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Evaluation of the critical success factors of dynamic enterprise risk management in manufacturing SMEs using an integrated fuzzy decision-making model

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ABSTRACT

To succeed, a firm essentially needs to take the right amount of risk. Thus, the great significance of risk management has attracted many researchers to focus on how to implement enterprise risk management (ERM) systems most effectively. Generally, smaller entrepreneurial firms have to cope with this challenge more informally. Most manufacturing small and medium-sized enterprises (SMEs) are family companies; as a result, family dynamics greatly impact how such companies do business. The q-rung orthopair fuzzy set (q-ROFS) provides a wide window for the preference elicitation of decision-makers (DMs). Inspired by the advantages of the q-ROFS, in the current paper, a novel decision framework, the q-ROF-entropy-rank sum (*RS*)-additive ratio assessment (ARAS), called the "q-ROF-entropy-RS-ARAS" approach, is developed. The q-ROF-entropy-RS approach is applied to compute the weights of critical success factors (CSFs) for dynamic ERM in SMEs, and the q-ROF-ARAS model is used to assess enterprise preferences. An empirical case study is conducted to evaluate the CSFs for dynamic enterprise risk management in SMEs. Additionally, the comparison and sensitivity investigation are carried out to show the superiority of the developed framework.

1. Introduction

In the current world, which is becoming increasingly digital, companies face several challenges in establishing and/or sustaining a competitive advantage in the market (Ganju et al., 2016; Rocha et al., 2016). Compared with conventional firms, responsive firms operate differently. Such companies are normally acquainted with dynamic, exponential, and disruptive thinking; through these experiences, they are made ready to adopt exponential growth (Ismail et al., 2014). How a company is structured and operates demonstrates its "Enterprise Risk Management (ERM)" system. As a result, to effectively manage risks, there is a need for constant alignment between the enterprise and its risk function (Knight, 1921), which could be achieved by incorporating ERM into the firm's decision-support processes. ERM, as a decision support tool, could be effectively used by every company (with a focus on organizational processes) to manage the risks that may arise during business operations in the real environment (ISO, 2018). ERM is defined as a "process that combines the organization's entire risk management activities in one integrated, holistic framework to achieve a comprehensive corporate perspective" (ISO, 2018). Currently, many firms use different ERM frameworks. Two popular risk frameworks are the ISO31000 and the "Committee of Sponsoring Organizations of the Treadway Commission (COSO)". The COSO helps firms enhance the quality of their model in the management of risks well to satisfy the demand of an evolving business environment. By adopting the COSO, companies would be capable of further understanding the risks that affect the outcome of their business strategies and goals. ISO3100 is presently used as a best practice in risk management; it also incorporates the best practices of the COSO (ISO, 2018). ISO3100 produces a general guideline to aid in managing risks; however, it does not aim to make risk management practices uniform. ISO31000 consists of a comprehensive list of principles proposed to manage risks and possesses an open system model that fits multiple requirements and contexts. In both ISO31000 and the COSO, the significant impacts of culture and bias on the decision-making process and risk management practices are considered. However, no guidelines are provided that show how responsive

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organizations operating within dynamic contexts can apply more dynamic risk management practices (Gatzert and Martin, 2015). Moreover, it is clear that when a firm operates its business within an uncertain environment, it needs satisfactory risk management capabilities (Walczak and Kuchta, 2013). This idea is not in line with the currently adopted systematic and linear risk management approaches (Nyfjord and Kajko-Mattsson, 2007), consistent with the organizational structure of conventional organizations, which are linear in nature (Ahmed and Manab, 2016). Responsive attributes provide guidance for organizations regarding how they can implement the essential components of risk management.

Within a dynamic market, companies generally implement a variety of sources and resources to attain competitive advantages and demonstrate superiority in terms of their performance (Evans and Bosua, 2017; Hartcher et al., 2003). More specifically, a "Small and Medium-Sized Enterprise (SME)" encounters several barriers due to financial constraints and the deficiency of its resources (Anwar et al., 2018; Brustbauer, 2014). As a result, such firms have to formulate various strategies to gain less risky resources to be able to compete in markets and achieve stable positions (Mazzarol et al., 2014). However, within such a dynamic environment, ERM (as an essential tool facilitating a company's success) has been overlooked by researchers working in the SME domain (Soltanizadeh et al., 2016).

Many companies (especially SMEs) have lack resources and reliable mechanisms to support their risk-management activities. Companies of larger sizes typically tend to manage risks collectively; on the other hand, in SMEs, these responsibilities are normally undertaken by the company owners, possibly backed by a small management team (Brustbauer, 2014). In general, entrepreneurs are labeled as 'risk takers' (Cantillon, 1756); they have to make the final decisions considering the risks that may be included in such situations (Tate et al., 1982). The way entrepreneurs perceive the risks and their capacity for managing them, which depend on their personal and company-related resources, greatly impacts the respective risk-management approaches (Nocco and Stulz, 2006). Recently, the risk management domain has experienced a paradigm shift. Instead of assessing the risks from an individual point of view, firms currently tend toward an all risks-encompassing perspective, known as ERM. ERM aims to identify, evaluate, and monitor all the opportunities and threats a company may encounter during its business (Pagach and Warr, 2011). Therefore, ERM increases risk-management awareness with the support of a firm-wide risk-management approach, which is going to finally result in the maturity of the operational and strategic management decisions made in the company (Nocco and Stulz, 2006). ERM adopts theoretical risk concepts to provide inclusive guidelines and suggest key principles, leaving the details to the company itself.

The existing literature offers nothing about applied ERM approaches and the differences among companies; instead, the existing research in this domain is mainly concentrated on large North American companies and studies ERM at a high level of aggregation (Beasley et al., 2005). ERM increases awareness about managing risks and supports a firm-wide risk management approach to help the further maturity of operational and strategic management decisions (Nocco and Stulz, 2006) and, consequently, offer competitive advantages (Stroh, 2005). As a result, ERM aids in developing business strategies, decreasing potential losses, and exploiting opportunity windows (Hoyt and Liebenberg, 2011a). The framework of ERM is drawn from theoretical risk concepts; it makes available broad guidance and suggests key principles but leaves details to the company itself. The theoretical guidelines are helpful to SMEs, though numerous companies have encountered open-ended questions when applying ERM with little concrete guidance at the instrumental and operational levels. Therefore, ERM approaches are different (Beasley et al., 2005). Different approaches are adopted practically, and the relevant literature has examined ERM at a high level of aggregation. In this context, a number of researchers have relied on data to appoint a "Chief Risk Officer (CRO)" as a sole indicator for the ERM application (Pagach and Warr, 2011). In some other studies, ordinal scales have been used, ranging from 'no plans exist to implement ERM' to 'complete ERM in place in order to capture the applied ERM approach (Paape and Speklé, 2012). These researchers have relied on the data collected from North American countries, particularly the listed firms by Paape and Speklé (2012), as an exception when investigating the European SMEs. However, they have overlooked the companies with fewer than 30 employees and less than €10 million in annual revenues. Only a few researchers have reported the impact of business strategies on ERM practices (Aghapour et al., 2017). Despite risk management's important role in companies, the literature still lacks research focusing on SMEs. Moreover, research into ERM and company performance is dealt with from a theoretical perspective, and there are insufficient insights into ERM and SMEs, particularly in case of emerging markets (Aghapour et al., 2017). For example, according to Yang et al. (2018), because of the deficiency of resources and capacities, Pakistani SMEs habitually attempt to decrease various risks in order to raise their chance of survival.

An enterprise-wide approach to risk management considers all these impacts in a way to arrange for a structured approach considering the potential influences of all types of risks on all the activities, processes, stakeholders, services, and products (Nair et al., 2014). Nowadays, internal and external stakeholders are much more concerned with risks (Nair et al., 2014); they understand that sufficient risk management capacities must operate effectively within uncertain environments (Walczak and Kuchta, 2013). Before selecting the most effective strategies or decisions, a company must understand the risks that may arise when making efforts to achieve the company goals; it also requires evaluating the company's exposure, risk profile, financial position, acceptable risks, and reward trade-off (Hopkin, 2018). Thus, ERM works effectively if it is connected directly to the firm strategy and also if it is designed in such a way that it can identify the events that may affect the organizational performance of the firm as defined by its strategic goals (Soltanizadeh et al., 2016). An efficient ERM initiative influences the probability and consequences of the risk materializing; it also helps to make more informed strategic decisions, successfully delivers the changes, and enhances the operational efficiency of the firm (Teece et al., 2016). Some other benefits provided by ERM to a company include reducing the cost of capital, providing financial reports of higher accuracy, offering competitive advantages, improving the firm's perceptions, and enhancing decision-making capacities (Aziz et al., 2016).

Therefore, it is important for risk management practices to improve the decision support procedures and consider the uncertainties and their impacts on the accomplishment of the firms' goals (Blanco et al., 2019). Furthermore, several researchers have attempted to find effective solutions to the dynamic risk management capability problem by integrating risk management procedures with agile development procedures (Nyfjord and Kajko-Mattsson, 2008). Thus, to help such responsive organizations to have more dynamic risk management, the following research question is considered in the current paper: What is the relative importance of "Critical Success Factors (CSFs)" that will enable dynamic ERM in manufacturing SMEs? The present study reflects upon this question by considering ERM in general, the nature of manufacturing SMEs, and the impacts of CSFs on managing more dynamic risks.

Due to the lack of information, uncertain human thinking, and time complexity, the "decision-makers (DMs)" are unable to give precise outcomes in real "Multi-criteria Decision-Making (MCDM)" problems. To conquer this concern, Yager (2017b) suggested the "Pythagorean Fuzzy Set (PFS)" concept as a tool to address the weaknesses of the "Intuitionistic Fuzzy Set (IFS)". The PFS is also depicted by "Belongingness Grade (BG)" and "Non-belongingness Grade (NG)", and fulfills a requirement that the squares addition of BG and NG is ≤ 1. PFS is used extensively as a tool more effective than IFS in handling the uncertainties that may arise in real-world MCDM problems. The literature in recent years has introduced numerous methods, approaches, and theories in relation to PFSs (Peng, 2019; Rani et al., 2019).

Nevertheless, a case may appear in the MCDM model in which the DMs might provide the BG to which an option S_i satisfies the criterion T_j is 0.6, and the grade to which an option S_i invalidates the criterion is 0.9. Thus, IFS and PFS cannot effectively manage such conditions since $0.6 + 0.9 > 1$ and $0.6^2 + 0.9^2 > 1$. Thus, Yager (2017a) proposed the "q-rung orthopair fuzzy sets (q-ROFSs)" to treat the issue. It fulfills a constraint that the q^{th} powers sum of the BG and NG is ≤ 1, where $q \geq 1$. The q-ROFSs can offer an effective solution to the above-noted issue. IFSs and PFSs are the specific forms of q-ROFSs. For that reason, with the use of q-ROFSs, the higher level of uncertain information could be flexibly and practically handled. Many researchers have introduced their studies under the q-ROFSs environment in recent years. For instance, Liu and Wang (2018) carried out different geometric and arithmetic operators for q-ROFSs. Darko and Liang (2020) carried out research into several "Q-rung Orthopair Fuzzy (q-ROF)"-based operators to treat realistic MCDM problems. A decision-making framework was developed by Krishankumar et al. (2020) based on q-ROF to find an effective solution to the "Renewable Energy Resource (RES)" assessment problem with q-ROF information. Rani and Mishra (2020) investigated the "weighted aggregated sum product assessment (WASPAS)" model for treating the fuel technologies selection on q-ROFSs.

During the past few decades, MCDM has been considered a key process in people's daily. Because of the increasing complexity and widespread alterations to today's environments, the conventional MCDM methods are generally inapplicable to the MCDM problems. Turskis and Zavadskas (2010) pioneered the Additive Ratio Assessment (ARAS) model, indicating that the events of this intricate world may be implicit using relative comparisons. ARAS makes use of the concept of an optimality degree in order to achieve prioritization. The most important benefits of ARAS include 1) direct and proportional relationship with attribute weights (Iordache et al., 2019), 2) having the ability to solve complicated problems (Büyüközkan and Güler, 2020), 3) involving some simple and direct steps for the assessment of a number of options or choices based on their performance in comparison with the chosen evaluation criteria that obtained suitable, sensible, and comparatively-accurate results (Zavadskas and Turskis, 2010). Most situations where the conventional ARAS has been recently utilized have been aimed at personnel evaluation purposes, the ranking of firms on the basis of indicators of corporate social accountability (Karabasevic et al., 2016). In recent years, this approach has been elaborated in various uncertain fields. Mishra et al. (2021) presented the ARAS model to assess and rank the "Electric Vehicle Charging Station (EVCS)" locations.

Nonetheless, in recent years, business communities and scholars working in this domain have become increasingly interested in ERM (Fraser et al., 2022; Kuo et al., 2021; Jonek-Kowalska, 2019; Shad et al., 2019). Some previously-conducted studies have reported that despite the fact that ERM has received positive attention, it has not been extensively implemented yet. The literature still lacks research into the determinants of ERM (Daud et al., 2011) and ERM CSFs. The majority of the past studies have concentrated on issues related to large enterprises and ignored SMEs. The current study is aimed at proposing an inclusive framework for the CSFs of ERM adoption in manufacturing SMEs. Accordingly, to take the flexibility and efficacy of q-RFOSs, the aim of the paper is to introduce an innovative discrimination measure and discuss its elegant properties. The ARAS framework for evaluating the MCDM problem on q-RFOSs has been developed based on it. Due to its flexibility and effectiveness, this study focuses on the setting of q-ROFSs. A new methodology of the q-ROF-weight finding technique is named a q-ROF-entropy-RS method to compute the weights or significance degrees of CSFs for dynamic ERM in SMEs. Then, the ARAS method is a new elegant approach to rank the enterprises of CSFs for dynamic ERM in SMEs. Thus, we have developed a new approach using the q-ROF-entropy-RS and q-ROF-ARAS methods and further implemented them to identify the CSFs for dynamic ERM in SMEs. The primary outcomes of the developed work are given:

- We are conducting a survey by interviewing the relevant experts and reviewing the literature to identify the CSFs for dynamic ERM in SMEs.
- We are developing an inclusive framework in order to analyze the CSFs for dynamic ERM in SMEs with the help of a new fuzzy approach.
- We are proposing an integrated MCDM approach with the use of the q-ROF-entropy-RS-ARAS method in order to rank the enterprises and analyze and evaluate the CSFs for dynamic ERM in SMEs.
- We are using the q-ROF-entropy-RS to evaluate and rank the CSFs for dynamic ERM in SMEs.

The remaining work is structured as Section 2 presents the literature about enterprise risk management in SMEs. Section 3 develops an integrated q-ROF-entropy-RS-ARAS method for solving MCDM problems. Section 4 presents a case study to assess and prioritize the CSFs for dynamic ERM in SMEs in manufacturing. Also discusses sensitivity and comparative investigations. Finally, Section 5 presents the conclusions and future direction.

2. Enterprise risk management in SMEs

ERM, in the current globalized economy, is a key issue that helps evaluate the companies' risk situations more effectively and enhances the decision-making processes with respect to strategic and operative development (Nocco and Stulz, 2006; Pagach and Warr, 2011). ERM has the required capacity to manage the risks holistically. Some scholars in this domain have used the term "enterprise-wide risk management (EWRM)" instead of ERM (Monda and Giorgino, 2013). From a historical perspective, ERM is rooted in the concept of risk management. The publication of the first risk management text, entitled *Risk Management and the Business Enterprise,* dates back to the year 1963. Risk management, at first, was only aimed at the maximization of the productive efficiency of enterprises. After that, this concept started focusing on pure and speculative risks (Razali and Tahir, 2011). Risk management has also been entitled "Traditional Risk Management (TRM)". According to Yazid et al. (2012), there are clear differences between TRM and ERM. The former treats and manages the risk in 'silos'; on the other hand, in ERM, all types of risks encountered by the firms concerned are integrated or aggregated (Razali and Tahir, 2011). The key differences between these two concepts are the scope of their risk coverage and how they manage the risks. Nevertheless, the fast growth of technology and management science caused business practitioners and the academic community to comprehend the incompetence of TRM (Rao, 2007). The incessant enhancements in management performance, together with the quick changes that occurred to internal and external factors (as explained by Gatzert and Martin, 2015), made numerous businesses more ready to adopt ERM to avert any debacle that could lead to any remarkable consequences. This happened because of the demands of broader risk scope, a higher risk complexity, and increasing interactions and dependencies among risk sources (Gatzert and Martin, 2015).

Previous studies focused on a wide range of subjects, including ERM's components and impacts. Holton (1996), for example, investigated the elements that determined ERM effectiveness and discovered that internal factors have a role. Corporate culture, procedures, and technology all play a role in risk management within firms, according to the conclusions of this study. According to the report, members or individuals on the "Board of Directors (BODs)" must also be able to manage risks in the business culture. On the other hand, organizations rely on procedures to change existing procedures to conform with ERM. Kleffner et al. (2003) conducted one of the first studies on the factors influencing ERM implementation in businesses. Over a third of respondents have implemented ERM, and a larger proportion of the remaining respondents are moving in that direction, according to the survey. The influence of the Risk Manager, Board of Directors support, and compliance with Stock Exchange standards were cited as reasons for

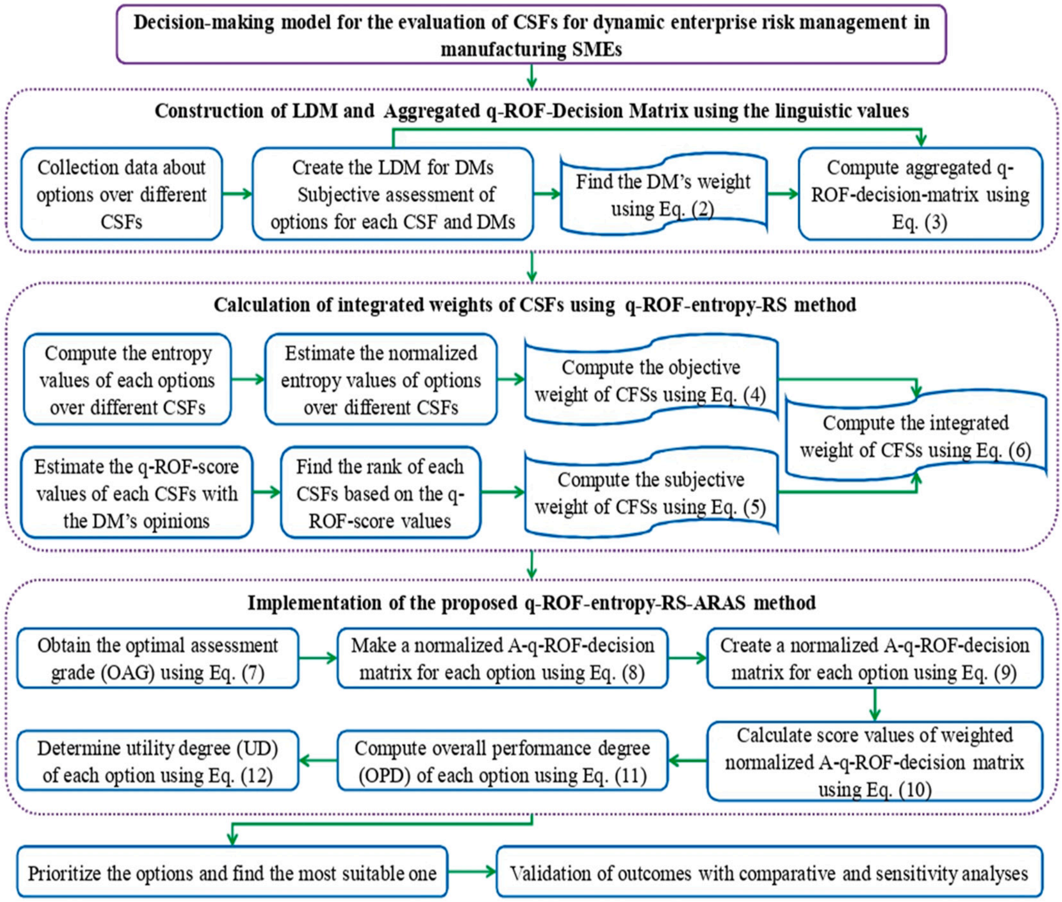

Fig. 1. Flowchart of the proposed q-ROF-entropy-RS-ARAS method.

Table 1
Performance ratings of alternatives over criteria and DEs regarding the LVs.

LVs	q-ROFNs
Absolutely high (AH)/Extremely significant (ES)	(0.95, 0.20, 0.240)
Very very high (VVH)/Very very significant (VVS)	(0.85, 0.30, 0.433)
Very high (VH)/Very significant (VS)	(0.80, 0.35, 0.487)
High (H)/ Significant (S)	(0.70, 0.45, 0.554)
Moderate high (MH)/Moderate significant (MS)	(0.60, 0.55, 0.581)
Moderate (M)/Average (A)	(0.50, 0.60, 0.624)
Moderate low (ML)/Moderate insignificant (MI)	(0.40, 0.70, 0.592)
Low (L)/Very insignificant (VI)	(0.30, 0.75, 0.589)
Very low (VL)/Very very insignificant (VVI)	(0.20, 0.85, 0.487)
Absolutely low (AL)/Extremely insignificant (EI)	(0.10, 0.95, 0.296)

Table 2
Weight of DEs for evaluation of the alternatives.

DEs	LVs	q-ROFNs	Score	Rank	Weights
g_1	Significant (S)	(0.70, 0.45, 0.554)	0.6437	3	0.2172
g_2	Very very significant (VVS)	(0.85, 0.30, 0.433)	0.8162	1	0.3486
g_3	Very significant (VS)	(0.80, 0.35, 0.487)	0.7588	2	0.2881
g_4	Moderate significant (MS)	(0.60, 0.55, 0.581)	0.5287	4	0.1462

implementing ERM, with organizational structure and overall aversion to change serving as major deterrents. According to Beasley et al. (2005), board and senior management leadership on ERM are critical for widespread adoption. According to the study, other organizational variables, like size, auditor type, industry, and country of residence, are also important in explaining the amount of ERM adoption.

In the beginning, most ERM studies are exploratory, intending to find the financial characteristics of ERM adopters (Lin et al., 2012; Liebenberg and Hoyt, 2003). For example, Liebenberg and Hoyt (2003) discovered that more leveraged firms are more likely to hire CROs. As a result, firms with a greater risk profile are more likely to use ERM. Similarly, Pagach and Warr (2007) find that firms that are highly leveraged, volatile, and have a history of bad stock market performance are more likely to use ERM. In addition, insurers with a higher reinsurance ratio and better geographical diversification are more likely to use ERM, according to (Lin et al., 2012). Insurers appear to reduce reinsurance purchases and reduce asset portfolio volatility while increasing derivatives positions after implementing ERM, implying that insurers reduce reinsurance costs while increasing financial risk costs through increased derivative usage and less volatile asset portfolios.

The previous economic crises demonstrated the high dynamicity and complexity of markets, which caused hot debates in regard to the significance of implementing ERM (McShane, 2018; Bromiley et al., 2015). Many researchers have reported that using ERM can decrease the firm's costs and improve its performance (Chen et al., 2020; Hoyt and Liebenberg, 2011b). According to Watkins (2012), risk management methods must be adopted by management to build a risk strategy in response to prospective risks. As a result, managers must be prepared with risk management abilities because they will oversee developing activities to mitigate any hazards. In addition, ERM improves risk response decisions by allowing managers to recognize and choose from a variety of risk mitigation options, including risk avoidance, reduction, sharing, and acceptance. ERM aids in the reduction of operational surprises and losses, allowing organizations to improve their ability to

Table 3
LVs of option by DEs for CSFs for dynamic ERM in SMEs.

CSFs	O_1	O_2	O_3	O_4	O_5
CF_1	(MH,L,VL,M)	(MH,ML,L, ML)	(H,M,M,MH)	(MH,M,H,L)	(VH,VH,H,M)
CF_2	(L,ML,M,MH)	(ML,VL,VL,M)	(VH,M,MH, M)	(M,MH,M,ML)	(VH,MH,ML, M)
CF_3	(H,VH,H,M)	(H,H,VH,M)	(ML,ML,H, MH)	(M,VH,MH,M)	(VH,M,VH, M)
CF_4	(ML,MH,H, M)	(VH,M,H,M)	(ML,ML,MH, H)	(ML,MH,M, ML)	(H,ML,VL,M)
CF_5	(M,MH,H,M)	(ML,H,H,MH)	(MH,ML,M, H)	(ML,M,VH,H)	(VVH,H,VH, M)
CF_6	(VH,MH,M, MH)	(M,VL,ML,M)	(VH,H,M, MH)	(H,M,MH,ML)	(H,MH,ML, MH)
CF_7	(ML,MH,L,M)	(L,ML,L,M)	(ML,MH,M, M)	(MH,M,ML,H)	(H,VL,ML,M)
CF_8	(H,VH,VH,M)	(M,VVH,VH, M)	(ML,M,MH, ML)	(M,MH,ML, MH)	(H,L,VL,MH)
CF_9	(H,MH,H,M)	(M,VH,H,MH)	(M,ML,H,ML)	(ML,VH,MH, M)	(VVH,H,MH, M)
CF_{10}	(ML,VH,H, MH)	(L,MH,H,M)	(M,MH,ML, H)	(MH,ML,MH, H)	(VH,M,VL,M)
CF_{11}	(ML,ML, L,M)	(MH,ML,L, ML)	(MH,VH,M, MH)	(H,M,MH,H)	(MH,MH,M, M)
CF_{12}	(ML,L,ML,M)	(ML,MH,ML, M)	(H,VH,M, MH)	(VH,M,MH,M)	(H,M,MH,H)
CF_{13}	(MH,M,H, MH)	(M,MH,H, MH)	(M,MH,ML, M)	(MH,ML,M, MH)	(H,M,VL,ML)
CF_{14}	(M,M,H,MH)	(M,MH,MH, M)	(ML,VH,MH, M)	(VH,MH,M,H)	(VVH,H,ML, H)
CF_{15}	(VH,MH,M, M)	(ML,VVH,H, MH)	(M,ML,VVH, H)	(ML,VH,MH, MH)	(H,M,M,ML)
CF_{16}	(ML,L,L,ML)	(M,ML,VL,M)	(MH,MH,VH, M)	(M,VH,H,MH)	(M,ML,L,L)
CF_{17}	(ML,ML,M, MH)	(L,L,ML,M)	(MH,ML,M, H)	(ML,M,MH,H)	(H,M,VL,VL)
CF_{18}	(MH,VH,H, MH)	(MH,VH,H,M)	(M,VL,ML,M)	(VL,ML,ML, M)	(VVH,H,ML, M)

foresee and respond to forthcoming events, reducing surprises and associated costs or losses. ERM also recognizes and manages numerous and cross-enterprise risks, where every organization faces a variety of risks that affect various elements of the business. ERM enables effective answers to the related consequences and integrated responses to multiple risks. ERM aids in proactively finding and realizing possibilities by assessing a wide range of possible occurrences, allowing management to better recognize and capitalize on opportunities. Better capital deployment allows management to review overall capital requirements and enhance capital allocation by receiving credible risk information.

SMEs are currently more aware of the vitality of managing risks and developing risk models (Tan and Lee, 2022; Altman et al., 2008) to show successful performance in such a competitive market (Yang et al., 2018). However, risks endangering the competitive advantages of SMEs generally come from the growth of innovative technologies, legislation, globalization, and the advent of new niche competitors (Laforet and Tann, 2006). ERM helps them to identify risks, recognize opportunities, and implement innovative business solutions. In addition, SMEs typically possess limited capital and human resources, which causes them to be more susceptible to external economic shocks (Rehman and Anwar, 2019; Wright et al., 2001). ERM can potentially alleviate the impacts of such shocks (Yang et al., 2018; Chen et al., 2020; Falkner and Hiebl, 2015).

Remember that ERM could be a sizeable cost factor for SMEs, which puts further pressure on the confined financial resources of such firms. Moreover, the entrepreneurs may be capable of informally identifying the risks without feeling any need for formalizing or rendering transparent information (Cantonnet et al., 2019). As a result, it seems that ERM does not have a straightforward effect on SMEs' performance quality. It seems important to evaluate such a basic relationship between ERM and SMEs' performance because informal management structures

Table 4
The A-q-ROF-DM for CSFs for dynamic ERM in SMEs.

CSFs	O_1	O_2	O_3	O_4	O_5
CF_1	(0.410, 0.704, 0.581)	(0.436, 0.678, 0.593)	(0.571, 0.557, 0.603)	(0.577, 0.560, 0.595)	(0.746, 0.407, 0.527)
CF_2	(0.453, 0.656, 0.604)	(0.317, 0.774, 0.547)	(0.624, 0.520, 0.583)	(0.528, 0.595, 0.606)	(0.612, 0.541, 0.576)
CF_3	(0.723, 0.430, 0.541)	(0.716, 0.437, 0.545)	(0.548, 0.595, 0.588)	(0.667, 0.485, 0.565)	(0.695, 0.457, 0.556)
CF_4	(0.591, 0.554, 0.586)	(0.654, 0.491, 0.575)	(0.527, 0.612, 0.589)	(0.510, 0.616, 0.600)	(0.479, 0.658, 0.581)
CF_5	(0.604, 0.536, 0.590)	(0.642, 0.510, 0.572)	(0.536, 0.596, 0.598)	(0.642, 0.509, 0.573)	(0.757, 0.400, 0.518)
CF_6	(0.639, 0.511, 0.574)	(0.394, 0.708, 0.586)	(0.674, 0.477, 0.565)	(0.575, 0.562, 0.595)	(0.584, 0.564, 0.583)
CF_7	(0.481, 0.642, 0.598)	(0.374, 0.709, 0.598)	(0.522, 0.602, 0.604)	(0.541, 0.590, 0.599)	(0.473, 0.665, 0.578)
CF_8	(0.754, 0.400, 0.522)	(0.755, 0.403, 0.516)	(0.503, 0.619, 0.603)	(0.533, 0.601, 0.596)	(0.475, 0.665, 0.576)
CF_9	(0.645, 0.503, 0.575)	(0.702, 0.452, 0.551)	(0.539, 0.596, 0.595)	(0.657, 0.501, 0.563)	(0.704, 0.455, 0.545)
CF_{10}	(0.693, 0.467, 0.550)	(0.581, 0.562, 0.588)	(0.554, 0.583, 0.594)	(0.565, 0.581, 0.586)	(0.560, 0.590, 0.582)
CF_{11}	(0.393, 0.698, 0.598)	(0.436, 0.678, 0.593)	(0.672, 0.482, 0.562)	(0.614, 0.527, 0.587)	(0.561, 0.571, 0.599)
CF_{12}	(0.388, 0.701, 0.598)	(0.499, 0.629, 0.596)	(0.692, 0.461, 0.556)	(0.624, 0.520, 0.583)	(0.614, 0.527, 0.587)
CF_{13}	(0.605, 0.535, 0.589)	(0.616, 0.529, 0.584)	(0.517, 0.608, 0.602)	(0.513, 0.613, 0.600)	(0.497, 0.637, 0.589)
CF_{14}	(0.587, 0.545, 0.599)	(0.568, 0.568, 0.596)	(0.657, 0.501, 0.563)	(0.654, 0.496, 0.570)	(0.696, 0.468, 0.545)
CF_{15}	(0.628, 0.518, 0.581)	(0.724, 0.443, 0.528)	(0.668, 0.497, 0.554)	(0.667, 0.495, 0.557)	(0.547, 0.576, 0.607)
CF_{16}	(0.341, 0.731, 0.591)	(0.403, 0.700, 0.590)	(0.667, 0.489, 0.562)	(0.702, 0.452, 0.551)	(0.389, 0.698, 0.602)
CF_{17}	(0.468, 0.646, 0.603)	(0.368, 0.712, 0.598)	(0.536, 0.596, 0.598)	(0.553, 0.580, 0.598)	(0.482, 0.656, 0.581)
CF_{18}	(0.714, 0.443, 0.542)	(0.706, 0.449, 0.548)	(0.394, 0.708, 0.586)	(0.387, 0.714, 0.584)	(0.674, 0.488, 0.555)

tend to dominate SMEs, pointing toward a trade-off due to the cost of the ERM implementation (Brustbauer, 2014; Arocena and Núñez, 2010). The research on ERM with the use of SME samples is in its infancy stage (Rehman and Anwar, 2019); the current body of knowledge suggests that certain ERM elements can influence SMEs' performance (Yakob et al., 2020), and ERM can play a moderating role in enhancing competitive advantages (Yang et al., 2018). In the case of any informal decision-making process, it should be remembered that most SMEs are indeed family companies (Chua et al., 2012).

Yazid et al. (2012) empirically found that only 18 % of manufacturing firms practice risk management and implement ERM in their strategic business operations. Furthermore, Daud et al. (2011) maintained that only around 43 % of public-listed firms practice ERM. The ERM adoption, in the context of Malaysia, is still slow. Therefore, effective risk management approaches enable organizations to accomplish their objectives while increasing the value of their stakeholders

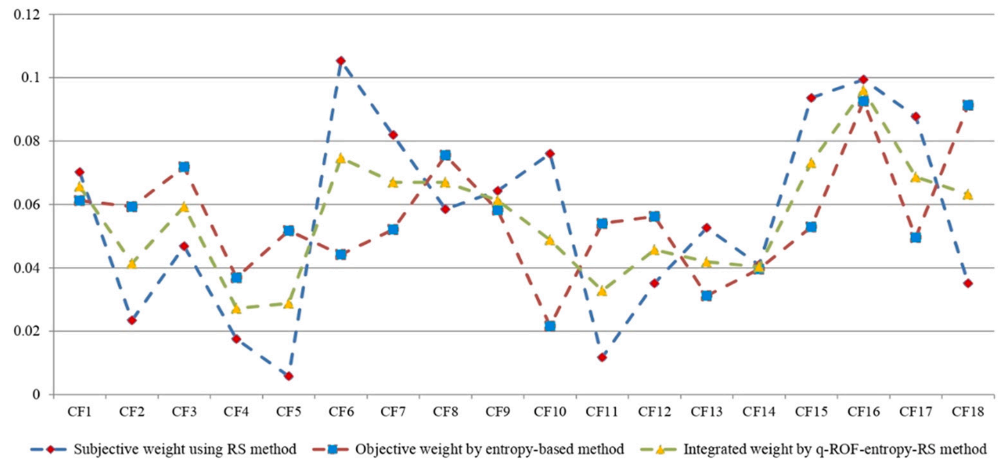

Fig. 2. Weight of CSFs for dynamic ERM in SMEs.

Table 5
Weights of CSFs for dynamic ERM in SMEs using the RS method.

CSFs	g_1	g_2	g_3	g_4	A-q-ROF-DM	Crisp values $\mathbb{S}(z_{kj})$	Rank of challenges	Weight w_j^s
CF_1	MH	M	M	MH	(0.540, 0.581, 0.608)	0.477	7	0.0702
CF_2	M	M	M	L	(0.478, 0.620, 0.622)	0.422	15	0.0234
CF_3	M	MH	L	M	(0.500, 0.621, 0.604)	0.432	11	0.0468
CF_4	MH	L	ML	M	(0.446, 0.665, 0.599)	0.378	16	0.0175
CF_5	L	ML	L	ML	(0.354, 0.725, 0.591)	0.300	18	0.0058
CF_6	M	H	MH	M	(0.611, 0.529, 0.588)	0.547	1	0.1053
CF_7	ML	M	H	L	(0.541, 0.570, 0.618)	0.484	5	0.0819
CF_8	MH	M	L	MH	(0.501, 0.620, 0.604)	0.434	9	0.0585
CF_9	ML	M	MH	ML	(0.503, 0.619, 0.603)	0.435	8	0.0643
CF_{10}	H	M	ML	MH	(0.551, 0.582, 0.598)	0.483	6	0.0760
CF_{11}	L	VL	MH	ML	(0.415, 0.709, 0.570)	0.334	17	0.0117
CF_{12}	ML	M	MH	L	(0.495, 0.625, 0.604)	0.427	13	0.0351
CF_{13}	H	ML	L	MH	(0.509, 0.626, 0.591)	0.433	10	0.0526
CF_{14}	H	L	ML	MH	(0.505, 0.629, 0.591)	0.430	12	0.0409
CF_{15}	MH	H	L	M	(0.575, 0.568, 0.589)	0.504	3	0.0936
CF_{16}	ML	H	M	M	(0.573, 0.561, 0.598)	0.507	2	0.0994
CF_{17}	ML	H	M	L	(0.556, 0.580, 0.596)	0.486	4	0.0877
CF_{18}	L	M	MH	ML	(0.490, 0.628, 0.604)	0.423	14	0.0351

(Yazid et al., 2008). Furthermore, an effective ERM implementation enables organizations to make the most use of their resources and thus maximize their profits (Yakob et al., 2020). Indeed, the recently updated ERM framework by COSO stated that integrating ERM across entities will allow for multiple benefits, including increasing opportunities, identifying, and managing risks across entities, encouraging positive outcomes and benefits, lowering negative shocks, decreasing performance variability, increasing utilization of resources, and the rising value of the firm. As a result, firms' risk exposure may be efficiently managed and reduced by implementing ERM and helping the firm accomplish its objectives. In this study, to evaluate the dynamic ERM in SMEs, several CSFs are identified, including joint practitioner and business contingency planning (CF_1), foster skills, diversity, and expertise (CF_2), adequate internal reporting of framework effectiveness (CF_3), iterative and responsive to change (CF_4), Facilitation of continual improvement and enhancement of the organization (CF_5), regular review of risk management policy and framework in response to changes (CF_6), appropriate and timeous communication of framework modification (CF_7), integration of risk management within the overall risk management system (CF_8), clear risk management framework development and implementation accountability (CF_9), an integral part of organizational processes (CF_{10}), consider the internal and external organizational context (CF_{11}), effectiveness, agility, and resilience dependent (CF_{12}), creates value for the organization (CF_{13}), the systematic, planned, and structured approach (CF_{14}), risk indicators tracking directly aligned to business performance indicators (CF_{15}), continuous suitability-checking of the risk management framework (CF_{16}), embedded in organizational decision making (CF_{17}) and risk management practice should accommodate changing organizations (CF_{18}).

3. Proposed q-ROF-entropy-RS-ARAS approach

First, we show some basic notions to assess the CSFs for dynamic ERM in SMEs.

For the first time, the idea of "q-rung orthopair fuzzy sets (q-ROFSs)" was given by Yager (2017a) as follows: A q-ROFS 'M' in $\Xi = \{z_1, z_2, \ldots, z_n\}$ is given by $M = \{(z_i, \mu_M(z_i), \nu_M(z_i)) | z_i \in \Xi\}$, where, μ_M and ν_M show the BG and NG of $z_i \in \Xi$, respectively, $\mu_M(z_i) \in [0,1]$, $\nu_M(z_i) \in [0,1]$, $0 \leq (\mu_M(z_i))^q + (\nu_M(z_i))^q \leq 1$ with $q \geq 1$. The indeterminacy grade, is defined as $\pi_M(z_i) = \sqrt[q]{1 - (\mu_M(z_i))^q - (\nu_M(z_i))^q}, \forall z_i \in \Xi$. The pair $(\mu_M(z_i), \nu_M(z_i))$ is referred as "q-rung orthopair fuzzy numbers (q-ROFN)", and is denoted by $\varphi = (\mu_\varphi, \nu_\varphi)$. To rank the diverse q-ROFNs, the score and accuracy functions of φ are presented as.

$$\mathbb{S}(\varphi) = 0.5\left(\left(\mu_\varphi^q - \nu_\varphi^q\right) + 1\right) \text{ and } H(\varphi) = \mu_\varphi^q + \nu_\varphi^q, \quad (1)$$

Next, an ARAS method under a q-ROFSs environment is developed for solving decision-making applications and named as q-ROF-entropy-RS-ARAS method (see Fig. 1). In this line, consider a set of ℓ DMs $g = \{g_1, g_2, \ldots, g_\ell\}$ determine the sets of m options $O = \{o_1, o_2, \ldots, o_m\}$ and n criteria $CF = \{CF_1, CF_2, \ldots, CF_n\}$, respectively. Owing to the vagueness of

Table 6
The WNA-q-ROF-DM for CSFs for dynamic ERM in SMEs.

	G_0	O_1	O_2	O_3	O_4	O_5
CF_1	(0.228, 0.943, 0.244)	(0.110, 0.977, 0.182)	(0.117, 0.975, 0.190)	(0.160, 0.962, 0.220)	(0.162, 0.963, 0.217)	(0.228, 0.943, 0.244)
CF_2	(0.142, 0.973, 0.180)	(0.097, 0.983, 0.158)	(0.066, 0.989, 0.129)	(0.142, 0.973, 0.180)	(0.116, 0.979, 0.169)	(0.139, 0.975, 0.174)
CF_3	(0.207, 0.951, 0.229)	(0.207, 0.951, 0.229)	(0.204, 0.952, 0.228)	(0.145, 0.970, 0.197)	(0.185, 0.958, 0.219)	(0.196, 0.955, 0.225)
CF_4	(0.123, 0.981, 0.151)	(0.108, 0.984, 0.141)	(0.123, 0.981, 0.151)	(0.094, 0.987, 0.132)	(0.090, 0.987, 0.134)	(0.084, 0.989, 0.124)
CF_5	(0.156, 0.974, 0.165)	(0.114, 0.982, 0.149)	(0.123, 0.981, 0.151)	(0.099, 0.985, 0.140)	(0.123, 0.981, 0.151)	(0.155, 0.974, 0.165)
CF_6	(0.210, 0.946, 0.246)	(0.196, 0.951, 0.239)	(0.112, 0.975, 0.194)	(0.210, 0.946, 0.246)	(0.172, 0.958, 0.230)	(0.175, 0.958, 0.226)
CF_7	(0.151, 0.965, 0.213)	(0.132, 0.971, 0.201)	(0.100, 0.977, 0.187)	(0.145, 0.967, 0.211)	(0.151, 0.965, 0.213)	(0.130, 0.973, 0.191)
CF_8	(0.234, 0.941, 0.244)	(0.234, 0.940, 0.247)	(0.235, 0.941, 0.244)	(0.139, 0.968, 0.207)	(0.149, 0.966, 0.210)	(0.130, 0.973, 0.190)
CF_9	(0.203, 0.953, 0.226)	(0.180, 0.959, 0.220)	(0.202, 0.952, 0.228)	(0.144, 0.969, 0.202)	(0.184, 0.959, 0.217)	(0.203, 0.953, 0.226)
CF_{10}	(0.177, 0.963, 0.201)	(0.177, 0.964, 0.201)	(0.141, 0.972, 0.186)	(0.133, 0.974, 0.183)	(0.136, 0.974, 0.182)	(0.135, 0.975, 0.179)
CF_{11}	(0.140, 0.976, 0.165)	(0.074, 0.988, 0.134)	(0.083, 0.987, 0.135)	(0.140, 0.976, 0.165)	(0.124, 0.979, 0.161)	(0.111, 0.982, 0.154)
CF_{12}	(0.171, 0.965, 0.197)	(0.086, 0.984, 0.157)	(0.114, 0.979, 0.169)	(0.171, 0.965, 0.197)	(0.149, 0.971, 0.189)	(0.146, 0.971, 0.188)
CF_{13}	(0.141, 0.974, 0.179)	(0.138, 0.974, 0.179)	(0.141, 0.974, 0.179)	(0.114, 0.979, 0.167)	(0.113, 0.980, 0.166)	(0.109, 0.981, 0.159)
CF_{14}	(0.162, 0.970, 0.182)	(0.130, 0.976, 0.176)	(0.125, 0.977, 0.170)	(0.150, 0.973, 0.178)	(0.149, 0.972, 0.181)	(0.162, 0.970, 0.182)
CF_{15}	(0.230, 0.942, 0.244)	(0.190, 0.953, 0.236)	(0.230, 0.942, 0.244)	(0.206, 0.950, 0.234)	(0.205, 0.950, 0.236)	(0.160, 0.960, 0.228)
CF_{16}	(0.251, 0.927, 0.280)	(0.109, 0.970, 0.216)	(0.130, 0.966, 0.222)	(0.234, 0.934, 0.271)	(0.251, 0.927, 0.280)	(0.125, 0.966, 0.226)
CF_{17}	(0.157, 0.963, 0.218)	(0.130, 0.970, 0.203)	(0.100, 0.977, 0.189)	(0.152, 0.965, 0.214)	(0.157, 0.963, 0.217)	(0.134, 0.971, 0.196)
CF_{18}	(0.210, 0.950, 0.232)	(0.210, 0.950, 0.232)	(0.206, 0.951, 0.232)	(0.103, 0.978, 0.179)	(0.101, 0.979, 0.178)	(0.194, 0.956, 0.222)

the human mind, lack of data, and imprecise knowledge about the options, the DMs allocate “linguistic values (LVs)” to evaluate his/her decision on option o_i concerning a criterion CF_j. Assume that $\mathbb{Z}^{(k)} = (z_{ij}^{(k)})_{m\times n}$, $i = 1, 2, \ldots, m$, $j = 1, 2, \ldots, n$ is the suggested “linguistic decision matrix (LDM)” by DMs, where $z_{ij}^{(k)}$ refer to the evaluation of an option o_i over a criterion CF_j in the form of LVs provided by k^{th} DM.

Step 1: Compute the weights of DMs.

To determine the DMs' weights, firstly, the importance ratings of the DMs are assumed as “linguistic values (LVs)” and then expressed by q-ROFNs. To compute the k^{th} DM, let $g_k = (\mu_k, \nu_k)$ be the q-ROFN. Now, the DM's weight is obtained by

$$\varpi_k = \frac{1}{2}\left(\frac{0.5\left(\left(\mu_k^q - \nu_k^q\right) + 1\right)}{\sum_{k=1}^{\ell}\left(0.5\left(\left(\mu_k^q - \nu_k^q\right) + 1\right)\right)} + \frac{n - r_k + 1}{\sum_{k=1}^{\ell}(n - r_k + 1)}\right), k = 1, 2, \ldots, \ell. \tag{2}$$

Here, $\varpi_k \geq 0$ and $\sum_{k=1}^{\ell}\varpi_k = 1$.

Table 7
The OPD and UD of enterprises of WNA-q-ROF-DM for CSFs for dynamic ERM in SMEs.

CSFs	G_0	O_1	O_2	O_3	O_4	O_5
CF_1	0.082	0.029	0.032	0.050	0.050	0.082
CF_2	0.036	0.022	0.013	0.036	0.028	0.034
CF_3	0.069	0.069	0.068	0.040	0.058	0.064
CF_4	0.027	0.022	0.027	0.018	0.017	0.015
CF_5	0.038	0.024	0.027	0.020	0.027	0.038
CF_6	0.074	0.067	0.031	0.074	0.056	0.056
CF_7	0.046	0.038	0.028	0.043	0.046	0.035
CF_8	0.085	0.085	0.085	0.041	0.044	0.035
CF_9	0.067	0.057	0.067	0.041	0.058	0.066
CF_{10}	0.052	0.052	0.037	0.035	0.035	0.034
CF_{11}	0.033	0.014	0.016	0.033	0.028	0.024
CF_{12}	0.049	0.020	0.027	0.049	0.040	0.039
CF_{13}	0.036	0.035	0.036	0.027	0.026	0.024
CF_{14}	0.043	0.032	0.030	0.038	0.039	0.043
CF_{15}	0.083	0.064	0.083	0.070	0.070	0.052
CF_{16}	0.102	0.035	0.042	0.092	0.102	0.041
CF_{17}	0.048	0.037	0.028	0.046	0.048	0.037
CF_{18}	0.071	0.071	0.069	0.027	0.026	0.062
OPD	1.039	0.772	0.744	0.779	0.798	0.782
Utility degree (UD)	–	0.7424	0.7155	0.7496	0.7675	0.7523
Ranking		4	5	3	1	2

Step 2: Obtain the “aggregated q-ROF-decision-matrix (A-q-ROF-DM)”.

To create the A-q-ROF-DM, the “q-ROF-weighted averaging (q-ROFWA)” operator is used and then $\mathbb{Z} = (z_{ij})_{m\times n}$, where

$$z_{ij} = \left(\mu_{ij}, \nu_{ij}\right) q - ROFWA_{\varpi}\left(z_{ij}^{(1)}, z_{ij}^{(2)}, \ldots, z_{ij}^{(\ell)}\right) = \left(\sqrt[q]{1 - \prod_{k=1}^{\ell}\left(1 - \left(\mu_{ij}^{(k)}\right)^q\right)^{\varpi_k}}, \prod_{k=1}^{\ell}\left(\nu_{ij}^{(k)}\right)^{\varpi_k}\right). \tag{3}$$

Step 3: Proposed “q-ROF-entropy-rank sum (q-ROF-entropy-RS)” method for assessing weights.

All the criteria are not presumed to be of equal importance. Suppose $w = (w_1, w_2, \ldots, w_n)^T$ be the weight of criteria with $\sum_{j=1}^{n} w_j = 1$ and $w_j \in [0, 1]$. Now, to find the criteria weights, the q-ROF-entropy-RS method is applied to the q-ROFSs setting.

To find the objective weight, the entropy-based model is extended under the q-ROFS environment as follows:

$$w_j^o = \frac{\sum_{i=1}^{m}\left(1 - \overline{E}(z_{ij})\right)}{\sum_{j=1}^{n}\left(\sum_{i=1}^{m}\left(1 - \overline{E}(z_{ij})\right)\right)}, \tag{4}$$

where, $\overline{E}(z_{ij}) = E(z_{ij})/max_{i=1,2,\ldots m}E(z_{ij})$ and $E(z_{ij}) = \frac{1}{n\left(1 - exp(-1/2)\right)}\sum_{i=1}^{n}\left[\left\{1 - exp\left(-\left(\frac{\nu_{ij}^q + 1 - \mu_{ij}^q}{2}\right)\right)\right\} I_{\left[\mu_{ij}^q \geq \nu_{ij}^q\right]} + \left\{1 - exp\left(-\left(\frac{\mu_{ij}^q + 1 - \nu_{ij}^q}{2}\right)\right)\right\} I_{\left[\mu_{ij}^q < \nu_{ij}^q\right]}\right]$. signifies the entropy measure of z_{ij} adopted by Mishra and Rani (2021).

Next, the subjective weighting system helps to reflect the intrinsic values and thoughts of decision-makers. Hopefully, these procedures are so relevant that the alternatives taken could be well considered, but the significance of the prevailing criteria could be illustrated. Here, the DMs give their subjective assessments (Stillwell et al., 1981; Narayanamoorthy et al., n.d.). For example, the following RS weighting procedure is presented as follows:

$$w_j^s = \frac{n - r_j + 1}{\sum_{j=1}^{n}\left(n - r_j + 1\right)}, \tag{5}$$

Table 8
The UD of option with different CSFs for dynamic ERM in SMEs weighting parameter values.

	τ = 0.0	τ = 0.1	τ = 0.2	τ = 0.3	τ = 0.4	τ = 0.5	τ = 0.6	τ = 0.7	τ = 0.8	τ = 0.9	τ = 1.0
O_1	0.7557	0.7530	0.7503	0.7476	0.7450	0.7424	0.7398	0.7373	0.7347	0.7322	0.7297
O_2	0.7074	0.7090	0.7106	0.7122	0.7138	0.7155	0.7171	0.7188	0.7206	0.7223	0.7241
O_3	0.7728	0.7680	0.7633	0.7586	0.7541	0.7496	0.7452	0.7409	0.7366	0.7324	0.7282
O_4	0.7864	0.7824	0.7786	0.7748	0.7711	0.7675	0.7640	0.7606	0.7573	0.7540	0.7508
O_5	0.7377	0.7406	0.7435	0.7464	0.7493	0.7523	0.7552	0.7581	0.7610	0.7640	0.7669

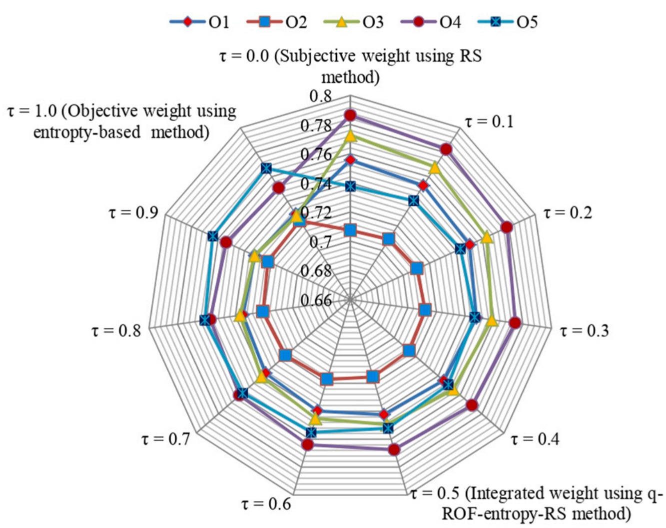

Fig. 3. Sensitivity analysis test on weighting parameter values.

Table 10
The *UD* of enterprises with CSFs for dynamic ERM in SMEs.

Options	q-ROF-WSM		q-ROF-WPM		q-ROF-WASPAS	Ranking
	$\mathbb{C}_i^{(1)}$	$\mathbb{S}\left(\mathbb{C}_i^{(1)}\right)$	$\mathbb{C}_i^{(2)}$	$\mathbb{S}\left(\mathbb{C}_i^{(2)}\right)$	$\mathbb{C}_i(\lambda)$	
O_1	(0.576, 0.572, 0.584)	0.5023	(0.529, 0.604, 0.597)	0.4575	0.4799	4
O_2	(0.577, 0.575, 0.580)	0.5014	(0.517, 0.614, 0.596)	0.4447	0.4730	5
O_3	(0.596, 0.550, 0.585)	0.5266	(0.578, 0.563, 0.591)	0.5088	0.5177	2
O_4	(0.603, 0.543, 0.584)	0.5347	(0.586, 0.555, 0.590)	0.5175	0.5261	1
O_5	(0.603, 0.549, 0.578)	0.5311	(0.570, 0.574, 0.588)	0.4982	0.5146	3

where w_j^s stands for the subjective weights for each criterion j, n denotes the total number of criteria, r_j signifies the rank of each criterion, $j = 1,2,3, \ldots, n$.

In the A-q-ROF-decision matrix, the decision-maker wants to utilize both subjective and objective weights, for the following integrated weighted equation is given

$$w_j = \tau w_j^o + (1-\tau) w_j^s, \tag{6}$$

where τ is an objective factor of criteria weights and $\tau \in [0,1]$. w_j^o represents the objective weight and w_j^s represents the subjective weight, respectively.

Step 4: Obtain the "Optimal Assessment Grade (OAG)".

$$G_0 = \begin{cases} \max z_{ij}, & j \in CF_b \\ \min z_{ij}, & j \in CF_n, \end{cases} \tag{7}$$

where CF_b and CF_n are benefit and cost-types criteria, respectively.

Step 5: Create the "normalized A-q-ROF-DM (NA-q-ROF-DM)".

The procedure for determining the NA-q-ROF-DM $U = (\varsigma_{ij})_{m\times n}$, as follows:

$$\varsigma_{ij} = \left(\overline{\mu}_{ij}, \overline{\nu}_{ij}\right) = \begin{cases} z_{ij} = \left(\mu_{ij}, \nu_{ij}\right), & j \in CF_b \\ \left(z_{ij}\right)^c = \left(\nu_{ij}, \mu_{ij}\right), & j \in CF_n. \end{cases} \tag{8}$$

Step 6: Find the "Weighted NA-q-ROF-DM (WNA-q-ROF-DM)".

Let $w = (w_1, w_2, \ldots, w_n)^T$ be the weights, using Eq. (7), of attributes $CF_j : j = 1, 2, \ldots, n$, then the WNA-q-ROF-DM $U_w = \left(\widetilde{\varsigma}_{ij}\right)_{m\times n}$ is generated by

$$\widetilde{\varsigma}_{ij} = \left(\widetilde{\mu}_{ij}, \widetilde{\nu}_{ij}\right) = \bigoplus_{j=1}^{n} w_j \varsigma_{ij} = \left(\sqrt[q]{1 - \prod_{j=1}^{n}\left(1 - \overline{\mu}_{ij}^q\right)^{w_j}}, \prod_{j=1}^{n}\left(\overline{\nu}_{ij}\right)^{w_j}\right) \tag{9}$$

Step 7: Assess the scores of WNA-q-ROF-DM.

From Eq. (1), the scores WNA-q-ROF-DM $U_w = \left(\widetilde{\varsigma}_{ij}\right)_{m\times n}$ are obtained by

$$\mathbb{S}\left(\widetilde{\varsigma}_{ij}\right) = \frac{1}{2}\left[\left(\left(\widetilde{\mu}_{ij}\right)^q - \left(\widetilde{\nu}_{ij}\right)^q\right) + 1\right], i = 1, 2, \ldots, m, j = 1, 2, \ldots, n. \tag{10}$$

Step 8: Estimate the "Overall Performance Degree (OPD)" and "Utility Degree (UD)".

The OPD value of each option is found as follows:

$$G_i = \sum_{j=1}^{n} \mathbb{S}(\widetilde{\varsigma}), i = 1, 2, \ldots, m \tag{11}$$

Through the MCDM process, it is necessary to calculate the optimum option and explore the virtual effect of the obtained options, considering the alternative of the highest favorability. The variant UD is computed by evaluating the observed variant with the optimum alternative G_0. The UD Q_i of each option $o_i : i = 1, 2, \ldots, m$ is given by

$$Q_i = \frac{G_i}{G_0}, i = 1, 2, \ldots, m. \tag{12}$$

where $Q_i \in [0, 1]$. The Q_i value can be set in an ascending degree in a way to achieve the ranking order.

4. Data collection and implementation results

A standard questionnaire is developed and verified by an industry focus group of academic experts for data collection in this study. Five manufacturing SMEs are selected to evaluate the critical success factors for dynamic enterprise risk management. Two different phases have been conducted in the data collection process. Therefore, in the first data collection phase, we sent the questionnaire to five experts in manufacturing SMEs. The experts were given one month to return the questionnaires, whereas three additional weeks were allocated for personal interviewing and telephoning that were required for missing information and incomplete questionnaires. In the second phase of data collection, we sent the questionnaire to five people who were experts in ERM and risk management. The same way has been carried out for this

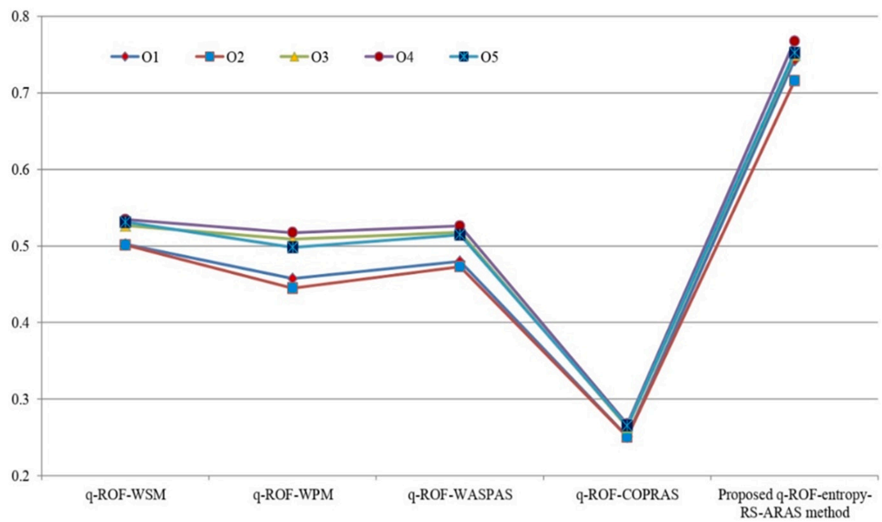

Fig. 4. Comparison of UDs of each enterprise with various methods.

data collection to collect the complete questionnaires. Out of ten experts, three experts declined to participate in the questionnaire survey due to lack of time, organizational policy, or other secret reasons; however, those experts mentioned their keen interest in this study subject. One questionnaire is sent back to the experts due to changing their organizations' addresses. One of the experts provided an incomplete questionnaire that was excluded from the data collection have been excluded in the analysis. Altogether, five usable questionnaires from different levels of management, such as top, front-line, and middle managers, were returned, and we analyzed and provided them in the study.

The implementation of the q-ROF-entropy-RS-ARAS method is given as follows:

Step 1: Table 1 depicts the significance of the DMs and criteria in the form of LVs and then converted into q-ROFNs. Table 2 presents the DM's weight based on Table 1 and Eq. (2). Table 3 describes the LDM of each DM to evaluate the CSFs for dynamic ERM in SMEs.

Step 2: Judgment provided by four DEs in the form of LDM expressed as (g_1, g_2, g_3, g_4) have been merged using Eq. (3) into an A-q-ROF-DM $\mathbb{Z} = (z_{ij})_{m\times n}$ and are provided in Table 4 for CSFs for dynamic ERM in SMEs.

Step 3: From Eq. (4), we have calculated the objective weights using the q-ROF-entropy-based procedure of each CSFs for dynamic ERM in SMEs. The resultant values are in Fig. 2.

w_j^o= (0.0612, 0.0593, 0.0718, 0.0369, 0.0517, 0.0442, 0.0521, 0.0755, 0.0582, 0.0216, 0.0540, 0.0562, 0.0312, 0.0396, 0.0529, 0.0926, 0.0496, 0.0913).

From Eq. (5), we have calculated the subjective weights using the q-ROF-RS weight procedure of each CSFs for dynamic ERM in SMEs. The resultant values are given in Table 5 and shown in Fig. 2.

From the algorithm of the proposed q-ROF-entropy-RS-ARAS, we have to combine the q-ROF-entropy for objective weighting and q-ROF-RS for subjective weighting by using Eq. (6). The integrated weight for $\tau = 0.5$ is shown in Fig. 2 and given as follows:

w_j = (0.0657, 0.0414, 0.0593, 0.0272, 0.0288, 0.0747, 0.0670, 0.0670, 0.0613, 0.0488, 0.0328, 0.0457, 0.0419, 0.0403, 0.0732, 0.0960, 0.0687, 0.0632).

Here, Fig. 2 represents the weight values of different CSFs for dynamic ERM in SMEs with respect to the goal. Continuous suitability-checking of the risk management framework (CF_{16}) with a weight value of 0.0960 has come out to be the most important CSFs for dynamic ERM in SMEs. Regular risk management policy and framework review in response to changes (CF_6) with a weight value of 0.0747 is the second most important CSFs for dynamic ERM in SMEs. Risk indicators tracking directly aligned to business performance indicators (CF_{15}) has third with a significance value of 0.0732, embedded in organizational decision making (CF_{17}) has fourth with a weight value of 0.0687, appropriate and timeous communication of framework modification (CF_7), and integration of risk management within the overall risk management system (CF_8) with significance value 0.0670 have fifth most important CSFs for dynamic ERM in SMEs and others are considered crucial CSFs for dynamic ERM in SMEs.

Step 4: Next, we obtain the OAG of each option to evaluate the CSFs for dynamic ERM in SMEs using Eq. (7). The obtained OAGs to rank the enterprises and analyze the main CSFs for dynamic ERM in SMEs are obtained as follows:

G_0={(0.746, 0.407, 0.527), (0.624, 0.520, 0.583), (0.723, 0.430, 0.541), (0.654, 0.491, 0.575), (0.757, 0.400, 0.518), (0.674, 0.477, 0.565), (0.541, 0.590, 0.599), (0.755, 0.403, 0.516), (0.704, 0.455, 0.545), (0.693, 0.467, 0.550), (0.672, 0.482, 0.562), (0.692, 0.461, 0.556), (0.616, 0.529, 0.584), (0.696, 0.468, 0.545), (0.724, 0.443, 0.528), (0.702, 0.452, 0.551), (0.553, 0.580, 0.598), (0.714, 0.443, 0.542)}.

Step 5: Since all criteria are beneficial-type criteria, thus, there is no need to transform aggregated q-ROF-DM into normalized q-ROF-DM. By using Eq. (9), the required weighted normalized A-q-ROF-DM is presented in Table 6.

Steps 6–8: Using Eq. (10)–Eq. (11), we compute the score value and OPDs of WNA-q-ROF-DM of enterprises to evaluate the CSFs for dynamic ERM in SMEs, which are presented in Table 7. Using Eq. (12), the UD $\mathbb{Q}_i$, is estimated as follows: $\mathbb{Q}_1 = 0.7424$, $\mathbb{Q}_2 = 0.7125$, $\mathbb{Q}_3 = 0.7496$ $\mathbb{Q}_4 = 0.7675$, and $\mathbb{Q}_5 = 0.7523$. According to the values of the aggregating compromise index, $\mathbb{Q}_i$,the preference order of the enterprises to evaluate the CSFs for dynamic ERM in SMEs is $O_4 \succ O_5 \succ O_4 \succ O_1 \succ O_2$, and thus, the enterprise-IV (O_4) is the ideal option over various CSFs for dynamic ERM in SMEs.

5. Comparative and sensitivity investigations

5.1. Sensitivity analysis

Here, we show the sensitivity investigation of the presented approach. We take various values of $\tau \in [0,1]$ of CSFs' weights for investigation. Varying the parameter τ from $\tau = 0.0$ to $\tau = 1.0$ can support to assessment of the sensitivity of the presented approach with objective weight to subjective weights of CSFs for dynamic ERM in SMEs. From Table 8 and Fig. 3, the rank of enterprises is discussed over the variations of CSFs for dynamic ERM in SMEs' weight values from different parameter $\tau \in [0,1]$ values. Thus, it is determined that the suitable enterprise over different CSFs for dynamic ERM in SMEs is reliant on and sensitive to considered CSFs for dynamic ERM in SMEs weights. Hence, the presented approach has an acceptable solidity over diverse CSFs for dynamic ERM in SMEs values. According to results, enterprise-IV (O_4) has obtained the first rank form $\tau = 0.0$ to $\tau = 0.7$ and enterprise-V (O_5) has obtained the first rank form $\tau = 0.8$ to $\tau = 1.0$, while enterprise-II (O_2) has obtained the worst rank form $\tau = 0.0$ to $\tau = 1.0$. Based on the aforementioned result, it is observed that using the diverse CSFs for dynamic ERM in SMEs values will enhance the stability of the q-ROF-entropy-RS-ARAS method.

5.2. Comparative discussion

This section compares the proposed framework with other extant methods under both theoretical and numerical factors for q-ROFSs. We consider the following method to compare the developed methodology as q-ROF-"stepwise weight assessment ratio analysis (SWARA)"-"complex proportional assessment (COPRAS)" (Krishankumar et al., 2019), q-ROF-WASPAS (Rani and Mishra, 2020), q-ROF-"weighted sum model (WSM)" (Rani and Mishra, 2020) and q-ROF-"weighted product model (WPM)" (Rani and Mishra, 2020).

The procedure of the q-ROF-WASPAS model is given as follows:

Steps 1–3: These steps are related to the previous model.

Step 4: Utilize the "weighted sum model (WSM)" $\mathbb{C}_i^{(1)}$ in the following expression

$$\mathbb{C}_i^{(1)} = \overset{n}{\underset{j=1}{\oplus}} w_j \varsigma_{ij}. \tag{13}$$

Step 5: Apply the "Weighted Product Model (WPM)" $\mathbb{C}_i^{(2)}$ in the following expression

$$\mathbb{C}_i^{(2)} = \overset{n}{\underset{j=1}{\otimes}} \varsigma_{ij}^{w_j}. \tag{14}$$

Step 6: Obtain the *UD* of each option in the following expression

$$\mathbb{C}_i = \lambda \mathbb{C}_i^{(1)} + (1-\lambda)\mathbb{C}_i^{(2)}, i = 1,2,\ldots,m, \tag{15}$$

where 'λ' means the decision strategy parameter, where $\lambda \in [0,1]$ (when $\lambda = 0$ and $\lambda = 1$, WASPAS is transformed into the WPM and the WSM, respectively).

Step 7: Based on *UD* $\mathbb{C}_i$, prioritize the options.

Steps 4–7: Using Table 5 and Eq. (13)-Eq. (14), the measures of WSM and WPM are estimated. After that, with the help of Eq. (15), the WASPAS measure (at $\lambda = 0.5$) is estimated and presented in Table 10. From Table 10, the ranking order of enterprises over different CSFs for dynamic ERM in SMEs is $O_4 \succ O_3 \succ O_5 \succ O_1 \succ O_2$. Therefore, O_4 is the most desirable enterprise with different CSFs for dynamic ERM in SMEs.

Next, the procedure of the q-ROF-COPRAS model is presented as follows:

Steps 1–3: These steps are analogous to the aforementioned model.

Step 4: Here, all CSFs are of benefit-type, thus, we compute the index value for each option to maximize the benefit preference $\beta_i = \oplus_{j=1}^{n} w_j z_{ij}$, $i = 1,2,\ldots,m$. The index value is similar to "relative degree (RD)" of each alternative and is estimated as $TR_1 = 0.2512$, $TR_2 = 0.2507$, $TR_3 = 0.2633$, $TR_4 = 0.2674$ and $TR_5 = 0.2656$.

Step 5: Compare the RD of the five enterprises using the priority TR_i and get the prioritization of these enterprises as $TR_4 \succ TR_5 \succ TR_3 \succ TR_1 \succ TR_2$. The prioritization reveals that option o_4 is the optimal one.

Step 6: Estimate the "utility degree (UD)" $\hbar_i = \frac{TR_i}{TR_{\max}} \times 100\%$, which reflects the association between each alternative and the best alternative. Then, we obtain $\hbar_1 = 93.94\ \%$, $\hbar_2 = 93.75\ \%$, $\hbar_3 = 98.47\ \%$, $\hbar_4 = 100.00\ \%$, and $\hbar_5 = 99.33\ \%$ ..

Here, a comparative discussion is given between the presented and some extant methods, including q-ROF-WSM (Rani and Mishra, 2020) and q-ROF-COPRAS (Krishankumar et al., 2019), and is mentioned in Fig. 4. By comparing with the q-ROF-COPRAS method, the final ranking of the manufacturing firm is $O_4 \succ O_5 \succ O_3 \succ O_1 \succ O_2$., and the most suitable enterprise is O_4 for the CSFs for dynamic ERM in SMEs. Hence, the optimal enterprise is the same with all the proposed q-ROF-COPRAS and q-ROF-WASPAS approaches, while the preference order outcomes vary slightly with different extant methods. In general, the advantages of the "q-ROF-entropy-RS-ARAS" approach over the existing methods are presented as follows:

- The criteria weights in the method developed in the present research were assessed by the q-ROF-entropy-RS method as q-ROFNs by DEs. In contrast, in Krishankumar et al. (2019), the criteria weights were calculated by a linear programming model, and q-ROF-WASPAS (Rani and Mishra, 2020), a similarity-measure-based model, calculated the objective weights.
- The q-ROF-entropy-RS-ARAS uses the idea of an ARAS with q-ROF-entropy and q-ROF-RS models to select the enterprise to evaluate the CSFs for dynamic ERM in SMEs problems in comparison to q-ROF-WASPAS (Utility degree), q-ROF-COPRAS (Compromise programming), q-ROF-WSM and q-ROF-WPM methods. The assessment procedure of the q-ROF-entropy-RS-ARAS methodology is simple and straightforward, and hence the accuracy and determination of the results are higher.
- The q-ROF-entropy-RS-ARAS is applied to compute the subjective and objective weights of the CSFs for dynamic ERM in SMEs, which makes the developed "q-ROF-entropy-RS-ARAS" approach more sensible, flexible, and efficient.

6. Conclusions

Business communities and scholars working in this domain have become increasingly interested in ERM. Some previously-conducted studies have reported that despite the fact that ERM has received positive attention, it has not been extensively implemented yet. The literature still lacks research into the determinants of ERM and ERM CSFs. Most past studies have concentrated on issues related to large enterprises and ignored SMEs. Accordingly, the current study proposes an inclusive framework for the CSFs of ERM adoption in manufacturing SMEs. To analyze, rank, and evaluate the CSFs for dynamic ERM in SMEs, this study introduced an integrated q-ROF-entropy-RS-ARAS. To rank critical success factors for dynamic ERM in SMEs, the q-ROF-entropy-RS is utilized for determining the integrated weight values. Afterward, the q-ROF-ARAS is used to prioritize different enterprises with the CSFs for dynamic ERM in SMEs in this process. To show the usefulness of the presented method, a case study is discussed on the critical success factors identified to be effective in applying dynamic ERM in SMEs. The outcome of the assessment shows that the enterprise-IV (O_4) with a utility degree of 0.7675 is the optimal choice for evaluating the CSFs for dynamic ERM in SMEs. To validation of the results of this study, a comparison is discussed between the performance of the presented approach and that of extant models. Finally, sensitivity analysis and comparison with some extant models have been presented to validate the robustness and stability of the obtained outcomes.

Further, some limitations of the presented model are: Though q-ROFSs handle uncertain and ambiguous expressions, DMs require training to handle the inference for rational MCDM. Next, the evaluation of each DM is not premeditated analytically. In realistic concerns, there is a need to consider the large number of DMs for evaluating CSFs for dynamic ERM in SMEs assessment, though we have considered only a set of four DMs. In future research, the MCDM structures, i.e., "measurement alternatives and ranking based on compromise solution (MARCOS)", "gained and lost dominance score (GLDS)", fault Diagnosis (Glowacz, 2021; AlShorman et al., 2020), malware detection approach (Alzubi et al., 2021), evaluation of risks in life insurance (Jain et al., 2019), sustainability in the "information and communication technology (ICT)" sector (Hamdoun et al., 2014) could be implemented to choose the most appropriate method for handling the MCDM within q-ROFSs. Furthermore, the presented study could be generalized by uniting the subjective and objective weighting tools into the q-ROFSs settings.

CRediT authorship contribution statement

Delong Zhu: Conceptualization, Supervision, Visualization, Resources, Writing-original draft, References, Review & editing.

Zhe Li: Conceptualization, Methodology, Validation, Resources, Visualization, Writing-original draft, Proofread and revision.

Arunodaya Raj Mishra: Methodology, Formal analysis, Comparison and sensitivity analysis, Writing - Review & Editing.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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