficult tasks in MCDM challenges is appropriately assigning weights to the criteria by which the alternatives are to be rated. The ENTROPY technique gives better accuracy in determining the objective weight of criterion. Value is assessed using the ENTROPY weight approach, which counts the degree of differentiation. The higher the degree of dispersion of the measured value, the higher the degree of differentiation of the index, and more information can be derived (Ghosh et al., 2021).

The steps to calculate the weights by ENTROPY method for the decision matrix are given as follows:

Step 1 Generate decision matrix by using data collected from different respondents with the help of questionnaire. Table 8 shows the decision matrix for all selected factors.

$$X = [X_{ij}]_{m \times n} = \begin{bmatrix} X_{11} & \cdots & X_{in} \\ \vdots & \ddots & \vdots \\ X_{21} & \cdots & X_{mn} \end{bmatrix} (i = 1, 2, \ldots, m \text{ and } j = 1, 2, \ldots, n) \quad (14)$$

X_{ij} presents the performance value of i^{th} alternative on j^{th} criterion.

Step 2 Construct normalised decision matrix by using following relation. Table 9 shows the normalised decision matrix for all selected factors.

$$r_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \quad i = 1, 2, 3, \ldots, m \text{ and } j = 1, 2, 3, \ldots, n \quad (15)$$

$$r_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \quad i = 1, 2, 3, \ldots, m \text{ and } j = 1, 2, 3, \ldots, n \tag{16}$$

Table 8 Decision matrix for ENTROPY

	TI	*TA*	*TC*	*TAD*	*TMS*	*IT*
TI	1	3	0.5	0.33	1	2
TA	0.33	1	1	0.5	0.2	2
TC	2	1	1	1	1	3
TAD	3	2	1	1	0.5	3
TMS	1	5	1	2	1	4
IT	0.5	0.5	0.33	0.33	0.25	1

Table 9 Normalised decision matrix for ENTROPY

	TI	*TA*	*TC*	*TAD*	*TMS*	*IT*
TI	0.1277	0.24	0.1035	0.064	0.2532	0.1333
TA	0.0421	0.08	0.207	0.0969	0.0506	0.1333
TC	0.2554	0.08	0.207	0.1938	0.2532	0.2
TAD	0.3831	0.16	0.207	0.1938	0.1266	0.2
TMS	0.1277	0.4	0.207	0.3876	0.2532	0.2667
IT	0.0639	0.04	0.0683	0.064	0.0633	0.0667

Step 3 For each criterion, ENTROPY values (e_j) are calculated.

$$e_j = \frac{-\sum_{i=1}^{m} f_{ij} \ln f_{ij}}{\ln m} \quad i = 1, 2, 3, \ldots, m \text{ and } j = 1, 2, 3, \ldots, n \tag{17}$$

where

$$f_{ij} = \frac{r_{ij}}{\sum_{j=1}^{m} r_{ij}} \text{ and } 0 < e_j < 1 \tag{18}$$

Step 4 The weights of ENTROPY (w_j) are calculated.

$$w_j = \frac{1 - e_j}{n - \sum_{i=1}^{m} e_j} \quad \text{where } \sum_{j=1}^{n} w_j = 1 \tag{19}$$

Table 10 Ranking of significant factors from ENTROPY method

	Sum	e_j	d_j	w_j	$+w_j$	*Rank*
0.1569	–1.6324	0.911	0.089	0.1569	0.1569	4
0.095	–1.8883	1.0539	–0.0539	–0.095	0.095	5
0.2274	–2.023	1.129	–0.129	–0.2274	0.2274	3
0.4767	–1.3073	0.7296	0.2704	0.4767	0.4767	2
0.7602	–1.0191	0.5688	0.4312	0.7602	0.7602	1
0.0714	–1.8644	1.0405	–0.0405	–0.0714	0.0714	6

Each criterion's inherent contrast intensity is represented by $(1 - e_j)$. The ranks based on ENTROPY are shown in Table 10. From Table 10, it is clear that factor having highest value of weight factor is considered as critical one and so on.

4.4 Decision making with MOORA method

The MOORA, also known as multi-criteria or multi-attribute optimisation was introduced by Brauers. By using this, two or more conflicting objectives can be solved simultaneously. This MCDM method can solve complex problems in manufacturing for decision making. This method has two components: a ratio system and a reference point method. The numeric value of each individual choice is compared to a denominator that represents all possibilities in a ratio system (Asjad and Talib, 2018).

Steps to calculate the weights by MOORA method for the decision matrix are as follows:

Step 1 Generate decision by using data collected from different respondents with the help of questionnaire as shown in Table 11.

Table 11 Decision matrix for MOORA

	TI	*TA*	*TC*	*TAD*	*TMS*	*IT*
TI	1	3	0.5	0.33	1	2
TA	0.33	1	1	0.5	0.2	2
TC	2	1	1	1	1	3
TAD	3	2	1	1	0.5	3
TMS	1	5	1	2	1	4
IT	0.5	0.5	0.33	0.33	0.25	1

Step 2 Construct normalised decision matrix by using following relation. Normalised decision matrix is shown in Table 12.

$$x_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \tag{20}$$

Table 12 Normalised decision matrix for MOORA

	TI	*TA*	*TC*	*TAD*	*TMS*	*IT*
TI	0.2552	0.4729	0.2395	0.1298	0.5462	0.305
TA	0.0842	0.1576	0.479	0.1966	0.1092	0.305
TC	0.5103	0.1576	0.479	0.3932	0.5462	0.4575
TAD	0.7655	0.3152	0.479	0.3932	0.2731	0.4575
TMS	0.2552	0.7881	0.479	0.7864	0.5462	0.61
IT	0.1276	0.0788	0.1581	0.1298	0.1365	0.1525

Step 3 In the step, weighted normalise decision matrix (W_{ij}) is constructed by multiplying the normalised performance values with the weight criteria as shown in Table 13. Here, equal weightage is given to each factor that is 1/6

therefore each value is multiplied with the same and a weighted normalised decision matrix is formed.

$$W_{ij} = \sum x_{ij}^{*} w_j \tag{21}$$

where w_j is weightage of each criteria (since equal weightage is given to each criteria so $w_j = 1/6$).

Table 13 Weighted normalise decision matrix for MOORA

	TI	*TA*	*TC*	*TAD*	*TMS*	*IT*
TI	0.0425	0.0788	0.0399	0.0216	0.091	0.0508
TA	0.014	0.0263	0.0798	0.0328	0.0182	0.0508
TC	0.085	0.0263	0.0798	0.0655	0.091	0.0762
TAD	0.1275	0.0525	0.0798	0.0655	0.0455	0.0762
TMS	0.0425	0.1313	0.0798	0.131	0.091	0.1016
IT	0.0213	0.0131	0.0263	0.0216	0.0227	0.0254

Step 4 In last step, sum of all the W_{ij} values is done and then ranking is done which is shown in Table 14. By using MOORA, the performance value having highest value of $\sum w_{ij}$ is given the first rank and so on.

Table 14 Ranking of significant factors from MOORA

	$\sum w_{ij}$	*Rank*
TI	0.3246	4
TA	0.2219	5
TC	0.4238	3
TAD	0.447	2
TMS	0.5772	1
IT	0.1304	6

4.5 Decision making with EDAS method

In MCDM, the standard EDAS method, which may take into account competing qualities, is a useful tool. The EDAS approach, in comparison to ABC classification methods, is more efficient and involves fewer computations. In this method, the alternatives of an MCDM problem are evaluated based on positive and negative distances from an average solution. The alternative with higher value of positive distance and lower value of negative distance is the best choice (Durmaz et al., 2020).

Procedure

Step 1 Design decision matrix. Table 15 shows the decision matrix for all selected factors.

Table 15 Decision matrix for EDAS

	TI	*TA*	*TC*	*TAD*	*TMS*	*IT*
TI	1	3	0.5	0.33	1	2
TA	0.33	1	1	0.5	0.2	2
TC	2	1	1	1	1	3
TAD	3	2	1	1	0.5	3
TMS	1	5	1	2	1	4
IT	0.5	0.5	0.33	0.33	0.25	1

Step 2 In this step, calculate element of the average solution (AV_J) by using the following formula:

$$AV_j = \frac{\sum_{i=1}^{n} x_{ij}}{n} \tag{22}$$

Step 3 Determine positive distance from average (P_{ij}^d). Table 16 presents positive distance from average (P_{ij}^d).

$$P_{ij}^d = \frac{\max\left(0, \left(x_{ij} - AV_{iJ}\right)\right)}{AV_J} \tag{23}$$

Table 16 Positive distance from average

	TI	*TA*	*TC*	*TAD*	*TMS*	*IT*
TI	0	0.44	0	0	0.519	0
TA	0	0	0.2422	0	0	0
TC	0.5326	0	0.2422	0.1628	0.519	0.2
TAD	1.2989	0	0.2422	0.1628	0	0.2
TMS	0	1.4	0.2422	1.3256	0.519	0.6
IT	0	0	0	0	0	0

Step 4 The negative distance from average (N_{ij}^d) is calculated. Table 17 presents negative distance from average (P_{ij}^d).

$$N_{ij}^d = \frac{\max\left(0, \left(AV_{iJ} - x_{ij}\right)\right)}{AV_J} \tag{24}$$

Step 5 In this step, weighted sum of PDA matrix was formed by multiplying each cell value with criteria weight, i.e., w_{ij} (1/6) as equal weightage has been given to each alternative. Each value of the normalised matrix is represented by x_{ij}. Weighted sum of PDA was calculated by using the formula given below:

$$P_i^w = \sum_{j=1}^{m} w_j P_{ij}^d \tag{25}$$

where w_j denotes the weight of the criteria j.

Table 17 Negative distance from average

	TI	*TA*	*TC*	*TAD*	*TMS*	*IT*
TI	0.2337	0	0.3789	0.6163	0	0.2
TA	0.7471	0.52	0	0.4186	0.6962	0.2
TC	0	0.52	0	0	0	0
TAD	0	0.04	0	0	0.2405	0
TMS	0.2337	0	0	0	0	0
IT	0.6169	0.76	0.5901	0.6163	0.6203	0.6

Step 6 Compute weighted sum of NDA (N_{ij}^{d}). After the calculation, weighted sum of NDA matrix was formed by multiplying each cell value with criteria weight, i.e., w_j (1/6) as equal weightage has been given to each alternative. Weighted sum of NDA were calculated by using the formula given below:

$$N_i^w = \sum_{j=1}^{m} w_j N_{ij}^d \tag{26}$$

Step 7 Compute normalised values of weighted sum by using the equations given below

$$P_i^n = \frac{P_i^w}{\max\left(N_i^w\right)} \tag{27}$$

$$N_i^n = 1 - \frac{N_i^w}{\max\left(N_w^k\right)} \tag{28}$$

Step 8 The appraisal score AS_i for all alternatives is calculated as:

$$AS_i = \frac{\left(P_i^n + N_i^n\right)}{2} \quad \text{where } 0 < AS_i > 1 \tag{29}$$

Step 9 The alternatives are ordered in decreasing order of appraisal score (AS_i). Table 18 presents ranks based on EDAS.

Table 18 Ranking based on EDAS method

	P_i^w	N_i^w	P_i^n	N_i^n	*ASi*	*Rank*
TI	0.1592	0.2372	0.2347	0.6244	0.4296	4
TA	0.0402	0.4286	0.0593	0.3213	0.1903	5
TC	0.275	0.0863	0.4054	0.8633	0.6344	3
TAD	0.316	0.0465	0.4658	0.9264	0.6961	2
TMS	0.6784	0.0388	1	0.9386	0.9693	1
IT	0	0.6315	0	0	0	6
	0.6784	0.6315				

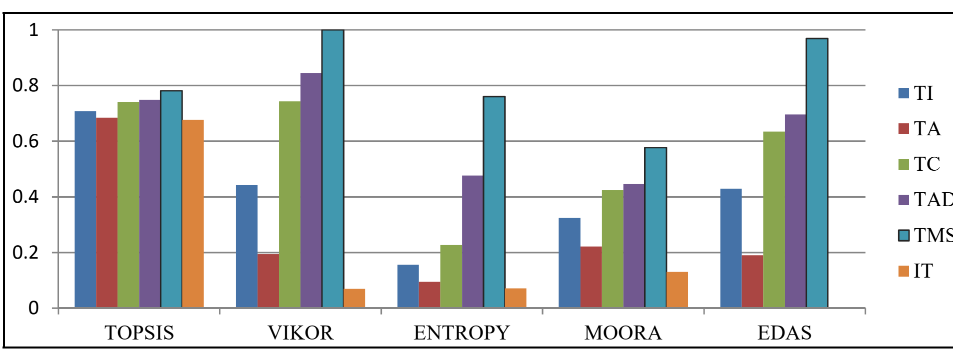
5 Results and discussion

The goal of the current study is to identify the technological competency factors that influence an organisation's performance. The TMS, TAD, technology capabilities (TC), technology infrastructure, technology acquisition (TA) and IT have been considered as significant technological competency factors in this study that affect the strategic business performance, production capacity, quality and production in manufacturing firms.

In various MCDM techniques, the normalisation procedure was performed on the decision matrix; the final weights of the factors calculated from the method are used to obtain the weighted matrix. In TOPSIS technique, the preferred alternative is the one with the most close to the positive ideal solution. With this technique, the top management is found to be closest to the ideal solution. In VIKOR, the factor with the highest performance score is considered more crucial than others. For other MCDM techniques, decision alternatives are formularised in the same way as stated previously in the TOPSIS and VIKOR methods. In case of ENTROPY method, the range of ENTROPY value E_i is [0, 1]. Higher value of weight factor is considered as critical one and so on. The weight of TMS, far more than any other factor become more critical. However, the weight of IT, the smallest among all the factors, is less critical. The MOORA method's fundamental tenet is to determine the performance's weighted sum. The best factor is determined by obtained the highest value calculated under the summated weighted normalised decision matrix. The desirability of alternatives in EDAS method is determined on the basis of their distances from an average solution because the average solution is determined by an arithmetic mean in this method. The appraisal scores (AS_i) for all alternatives are calculated and alternatives priority are based on decreasing value of appraisal score. TMS is positioned at first rank with maximum value of appraisal score and so on.

The maximum relative importance weight is used for obtaining the preference score. The factors with higher value of preference score (ranked 1), is most important factor in this study. Table 19 compares the ranking using various MCDM techniques. Figure 1 shows a column graph of the variables together with the variables overall rankings.

Figure 1 Ranking of variables during MCDM analysis (see online version for colours)



Out of six selected factors, the ranking order obtained as TMS is > TAD > TC > TI > TA > IT, respectively. The obtained results depict that assigning same weights to criteria causes similarity in alternatives' rankings.

Table 19 Comparison of rank using different MCDM techniques

	TOPSIS	*VIKOR*	*ENTROPY*	*MOORA*	*EDAS*
TI	4	4	4	4	4
TA	5	5	5	5	5
TC	3	3	3	3	3
TAD	2	2	2	2	2
TMS	1	1	1	1	1
IT	6	6	6	6	6

According to ranking, factors are split into two groups: those with strong and low influence. TMS, technological adoption, technological capability and TI play a vital role in the organisation for improving the performance from all aspects than other ones.

6 Conclusions

The issue of technology competency is crucial right now and will become even more significant in the future. It is important for Indian organisations to understand the competitive advantage that new technologies provide over those that already exist, but many of them are reluctant to investigate new technology. This paper has tried to identify several sources of a company's technological competencies. Following a thorough review of the available literature, six key technological competency factors were taken into account. The impact of these factors on the performance of manufacturing firms has been observed using a variety of qualitative methodologies, including TOPSIS, VIKOR, ENTROPY, MOORA and EDAS. All of the important factors are ranked from most to least importance on the basis of the score calculated.

It is found that on the basis of the score calculated, the factors: TMS, TAD, TC, TI were categorised as highly influential variables and the factors: TA, IT respectively were categorised as lowly influential variables. Further, issues related to TMS occupy the top most ranking, imply that to avail synergistic benefits for betterment of performance, it is essential for organisations to address the issues related to it. Without TMS, training and development of employees for embracing new technologies is not possible. So, top management has to take initiatives for developing technological competency issues like continuous improvement, workforce development by providing trainings. The integration of latest technologies into existing production system will improve technological competency of firm. The adoption of new technologies is a second significant component for the synergistic benefits because organisations that can quickly modify and adapt to new technologies might gain a competitive advantage over slower and less informed rivals. Third important factor is related to technological capability that can be assessed through the R and D of the organisation in improving the innovation performance. Another important factor for technological competency of organisations is TI. Without a proper infrastructure, enterprises cannot be considered as technologically competent.

Although multiple MCDM approaches used in this study were quite helpful in prioritising various factors. In order to improve future research outcomes, fuzzy MCDM approaches can be used to remove ambiguity and vagueness in this study. The context of this study is large and medium-sized Indian manufacturing firms. More than a hundred specialists, in order to choose the drivers for this research, were contacted for information. The number of specialists can be raised to improve the result's reliability. The outcomes of this empirical investigation will need to be modified before being used for other demographic regions and different sorts of sectors, such as the service industries, because all of the experts were from North India.

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