Tavana, M, Shaabani, A and Valaei, N

An Integrated Fuzzy Framework for Analyzing Barriers to the Implementation of Continuous Improvement in Manufacturing

Article

An Integrated Fuzzy Framework for Analyzing Barriers to the Implementation of Continuous Improvement in Manufacturing

Abstract

Purpose – Delivering premium services and quality products are critical strategies for success in manufacturing. Continuous improvement (CI), as an underlying foundation for quality management, is an ongoing effort allowing manufacturing companies to see beyond the present to create a bright future. We propose a novel integrated fuzzy framework for analyzing the barriers to the implementation of CI in manufacturing companies.

Design/methodology/approach – We use the fuzzy failure mode and effect analysis (FMEA) and a fuzzy Shannon's entropy to identify and weigh the most significant barriers. We then use fuzzy multi-objective optimization based on ratio analysis (MOORA), the fuzzy technique for order of preference by similarity to ideal solution (TOPSIS), and fuzzy simple additive weighting (SAW) methods for prioritizing and ranking the barriers with each method. Finally, we aggregate these results with Copeland's method and extract the main CI implementation barriers in manufacturing.

Findings – We show "low cooperation and integration of the team in CI activities" is the most important barrier in CI implementation. Other important barriers are "limited management support in CI activities," "low employee involvement in CI activities," "weak communication system in the organization," and "lack of knowledge in the organization to implement CI projects."

Originality/value – We initially identify the barriers to the implementation of CI through rigorous literature review and then apply a unique integrated fuzzy approach to identify the most important barriers based on the opinions of industry experts and academics.

Keywords: Continuous improvement; failure mode and effect analysis; fuzzy logic; Shannon's entropy; Copeland's method.

Introduction

Companies are required to minimize the level of waste, preserve the quality-low price ratio, accelerate manufacturing the process, and trim the product lines to foster core competencies. These core competencies can be achieved by implementing a rigorous continuous improvement (CI) (Bhuiyan *et al*., 2006). In competitive environments, organizations' prosperity depends upon the rate of process optimization and improvement (Salah *et al*., 2010) as well as the degree of progressive innovation (Bessant *et al*., 1994). Grounded in total quality management principles, CI is considered as an essential strategy in attaining manufacturing excellence (Tanco *et al*., 2012), minimizing failure, and achieving success (Bhuiyan *et al*., 2006). "CI must be adopted by each member of the organization" (Cheng and Podolsky, 1996), and one of the main challenges in implementing CI is the successful execution of its methodologies. The most widely-used CI methodologies in manufacturing are lean manufacturing (Kovach *et al*., 2008), Six Sigma (Kovach *et al*., 2008; Savolainen and Haikonen, 2007), lean Six Sigma (Timans *et al.,* 2016), structural equation modeling (Kovach *et al*., 2008; Lee, 2004; Ni and Sun, 2009; Singh and Singh, 2010), the interpretive structural model (Jurburg *et al*., 2017), non-parametric tests (Oprime *et al*., 2011), failure mode and effect analysis (Doshi and Desai, 2017), activity based costing (Waeytens and Bruggeman, 1994), achieving competitive excellence (Bhuiyan *et al*., 2006), plan-do-check-act (Singh and Singh, 2015; Afrin *et al*., 2019), balanced scorecard (Dabhilkar and Bengtsson, 2004), theory of Inventive Problem Solving (Maia *et al*., 2015), Bayesian belief networks (Mark and Oppenheim, 2019), the Kaizen approach and just-in-time management (Afrin *et al*., 2019), and decision-making trail and evaluation laboratory (Costa *et al*., 2019).

CI can be either incremental or radical. In the incremental phase, minor changes are incurred, and in the radical phase, significant changes are made, which may result in idea generation or innovative technology (Bhuiyan *et al*., 2006). Even though it happens gradually, a successful CI is a long-run process (Ni and Sun, 2009), and it requires changes in cultural, behavioral, and learning processes (Savolainen and Haikonen, 2007). In the manufacturing discipline, CI principles are applied for boosting quality and "diminishing costs while maintaining the same level of service" (Ross, 2015).

A science and technology parks (STPs) is an organization managed by specialized professionals, whose main purpose is increasing societal wealth and promoting justice and culture of competitiveness and innovation among its member companies and institutions (Tavares *et al*., 2009). As policy tools, STPs foster growth and promote innovation (Arauzo-Carod *et al*., 2018). They are also considered as driving forces of regional development. One of the main goals of the STPs is to create products and services based on the most current science practices and customers' needs. The knowledge spillovers of STPs can also benefit out-park firms and other stakeholders, such as providers, research centers, and clients (Díez-Vial and Fernández-Olmos, 2015). This requires them to improve their activities continuously, although there may be some barriers to its implementation.

Although the previous literature examined the impact of on-park location on companies' sales growth, improved R&D (Vásquez-Urriago *et al*., 2014), innovation (Vásquez-Urriago et al., 2016), employment growth (Hobbs *et al*., 2017), and cooperation with universities (Albahari *et al*., 2019), research is scant on the barriers to implement CI in STPs. In this regard, with a rigorous literature review, this study initially explores the barriers of implementing CI. Secondly, based on the opinions of industry experts and academics active in STPs and using a unique integrated fuzzy approach, this study ranks the barriers to identify the most important factors.

The failure mode and effect analysis (FMEA) is a systematic and structured method for discovering potential failures in processes, products, and/or services (Shaker *et al.*, 2019). FMEA evaluates three key process failure dimensions of severity, occurrence, and detection. Severity measures the seriousness, and occurrence measures the frequency of failures. A failure that occurs several times a day is more critical than a failure that occurs now and then. Detection measures the likeliness of detecting the failure before it occurs. FMEA has resulted in higher product quality and CI in manufacturing. In addition, FMEA documents current knowledge about the risks of failures, for use in CI. In FMEA, a matrix is constructed based on the three dimensions of severity, occurrence, and detection. This matrix is then analyzed with various multi-criteria decision making methods such as multi-objective optimization based on ratio analysis (MOORA), the technique for order of preference by similarity to ideal solution (TOPSIS), or simple additive weighting method (SAW). Finally, Copeland's method is used to determine the most important factors.

The novelty of this research is twofold. First, this study sheds light on the CI implementation barriers in STPs. Understanding the potential barriers are crucial for STPs as Cumming *et al.* (2019) argue technology parks are more likely to grow and succeed if they are supported by eliminating their barriers to success. Policymakers and top managers can nurture creativity and innovation in organizations if they recognize the CI implementation barriers and develop policies and procedures to alleviate them. Second, the novelty of this research also resides on a unique and seamless integrated fuzzy framework where the fuzzy FMEA and fuzzy Shannon's entropy are methodically combined to identify and weigh the most significant barriers; and fuzzy MOORA, fuzzy TOPSIS, fuzzy SAW, and Copeland's method are systematically combined to prioritize and rank the barriers. This integrated framework is novel and has not been implemented in previous research.

This paper is organized as follows. In Section 2, we review the literature and pinpoint factors associated with the barriers to CI implementation. In Section 3, we introduce an integrated model for analyzing barriers to CI implementation. The proposed model integrates fuzzy FMEA, fuzzy Shannon's entropy, fuzzy MOORA, fuzzy TOPSIS, and fuzzy SAW. In Section 4, we present a case study in the consumer electronics industry to demonstrate the applicability and efficacy of the proposed model. In Section 5, we present our conclusions and discussions. In Section 6, we discuss the managerial implications of our study followed by the limitations and future research directions in Section 7.

Literature review

Continuous improvement

Previous researches referred to CI as a process of continuous and focused incremental innovation extending throughout a company (Bessant *et al*., 1994; Bessant *et al*., 1999; Caffyn, 1999; Kumar *et al.*, 2018; Savolainen and Haikonen, 2007; Tanco *et al*., 2012). Deming (1982) defines CI as improving continuously in the system of service and production (Principle 5 of transformation) (Sanchez and Blanco, 2014). CI also denotes a methodical endeavor undertaken to find and use novel approaches to continuous process improvement. Anand *et al*. (2009), Jha *et al*. (1996), and Terziovski (2002) indicate that CI is a set of activities which is consists of a process aimed to bolster performance improvement. The notion of a CI system refers to the intertwined collection of systematic, organized, and planned processes of steady transformation within the whole organization emphasizing on reaching higher quality, ergonomics, safety, business productivity, and competitiveness (Jurburg *et al*., 2016, 2017). In this study, CI is defined as an ongoing effort to improve processes, products, and/or services through incremental and breakthrough improvements.

CI is about "constant focus on achieving better outcomes" (Langabeer, 2008). The CI has its roots in the Kaizen concept and the Deming cycle (Terziovski and Sohal, 2000). Kaizen, which means improvement and perfection in Japanese (Singh and Singh, 2010), is intertwined with four characteristics: incremental, participative, continuous (Tanco *et al*., 2012), and betterment of the standard way of work (Singh & Singh, 2014). Deming adopted the CI concept as his main quality criterion and the core of the popular "plan-do-check-act" cycle (Eaidgah Torghabehi *et al*., 2016). In addition, the CI concept is also a part of quality management (Nilsson-Witell *et al*., 2005) and previous research considers the strategic pillars of TQM as CI, employee involvement, teamwork, process and customer focus (Dean Jr and Bowen, 1994; Murray and Chapman, 2003; van Assen, 2018), fact-based emphasis, and management devotion (Dahlgaard *et al*., 1998).

Savolainen (1999) mentions that ideological views bring forward practical intuitions and new conceptual ideas to CI implementation resulting in a unique competitive advantage. Drawing on five-year research work, Bessant and Caffyn (1997) investigate the issues pertinent to CI implementation. Based on a comprehensive case study, they develop a behavioral framework model of CI performance pinpointing its enablers and barriers, and they argue that "CI is about behavioral change, and it involves both learning and unlearning" (p. 21). In addition, examining CI strategies in the context of manufacturing companies in Australia, Terziovski and Sohal, (2000) indicate that the stimulation to CI adoption is contingent upon several factors, namely cost reduction, enhanced delivery reliability, high productivity, and refined quality conformance. Thus, managers should comprehend the merits of CI activities in terms of "soft" management initiatives. In a rigorous case-based investigation, Bessant *et al*. (2001) consider CI as organizational merit that is empowered by high involvement in behavioral transformation (culture change). They also indicate that, as this merit evolves, it triggers innovative capabilities, which leads to a reference model of progress appraisal. Investigating ten Singaporean and Australian case studies, Hyland *et al*. (2003) propose a methodology for delineating learning behaviors, and they construct a framework for persistent, innovative activities in product development practices.

Oprime *et al*. (2011) conduct a study on the main variables of CI initiatives in Brazilian firms. The results of their explorative research highlight the significance of employees' reciprocal interaction, motivations for suggestions, and training for using problem-solving tools in CI success. They also indicate that CI operational activities are conducive to firm performance in terms of higher quality and customer satisfaction, lower associated cost, and improvement in staffs' capabilities.

Davison *et al*. (2005) have a different perspective on improving CI success. The CI effectiveness results from recognizing the knowledge resources for disseminating the best practice by utilizing a knowledge structure mapping technique. The study by Barber *et al*. (2006) showed an applied methodology for a knowledge-based system in aiding CI activities by using the data being stored in the company's maintenance, quality, and production databases. They argue that such process-based systems can instigate CI. Furthermore, Anand *et al*. (2009) have a different perspective towards CI, while, in their proposed model, they view it as a dynamic potency to the organizations which broadens the knowledge on the CI concept, and their framework provides the crucial dimensions of infrastructure for CI.

Heavey *et al*. (2014) validated a new framework consisting of the main forces of CI. These forces are enhanced methodology, better experts who are knowledgeable about employee performance, customer centralized strategic goals, and customer-driven co-leadership. They argue that their proposed model sheds more light on process-based organizations, improves employees' role in companies, and results in positive outcomes, namely ROI.

More researches are required for investigating the forces/barriers to CI implementation, as the relevant variables may change across the context/industry of the study. Moreover, Murray and Chapman (2003) raise the issue of lacking proper methodologies for CI, and they underline the need for an advanced, holistic, and unified CI methodology. Thus, this research proposes a unique integrated fuzzy approach. Finally, as shown in Table 1, this study summarizes the barriers of CI implementation based on a rigorous literature review.

Insert Table 1 Here

Science and Technology Parks (STPs)

STPs are locations where R&D facilities and startup incubators are gathered together to conduct joint R&D for universities, public research institutions, and private research labs in support of high-tech industries (Kang, 2017). STPs are relatively new phenomena, arising from the idea of promoting economic and social development, acting on the undiscovered or unused potentialities of science, technology, and innovation (Rubini, 2002). STPs play an increasingly influential role in the promotion and development of the knowledge economy (Ribeiro *et al*., 2016). STPs provide technical substructure, logistics, and administration for small businesses to expand their products, increase their competitiveness, by creating an innovation culture (Ribeiro *et al*., 2016).

Murat Ar and Baki (2011) examined the antecedents of firms' performance by using data collected from 270 managers in small and medium-sized enterprises (SMEs) located in Turkish STPs. The results show that product and process innovation, strategy, top management support, customer focus, organizational learning, creative capability, organizational collaboration, and supplier relationship have a positive association with a firm's performance in STPs.

Magalhaes and Zouain (2008) proposed an innovation service structure model for STPs in local or regional development. They created tools used to consider basic stakeholders' needs in the STPs, especially SMEs, to increase their ongoing partnership with firms, universities and R&D centers, and government agencies.

Basile (2011) investigated the relationship between networking and science parks' innovative capability in providing the connection to all companies and agents in an inter-organizational system of innovation. The empirical evidence of this research included 15 Italian STPs. The results showed that displaying the networking process facilitates innovation projects, but it will not necessarily lead to innovation success.

Herrero-Villa *et al*. (2014) evaluated the performance of STPs by utilizing the SIGRID model, which is based on the sustainable models of the European Foundation for Quality Management (EFQM) and the balanced scorecard. They showed (i) most of the factors in their proposed model are coincidental in importance and comparability, (ii) the model in its primary proposal is not helpful in the comparison of parks and, (iii) the model offers helpful information for the interior management and exterior relationship of every park.

Martínez-Cañas *et al*. (2011) used the concept of social capital to analyze how STPs facilitate the generation of goodwill and resources that companies obtain from their communications with other economic agents in the park. In their theoretical method, they proposed a model to understand how STPs make a valuable substructure for generating social benefits. They also proposed a theoretical approach for checking sources and materials, which create value at the company level.

Mian *et al*. (2012) showed successful STPs could operate as platforms for incubating science and technology businesses. In addition, Díez-Vial and Fernández-Olmos (2015) evaluated the role of STPs as places fostering local knowledge exchange. Empirical evidence was collected between 2007 and 2011 in a longitudinal analysis of 11,201 companies by using the Spanish database PITEC (Technological Innovation Panel). They concluded product innovation is higher when companies with interior R&D reciprocally share their knowledge with other companies active in R&D.

Vásquez-Urriago *et al.* (2016) investigated how STPs influence the cooperation between park companies and how this influence is channeled. Their findings indicated that being part of an STP increases the likelihood of collaboration for innovation and the intangible results of working with major innovation partners, mainly because of the higher degree of communication.

In summary, previous studies show the role of STPs is crucial in achieving economic prosperity. STPs need a structure that fits their purposes, prophecies (prospects), functions, duties, and activities for accomplishing their goals. STPs should stay current with the rapidly increasing up-to-date knowledge and scientific practices in a broad range of disciplines to implement CI in an ongoing and effective manner. STPs contribute to the growth and regional development when they are supported by creative and innovative stakeholders regularly. Furthermore, CI is a process allowing manufacturing companies to envision beyond the present time and focus on building a bright future. According to Albahari *et al.* (2019), there is no unanimity on how companies inside the STPs create value. In this study, we reveal the STPs' successful implementation gaps by identifying the barriers to CI implementation. We further develop a unique, systematic, and integrated fuzzy framework to identify, weigh, prioritize, and rank the most significant CI implementation barriers. The elimination of the CI implementation barriers is a prerequisite to STPs successfully appraise their goals, programs, and prospects, and achieve competitive advantage.

Methodology

In this study, a questionnaire was designed and distributed among industry experts and academics. The process of selecting the experts is purposeful/judgmental sampling. Purposeful/judgmental sampling seeks information-rich cases that can be studied in depth (Hoepfl, 1997) and is a conscious selection of a small number of data sources that meet particular criteria (Russell and Gregory, 2003). In this sampling method, the goal is to select experts who are knowledgeable about the study and its purposes. This is one of the few sampling methods that can be used to get information from specific people who have knowledge about the study and can provide the researcher with insightful information. This method is applicable when the number of qualified people in the field of the study is limited. Therefore, the current study used fuzzy FMEA, and the decision matrix of expert opinions was obtained in the pattern of linguistic variables, which were converted to triangular fuzzy numbers. For the fuzzy FMEA method, we used the opinions of three experts who are professors and active participants in STPs. We used a purposeful/judgmental sampling method since the number of qualified people who have the required knowledge and are willing to participate in the study is limited. In addition, for obtaining weighted and importance of expert opinions for failure modes (S, O, and D), this study applied fuzzy Shannon's entropy method, based on the expert opinions in the form of linguistic variables, and for this reason, we utilized the opinions of two other experts who are active members of the STPs.

In the next stage, for prioritizing and ranking the barriers, this research used fuzzy MOORA, fuzzy TOPSIS, and fuzzy SAW methods. Finally, this study applied the Copeland method to compare the result of the rankings. All the necessary steps of the proposed approach are illustrated in Figure 1.

Insert Figure 1 Here

The steps described in this research are as follows:

Step 1: Identify barriers using a literature review.

Step 2: Create the FMEA team, and make a list of the possible failure modes, and explain the relevant barriers.

Step 3: Assess expert opinions on barrier factors concerning the failure mode.

Step 4: Aggregate the fuzzy normalized matrix for "S, O, and D."

Step 5: Evaluate and obtain the subjective weights of the experts for the significance of "S, O, and D" of the barriers by fuzzy Shannon's entropy approach:

- The team members' linguistic assessments of every failure mode for "S, O, and D."
- Determine the decision matrix normalized for "S, O, and D."
- Acquire the subjective fuzzy weights of the barrier variables.

Step 6: Determine the weighted normalized fuzzy decision matrix for "S, O, and D."

Step 7: Rank the barriers using fuzzy MOORA concerning the weighted normalized fuzzy decision matrix obtained in Step 6.

Step 8: Rank the barriers using fuzzy TOPSIS concerning the weighted normalized fuzzy decision matrix obtained in Step 6.

Step 9: Calculating the fuzzy SAW method and ranking of the barriers by fuzzy SAW, concerning the weighted normalized fuzzy decision matrix obtained in Step 6.

Step 10: Using aggregation techniques by Copeland's method.
Step 11: Final ranking of the barriers.
The followings describe the details of the integrated approach used in this study.

Fuzzy FMEA

FMEA is generally applied as a strong method for determining and evaluating possible failures in different stages of the product lifecycle (Zhang and Zhang, 2015), and is typically used as a problem prevention tool (Shahin, 2004). FMEA is "a systematic method of analysis and ranking the risks associated with various product (or process) failure modes (both existing and potential), prioritizing them for remedial action, acting on the highest-ranked items, revaluating those items and returning to the prioritization step in a continuous loop until marginal returns set in" (Paciarotti *et al*., 2014). The main goal of FMEA is to find and rank the possible failure modes that harm the performance of a system (Sharma and Sharma, 2010). FMEA includes the review of the following steps in its processes: Severity of the failure modes (what could go wrong?), denoting the extent of the "end effect" of a system failure. The occurrence of the possibility of the failure causes (why would the failure happen?), denoting the rate at which a "root cause" is probable to happen, which is portrayed in qualitative terms. Detection of the failure modes (what would be the consequences of each failure?), denoting the probability of discovering a "root cause" before a failure that could happen (Victor et al., 2014; Jain, 2017).

The fuzzy FMEA is an appropriate method for a review of disorders and problems in a CI project. For example, the study by Doshi and Desai (2017) showed that in the context of automotive SMEs, continuous quality improvement is obtained by efficient FMEA implementation. Their study also indicated that even though FMEA's implementation needs to be monitored, it has the potency to determine the associated risks of the processes and their remedies.

Researches of the fuzzy FMEA method consider the experts that define the elements of risk in terms of O, S, and D by applying the fuzzy linguistic variables (Kutlu & Ekmekçioğlu, 2012). The merits of this rule-based fuzzy method to FMEA (Chanamool and Naenna, 2016; Kumru and Kumru, 2013) is outlined below:

- Using the linguistic elements of the fuzzy method allows the experts to allocate the relevant values for the variables being examined; therefore, improving the FMEA's pertinence. In addition, it aids the analysts to apply the linguistic elements to evaluate the related risks of failure instantly.

- Another merit is that both qualitative and quantitative data, implicit information, and ambiguity can be applied in the FMEA's evaluation and management consistently.
- The arrangement in the composition of the parameters S, O, and D, have more flexibility.

As experts allocate the different level of weights to the measures, they need to comprehend the implication of the linguistic terms as well as their assigned fuzzy numbers. The notion of linguistic variables is important for handling complicated instances which are not specified in detail and is less likely to be delineated by common quantitative statements (Zadeh, 1975). Fuzzy linguistic variables refer to the lingual statements or expressions such as sentences or words that are expressed in normal or unnatural language. In addition, a fuzzy digit that is suitably established for indicating the linguistic variable can be considered as a set value. The domain of this set value range between 0 and 1 and consists of real positive numbers (Zadeh, 1975).

Table 2 shows the set of linguistic terms and their relevant fuzzy numbers to evaluate the rating as well as the preference weight versus the expert assessment indices (Amiri, 2010).

Insert Table 2 Here

Fuzzy Shannon's entropy in terms of α-level sets

Shannon (1948) introduced the entropy method as a measurement for indeterminacy in a discrete distribution whose origin is grounded in the "Boltzmann entropy" of traditional statistical methods (Pourhamidi, 2013; Shannon, 1948). Shannon's entropy is a useful approach in achieving the weights for a MADM method (Lotfi and Fallahnejad, 2010), and it is referred to as a measure of uncertainty which has its roots in probability theory as well (Liu *et al*., 2015). Lotfi and Fallahnejad (2010) enhanced this method for obscure data, particularly for fuzzy data and interval cases (Ebrahimi *et al*., 2016; Mohamadi *et al*., 2017). This study also employs fuzzy Shannon's entropy method. The details of the fuzzy Shannon phases are expressed below:

Step 1: Converting the fuzzy digits into set-level data by applying the α-level sets. The α-level set of a fuzzy variable $\tilde{x}_{ij}$ refers to a class of terms about the fuzzy variable $\tilde{x}_{ij}$ with the participation of at least α, i.e., $\left(\tilde{x}_{ij}\right)_{\alpha} = \left\{ X_{ij} \in R \, l \, u_{\tilde{x}_{ij}} \left(X_{ij}\right) \geq \alpha \right\}$. The α-levels set formula is shown subsequently:

$$\left[\left(\tilde{x}_{ij}\right)_{\alpha}^{l},\left(\tilde{x}_{ij}\right)_{\alpha}^{u}\right]=\left[\ Min_{x_{ij}}\left\{x_{ij}\in R\middle|u_{x_{ij}}\left(X_{ij}\right)\geq\alpha\right\},\ Max_{x_{ij}}\left\{x_{ij}\in R\middle|u_{x_{ij}}\left(X_{ij}\right)\geq\alpha\right\}\ \right]$$

where $0 < \alpha \leq 1$.

Based on situating a disparate degree of the confidence interval, specifically $1-\alpha$, the fuzzy data are hereupon converted to varying α -level sets $\{(\tilde{x}_{ij})_{\alpha} \ |0\langle\alpha\leq 1\}$, where all of them are interval values.

Step 2: The normalized numbers of p_{ij}^{l} and p_{ij}^{u} are computed using the following formulas:

$$p_{ij}^{l}=\frac{x_{ij}^{l}}{\sum_{j=1}^{m}x_{ij}^{u}},\ p_{ij}^{u}=\frac{x_{ij}^{u}}{\sum_{j=1}^{m}x_{ij}^{u}}\ ,\quad j=1,...,m\ ;\ i=1,...,n \tag{1}$$

Step 3: In this step, the lower limit of h_{i}^{l} and the upper limit of h_{i}^{u} in the interval entropy, are extracted in the following formulas:

$$\begin{aligned}h_{i}^{l}&=Min\left\{-h_{0}\sum_{j=1}^{m}p_{ij}^{l}.\ln p_{ij}^{l},-h_{0}\sum_{j=1}^{m}p_{ij}^{u}.\ln p_{ij}^{u}\right\},i=1,...,n\\h_{i}^{u}&=Max\left\{-h_{0}\sum_{j=1}^{m}p_{ij}^{l}.\ln p_{ij}^{l},-h_{0}\sum_{j=1}^{m}p_{ij}^{u}.\ln p_{ij}^{u}\right\},i=1,...,n\end{aligned} \tag{2}$$

where $h_{0}=(\ln m)^{-1}$, and $p_{ij}^{l}.\ln p_{ij}^{l}$ or $p_{ij}^{u}.\ln p_{ij}^{u}$ has a value of 0 if $p_{ij}^{l}=0$ or $p_{ij}^{u}=0$.

Step 4: Assigning the lower limit and upper limit of the diversification interval of d_{i}^{l} and h_{i}^{u} as shown below:

$$d_{i}^{l}=1-h_{i}^{u},\ d_{i}^{u}=1-h_{i}^{l}\ ,\ i=1,...,n \tag{3}$$

Step 5: Set $w_{i}^{l}=\frac{d_{i}^{l}}{\sum_{s=1}^{n}d_{s}^{u}}$, $w_{i}^{u}=\frac{d_{i}^{u}}{\sum_{s=1}^{n}d_{s}^{l}}$, $i=1,...,n$ as the lower limit and upper limit of the interval weight of attribute i.

Step 6: To obtain the final weight, this study calculated $w_{i}^{'}=\frac{w_{i}^{l}+w_{i}^{u}}{2}$, then computed $\sum_{i}^{n}w_{i}^{'}$, and subsequently calculated $w_{i}=\frac{w_{i}^{'}}{\sum_{i}^{n}w_{i}^{'}}$.

Fuzzy MOORA

In the literature, the MOORA method is characterized as an MCDM method (Akkaya et al., 2015).

Initially indicated in a study by Brauers and Zavadskas (2006), MOORA refers to an optimization process of two or more contradictory attributes happening synchronously, which is conditional upon specified constraints. This method is applicable to a variety of complicated decision-making issues in different industries: process/product design problems, the manufacturing sector, automobile design, the oil and gas industry, aircraft design, finance, and in any instances where the best decisions are desired considering the balance between two or more contradictory attributes (Chakraborty, 2011; Gadakh *et al*., 2013).

Previous research builds upon a ranking criterion diverging from three computations: the "Ratio System," the "Reference Point," and the "Full Multiplicative Form of Multiple Objectives" (Ceballos *et al*., 2016). Then Brauers and Zavadskas (2006) introduced fuzzy MOORA as an MCDM method, and their study was the first that applied the method in the subsistence economy. According to the current literature, there are three distinguished ways to treat the issues emerging from fuzzy MOORA: the fuzzy ratio method, the full multiplicative form, and the reference point method. This study follows the guidelines of (Akkaya *et al*., 2015) in the fuzzy ratio approach. Following are the phases of the fuzzy ratio method applied in the current study:

Step 1: Determine the decision matrix by applying for the relevant triangular fuzzy numbers.

Step 2: Change the decision matrix to the normalized fuzzy decision matrix (according to the subsequent Equations (4), (5), and (6).

As $\tilde{X}_{ij}^{*} = \left(x_{ij}^{l*}, x_{ij}^{m*}, x_{ij}^{u*}\right)$ and $\forall i, j$;

$$x_{ij}^{l*} = x_{ij}^{l} / \sqrt{\sum_{i=1}^{m}\left[(x_{ij}^{l})^2 + (x_{ij}^{m})^2 + (x_{ij}^{u})^2\right]} \tag{4}$$

$$x_{ij}^{m*} = x_{ij}^{m} / \sqrt{\sum_{i=1}^{m}\left[(x_{ij}^{l})^2 + (x_{ij}^{m})^2 + (x_{ij}^{u})^2\right]} \tag{5}$$

$$x_{ij}^{u*} = x_{ij}^{u} / \sqrt{\sum_{i=1}^{m}\left[(x_{ij}^{l})^2 + (x_{ij}^{m})^2 + (x_{ij}^{u})^2\right]} \tag{6}$$

Step 3: Determine and calculate the weighted normalized fuzzy decision matrix by applying *W, which* is computed using the fuzzy Shannon method (please refer to step 6 of the fuzzy Shannon method).

As $V_{ij} = (v_{ij}^{l}, v_{ij}^{m}, v_{ij}^{u})$;

$$v_{ij}^{l} = w_j \chi_{ij}^{l*} \tag{7}$$

$$v_{ij}^{m} = w_j \chi_{ij}^{m*} \tag{8}$$

$$v_{ij}^{u} = w_j \chi_{ij}^{u*} \tag{9}$$

Step 4: Calculate the normalized performance values by deducting the wasteful measures from the overall value of the determined beneficial measures.

$$\tilde{y}_i = \sum_{j=1}^{g} \tilde{v}_{ij} - \sum_{j=g+1}^{n} \tilde{v}_{ij} \tag{10}$$

$\sum_{j=1}^{g} \tilde{v}_{ij}$: Benefit criteria for $1, \ldots, g$

$\sum_{j=g+1}^{n} \tilde{v}_{ij}$: Cost criteria for $g+1, \ldots, n$

g: refers to the utmost number of measures

(*n*-*g*): refers to the least number of measures

Step 5: Because normalized performance measures refer to fuzzy elements too, therefore, these measures ought to be converted to a non-fuzzy performance measure known as "best non-fuzzy performance" (BNP). In this research, the subsequent formula is applied to compute the BNP values:

As $\tilde{y}_i = (y_i^l, y_i^m, y_i^u)$;

$$BNP_i(y_i) = \frac{(y_i^u - y_i^l) + (y_i^m - y_i^l)}{3} + y_i^l \tag{11}$$

Finally, the calculated y_i values are ranked.

Fuzzy TOPSIS

Hwang and Yoon (1981) initially introduced the TOPSIS technique, which is a classic approach to untangle MCDM problems and provides a solution from a limited set of variables (Han and Trimi, 2018). This method is mainly applied to rank the issues (Sirisawat and Kiatcharoenpol, 2018). The notion of the TOPSIS method is contingent upon the criterion that the selected alternative need to have the smallest distance from the "positive ideal solution" (PIS) and the greatest distance from the "negative ideal solution" (NIS) (Keshteli and Davoodvandi, 2017; Kutlu and Ekmekçioğlu, 2012). In addition, the fuzzy TOPSIS method was introduced by Chen (2000) to untangle MCDM problems in a fuzzy setting to address indeterminacy in adjudication and assessments (Seyedmohammadi *et al*., 2018). Research indicates that the fuzzy TOPSIS technique is more efficient than the traditional TOPSIS technique in solving MCDM problems in addressing the uncertainties in decision-makers' assessments (Sirisawat and Kiatcharoenpol, 2018; Ighravwe and Ayoola Oke, 2017). This study follows the guidelines of Sun (2010) for the fuzzy TOPSIS technique as mentioned below:

Step 1. Determining the fuzzy-decision matrix.

Step 2. Creating the normalized fuzzy-decision matrix by Equations (4), (5), and (6).

Step 3. Calculating the weighted normalized fuzzy decision matrix by Equations (7), (8), and (9).

Step 4. Calculating the fuzzy PIS and the fuzzy NIS.

Based on the weighted normalized fuzzy-decision matrix, it can be noticed that elements of $\tilde{v}_{ij}$ are positively normalized TFN, and the spans of the sets are placed in the range between 0 and 1. Afterward, the fuzzy PIS A^+ (aspiration levels) and the fuzzy NIS A^- (the worst levels) can be specified as shown in the following formulas:

$$A^+ = \left(\tilde{v}_1^*, \tilde{v}_2^*, \ldots, \tilde{v}_n^*\right) \tag{12}$$

$$A^- = \left(\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\right) \tag{13}$$

Here:

$$\tilde{v}_j^* = (1,1,1) \otimes \tilde{w}_j = \left(lw_j, mw_j, uw_j\right) \text{ and } \tilde{v}_j^- = (0,0,0); j = 1,2,\ldots,n. \tag{14}$$

Step 5. Calculating $\tilde{d}_i^+$ and $\tilde{d}_i^-$ of each criterion by Equations (15), (16), and (17).

$$d_i^+ = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^*\right), \ i = 1,2,\ldots,m; \ \ j = 1,2,\ldots,n \tag{15}$$

$$d_i^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right), \ i = 1,2,\ldots,m; \ \ j = 1,2,\ldots,n \tag{16}$$

$$d\left(\tilde{A}, \tilde{B}\right) = \sqrt{\frac{1}{3}\left[\left(a_1 - b_1\right)^2 + \left(a_2 - b_2\right)^2 + \left(a_3 - b_3\right)^2\right]} \tag{17}$$

Step 6. Calculating the closeness coefficients using Equation (18):

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{18}$$

Fuzzy SAW

This method was initially introduced by Churchman and Ackoff (1954), and they used the SAW approach in solving a portfolio selection problem. The SAW approach is one of the optimal methods which has been extensively applied for MADM problems. One of the reasons for its popularity is the simplicity of the method in addressing MADM issues. Some studies also refer to the SAW approach as the "weighted summation approach" (Deni *et al*., 2013; Kumar *et al*., 2013). This study follows the guidelines of Roszkowska and Kacprzak (2016) for the fuzzy SAW approach where positive trapezoidal ordered fuzzy numbers are explained by the phases mentioned below:

Step 1: Create a fuzzy decision matrix $\hat{X} = \left(\hat{x}_{ij}\right)$.

Step 2: Determine the normalized fuzzy-decision matrix.

Step 3: Calculate the weighted normalized decision-matrix by applying the important measures of every benchmark $\hat{V} = \left(\hat{r}_{ij}\right)$, where

$$\hat{r}_{ij} = w_j . \hat{z}_{ij} \tag{19}$$

Step 4: Cumulate the performance ratings considering the whole specifications for every available possibility utilizing the subsequent formula:

$$FSAW\left(A_i\right) = \sum_{j=1}^{n} \hat{r}_{ij} \left(i = 1,...,m\right) \tag{20}$$

Step 5: The Rank ordering of the alternatives.

Results

We applied the method proposed in this study to find the barriers that hinder creativity and innovation in CI. Barriers to the implementation of the CI are identified through a rigorous and exhaustive literature review. Next, we formed the FMEA team and made a comprehensive list of the possible failure modes. We then used the fuzzy FMEA method to determine the S, O, and D, by using the assessments provided by the three experts, as shown in Table 2. This table shows the linguistic terms and their associated fuzzy numbers used to evaluate the ratings as well as the preference weights. Table 3 presents the expert judgments on the barriers concerning the failure modes.

Insert Table 3 Here

Subsequently, we aggregated the evaluation matrices of the fuzzy failure modes obtained by the three experts into one evaluation matrix, as shown in Table 4. We then normalized the evaluation matrix using Equations (4), (5), and (6), as shown in Table 4.

Insert Table 4 Here

In the next step, the evaluation of two experts in linguistic variables is presented in Table 2 to assess and obtain the subjective weight of barriers by using fuzzy Shannon's entropy method. Next, the team members' linguistic judgments are assessed for the S, O, and D failure modes, and the decision matrix is normalized for S, O, and D. Based on the interval data provided in Table 5, we calculated the values of the weights using Equations (1), (2), and (3). The fuzzy values are expressed as intervals using α-level sets. Jafarnejad Chaghooshi *et al*. (2012) found 0.3 alpha as an appropriate value for the Likert scale (see Table 2). The weighted barriers obtained by fuzzy Shannon's entropy provided in Table 6.

Insert Tables 5 and 6 Here

After identifying the barrier weights according to fuzzy Shannon's entropy method, we calculated the weighted normalized fuzzy-decision matrix. The results of the weighted normalized values are presented in Table 7. We then use the weighted normalized fuzzy decision matrix given in Table 7 and Equations (10) and (11) to rank the barriers based on fuzzy MOORA, fuzzy TOPSIS, and fuzzy SAW methods. The ranking results for the fuzzy MOORA method are presented in Table 8.

Insert Tables 7 and 8 Here

In the next step, we utilized the fuzzy TOPSIS method to obtain d_i^+, d_i^- for each barrier, using the weighted normalized fuzzy decision-matrix given in Table 8 and Equations (15), (16), and (17). The results are presented in Table 9. The fuzzy PIS (aspiration levels) and fuzzy NIS (the worst levels) are determined based on Equation (14), and the closeness coefficient of the barriers are determined based on Equation (18). The barriers are then ranked according to their closeness coefficients.

Insert Table 9 Here

Afterward, we used the fuzzy SAW method to rank the barriers to CI implementation based on the weighted normalized fuzzy decision-matrix given in Table7. We first determined the average fuzzy weight for each barrier, according to S, O, and D, and then calculated the aggregated S, O, and D based on Equation (20). Table 10 presents the rankings of the barriers to CI implementation.

Insert Table 10 Here

MCDM approaches may produce different rankings for the same set of options, putting the decision-maker(s) in a dilemma on choosing the most suitable option (Azimi et al., 2014). In these situations, it is important to examine alternative solutions carefully. However, examining different solutions produced by various MCDM approaches may turn into a complicated process (Ustinovichius *et al*., 2007). Several methods, known as "aggregation techniques," have been proposed to solve this problem. These techniques include the average rank method, the Borda's technique, and Copeland's method. We use Copeland's method to count the number of wins and the number of losses for each option because of its consistency and simplicity (Purjavad and Shirouyehzad, 2011). If the number of nodes in the method is higher, we encode it with *M*, where the row is in the column, and if the column is in line or the number of votes is equal, we encode it with *X*. In this method, the basis for the ranking is the diversity among the number of Ms in row i and the number of Xs in the column j ($i = j$); where the difference between the wins and the losses will be the basis of ranking (Moghimi and Taghizadeh Yazdi, 2016). The last row in Table 11 (ΣR) shows the number of losses for each option. The score produced by Copeland's method for each option reduces the number of losses (ΣR) from the number of wins (ΣC). The final ranking results of the barriers in CI implementation are presented in Figure 2 in addition to the ranking results produced by fuzzy MOORA, fuzzy TOPSIS, fuzzy SAW, and Copeland's methods.

Insert Table 11 and Figure 2 Here

Conclusions and discussion

STPs foster growth where creativity and innovation practices take place frequently, and they are considered the driving forces of regional development. Further, as the backbone of quality management and innovative practices, CI is an ongoing effort allowing manufacturing companies to see beyond the present, and to create a bright future. In the first step of this study, a rigorous and exhaustive literature review was conducted to identify the barriers to CI implementation in the STP companies. In addition, this study used fuzzy FMEA and fuzzy Shannon's entropy to identify and weigh the most significant barriers. Fuzzy MOORA, fuzzy TOPSIS, and fuzzy SAW methods were used to prioritize and rank the barriers with each method. Finally, the results for each fuzzy method were aggregated using Copeland's method to identify the pivotal CI implementation barriers in manufacturing. This research was first of its kind to develop a unique integrated fuzzy approach in CI. Organizations need to implement CI to improve the performance and develop products and services with less waste, less cost, and higher quality to maintain their core competency in the competitive marketplace. Arauzo-Carod et al. (2018) quote that "being located inside the STPs has a dual effect on firm performance," and there is a debate on how companies inside the STPs should create value (Albahari *et al.*, 2019).

In a rigorous and exhaustive literature review, we showed several barriers to CI implementation. These barriers were ranked using an integrated fuzzy FMEA, fuzzy Shannon's entropy, fuzzy MOORA, fuzzy TOPSIS, and fuzzy SAW approach based on the expert opinions. In addition, to compare the outputs of fuzzy MOORA, fuzzy TOPSIS, and fuzzy SAW, we used Copeland's method to aggregate the results and produce a final ranking of the barriers to CI implementation. "Low cooperation and integration of the team in CI activities" received the highest priority and other important barriers were identified as "limited management support in CI activities," "low employee involvement in CI activities," "weak communication system in the organization," and "lack of knowledge in the organization to implement CI projects."

Our study emphasized the importance of teamwork and cooperation among organizational members. Organizations must create necessary programs to ensure the coordination and communication between the staff and the stakeholders. We also showed the importance of top management's role in providing the necessary resources and the need for using the senior leadership capabilities incentivizing the staff. The top management must ensure the front-line managers are knowledgeable and supportive of the CI project implementation. In addition, we concluded that one of the main strategies conducive to CI success is a high level of employee involvement. Without employee involvement, CI is doomed to deadlock. Therefore, before implementing any CI programs, the organization needs to train the employees and ensure their involvement and devotion to the process.

An important barrier to CI implementation in our study is a weak communication system within the organization. For a successful CI implementation, effective communication systems need to be established to make sure that timely and adequate information flows within all levels of the organization (both bottom-up and top-down). Knowledge is a necessary ingredient for the successful implementation of the CI projects in organizations, and organizations need to conduct necessary training for both managers and employees. Knowledge-sharing leads to learning, and all stakeholders must participate in knowledge-sharing practices to circumvent challenges. There will be a disruption in the CI implementation if knowledge is not shared, and the information does not flow horizontally and vertically within the organization. A knowledge-sharing culture should be established before the CI implementation project commences.

Our ranking results also identified a lack of teamwork as an important barrier. Teamwork helps improve the employees' understanding of the opportunities and threats in CI implementation. Face-to-face communication and team collaboration among employees lead to high motivation and, in turn, results in successful CI implementation. Lack of a predefined role and responsibilities in the team is also found to be a barrier to CI implementation. Top managers need to lay down detailed responsibilities without obscurity. Employees need to be aware of the importance of their role in CI implementation. This will ignite a sense of responsibility amongst employees and resonate a feeling of being part of the company's success. In addition, organizations need to support employees' involvement in the CI implementation by using motivation and employee satisfaction practices.

Lack of management commitment to CI activities is another barrier to CI implementation. This barrier can have a direct impact on motivation, involvement, and teamwork. The lack of problem-solving skills is also a detrimental barrier to CI implementation. The results also suggest that lack of organizational culture and environment is another barrier to CI implementation. Successful and sustainable CI implementation needs a robust organizational system. As a result, the support of managers is important because they may otherwise prefer the status quo. A first and foremost matter in CI implementation is the corporate culture. The CI value needs to be injected into the organization and embraced by the employees. Garcia-sabater and Marin-garcia (2011) have shown that culture is a decisive factor in CI. While CI is likely to be adopted enthusiastically in non-traditional cultural settings (because people are less resistant to change), more effort is needed in aging organizations where employees spent several years with traditional culture. Finally, the lack of a specific CI strategy is another barrier to CI implementation, and organizations must formulate an effective CI implementation strategy consistent with organizational mission, objectives, and culture.

Managerial implications

STPs are the main mechanisms for public-private partnerships and initiatives, and the promotion of research, development, innovation, and technology transfer (Guadix *et al*., 2016). It is widely recognized that STPs are effective vehicles for promoting new technology-oriented companies, facilitating the commercialization of scientific study, and revitalizing regional economies (Zhang and Sonobe, 2011). STPs are generally staffed by academics and professionals with proven records of creating opportunities leading to innovation and economic growth. Through transferring R&D activities to other stakeholders such as start-ups, SMEs, large firms, universities, as well as public and private R&D, STPs create opportunities for innovation, economic development, and commercialization of new and emerging technologies. STPs need to appraise their goals, programs, and prospects to grow continuously to achieve a competitive advantage. The findings of this study are useful for practicing managers and researchers in STPs. Findings such as the need for communicating the values in STPs, facilitating cooperation and integration in cross-functional teams, the idea that management support resonates a successful innovation strategy and plays a major role in CI activities, ensuring a sound communication system to circulate a shared value across teams facilitating CI, and bolstering a culture of innovation and involvement in CI activities all foster growth and financial stability for emerging companies as well as established corporations. In summary, we believe this paper has useful and practical implications for research, practice and/or society. Our study shows the importance and impact of CI and STPs on economic and commercial growth, research and teaching, and public policy.

Limitations and further research directions

This study proposes a unique integrated fuzzy approach to distill the barriers to CI implementation. One of the limitations of the study is its reliance on the literature review. Therefore, future studies could employ inductive methods for investigating the barriers to CI implementation by using observations or interviews with top managers of STPs to revealing new factors, which are overlooked in the literature review. Using inductive methods, future researchers can start with a set of observations and then move from particular experiences to general propositions (or from data to theory) about those experiences. In addition, the chances are that some barriers to CI implementation are context-specific, and further research is needed to test the proposed integrated fuzzy approach in different contexts. Future research could also conduct a gap analysis to examine the extent to which the results vary across different contexts, industries, or cultures.

References

Afrin, A. B., Islam, R., Fontaine, R. A. H., Ali, M. Y., & Rahman, M. (2019). A new model of continuous improvement in total quality management from an islamic perspective. *Asian Academy of Management Journal*, Vol. 12 No. 1, pp. 129–149.

Ahmad, M. F., Yan, T. L., Wei, C. S., Aizat Ahmad, A. N., Raja Mohd Rasi, R. Z., Abdul Rahman, N. A., … Hashim, F. A. (2017). Continuous Improvement and its Barriers in Electrical and Electronic Industry. *MATEC Web of Conferences*, *135*, 00045.

Akkaya, G., Turanoǐlu, B., & Öztaş, S. (2015). An integrated fuzzy AHP and fuzzy MOORA approach to the problem of industrial engineering sector choosing. *Expert Systems with Applications*, Vol. 42 No. 24, pp. 9565–9573.

Albahari, A., Klofsten, M., & Rubio-Romero, J. C. (2019). Science and Technology Parks: a study of value creation for park tenants. *The Journal of Technology Transfer*, Vol. 44 No. 4, pp. 1256–1272.

Amiri, M. P. (2010). Project selection for oil-fields development by using the AHP and fuzzy TOPSIS methods. *Expert Systems with Applications*, Vol. 37 No. 9, pp. 6218–6224.

Anand, G., Ward, P. T., Tatikonda, M. V., & Schilling, D. A. (2009). Dynamic capabilities through continuous improvement infrastructure. *Journal of Operations Management*, Vol. 27 No. 6, pp. 444–461.

Anh, P., Alan, N., Nguyen, P. A., & Robinson, A. G. (2015). Continuous improvement in Vietnam: unique approaches for a unique culture. *Journal of Asia Business Studies*, Vol. 9 No. 2, pp. 195–211.

Arauzo-Carod, J.-M., Segarra-Blasco, A., & Teruel, M. (2018). The role of science and technology parks as firm growth boosters: an empirical analysis in Catalonia. *Regional Studies*, Vol. 52 No. 5, pp. 645–658.

Azimi, M. H., Taghizadeh, H., & Farahmand, N. F. (2014). Selection of industrial robots using the Polygons area method. *International Journal of Industrial Engineering Computations*, Vol. 5 No. 4, pp. 631–646.

Barber, K. D., Eduardo Munive-Hernandez, J., & Keane, J. P. (2006). Process-based knowledge management system for continuous improvement. *International Journal of Quality & Reliability Management*, Vol. 23 No. 8, pp. 1002–1018.

Basile, A. (2011). Networking System and Innovation Outputs: The Role of Science and

Technology Parks. *International Journal of Business and Management*, Vol. 6 No. 5, pp. 3–14.

Bessant, J., & Francis, D. (1999). Developing strategic continuous improvement capability. *International Journal of Operations & Production Management*, Vol. 19 No. 11, pp. 1106-1119.

Bessant, J., Caffyn, S., Gilbert, J., Harding, R., & Webb, S. (1994). Rediscovering continuous improvement. *Technovation*, Vol. 14 No. 1, pp. 17–29.

Bessant, J, & Caffyn, S. (1997). High involvement innovation through continuous improvement. *International Journal of Technology Management*, Vol. 14 No. 1, pp. 7–28.

Bessant, J, Caffyn, S., & Gallagher, M. (2001). An evolutionary model of continuous improvement behaviour. *Technovation*, Vol. 21 No. 2, pp. 67–77.

Bhuiyan, N., Baghel, A., & Wilson, J. (2006). A sustainable continuous improvement methodology at an aerospace company. *International Journal of Productivity and Performance Management*, Vol. 55 No. 8, pp. 671–687.

Brauers, W. K. M., & Zavadskas, E. K. (2006). The MOORA method and its application to privatization in a transition economy. *Control and Cybernetics*, Vol. 35 No. 2, pp. 445–469.

Caffyn, S. (1999). Development of a continuous improvement self-assessment tool. *International Journal of Operations & Production Management*, Vol. 19 No. 11, pp. 1138–1153.

Ceballos, B., Lamata, M. T., & Pelta, D. A. (2016). A comparative analysis of multi-criteria decision-making methods. *Progress in Artificial Intelligence*, Vol. 5 No. 4, pp. 315–322.

Chakraborty, S. (2011). Applications of the MOORA method for decision making in manufacturing environment. *International Journal of Advanced Manufacturing Technology*, Vol. 54 No. 9–12, pp.1155–1166.

Chan, M., Dowden, M., McAullay, D., Sibthorpe, B., Sargent, G., & Gardner, K. (2018). Impacts of continuous quality improvement in Aboriginal and Torres Strait islander primary health care in Australia. *Journal of Health Organization and Management*, Vol. 32 No. 4, pp. 545–571.

Chanamool, N., & Naenna, T. (2016). Fuzzy FMEA application to improve decision-making process in an emergency department. *Applied Soft Computing Journal*, Vol. 43, pp. 441–453.

Chen, C.-T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets and Systems*, Vol. 114 No. 1, pp. 1–9.

Cheng, T. C., & Podolsky, S. (1996). *Just-in-time manufacturing: an introduction*. Springer Science & Business Media.

Choudhury, S., & Pattnaik, S. (2020). Emerging themes in e-learning: A review from the stakeholders' perspective. *Computers & Education*, Vol. 144, Article 103657, https://doi.org/10.1016/j.compedu.2019.103657.

Churchman, C. W., & Ackoff, R. L. (1954). An approximate measure of value. *Journal of the Operations Research Society of America*, Vol. 2 No. 2, pp. 172–187.

Costa, F., Lispi, L., Staudacher, A. P., Rossini, M., Kundu, K., & Cifone, F. D. (2019). How to foster Sustainable Continuous Improvement: A cause-effect relations map of Lean soft practices. *Operations Research Perspectives*, *6*, pp. 100091.

Cumming, D., Werth, J.C., & Zhang, Y. (2019). Governance in entrepreneurial ecosystems: venture capitalists vs. technology parks. *Small Business Economics,* Vol. 52 No. 2, pp. 455-484.

da Veiga, A., Astakhova, L.V., Botha, A., & Herselman, M. (2020). Defining organisational information security culture – Perspectives from academia and industry. *Computers and Security*, Article 101713, https://doi.org/10.1016/j.cose.2020.101713.

Dabhilkar, M., & Bengtsson, L. (2004). Balanced scorecards for strategic and sustainable continuous improvement capability. *Journal of Manufacturing Technology Management*, Vol. 15 No. 4, pp. 350–359.

Dahlgaard, J. J., Kristensen, K., Kanji, G. K., Juhl, H. J., & Sohal, A. S. (1998). Quality management practices: a comparative study between East and West. *International Journal of Quality & Reliability Management*, Vol. 15 No. 8/9, pp. 812–826.

Davison, S., Gordon, J. L., & Robinson, J. A. (2005). Studying continuous improvement from a knowledge perspective. *Knowledge-Based Systems*, Vol. 18 No. 4, pp. 197–206.

Victor B. de Souza, R., & Cesar R. Carpinetti, L. (2014). A FMEA-based approach to prioritize waste reduction in lean implementation. *International Journal of Quality & Reliability Management*, Vol. 31 No. 4, pp. 346–366.

Dean Jr, J. W., & Bowen, D. E. (1994). Management theory and total quality: improving research and practice through theory development. *Academy of Management Review*, Vol. 19 No. 3, pp. 392–418.

Deming, W. E. (1982). Out of the crisis. Cambridge, MA: Center for Advanced Engineering Study.

Deni, W., Sudana, O., & Sasmita, A. (2013). Analysis and implementation fuzzy multi-attribute decision making SAW method for selection of high achieving students in faculty level. *International Journal of Computer Science Issues (IJCSI)*, Vol. 10 No. 1, pp. 674.

Díez-Vial, I., & Fernández-Olmos, M. (2015). Knowledge spillovers in science and technology parks: how can firms benefit most? *The Journal of Technology Transfer*, Vol. 40 No. 1, pp. 70–84.

Doshi, J., & Desai, D. (2017). Application of failure mode & effect analysis (FMEA) for continuous quality improvement - multiple case studies in automobile SMEs. *International Journal for Quality Research*, Vol. 11 No. 2, pp. 345–360.

Eaidgah Torghabehi, Y., Maki, A. A., Kurczewski, K., & Abdekhodaee, A. (2016). Visual management, performance management and continuous improvement: A lean manufacturing approach. *International Journal of Lean Six Sigma*, Vol. 7 No. 2, pp. 187–210.

Ebrahimi, E., Fathi, M. R., & Irani, H. R. (2016). A new hybrid method based on fuzzy Shannon's Entropy and fuzzy COPRAS for CRM performance evaluation (Case: Mellat Bank). *Iranian Journal of Management Studies*, Vol. 9 No. 2, pp. 333–358.

Fryer, K. J., Antony, J., & Douglas, A. (2007). Critical success factors of continuous improvement in the public sector: A literature review and some key findings. *TQM Magazine*, Vol. 19 No. 5, pp. 497–517.

Gadakh, V. S., Shinde, V. B., & Khemnar, N. S. (2013). Optimization of welding process parameters using MOORA method. *International Journal of Advanced Manufacturing Technology*, Vol. 69 No. 9-12, pp. 2031–2039.

Garcia-sabater, J. J., & Marin-garcia, J. A. (2011). Can we still talk about continuous improvement ? Rethinking enablers and inhibitors for successful implementation. *Int. J. Technology Management*, Vol. 55 No. 1/2, pp. 28–42.

Guadix, J., Carrillo-Castrillo, J., Onieva, L., & Navascues, J. (2016). Success variables in science and technology parks. *Journal of Business Research*, Vol. 69 No. 11, pp. 4870–4875.

Han, H., & Trimi, S. (2018). A fuzzy TOPSIS method for performance evaluation of reverse logistics in social commerce platforms. *Expert Systems with Applications*, Vol. 103, pp. *103*, 133–145.

Heavey, C., Ledwith, A., & Murphy, E. (2014). Introducing a new continuous improvement framework for increased organisational return on investment. *TQM Journal*, Vol. 26 No. 6, pp. 594–609.

Herrero-Villa, M. ., López, S., & Molero, J. (2014). for Sigrid1 Validation Methodology as an Evaluation Method for Science Parks Management: The Case of the Madrid Science Park and Park of the University. *Aijssnet.Com*, Vol. 3 No. 5, pp. 72–82.

Hobbs, K. G., Link, A. N., & Scott, J. T. (2017). The growth of US science and technology parks: does proximity to a university matter? *The Annals of Regional Science*, Vol. 59 No. 2, pp. 495–511.

Hoepfl, M. C. (1997). Choosing qualitative research: A primer for technology education researchers. Vol. 9 No. 1, pp. *(Fall 1997)*.

Hwang, C.-L., & Yoon, K. (1981). *Multiple Attribute Decision Making*. Chapman and Hall/CRC.

Hyland, P. W., Soosay, C., & Sloan, T. R. (2003). Continuous improvement and learning in the supply chain. *International Journal of Physical Distribution & Logistics Management*, Vol. 33 No. 4, pp. 316–335.

Ighravwe, D., & Ayoola Oke, S. (2017). Ranking maintenance strategies for sustainable maintenance plan in manufacturing systems using fuzzy axiomatic design principle and fuzzy-TOPSIS. *Journal of Manufacturing Technology Management*, Vol. 28 No. 7, pp. 961–992.

Jafarnejad Chaghooshi, A., Fathi, M. R., & Kashef, M. (2012). Integration of fuzzy Shannon's entropy with fuzzy TOPSIS for industrial robotic system section. *Journal of Industrial Engineering and Management*, Vol. 5 No. 1, pp. 102–114.

Jain, K. (2017). Use of failure mode effect analysis (FMEA) to improve medication management process. *International Journal of Health Care Quality Assurance*, Vol. 30 No. 2, pp. 175–186.

Jha, S., Noori, H., & Michela, J. L. (1996). The dynamics of continuous improvement; aligning organisationa attributes and activities for quality and productivity. *International Journal of Quality Science*, Vol. 1 No. 1, pp. 19–47.

Jing, S., Li, R., Niu, Z., & Yan, J. (2020). The application of dynamic game theory to participant's interaction mechanisms in lean management. *Computers and Industrial Engineering*, Vol. 139, Article 106196, https://doi.org/10.1016/j.cie.2019.106196.

Jurburg, D., Viles, E., Tanco, M., & Mateo, R. (2017). What motivates employees to participate in continuous improvement activities? *Total Quality Management and Business Excellence*, Vol. 28 No. 13-14, pp. 1469–1488.

Jurburg, D., Viles, E., Tanco, M., & Mateo, R. (2016). Continuous improvement leaders, followers and laggards: understanding system sustainability. *Total Quality Management & Business Excellence*, Vol. 29 No. 7-8, pp. 817-833.

Kang, B.-J. (2017). Role and Policies of STP in the Era of 4th Industrial Revolution from Triple Helix Viewpoint. *World Technopolis Review*, Vol. 6 No. 2, pp. 90–101.

Keshteli, R. N., & Davoodvandi, E. (2017). Using fuzzy AHP and fuzzy TOPSIS in fuzzy QFD: A case study in ceramic and tile industry of Iran. *International Journal of Productivity and Quality Management*, Vol. 20 No. 2, pp. 197–216.

Kovach, J., de la Torre, L., & Walker, D. (2008). Continuous improvement efforts in healthcare: A case study exploring the motivation, involvement and support necessary for success. *International Journal of Six Sigma and Competitive Advantage*, Vol. 4 No. 3, pp. 254–269.

Kumar, M., Jayaswal, P., & Kushwah, K. (2013). Exploring Fuzzy SAW Method for Maintenance Strategy Selection Problem of Material Handling Equipment. *International Journal of Current Engineering and Technology*, Vol. 3 No. 2, pp. 600–605.

Kumar, P., Maiti, J., & Gunasekaran, A. (2018). Impact of quality management systems on firm performance, *International Journal of Quality & Reliability Management*, Vol. 35 No. 5, pp. 1034–1059.

Kumru, M., & Kumru, P. Y. (2013). Fuzzy FMEA application to improve purchasing process in a public hospital. *Applied Soft Computing Journal*, Vol. 13 No. 1, pp. 721–733.

Kutlu, A. C., & Ekmekçioğlu, M. (2012). Fuzzy failure modes and effects analysis by using fuzzy TOPSIS-based fuzzy AHP. *Expert Systems with Applications*, Vol. 39 No. 1, pp. 61–67.

Langabeer, J. R. (2008). Health care operations management: a quantitative approach to business and logistics. In *Jones & Bartlett Learning,*.

Lee, H.-J. (2004). The role of competence-based trust and organizational identification in continuous improvement. *Journal of Managerial Psychology*, Vol. 19 No. 6, pp. 623–639.

Liu, H. C., You, J. X., You, X. Y., & Shan, M. M. (2015). A novel approach for failure mode and effects analysis using combination weighting and fuzzy VIKOR method. *Applied Soft Computing Journal*, Vol. 28, pp. 579–588.

Lodgaard, E., Ingvaldsen, J. A., Aschehoug, S., & Gamme, I. (2016). Barriers to Continuous Improvement: Perceptions of Top Managers, Middle Managers and Workers. *Procedia CIRP*, Vol. 41, pp.1119–1124.

Lotfi, F. H., & Fallahnejad, R. (2010). Imprecise Shannon's entropy and multi attribute decision making. *Entropy*, Vol. 12 No. 1, pp. 53–62.

Magalhaes, A. B. V. B., & Zouain, D. M. (2008, June). Innovation Services Structure for Science Technology Parks (STPs)–forging regional improvement mechanisms for companies, university and R&D centers and government partnership. In *The Proceedings of the XIX ISPIM Conference*.

Maia, L. C., Alves, A. C., & Leão, C. P. (2015). How could the TRIZ tool help continuous improvement efforts of the companies? *Procedia Engineering*, Vol. 131, pp. 343–351.

Mark, R., & Oppenheim, R. (2019). Ishikawa diagrams and Bayesian belief networks for continuous improvement applications. *The TQM Journal*, Vol. 31 No. 3, pp. 294–318.

Martínez-Cañas, R., Ruiz-Palomino, P., & Sáez-Martínez, F. J. (2011). A literature review of the effect of science and technology parks on firm performance: A new model of value creation through social capital. *African Journal of Business Management*, Vol. 5 No. 30, pp. 11999.

Message Costa, L.B., Godinho Filho, M., Fredendall, L.D., & Devós Ganga, G.M. (2020). The effect of Lean Six Sigma practices on food industry performance: Implications of the Sector's experience and typical characteristics. *Food Control*, Vol. 112, Article 107110, https://doi.org/10.1016/j.foodcont.2020.107110.

McLean, R. S., Antony, J., & Dahlgaard, J. J. (2017). Failure of continuous improvement initiatives in manufacturing environments: a systematic review of the evidence. *Total Quality Management & Business Excellence*, Vol. 28 No. (3-4), pp. 219-237.

Mian, S., Fayolle, A., & Lamine, W. (2012). Building sustainable regional platforms for incubating science and technology businesses: Evidence from US and French science and technology parks. *The International Journal of Entrepreneurship and Innovation*, Vol. 13 No. 4, pp. 235-247.

Moghimi, M., & Taghizadeh Yazdi, M. (2016). *Applying Multi-Criteria Decision-Making (MCDM) Methods for Economic Ranking of Tehran-22 Districts to Establish Financial and Commercial Centers (Case : City of Tehran)*. Vol. 5 No. 20, pp. 43–55.

Mohamadi, S., Ebrahimi, A., & Alimohammadlou, M. (2017). An application of fuzzy screening, fuzzy AHP and fuzzy Shannon's entropy on identification and prioritisation of effective factors in assessment of contractors in Fars Electric Power Distribution Company, Iran. *International Journal of Procurement Management*, Vol. 10 No. 2, pp. 194.

Murat Ar, I., & Baki, B. (2011). Antecedents and performance impacts of product versus process innovation. *European Journal of Innovation Management*, Vol. 14 No. 2, pp. 172–206.

Murray, P., & Chapman, R. (2003). From continuous improvement to organisational learning: developmental theory. *The Learning Organization*, Vol. 10 No. 5, pp. 272–282.

Newham, J., Schierhout, G., Bailie, R., & Ward, P. R. (2016). "There's only one enabler; Come up, help us": Staff perspectives of barriers and enablers to continuous quality improvement in Aboriginal primary health-care settings in South Australia. *Australian Journal of Primary Health*, Vol. 22 No. 3, pp. 244–254.

Ngai, E. W. T., & Cheng, T. C. E. (1997). Identifying potential barriers to total quality management using principal component analysis and correspondence analysis. *International Journal of Quality & Reliability Management*, Vol. 14 No. 4, pp. 391–408.

Ni, W., & Sun, H. (2009). The relationship among organisational learning, continuous improvement and performance improvement: An evolutionary perspective. *Total Quality Management and Business Excellence*, Vol. 20 No. 10, pp. 1041–1054.

Nilsson-Witell, L., Antoni, M., & Dahlgaard, J. J. (2005). Continuous improvement in product development. *International Journal of Quality & Reliability Management*, Vol. 22 No. 8, pp. 753–768.

Oprime, P. C., Henrique de Sousa Mendes, G., Lopes Pimenta, M., Henrique, G., Mendes, D. S., & Pimenta, M. L. (2011). Continuous improvement: critical factors in Brazilian industrial companies. *International Journal of Productivity and Performance Management*, Vol. 61 No. 1, pp. 69–92.

Paciarotti, C., Mazzuto, G., & D'Ettorre, D. (2014). A revised FMEA application to the quality control management. *International Journal of Quality & Reliability Management*, Vol. 31 No. 7, pp. 788–810.

Pourhamidi, M. (2013). Prioritisation of knowledge management strategies in the learning organisation: an integrated Shannon's entropy-TOPSIS methodology. *International Journal of Learning and Intellectual Capital*, Vol. 10 No. (3/4), pp. 213.

Purjavad, E., & Shirouyehzad, H. (2011). A MCDM Approach for Prioritizing Production Lines: A Case Study. *International Journal of Business and Management*, Vol. 6 No. 10, pp. 221–229.

Ribeiro, J., Higuchi, A., Bronzo, M., Veiga, R., & De Faria, A. (2016). A framework for the strategic management of science & technology parks. *Journal of Technology Management and Innovation*, Vol. 11 No. 4, pp. 80–90.

Ross, D. F. (2015). *Distribution Planning and control: managing in the era of supply chain management*. Springer.

Roszkowska, E., & Kacprzak, D. (2016). The fuzzy saw and fuzzy TOPSIS procedures based on ordered fuzzy numbers. *Information Sciences*, Vol. 369, pp. 564–584.

Rubini, D. (2002). *A critical analysis of Science and Technology Parks: Learning from the Italian Experience* (Doctoral dissertation, Thesis for the Degree of Master of Science in Engineering Policy and Technology Management, Supervised by Manuel Fredrico Tojal de Valsassina Heitor, Universidade Tecnica de Lisboa, Instituto Superior Tecnico).

Russell, C. K., & Gregory, D. M. (2003). Evaluation of qualitative research studies EBN users ' guide Evaluation of qualitative research studies. *Evidence Based Nursing*, Vol. 6, pp. 36–40.

Salah, S., Carretero, J. A., & Rahim, A. (2010). The integration of quality management and continuous improvement methodologies with management systems. *International Journal of Productivity and Quality Management*, Vol. 6 No. 3, pp. 269.

Sanchez, L., & Blanco, B. (2014). Three decades of continuous improvement. *Total Quality Management and Business Excellence*, Vol. 25 No. 9-10, pp. 986–1001.

Savolainen, T., & Haikonen, A. (2007). Dynamics of organizational learning and continuous improvement in six sigma implementation. *The TQM Magazine*, Vol. 19 No. 1, pp. 6–17.

Savolainen, T. I. (1999). Cycles of continuous improvement. *International Journal of Operations & Production Management*, Vol. 19 No. 11, pp. 1203–1222.

Seyedmohammadi, J., Sarmadian, F., Jafarzadeh, A. A., Ghorbani, M. A., & Shahbazi, F. (2018). Application of SAW, TOPSIS and fuzzy TOPSIS models in cultivation priority planning for maize, rapeseed and soybean crops. *Geoderma*, *310*(November 2016), pp. 178–190.

Shahin, A. (2004). Integration of FMEA and the Kano model: An exploratory examination. *International Journal of Quality and Reliability Management*, Vol. 21 No. 7, pp.731–746.

Shaker, F., Shahin, A., & Jahanyan, S. (2019). Developing a two-phase QFD for improving FMEA: an integrative approach. *International Journal of Quality & Reliability Management*, Vol. 36 No. 8, pp. 1454–1474.

Shannon, C. E. (1948). A Mathematical Theory of Communication. *Bell System Technical Journal*, Vol. 27 No. 3, pp. 379–423.

Sharma, R. K., & Sharma, P. (2010). System failure behavior and maintenance decision making using, RCA, FMEA and FM. *Journal of Quality in Maintenance Engineering*, Vol. 16 No. 1, pp. 64–88.

Singh, J, & Singh, H. (2018). Modelling of barriers and initiatives of continuous improvement approach for enhancing the performance of SMEs of Northern India. *International Journal of Services and Operations Management*, Vol. 29 No. 2, pp. 184–213.

Singh, J, & Singh, H. (2010). Assessment of continuous improvement approach in SMEs of Northern India. *International Journal of Productivity and Quality Management*, Vol. 5 No. 3, pp. 252–268.

Singh, J, & Singh, H. (2014). Performance enhancement of a manufacturing industry by using continuous improvement strategies - a case study. *International Journal of Productivity and Quality Management*, Vol. 14 No. 1, pp. 36.

Singh, J, & Singh, H. (2015). Continuous improvement philosophy – literature review and directions. *Benchmarking: An International Journal*, Vol. 22 No. 1, pp. 75–119.

Sirisawat, P., & Kiatcharoenpol, T. (2018). Fuzzy AHP-TOPSIS approaches to prioritizing solutions for reverse logistics barriers. *Computers and Industrial Engineering*, *117*(April 2017), pp. 303–318.

Sola, A.V.H., & Mota, C.M.M. (2020). Influencing factors on energy management in industries. *Journal of Cleaner Production*, Vol. 248, Article 119263, https://doi.org/10.1016/j.jclepro.2019.119263.

Stelson, P., Hille, J., Eseonu, C., & Doolen, T. (2017). What drives continuous improvement project success in healthcare? *International Journal of Health Care Quality Assurance*, *30*(1).

Sun, C. C. (2010). A performance evaluation model by integrating fuzzy AHP and fuzzy TOPSIS methods. *Expert Systems with Applications*, Vol. 37 No. 12, pp. 7745–7754.

Swuste, P., Groeneweg, J., Gulijk, C., Zwaard, W., Lemkowitz, S., & Oostendorp, Y. (2020). The future of safety science. *Safety Science*, Vol. 125, Article 104593, https://doi.org/10.1016/j.ssci.2019.104593.

Talib, F., Asjad, M., Attri, R., Siddiquee, A., & Khan, Z. (2019). Ranking model of total quality management enablers in healthcare establishments using the best-worst method. *The TQM Journal*, Vol. 31 No. 5, pp. 790–814.

Tanco, M., Mateo, R., Santos, J., Jaca, C., & Viles, E. (2012). On the relationship between continuous improvement programmes and their effect on quality defects: An automotive case study. *Total Quality Management & Business Excellence*, Vol. 23 No. 3-4, pp. 277–290.

Tavares, R., Superiore, S., & Anna, S. (2009). Science and technology parks: An overview of the ongoing initiatives in Africa. *African Journal of Political Science and International Relations*, Vol. 3 No. 5, pp. 208–223.

Terziovski, M. (2002). Achieving performance excellence through an integrated strategy of radical innovation and continuous improvement. *Measuring Business Excellence*, Vol. 6 No. 2, pp. 5–14.

Terziovski, M., & Sohal, A. S. (2000). The adoption of continuous improvement and innovation strategies in Australian manufacturing firms. *Technovation*, Vol. 20 No. 10, pp. 539–550.

Timans, W., Ahaus, K., van Solingen, R., Kumar, M., & Antony, J. (2016). Implementation of continuous improvement based on Lean Six Sigma in small-and medium-sized enterprises. *Total Quality Management & Business Excellence* Vol. 27 No. 3-4, pp., 309–324.

Ustinovichius, L., Zavadskas, E. K., & Podvezko, V. (2007). Application of a quantitative multiple criteria decision making (MCDM-1) approach to the analysis of investments in construction. *Control and Cybernetics*, Vol. 36 No. 1, pp. 251–268.

van Assen, M. F. (2018). The moderating effect of management behavior for Lean and process improvement. *Operations Management Research*. Vol. 11, No. 1–2, pp. 1–13.

Vásquez-Urriago, Á. R., Barge-Gil, A., & Rico, A. M. (2016). Science and technology parks and cooperation for innovation: Empirical evidence from Spain. *Research Policy*, Vol. 45 No. 1, pp. 137–147.

Vásquez-Urriago, Á. R., Barge-Gil, A., Rico, A. M., & Paraskevopoulou, E. (2014). The impact of science and technology parks on firms' product innovation: empirical evidence from Spain. *Journal of Evolutionary Economics*, Vol. 24 No. 4, pp. 835–873.

Waeytens, D., & Bruggeman, W. (1994). Barriers to successful implementation of ABC for continuous improvement: A case study. *International Journal of Production Economics*, Vol. 36 No. 1, pp. 39–52.

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning-I. *Information Sciences*, Vol. 8 No. 3, pp. 199–249.

Zhang, F., & Zhang, W. (2015). Failure modes and effects analysis based on fuzzy TOPSIS. *2015 IEEE International Conference on Grey Systems and Intelligent Services (GSIS)*, (2008), pp.588–593.

Zhang, H., & Sonobe, T. (2011). Development of Science and Technology Parks in China, 1988–2008. *Economics: The Open-Access, Open-Assessment E-Journal*, Vol. 5 No. 6.

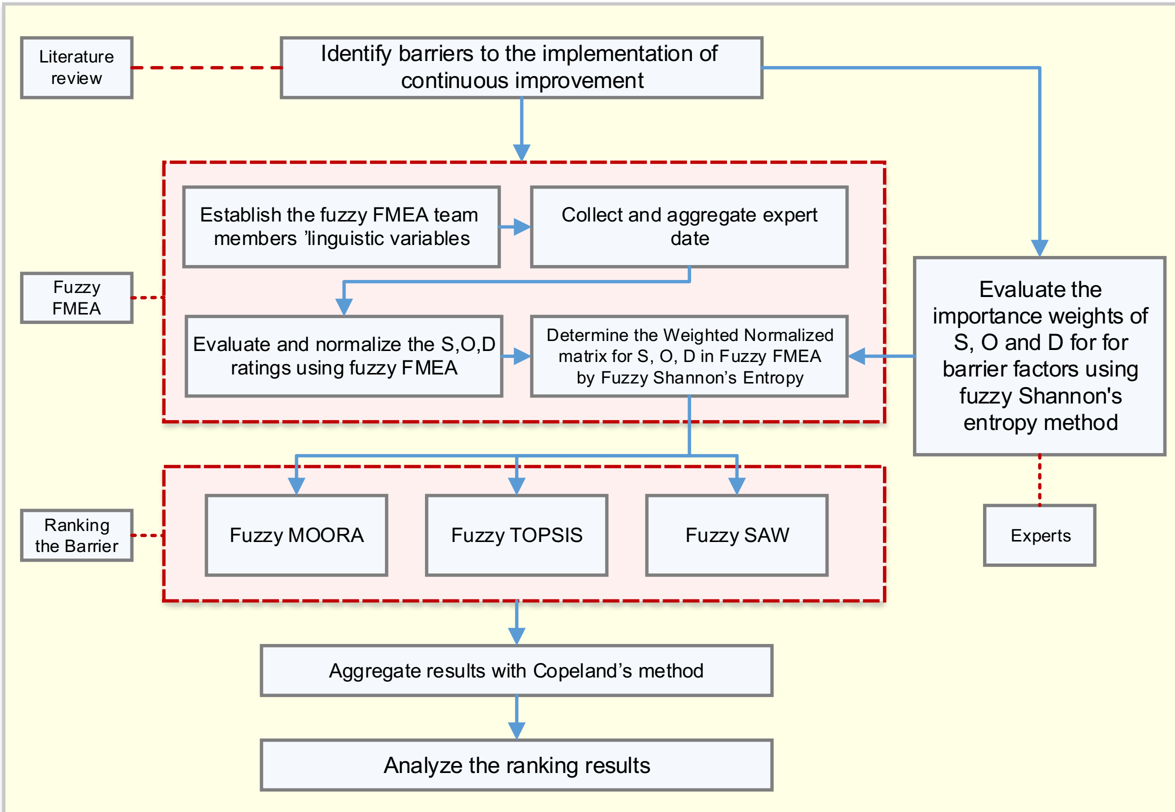

Figure 1: Proposed flowchart of the study

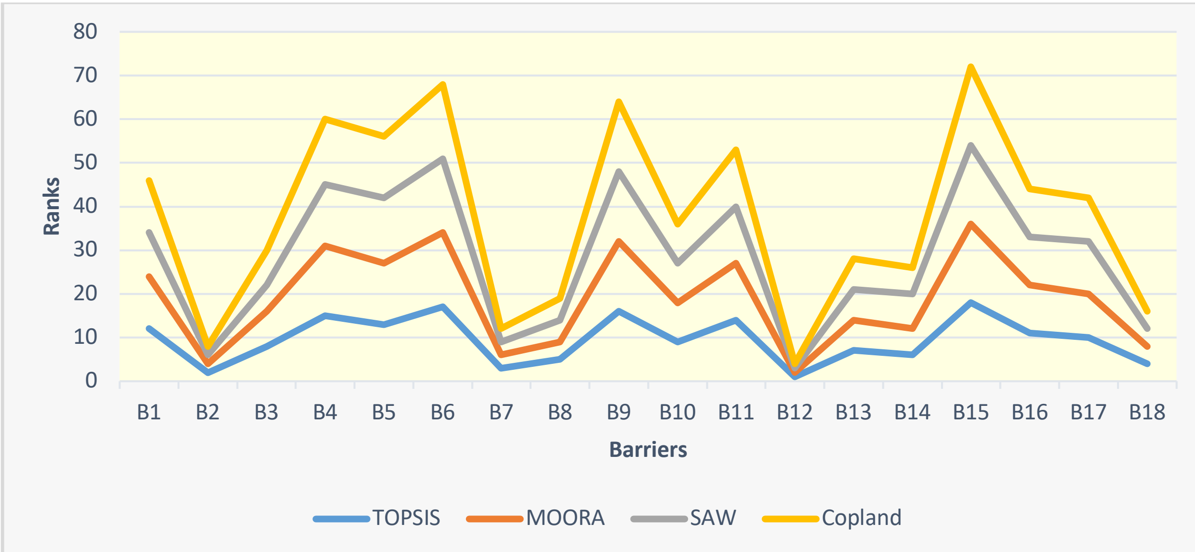

Figure 2: Comparing the ranking result of the barriers

Table 1: Barriers to the implementation of continuous improvement

	Barrier to CI	Resources	Methodology
B1	Lack of management commitment to CI activities	(Anh *et al*., 2015), (Singh and Singh, 2015) , (Ngai and Cheng, 1997), (Singh and Singh, 2018), (Ahmad *et al*., 2017)	Case study (Anh *et al*., 2015), Literature review (Singh and Singh, 2015), Lean Manufacturing tool (Ahmad *et al*., 2017), Principal component analysis (PCA) and Correspondence analysis (CA) (Ngai and Cheng, 1997), Options Field Methodology (OFM), Options Profile Methodology (OPM), Analytic Hierarchy Process (AHP), Fuzzy Set Theory (FST) and Structural Equation Modelling SEM (Singh and Singh, 2018)
B2	Limited support from management to CI activities	(Stelson *et al*.,2017), (Fryer *et al*., 2007), (Newham *et al*., 2016), (Garcia-sabater and Marin-garcia, 2011)	Literature review (Stelson *et al*., 2017; Choudhury and Pattnaik, 2020), Literature review (Fryer *et al*., 2007), Multiple case study approach (Newham *et al*., 2016), Grounded theory (Garcia-sabater and Marin-garcia, 2011) , Survey (Message Costa *et al*., 2020)
B3	Lack of management involvement in CI activities	(Lodgaard *et al*., 2016), (*Talib et al*., 2019)	Case study (Lodgaard *et al*., 2016) Best-Worst-Method (*Talib et al*., 2019)
B4	Lack of a specific strategy in the field of CI	(Bessant et al., 1994)	Literature review (Choudhury and Pattnaik, 2020) Case study (Bessant *et al*., 1994)
B5	Lack of organizational culture and environment to support CI	(Mclean *et al*., 2015)	Literature review (Systematic reviews) (Mclean *et al*., 2015)
B6	Lack of employee motivation in the organization	(Oprime *et al*., 2011), (Ahmad *et al*., 2017), (Garcia-sabater and Marin-garcia, 2011)	Non-parametric tests (Oprime *et al*., 2011), Lean Manufacturing tool(Ahmad *et al*., 2017), Grounded theory (Garcia-sabater and Marin-garcia, 2011)
B7	Low employee involvement in CI activities	(Oprime *et al*., 2011), (Mclean *et al*., 2015), (Ngai and Cheng, 1997), (Singh and Singh, 2015)	Non-parametric tests (Oprime *et al*., 2011), Principal component analysis (PCA) and Correspondence analysis (CA) (Ngai and Cheng, 1997), Literature review (Systematic reviews) (Mclean *et al*., 2015) Literature review (Singh and Singh, 2015)
B8	Lack of knowledge in CI implementation	(Ahmad *et al*., 2017)	Survey (Sola and Mota, 2020; Message Costa et al., 2020) Lean Manufacturing tool (Ahmad *et al*., 2017) Literature review (Swuste et al., 2020)
B9	Lack of a culture of knowledge capturing among employees	(Lodgaard *et al*., 2016)	Survey (Sola and Mota, 2020; Message Costa et al., 2020) Case study (Lodgaard *et al*., 2016; Jing et al., 2020)
B10	Lack of knowledge sharing culture among employees	(Lodgaard *et al*., 2016)	Survey (Sola and Mota, 2020) Case study (Lodgaard *et al*., 2016; Jing et al., 2020) Literature review (Swuste et al., 2020)
B11	Lack of abilities and skills in problem-solving of the teams in CI implementation	(Oprime *et al*., 2011), (Stelson *et al*., 2017), (Bessant and Caffyn, 1997)	Non-parametric tests (Oprime *et al*., 2011), Literature review (Kaizen event) (Stelson *et al*., 2017), Literature review(Bessant and Caffyn, 1997)
B12	Low cooperation and integration of the team in CI activities	(Oprime *et al*., 2011), (Stelson *et al*., 2017)	Non-parametric tests (Oprime *et al*., 2011), Literature review (Kaizen event) (Stelson *et al*., 2017)
B13	Lack of teamwork	(Fryer *et al*., 2007),(Newham *et al*., 2016), (Ahmad *et al*., 2017), (Chan *et al*., 2018)	Literature review (Fryer *et al*., 2007), Case study (Newham *et al*., 2016), Lean Manufacturing tool (Ahmad *et al*., 2017), Systematic database review (Chan *et al*., 2018)
B14	Lack of covering all relevant CI initiatives	(Lodgaard *et al*., 2016)	Case study (Lodgaard *et al*., 2016)
B15	Not user-friendly system [technical] in CI method	(Lodgaard *et al*., 2016)	Case study (Lodgaard *et al*., 2016)
B16	Lack of employee reward system	(Anh *et al*., 2015), (Ngai and Cheng, 1997)	Case study (Anh *et al*., 2015), Principal component analysis (PCA) and Correspondence analysis (CA) (Ngai and Cheng, 1997)
B17	Lack of defined role and responsibilities of each person in the team in CI implementation	(Lodgaard *et al*., 2016)	Survey (da Veiga *et al*., 2020) Case study (Lodgaard *et al*., 2016)
B18	A weak communication system in the organization	(Oprime *et al*., 2011)	Non-parametric tests (Oprime *et al*., 2011)

Table 2: Linguistic variables

Linguistic variables for rating the failure modes		Linguistic variables for the weighting of each criterion		Interval values for linguistic variables
Linguistic variables	**Triangular fuzzy number for fuzzy FMEA**	**Linguistic variables (priority weights)**	**Triangular fuzzy number for fuzzy Shannon**	**Interval data at** 0.3α
Very low (VL)	(0,0.1,0.3)	Unimportant (UI)	(0,0,0.2)	[0,0.17]
Low (L)	(0.1,0.3,0.5)	Slightly important (SI)	(0,0.2,0.4)	[0.07,0.42]
Medium (M)	(0.3,0.5,0.7)	Fairly important (FI)	(0.2,0.4,0.6)	[0.32,0.67]
High (H)	(0.5,0.7,0.9)	Important (I)	(0.4,0.6,0.8)	[0.57,0.92]
Very High (VH)	(0.7,0.9,1)	Very important (VI)	(0.6,0.8,1)	[0.82,1]

Table 3: Assessment of experts in linguistic variables of the barriers factors according to any failure mode

DM	Severity(S)			Occurrence(O)			Detection(D)			DM	Severity(S)			Occurrence(O)			Detection(D)		
	DM1			DM2			DM3				DM1			DM2			DM3		
B1	0.5	0.7	0.9	0.3	0.5	0.7	0.5	0.7	0.9	**B10**	0.1	0.3	0.5	0.1	0.3	0.5	0.3	0.5	0.7
B2	0.5	0.7	0.9	0.5	0.7	0.9	0.7	0.9	1	**B11**	0.3	0.5	0.7	0.1	0.3	0.5	0.5	0.7	0.9
B3	0.5	0.7	0.9	0.5	0.7	0.9	0.5	0.7	0.9	**B12**	0.3	0.5	0.7	0.5	0.7	0.9	0.5	0.7	0.9
B4	0.3	0.5	0.7	0.5	0.7	0.9	0.5	0.7	0.9	**B13**	0.5	0.7	0.9	0.7	0.9	1	0.3	0.5	0.7
B5	0.5	0.7	0.9	0.1	0.3	0.5	0.7	0.9	1	**B14**	0.5	0.7	0.9	0.3	0.5	0.7	0.5	0.7	0.9
B6	0.7	0.9	1	0.5	0.7	0.9	0.5	0.7	0.9	**B15**	0.5	0.7	0.9	0.1	0.3	0.5	0.5	0.7	0.9
B7	0.7	0.9	1	0.7	0.9	1	0.5	0.7	0.9	**B16**	0.7	0.9	1	0.3	0.5	0.7	0.5	0.7	0.9
B8	0.5	0.7	0.9	0.7	0.9	1	0.5	0.7	0.9	**B17**	0.3	0.5	0.7	0.3	0.5	0.7	0.5	0.7	0.9
B9	0.3	0.5	0.7	0.3	0.5	0.7	0.7	0.9	1	**B18**	0.5	0.7	0.9	0.7	0.9	1	0.5	0.7	0.9

Table 4: Aggregation of the experts and evaluation of the fuzzy normalized matrix for S, O and D

DM	Severity(S)			Occurrence(O)			Detection(D)			DM	Severity(S)			Occurrence(O)			Detection(D)		
	Aggregate DM			Aggregate DM			Aggregate DM				Aggregate DM			Aggregate DM			Aggregate DM		
B1	0.433	0.633	0.833	0.433	0.633	0.833	0.233	0.433	0.633	**B10**	0.166	0.366	0.566	0.500	0.700	0.900	0.433	0.633	0.800
B2	0.566	0.766	0.933	0.500	0.700	0.900	0.433	0.633	0.800	**B11**	0.300	0.500	0.700	0.500	0.700	0.900	0.233	0.433	0.800
B3	0.500	0.700	0.900	0.500	0.700	0.900	0.300	0.500	0.700	**B12**	0.433	0.633	0.833	0.566	0.766	0.900	0.566	0.766	0.900
B4	0.433	0.633	0.833	0.400	0.566	0.733	0.233	0.433	0.633	**B13**	0.500	0.700	0.866	0.366	0.566	0.766	0.433	0.633	0.800
B5	0.433	0.633	0.800	0.333	0.500	0.700	0.300	0.500	0.700	**B14**	0.433	0.633	0.833	0.300	0.500	0.700	0.500	0.700	0.866
B6	0.566	0.766	0.933	0.266	0.433	0.633	0.200	0.366	0.566	**B15**	0.366	0.566	0.766	0.233	0.433	0.633	0.300	0.500	0.700
B7	0.633	0.833	0.966	0.433	0.633	0.633	0.366	0.566	0.733	**B16**	0.500	0.700	0.866	0.233	0.433	0.633	0.300	0.500	0.700
B8	0.566	0.766	0.933	0.433	0.633	0.833	0.366	0.566	0.733	**B17**	0.366	0.566	0.766	0.333	0.500	0.700	0.366	0.566	0.733
B9	0.433	0.633	0.800	0.366	0.566	0.766	0.233	0.433	0.633	**B18**	0.566	0.766	0.933	0.500	0.700	0.900	0.300	0.500	0.700
DM	**Severity(S)**			**Occurrence(O)**			**Detection(D)**			**DM**	**Severity(S)**			**Occurrence(O)**			**Detection(D)**		
	Normalized			**Normalized**			**Normalized**				**Normalized**			**Normalized**			**Normalized**		
B1	0.037	0.080	0.139	0.040	0.087	0.150	0.013	0.045	0.097	**B10**	0.005	0.027	0.064	0.054	0.106	0.175	0.045	0.097	0.154
B2	0.064	0.118	0.017	0.054	0.106	0.175	0.045	0.097	0.154	**B11**	0.018	0.050	0.098	0.054	0.106	0.175	0.017	0.045	0.087
B3	0.500	0.980	0.163	0.054	0.106	0.175	0.021	0.060	0.118	**B12**	0.037	0.080	0.139	0.069	0.127	0.175	0.077	0.142	0.196
B4	0.037	0.080	0.139	0.034	0.069	0.116	0.013	0.045	0.097	**B13**	0.050	0.098	0.151	0.029	0.069	0.127	0.045	0.097	0.154
B5	0.370	0.800	0.128	0.024	0.054	0.106	0.021	0.060	0.118	**B14**	0.037	0.080	0.139	0.019	0.054	0.127	0.060	0.118	0.181
B6	0.064	0.118	0.175	0.015	0.040	0.087	0.009	0.032	0.077	**B15**	0.027	0.064	0.118	0.011	0.040	0.087	0.021	0.060	0.118
B7	0.080	0.139	0.188	0.040	0.087	0.138	0.032	0.077	0.130	**B16**	0.050	0.098	0.151	0.024	0.054	0.106	0.021	0.060	0.118
B8	0.064	0.118	0.175	0.040	0.087	0.015	0.032	0.077	0.120	**B17**	0.027	0.064	0.118	0.029	0.069	0.127	0.032	0.077	0.130
B9	0.037	0.080	0.128	0.029	0.069	0.127	0.013	0.045	0.097	**B18**	0.064	0.118	0.175	0.054	0.106	0.175	0.060	0.118	0.118

Table 5: Interval decision matrix of fuzzy Shannon's entropy method

Barriers	Severity (S)				Occurrence (O)				Detection (D)				Barriers	Severity (S)		Occurrence (O)		Detection (D)	
	DM1		DM2		DM1		DM2		DM1		DM2			Aggregate DMs					
B1	0.57	0.92	0.32	0.67	0.57	0.92	0.32	0.67	0.07	0.42	0.07	0.42	**B1**	0.445	0.795	0.455	0.795	0.070	0.420
B2	0.57	0.92	0.57	0.92	0.57	0.92	0.57	0.92	0.57	0.92	0.07	0.42	**B2**	0.570	0.920	0.570	0.920	0.320	0.670
B3	0.57	0.92	0.57	0.92	0.57	0.92	0.57	0.92	0.32	0.67	0.07	0.42	**B3**	0.570	0.920	0.570	0.920	0.195	0.545
B4	0.32	0.67	0.57	0.92	0.82	1	0	0.17	0.32	0.67	0.07	0.42	**B4**	0.445	0.795	0.410	0.585	0.195	0.545
B5	0.57	0.92	0.07	0.42	0.57	0.92	0	0.17	0.07	0.42	0.32	0.67	**B5**	0.320	0.670	0.285	0.545	0.195	0.545
B6	0.82	1	0.57	0.92	0.57	0.92	0	0.17	0.07	0.42	0	0.17	**B6**	0.695	0.96	0.285	0.545	0.035	0.295
B7	0.82	1	0.82	1	0.82	1	0.07	0.42	0.32	0.67	0.07	0.42	**B7**	0.820	1	0.445	0.710	0.195	0.545
B8	0.57	0.92	0.82	1	0.57	0.92	0.32	0.67	0.07	0.42	0.32	0.67	**B8**	0.695	0.960	0.445	0.795	0.195	0.545
B9	0.32	0.67	0.32	0.67	0.57	0.92	0.07	0.42	0.32	0.67	0.07	0.42	**B9**	0.320	0.670	0.320	0.670	0.195	0.545
B10	0.07	0.42	0.07	0.42	0.57	0.92	0.57	0.92	0.07	0.42	0.57	0.92	**B10**	0.070	0.420	0.570	0.920	0.320	0.670
B11	0.32	0.67	0.07	0.42	0.57	0.92	0.57	0.92	0.07	0.42	0	0.17	**B11**	0.195	0.545	0.570	0.920	0.035	0.295
B12	0.32	0.67	0.57	0.92	0.32	0.67	0.82	1	0.32	0.67	0.82	1	**B12**	0.445	0.795	0.570	0.835	0.570	0.835
B13	0.57	0.92	0.82	1	0.32	0.67	0.32	0.67	0.07	0.42	0.82	1	**B13**	0.695	0.960	0.320	0.670	0.445	0.710
B14	0.57	0.92	0.32	0.67	0.32	0.67	0.07	0.42	0.32	0.67	0.82	1	**B14**	0.445	0.795	0.195	0.545	0.570	0.835
B15	0.57	0.92	0.07	0.42	0.32	0.67	0.07	0.42	0.07	0.42	0.32	0.67	**B15**	0.320	0.670	0.195	0.545	0.195	0.545
B16	0.82	1	0.32	0.67	0.57	0.92	0	0.17	0.32	0.67	0.07	0.42	**B16**	0.570	0.835	0.285	0.545	0.195	0.545
B17	0.32	0.67	0.32	0.67	0.32	0.67	0.32	0.67	0.32	0.67	0.07	0.42	**B17**	0.320	0.670	0.320	0.670	0.195	0.545
B18	0.57	0.92	0.82	1	0.57	0.92	0.57	0.92	0.07	0.42	0.32	0.67	**B18**	0.695	0.960	0.570	0.920	0.195	0.545

Table 6: Final weight of fuzzy Shannon's entropy method for S, O and D

	Severity (S)	**Occurrence (O)**	**Detection (D)**
h^{l}	0.6880	0.6650	0.5210
h^{u}	0.9920	0.0992	0.9880
d^{l}	0.0072	0.0073	0.0111
d^{u}	0.3110	0.3340	0.4780
w^{l}	0.0064	0.0065	0.0099
w^{u}	12.069	12.962	18.528
W'	6.0379	6.4840	9.2690
W_i	0.2771	0.2976	0.4254

Table 7: The weighted normalized fuzzy decision matrix for S, O and D

Barriers	Severity(S)			Occurrence(O)			Detection(D)		
Weighted fuzzy Shannon	0.2770713			0.2975708			0.4253578		
B1	0.010	0.022	0.038	0.012	0.025	0.044	0.005	0.019	0.041
B2	0.017	0.032	0.048	0.016	0.031	0.052	0.010	0.041	0.065
B3	0.013	0.027	0.045	0.016	0.031	0.052	0.009	0.025	0.050
B4	0.010	0.022	0.038	0.01	0.020	0.034	0.005	0.019	0.041
B5	0.010	0.022	0.035	0.007	0.016	0.031	0.009	0.025	0.050
B6	0.017	0.032	0.048	0.004	0.012	0.025	0.004	0.013	0.033
B7	0.022	0.038	0.052	0.012	0.025	0.041	0.013	0.033	0.055
B8	0.017	0.032	0.048	0.012	0.025	0.044	0.013	0.033	0.055
B9	0.010	0.022	0.035	0.008	0.020	0.037	0.005	0.019	0.041
B10	0.001	0.007	0.017	0.016	0.031	0.052	0.019	0.041	0.065
B11	0.005	0.013	0.027	0.016	0.031	0.052	0.007	0.019	0.037
B12	0.010	0.022	0.038	0.02	0.037	0.052	0.033	0.060	0.083
B13	0.013	0.027	0.041	0.008	0.020	0.037	0.019	0.041	0.065
B14	0.010	0.022	0.038	0.005	0.016	0.031	0.026	0.050	0.077
B15	0.007	0.017	0.032	0.003	0.016	0.037	0.009	0.026	0.050
B16	0.013	0.027	0.041	0.007	0.016	0.031	0.009	0.025	0.050
B17	0.007	0.017	0.032	0.008	0.020	0.037	0.013	0.033	0.055
B18	0.017	0.032	0.048	0.016	0.031	0.052	0.009	0.025	0.050

Table 8: Best non-fuzzy performance value and ranking of the barriers by fuzzy MOORA

Barriers	y_i^l	y_i^m	y_i^u	y_i	**Ranks**	**Barriers**	y_i^l	y_i^m	y_i^u	y_i	**Ranks**
B1	0.0280	0.0670	0.1240	0.073	12	**B10**	0.0370	0.0800	0.136	0.084	9
B2	0.0530	0.1050	0.1660	0.108	2	**B11**	0.0284	0.0640	0.116	0.070	13
B3	0.0390	0.0840	0.1470	0.090	8	**B12**	0.0640	0.1200	0.174	0.119	1
B4	0.0260	0.0620	0.1140	0.067	15	**B13**	0.0410	0.0890	0.145	0.092	7
B5	0.0260	0.0640	0.1170	0.069	14	**B14**	0.0420	0.0880	0.147	0.092	6
B6	0.0260	0.0580	0.1070	0.064	17	**B15**	0.0200	0.0550	0.109	0.061	18
B7	0.0483	0.0970	0.1480	0.098	3	**B16**	0.0300	0.0690	0.123	0.074	11
B8	0.0438	0.0917	0.1480	0.094	5	**B17**	0.0300	0.0716	0.126	0.075	10
B9	0.0240	0.0620	0.1149	0.067	16	**B18**	0.0430	0.0900	0.151	0.094	4

Table 9: Determining d_i^+ , d_i^- , closeness coefficient and ranking order by fuzzy TOPSIS

Barriers	d_i^+	d_i^-	CC_i	Ranks	Barriers	d_i^+	d_i^-	CC_i	Ranks
B1	2.926719	0.083746	0.0278182	12	**B10**	2.915815	0.094000	0.0312310	9
B2	2.891763	0.118140	0.0392505	2	**B11**	2.930209	0.078944	0.0262347	14
B3	2.909690	0.101156	0.0335972	8	**B12**	2.880546	0.128170	0.0425995	1
B4	2.932368	0.077142	0.0256327	15	**B13**	2.907983	0.101703	0.0337920	7
B5	2.930608	0.079112	0.0262854	13	**B14**	2.907469	0.102637	0.0340974	6
B6	2.935891	0.072933	0.0242397	17	**B15**	2.938520	0.071762	0.0238389	18
B7	2.902024	0.106741	0.0354766	3	**B16**	2.925745	0.084030	0.0279189	11
B8	2.905524	0.104162	0.0346089	5	**B17**	2.924341	0.085537	0.0284189	10
B9	2.932862	0.077048	0.0255980	16	**B18**	2.905410	0.105011	0.0348824	4

Table 10: Ranking of the barriers by fuzzy SAW

Barriers	Severity(S)			Average	Occurrence(O)			Average	Detection(D)			Average	Aggregate S, O, D	Ranks
B1	0.01	0.022	0.038	**0.031**	0.012	0.025	0.044	**0.033**	0.005	0.019	0.041	**0.019**	**0.0840**	10
B2	0.017	0.032	0.048	**0.042**	0.016	0.031	0.052	**0.040**	0.01	0.041	0.065	**0.035**	**0.1180**	2
B3	0.013	0.027	0.045	**0.037**	0.016	0.031	0.052	**0.040**	0.009	0.025	0.05	**0.024**	**0.1020**	6
B4	0.01	0.022	0.038	**0.031**	0.01	0.02	0.034	**0.026**	0.005	0.019	0.041	**0.019**	**0.0774**	14
B5	0.01	0.022	0.035	**0.029**	0.007	0.016	0.031	**0.022**	0.009	0.025	0.05	**0.024**	**0.0772**	15
B6	0.017	0.032	0.048	**0.042**	0.004	0.012	0.025	**0.017**	0.004	0.013	0.033	**0.015**	**0.0755**	17
B7	0.022	0.038	0.052	**0.047**	0.012	0.025	0.041	**0.032**	0.013	0.033	0.055	**0.029**	**0.1090**	3
B8	0.017	0.032	0.048	**0.042**	0.012	0.025	0.044	**0.033**	0.013	0.033	0.055	**0.029**	**0.1050**	5
B9	0.01	0.022	0.035	**0.029**	0.008	0.02	0.037	**0.027**	0.005	0.019	0.041	**0.019**	**0.0760**	16
B10	0.001	0.007	0.017	**0.012**	0.016	0.031	0.052	**0.040**	0.019	0.041	0.065	**0.035**	**0.0880**	9
B11	0.005	0.013	0.027	**0.020**	0.016	0.031	0.052	**0.040**	0.007	0.019	0.037	**0.018**	**0.0790**	13
B12	0.01	0.022	0.038	**0.031**	0.02	0.037	0.052	**0.043**	0.033	0.06	0.083	**0.049**	**0.1240**	1
B13	0.013	0.027	0.041	**0.035**	0.008	0.02	0.037	**0.027**	0.019	0.041	0.065	**0.035**	**0.0993**	7
B14	0.01	0.022	0.038	**0.031**	0.005	0.016	0.031	**0.022**	0.025	0.05	0.077	**0.043**	**0.0967**	8
B15	0.007	0.017	0.032	**0.025**	0.003	0.016	0.037	**0.017**	0.009	0.025	0.05	**0.024**	**0.0670**	18
B16	0.013	0.027	0.041	**0.035**	0.007	0.016	0.031	**0.022**	0.009	0.025	0.05	**0.024**	**0.0830**	11
B17	0.007	0.017	0.032	**0.025**	0.008	0.02	0.037	**0.027**	0.013	0.033	0.055	**0.029**	**0.0825**	12
B18	0.017	0.032	0.048	**0.042**	0.016	0.031	0.052	**0.040**	0.009	0.025	0.05	**0.024**	**0.1070**	4

Table 11: The result of Copeland's method

Barriers	**ΣC**	**ΣR**	***ΣC- ΣR***	**Ranks**	**Barriers**	**ΣC**	**ΣR**	***ΣR- ΣC***	**Ranks**
B1	6	10	*-4*	12	**B10**	9	9	*0*	9
B2	16	1	*15*	2	**B11**	4	11	*-7*	13
B3	10	7	*3*	8	**B12**	17	1	*16*	1
B4	3	14	*-11*	15	**B13**	11	6	*5*	7
B5	4	12	*-8*	14	**B14**	12	6	*6*	6
B6	1	16	*-15*	17	**B15**	0	16	*-16*	18
B7	15	2	*13*	3	**B16**	7	10	*-3*	11
B8	13	5	*8*	5	**B17**	8	9	*-1*	10
B9	2	14	*-12*	16	**B18**	14	3	*11*	4