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A Rough Number-Based Copula-Dombi Aggregation Framework for Selection of Agile Methods for Software Development Projects

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Abstract. Agile methodology follows the Agile Manifesto, encompassing principles, frameworks, and tools for implementation. Selecting an appropriate agile method is a complex multi-criteria decision problem. To address uncertainty objectively, this study employs rough number theory, while Copula-Dombi aggregation operators preserve information and capture interrelationships. A group decision-making framework is developed, with criteria weights derived using cross-entropy and dispersion measures. A case study is conducted to demonstrate the applicability of the proposed framework. The results indicate Dynamic System Development Model as the most suitable method, while project vision and customer involvement emerged as the most influential criteria, demonstrating robustness and practical relevance.

Key words: software development projects, agile methods, rough numbers, hybrid aggregation, group decision-making.

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1. Introduction

Software engineering, often described as the application of engineering principles to software development (SD), involves the management and maintenance of software through systematic, rigourous, and quantitative methods. Every phase of the software life cycle demands a methodical, disciplined, and measurable approach to ensure that the development processes are as important as the final product. Effective software engineering relies on well-defined practices and best practices to address complex software requirements. Accurate software development effort estimation is critical for successful project planning, resource allocation, and avoiding delays and cost overruns, ultimately determining the success or failure of a software project (Moosavi and Bardsiri, 2017). Approaches such as agile, waterfall, and DevOps provide structured frameworks that guide teams through iterative development, continuous integration, and delivery. Selecting an appropriate approach for SD depends on several factors, including project scope, team dynamics, and stakeholder needs. Adhering to disciplined practices in software engineering is aimed at enhancing productivity, improving software quality, and ensuring that the final product meets user expectations and industry standards. This comprehensive and integrated approach ensures that software projects are delivered on time, within budget, and with the desired functionality and performance. When these procedures are followed, the resulting software will meet requirements, be easier to maintain, and be more dependable, particularly for large and feature-rich applications (Braude and Bernstein, 2016). SD and engineering require teamwork; tasks are often split among multiple teams and should be managed and organized as per specific guidelines. Although certain activities may proceed in parallel, many rely on the successful completion of earlier stages, requiring careful coordination to ensure efficient and high-quality software delivery (Giuffrida and Dittrich, 2015). There are many traditional approaches to SD, such as the waterfall method, spiral method, evolutionary method, and incremental and iterative approaches (Mall, 2018). These heavyweight software development approaches are particularly suited to large and complex systems. By replacing informal practices with well-defined processes, they support systematic development that addresses user requirements while adhering to specified timelines. However, projects using traditional techniques often face challenges with maintenance and user-requested improvements. Significant changes due to modifications can disrupt the development process. The increasing adoption of Agile methodologies alongside traditional methods is crucial for the success of software development projects, especially in the digital age accelerated by the COVID-19 pandemic, as it enhances project management and improves outcomes by aligning methods with project characteristics (Yel *et al.*, 2023).

To address this, lightweight SD techniques have emerged, focusing on expediting development and efficiently handling change requests. These lightweight methods, collectively known as Agile Software Development (ASD) methods, aim to improve flexibility and, responsiveness in the development process. Agile methodologies prioritize iterative progress, continuous feedback, and adaptive planning, allowing teams to respond swiftly to changing requirements and deliver high-quality software that meets user expectations.

This approach fosters better collaboration, reduces time to market, and enhances the overall reliability and maintainability of the software. By integrating the agile principles, teams can achieve more efficient and adaptive software development processes, ensuring that projects are completed on time, within budget, and with the desired functionality and performance. This comprehensive strategy not only addresses the limitations of traditional methods but also aligns with the dynamic nature of modern SD needs.

Dyba and Dingsoyr (2008) identified 36 empirical studies, which were subsequently categorized into four themes: introduction and adoption, social and human factors, opinions regarding agile ASD methods, and comparative studies. Dyba and Dingsoyr (2009) again talked about a number of ASD methods. Agile approaches like Extreme Programming (XP), Feature-Driven Development (FDD), Dynamic Systems Development Method (DSDM), Crystal, and Pragmatic Programming have been widely discussed by Williams (2010). Devedzic (2010) talked about how to get around possible obstacles when teaching ASD methods and increase the effectiveness of their adoption. A quantitative analysis of the advantages of ASD methods in practice was presented by Ahmad *et al.* (2010). Greer and Haman (2011) talked about how ASD methods relate to UX design. A case of user and customer participation in an ASD project was examined by Kautz (2011). A theoretical model of coordination in the context of ASD was presented by Strode *et al.* (2012) based on empirical data from three cases of co-located ASD. Dingsoyr *et al.* (2012) summarized research on ASD methods, while Mishra *et al.* (2012) described the principles and history of ASD practices. To facilitate the adoption of ASD practices, Kruchten (2013) provided a contextual model for software-intensive systems development. Usman *et al.* (2014) gave a thorough summary of the current state of the art in effort estimation in ASD. Based on a case study analysis, it was asserted by Papadopoulos (2015) that ASD methods outperform traditional methodologies in large-scale, distributed projects. The effectiveness of Agile development methods in international software projects was discussed by Jain and Usman (2016). Dependencies in three typical cases of co-located ASD were examined by Strode (2016) and presented as a taxonomy with decision rules for categorization. An empirical study on the interpretation and prioritization of value in ASD projects was conducted by Alahyari *et al.* (2017).The application of ASD methods with a design thinking approach was investigated by Pereira and Russo (2018). Al-Saqqa *et al.* (2020) provided a detailed discussion of core agile values and principles and examined the differences between agile approaches and traditional development methods. Mishra *et al.* (2020) aimed to provide metrics that could be used to gauge the quality and progress of a product being developed with ASD methods. The most recent developments in the field of using intelligent techniques to treat ASD were compiled and examined by Perkusich *et al.* (2020). According to Tam *et al.* (2020), ‘customer involvement’ and ‘team capability’ are the key elements influencing the success of ongoing ASD projects. The advantages and drawbacks of agile approaches for software development projects were covered by Gheorghe *et al.* (2020). The literature reviews of the primary large-scale agile approaches like SAFe, LeSS, Scrum-at-scale, DAD, and Spotify model were accomplished by Edison *et al.* (2021). The impact of software security engineering activities in relation to ASD was examined by Rindell *et al.* (2021). The role of a project manager in ASD projects was outlined by Shastri *et* *al.* (2021) in terms of routine tasks like facilitating, coordinating, and management techniques. A tool for risk management in agile software development projects was presented by (Tavares *et al.*, 2021). Appropriate strategies for handling user experience in the context of ASD were examined by Hinderks *et al.* (2022). Alami *et al.* (2022) investigated the interpretations of ASD concept of technical excellence by agile practitioners. Baham and Hirschheim (2022) provided a theoretical framework for the study of ASD and explained the components of agility. Ghimire and Charters (2022) concentrated on the examination of the information gathered from participants in ASD teams. For collocated ASD teams, Strode *et al.* (2022) developed an agile teamwork effectiveness model based on data from case studies, focus groups, and multi-vocal literature. Grounded theory methodology was used by Ouriques *et al.* (2023) to investigate the function of knowledge-based resources in ASD. Bomstrom *et al.* (2023) studied what information is needed and how it should be represented to support different stakeholders involved in ASD project. Shameem *et al.* (2023) employed a genetic algorithm to illustrate the most influential agile project features in software development project outcomes. Mishra and Alzoubi (2023) compared structured software development with ASD. Habib *et al.* (2023) conducted a systematic literature review to identify applicable components supporting ASD documentation. Chugh and Chugh (2023) systematically analysed ASD methods from the perspective of software quality assurance. Barros *et al.* (2024) examined critical human-related success factors for ASD projects.

Over the past two decades, agile methodologies have revolutionized the process of software development approaches and offered tremendous opportunities to the software development organizations (Dikert *et al.*, 2016). Agile methodology offers various advantages over the traditional software process to manage the challenges in the current era of digital world where agility has become the important aspect in the business which cause to the changing the business needs of the customers (Bowen and Maurer, 2002). Figure 1 illustrates the comparison between 'traditional methods' and 'agile methods'. The agile method is characterized by a process tailored to support its principles. Each agile method encompasses a distinct set of practices that outline the daily operations of a software developer. As described by Elbanna and Sarker (2016), these methods differ in terms of specific terminologies and practices chosen. Agile methods contribute significantly to enhance the effectiveness and the speed of the production process to improving productivity using the high performing self-organizing teams (Shameem *et al.*, 2018). Crystal, DSDM, XP, Kanban and Scrum method are examples of popular agile methods (Al-Saqqa *et al.*, 2020; Ouriques *et al.*, 2023; Itzik and Roy, 2023). They have their own roles, principles, life cycles (phases), advantages and challenges (Fig. 2).

1.1. *Research Gaps and Motivations*

In software development projects, companies creating custom software must choose a methodology from a range of options to best meet the demands of an IT project in a particular setting (Silva *et al.*, 2016; Simhadri and Shameem, 2023). There are several studies that have been conducted on adopting agile methods for developing cost effective, viable,

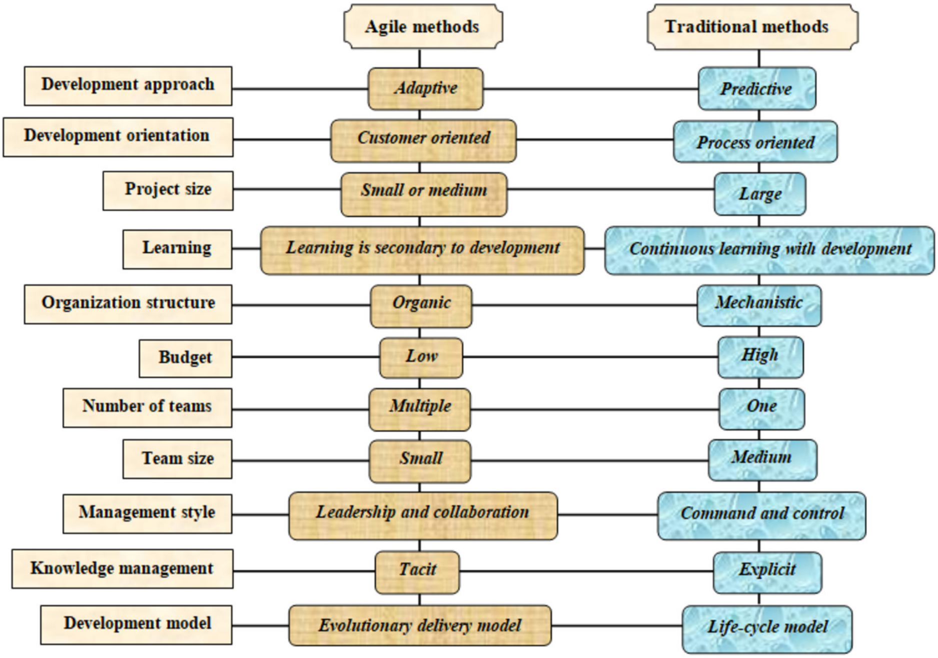

Fig. 1. Agile methods vs traditional methods.

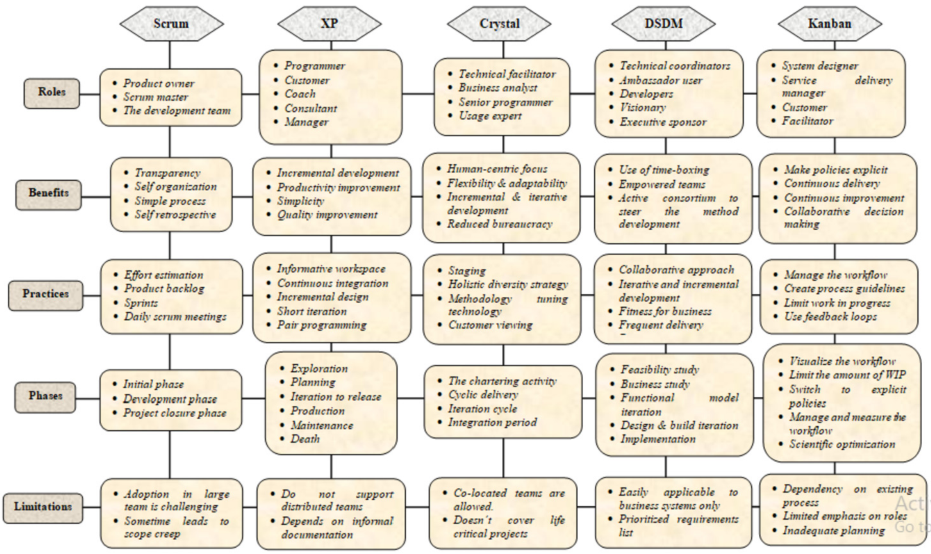

Fig. 2. Comparison of various agile methods.

and quality products. Al-Saqqa *et al.* (2020) highlighted how to select the most preferable agile methodology based on their life cycles, roles, advantages, and disadvantages. Silva *et al.* (2016) have conducted a multi-criteria decision-making (MCDM) based study to select agile methods based on the needs of specific projects. They have used Simple Multi-Attribute Rating Technique Exploiting Ranks (SMARTER) method for evaluating the preferences of the four agile methods, namely: XP, crystal, DSDM, and scrum. Sayed *et al.* (2017) conducted Analytic Hierarchy Process (AHP)-based decision-making study to select the agile methods based on various criteria. For effectively implementing agile process, an Agile Adoption and Improvement Model (AAIM) was proposed by Asif and Henderson-Sellers (2008). It includes an Agile Toolkit and offers a general framework for examining agile techniques, knowledge, and governance. However, their proposed model did not consider several aspects, i.e. team size, project development cycle, level of organization maturity (Geambaşu *et al.*, 2011; Schramm *et al.*, 2023). Casper *et al.* (2015) emphasized the crucial role of effective communication and coordination in small, co-located teams of software professionals and customers within a collaborative environment. A limitation of their study is the incomplete evaluation of relevant factors, affecting the decision-making process for selecting an agile method. This selection process is complex due to the multiple criteria involved, making it an MCDM problem. Uncertainty and vagueness in expert opinions add further complications to this problem (Hamed and Abushama, 2013).

Rough set theory (Zhao *et al.*, 2023) is a powerful tool for handling imprecise and uncertain information. In rough set, boundaries are defined with the help of approximate areas and the ambiguity governing them. Rough numbers (RNs), which operate on the principle that actual data should be self-explanatory, determine uncertainty through approximation (Yazdani *et al.*, 2020). By creating distinct interval limits for each expert evaluation, RNs address the limitations of the conventional fuzzy approach regarding interval limits. These limits are based on data uncertainty and imprecision rather than subjective evaluations. Some applications of rough numbers are: selection of logistic centres and logistics (Zavadskas *et al.*, 2018), manufacturing supplier selection (Stojić *et al.*, 2018), evaluation of customer involved design (Qi *et al.*, 2020), floating photovoltaic site selection (Deveci *et al.*, 2022), formwork system selection for building construction project (Terzioglu and Polat, 2022), evaluation of the legatum prosperity pillars (Alshamrani and Hezam, 2023), block-chain platform selection (Erol *et al.*, 2023), prioritization of the connected autonomous vehicles (Gokasar *et al.*, 2023), etc. However, no decision-making approach using rough numbers has been developed for selecting agile methods in software development projects. Additionally, the ranking results from sorting methods like rough-WASPAS (Weighted Aggregated Sum Product Assessment) (Stojić *et al.*, 2018), rough-VIšeKriterijumska Optimizacija I Kompromisno Rešenje (VIKOR) (Qi *et al.*, 2020), rough-Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Alshamrani and Hezam, 2023), rough-Evaluation based on Distance from Average Solution (EDAS) (Terzioglu and Polat, 2022), and rough-Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH) (Gokasar *et al.*, 2023) can vary significantly with changes in the weight distributions of characteristics, making existing aggregation methods (Qi *et al.*, 2020; Terzioglu and Polat, 2022; Alshamrani and Hezam, 2023; Gokasar *et al.*, 2023) less reliable.

Aggregation operators (AOs) are widely used to merge multiple input sources into a single representation and are particularly effective for addressing decision-making problems involving uncertainty. Many well-known AOs, such as Archimedean, Hamacher, Einstein, and Aczel-Alsina are used to address decision-making problems. However, these AOs have some limitations, including (i) their inability to connect with multi marginal distributions, (ii) reflect correlations among variables, and (iii) neglect loss of data during aggregation. Copula (Nelsen, 2013; Bacigal *et al.*, 2015) overcomes these difficulties. Dombi operations (Dombi, 1982) are more flexible than other operators due to the inclusion of Dombi parameter. Despite these advancements, no AO has yet been developed that combines RNs with Copula and Dombi operations. In real-world applications, it is essential to assign weights to criteria in a structured way, as different attributes or criteria do not contribute equally to the decision-making process. In the existing methodologies (Yazdani *et al.*, 2020; Qi *et al.*, 2020; Terzioglu and Polat, 2022), concern has been raised over the calculation of criteria weights, due to their many dependencies on subjective methods like AHP, Step-wise Weight Assessment Ratio Analysis (SWARA) and Full Consistency Method (FUCOM). Errors in decision-making may result from improperly determined weights. The determination of criteria weights remains an open problem, as existing approaches do not adequately represent the complexity of decision environments. Addressing this limitation is essential for improving the reliability of decision models and supports continued development of improved approaches for criteria weighting.

1.2. *Contributions*

This study focuses on a rational approach to decision-making, addressing the uncertainties and ambiguities inherent in evaluating agile methods for software development projects. The key aspects of this study are outlined below:

- ✓ Copula-Dombi AOs based on rough numbers are formulated to handle decision-making during result aggregation.
- ✓ A cross-entropy-based optimization model is applied to derive criteria weights for ranking agile methods.
- ✓ Sensitivity analyses of parameters and criteria weights are conducted to validate the findings.
- ✓ A comparative analysis is provided to demonstrate the superiority of the developed approach.

1.3. *Structure of the Paper*

The paper is structured as follows: Section 2 deals with the concept of RNs, Copula and Dombi operations. The development of rough Copula-Dombi weighted averaging (RCDWA) and rough Copula-Dombi weighted geometric (RCDWG) AOs are furnished in Section 3. A rough decision-making methodology is presented in Section 4. Section 5 defines the investigated problem in a real-life context and provides the solution. Discussions on sensitivity analysis, validity test, managerial implications, and comparative study are added in Section 6. Section 7 concludes the paper.

2. Basic Concepts

2.1. *Copula and Dombi Operations*

Definition 1 (Nelsen, 2013; Bacigal *et al.*, 2015). A copula is a function F which satisfies:

(i) $F(w,0) = F(0,w) = 0, \quad F(w,1) = F(1,w) = w, \quad \forall w \in [0,1]$.
(ii) $F(w_1,v_1) + F(w_2,v_2) - F(w_2,v_1) - F(w_1,v_2) \geqslant 0$, for $w_1, v_1, w_2, v_2 \in [0,1]$ with $w_1 \leqslant w_2$ and $v_1 \leqslant v_2$.

Definition 2 (Nelsen, 2013; Bacigal *et al.*, 2015). An Archimedean copula (AC) $F : [0,1] \times [0,1] \to [0,1]$ is expressed as: $F(w,v) = B(\hbar(w) + \hbar(v))$ where $\hbar : [0,1] \to [0,\infty)$ is strictly decreasing and $B : [0,\infty) \to [0,1]$ is expressed as: $B(w) = \begin{cases} \hbar^{-1}(w), & w \in [0,\hbar(0)], \\ 0, & w \in [\hbar(0),\infty]. \end{cases}$

For a strict AC, $F(w,v) = \hbar^{-1}(\hbar(w) + \hbar(v))$.

Definition 3 (Saha *et al.*, 2024). The Dombi t-norm and Dombi t-conorm can be presented as:

$$\square(s,t) = \left(1 + \left\{\left(\frac{1-s}{s}\right)^{Q} + \left(\frac{1-t}{t}\right)^{Q}\right\}^{\frac{1}{Q}}\right)^{-1},$$

$$\diamondsuit(a,b) = 1 - \left(1 + \left\{\left(\frac{s}{1-s}\right)^{Q} + \left(\frac{t}{1-t}\right)^{Q}\right\}^{\frac{1}{Q}}\right)^{-1},$$

where $s, t \in [0,1]$ and $Q \geqslant 1$.

2.2. *Rough Numbers (RNs)*

RNs (Zhao *et al.*, 2023; Yazdani *et al.*, 2020) represent precise concepts through the use of lower and upper approximations. Let $z \in V$, where V denotes a given universe of objects, and let $\Re$ represent a collection of k ordered classes $\{\mathbb{C}_1, \mathbb{C}_2, \dots, \mathbb{C}_k\}$, that collectively cover all attributes in V. Assuming the order $\mathbb{C}_1 < \mathbb{C}_2 < \cdots < \mathbb{C}_k$ is preserved, then for any $\forall z \in V, \mathbb{C}_q \in \Re$ $(1 \leqslant q \leqslant k)$, the corresponding lower approximation $(LA(\mathbb{C}_q))$ and upper approximation $(UA(\mathbb{C}_q))$ of $\mathbb{C}_q$ are defined as follows:

$$LA(\mathbb{C}_q) = \bigcup \{z \in V : \Re(z) \leqslant \mathbb{C}_q\}, \tag{1}$$

$$UA(\mathbb{C}_q) = \bigcup \{z \in V : \Re(z) \geqslant \mathbb{C}_q\}. \tag{2}$$

Then an RN can be represented as $RN(\mathbb{C}_q)$, characterized by its corresponding lower and upper bounds. The lower bound is denoted by $\underline{\lim}\mathbb{C}_q$ and the upper bound by $\overline{\lim}\mathbb{C}_q$, which are formally defined as follows:

$$\underline{\mathbb{C}}_q = \frac{1}{\#LA(\mathbb{C}_q)} \sum_{z \in LA(\mathbb{C}_q)} \Re(z), \tag{3}$$

$$\bar{\mathbb{C}}_q = \frac{1}{\#UA(\mathbb{C}_q)} \sum_{z \in UA(\mathbb{C}_q)} \Re(z) \tag{4}$$

(# denotes number of objects).

We can express $RN(\mathbb{C}_q)$ as: $RN(\mathbb{C}_q) = [\underline{\mathbb{C}}_q, \bar{\mathbb{C}}_q]$.

3. Rough Copula-Dombi (RCD) Aggregation Operators

3.1. *RCD Operations*

Definition 4. Suppose $T_1 = [\underline{T}_1, \bar{T}_1]$, $T_2 = [\underline{T}_2, \bar{T}_2]$ be two RNs with $\underline{T}_1, \bar{T}_1, \underline{T}_2, \bar{T}_2 \in [0, 1]$ and $Q \geqslant 1$. Then RCD operations are as follows:

$$1)\ T_1 \oplus T_2 = \begin{bmatrix} 1 - \hbar^{-1}\big(1 - \big(1 + \big\{\big(\big(\hbar(1 - \underline{T}_1)\big)/\big(1 - \hbar(1 - \underline{T}_1)\big)\big)^Q \\ + \big(\big(\hbar(1 - \underline{T}_2)\big)/\big(1 - \hbar(1 - \underline{T}_2)\big)\big)^Q\big\}^{\frac{1}{Q}}\big)^{-1}\big), \\ 1 - \hbar^{-1}\big(1 - \big(1 + \big\{\big(\big(\hbar(1 - \bar{T}_1)\big)/\big(1 - \hbar(1 - \bar{T}_1)\big)\big)^Q \\ + \big(\big(\hbar(1 - \bar{T}_2)\big)/\big(1 - \hbar(1 - \bar{T}_2)\big)\big)^Q\big\}^{\frac{1}{Q}}\big)^{-1}\big) \end{bmatrix}. \tag{5}$$

$$2)\ T_1 \otimes T_2 = \begin{bmatrix} \hbar^{-1}\big(\big(1 + \big\{\big(\big(1 - \hbar(\underline{T}_1)\big)/\hbar(\underline{T}_1)\big)^Q + \big(\big(1 - \hbar(\underline{T}_2)\big)/\hbar(\underline{T}_2)\big)^Q\big\}^{\frac{1}{Q}}\big)^{-1}\big), \\ \hbar^{-1}\big(\big(1 + \big\{\big(\big(1 - \hbar(\bar{T}_1)\big)/\hbar(\bar{T}_1)\big)^Q + \big(\big(1 - \hbar(\bar{T}_2)\big)/\hbar(\bar{T}_2)\big)^Q\big\}^{\frac{1}{Q}}\big)^{-1}\big) \end{bmatrix}, \tag{6}$$

$$3)\ \vartheta T_1 = \begin{bmatrix} 1 - \hbar^{-1}\big(1 - \big(1 + \big\{\vartheta\big(\big(\hbar(1 - \underline{T}_1)\big)/\big(1 - \hbar(1 - \underline{T}_1)\big)\big)^Q\big\}^{\frac{1}{Q}}\big)^{-1}\big), \\ 1 - \hbar^{-1}\big(1 - \big(1 + \big\{\vartheta\big(\big(\hbar(1 - \bar{T}_1)\big)/\big(1 - \hbar(1 - \bar{T}_1)\big)\big)^Q\big\}^{\frac{1}{Q}}\big)^{-1}\big) \end{bmatrix} \quad (\vartheta > 0). \tag{7}$$

$$4)\ T_1^{\vartheta} = \begin{bmatrix} \hbar^{-1}\big(\big(1 + \big\{\vartheta\big(\big(1 - \hbar(\underline{T}_1)\big)/\hbar(\underline{T}_1)\big)^Q\big\}^{\frac{1}{Q}}\big)^{-1}\big), \\ \hbar^{-1}\big(\big(1 + \big\{\vartheta\big(\big(1 - \hbar(\bar{T}_1)\big)/\hbar(\bar{T}_1)\big)^Q\big\}^{\frac{1}{Q}}\big)^{-1}\big) \end{bmatrix} \quad (\vartheta > 0). \tag{8}$$

Theorem 1. *For $\vartheta, \vartheta_1, \vartheta_2 > 0$, we have*:

1) $T_1 \oplus T_2 = T_2 \oplus T_1$;
2) $T_1 \otimes T_2 = T_2 \otimes T_1$;
3) $\vartheta(T_1 \oplus T_2) = (\vartheta T_1) \oplus (\vartheta T_2)$;
4) $(T_1 \otimes T_2)^{\vartheta} = (T_1)^{\vartheta} \otimes (T_2)^{\vartheta}$;
5) $(\vartheta_1 + \vartheta_2)T_1 = (\vartheta_1 T_1) \oplus (\vartheta_2 T_1)$;
6) $T_1^{\vartheta_1+\vartheta_2} = \big(T_1^{\vartheta_1}\big) \otimes \big(T_1^{\vartheta_2}\big)$.

Proof. Added in Supplementary Material. □

3.2. *Rough Copula-Dombi Weighted Averaging (RCDWA) and Rough Copula-Dombi Weighted Geometric (RCDWG) Aggregation Operators*

Suppose $T_r = [\underline{T}_r, \bar{T}_r]$ $(r = 1, 2, \dots, L)$ be a set of RNs with $\underline{T}_r, \bar{T}_r \in [0, 1]$ having weight θ_r with $\theta_r \in [0, 1]$, $\sum_{r=1}^{L} \theta_r = 1$.

Definition 5. RCDWA AO can be defined as:

$$RCDWA(T_1, T_2, \dots, T_L) = \bigoplus_{r=1}^{L} (\theta_r T_r). \tag{9}$$

Theorem 2. *The output value $RCDWA(T_1, T_2, \dots, T_L)$ is also a RN. In addition, we get*:

$$\begin{aligned} &RCDWA(T_1, T_2, \dots, T_L) \\ &= \left[\begin{array}{l} 1 - \hbar^{-1}\Big(1 - \Big(1 + \Big\{\sum_{r=1}^{L} \theta_r \big(\big(\hbar(1 - \underline{T}_r)\big)/\big(1 - \hbar(1 - \underline{T}_r)\big)\big)^{Q}\Big\}^{\frac{1}{Q}}\Big)^{-1}\Big), \\ 1 - \hbar^{-1}\Big(1 - \Big(1 + \Big\{\sum_{r=1}^{L} \theta_r \big(\big(\hbar(1 - \bar{T}_r)\big)/\big(1 - \hbar(1 - \bar{T}_r)\big)\big)^{Q}\Big\}^{\frac{1}{Q}}\Big)^{-1}\Big) \end{array} \right]. \end{aligned} \tag{10}$$

Proof. Added in Supplementary Material. □

Below we furnish a few properties of *RCDWA* operator.

Theorem 3. *If $T_0 = [\underline{T}_0, \bar{T}_0]$ $(\neq T_r$ for any $r)$ is a RN, then $RCDWA(T_0 \oplus T_1, T_0 \oplus T_2, \dots, T_0 \oplus T_L) = T_0 \oplus RCDWA(T_1, T_2, \dots, T_L)$.*

Theorem 4. *If T_0 $(= T_r$ for every $r)$ is a RN, then $RCDWA(T_1, T_2, \dots, T_L) = T_0$.*

Theorem 5. *If $T_r^{\#} = [\underline{T}_r^{\#}, \bar{T}_r^{\#}]$ $(r = 1, 2, \dots, L)$ be a set of RNs satisfying $\underline{T}_r \leqslant \underline{T}_r^{\#}$, $\bar{T}_r \leqslant \bar{T}_r^{\#}$, then $RCDWA(T_1, T_2, \dots, T_L) \prec RCDWA(T_1^{\#}, T_2^{\#}, \dots, T_L^{\#})$.*

Definition 6. RCDWG AO can be defined as:

$$RCDWG(T_1, T_2, \dots, T_L) = \bigotimes_{r=1}^{L} (T_r)^{\theta_r}. \tag{11}$$

Theorem 6. *The output value $RCDWG(T_1, T_2, \dots, T_L)$ is also a RN. In addition, we get*:

$$\begin{aligned} & RCDWG(T_1, T_2, \dots, T_L) \\ & \quad = \Bigg[\hbar^{-1}\Bigg(\Bigg(1 + \Bigg\{\sum_{r=1}^{L}\theta_r\big(\big(1-\hbar(\underline{T}_r)\big)/\hbar(\underline{T}_r)\big)^{Q}\Bigg\}^{\frac{1}{Q}}\Bigg)^{-1}\Bigg), \\ & \qquad \hbar^{-1}\Bigg(\Bigg(1 + \Bigg\{\sum_{r=1}^{L}\theta_r\big(\big(1-\hbar(\bar{T}_r)\big)/\hbar(\bar{T}_r)\big)^{Q}\Bigg\}^{\frac{1}{Q}}\Bigg)^{-1}\Bigg)\Bigg]. \end{aligned} \tag{12}$$

Proof. Similar to Theorem 2. □

Below we furnish a few properties of *RCDWG* operator.

Theorem 7. *If $T_0 = [\underline{T}_0, \bar{T}_0]$ ($\neq T_r$ for any r) is a RN, then $RCDWG(T_0 \oplus T_1, T_0 \oplus T_2, \dots, T_0 \oplus T_L) = T_0 \oplus RCDWG(T_1, T_2, \dots, T_L)$.*

Theorem 8. *If T_0 ($= T_r$ for every r) is a RN, then $RCDWG(T_1, T_2, \dots, T_L) = T_0$.*

Theorem 9. *If $T_r^{\#} = [\underline{T}_r^{\#}, \bar{T}_r^{\#}]$ ($r = 1, 2, \dots, L$) be a set of RNs satisfying $\underline{T}_r \leqslant \underline{T}_r^{\#}$, $\bar{T}_r \leqslant \bar{T}_r^{\#}$, then $RCDWG(T_1, T_2, \dots, T_L) \prec RCDWG(T_1^{\#}, T_2^{\#}, \dots, T_L^{\#})$.*

4. Copula-Dombi Group-Decision Making Methodology

Consider a group decision-making problem where the alternatives A_s ($s = 1, 2, \dots, p$) are evaluated by decision-makers DM_v ($v = 1, 2, \dots, k$) with respect to criteria E_t ($t = 1, 2, \dots, q$). The following steps outline the RCD operator-based decision-making model (Fig. 3).

Step 1: Form the aggregated rough matrix by transforming the individual assessment matrices using RNs.

Let $x \in U$, U being the collection of given attributes E_t ($t = 1, 2, \dots, q$) and $\Re$ denotes the collection of k classes $\{\mathbb{C}_1^{(st)}, \mathbb{C}_2^{(st)}, \dots, \mathbb{C}_k^{(st)}\}$, which includes all attributes from U. If the ordering $\mathbb{C}_1^{(st)} < \mathbb{C}_2^{(st)} < \cdots < \mathbb{C}_k^{(st)}$ holds, then $\forall x \in U$, $\mathbb{C}_v^{(st)} \in \Re (1 \leqslant v \leqslant k)$, the lower approximation ($LA(\mathbb{C}_v^{(st)})$) and upper approximation ($UA(\mathbb{C}_v^{(st)})$) of $\mathbb{C}_v^{(st)}$ are presented as:

$$LA\big(\mathbb{C}_v^{(st)}\big) = \bigcup\big\{x \in U : \Re(x) \leqslant \mathbb{C}_v^{(st)}\big\}, \tag{13}$$

$$UA\big(\mathbb{C}_v^{(st)}\big) = \bigcup\big\{x \in U : \Re(x) \geqslant \mathbb{C}_v^{(st)}\big\}. \tag{14}$$

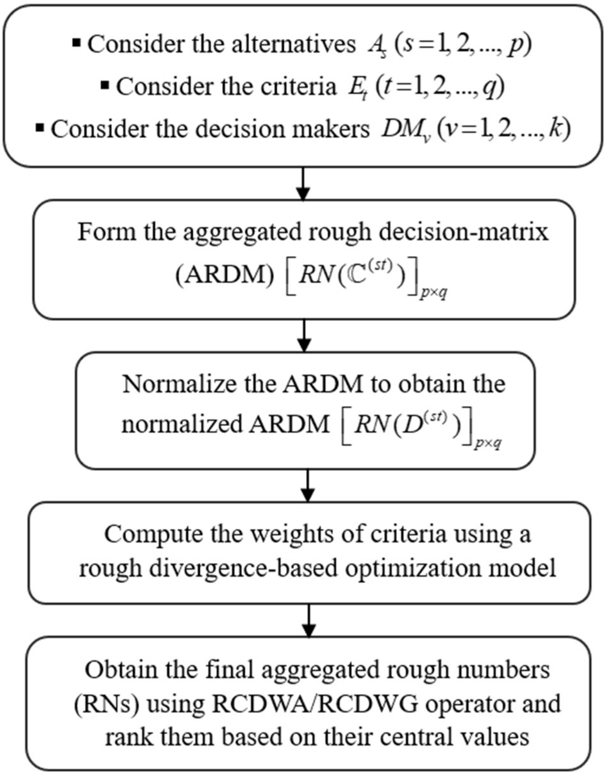

Fig. 3. Methodological flowchart.

It can be represented as a RN $RN(\mathbb{C}_v^{(st)})$, which is calculated using its corresponding lower limit $\underline{\mathbb{C}}_q^{(uv)}$ and upper limit $\bar{\mathbb{C}}_q^{(uv)}$ defined as follows:

$$\underline{\mathbb{C}}_v^{(st)} = \frac{1}{\#LA(\mathbb{C}_v^{(st)})} \sum_{x\in LA(\mathbb{C}_v^{(st)})} \Re(x), \tag{15}$$

$$\bar{\mathbb{C}}_v^{(st)} = \frac{1}{\#UA(\mathbb{C}_v^{(st)})} \sum_{x\in UA(\mathbb{C}_v^{(st)})} \Re(x). \tag{16}$$

Then $RN(\mathbb{C}_v^{(st)})$ is given by: $RN(\mathbb{C}_v^{(st)}) = [\underline{\mathbb{C}}_v^{(st)}, \bar{\mathbb{C}}_v^{(st)}]$. By aggregating all the $RN(\mathbb{C}_v^{(st)})$ $(1 \leqslant v \leqslant k)$, the aggregated rough decision-matrix (ARDM) $[RN(\mathbb{C}^{(st)})]_{p\times q}$ is constructed.

Step 2: Perform normalization on ARDM $[RN(\mathbb{C}_v^{(st)})]_{p\times q} = [\underline{\mathbb{C}}^{(st)}, \bar{\mathbb{C}}^{(st)}]_{p\times q}$.

Assume that the ADRM has been normalized as follows:

$$\left[RN\left(D^{(st)}\right)\right]_{p\times q} = \left(\left[\underline{D}^{(st)}, \bar{D}^{(st)}\right]\right)_{p\times q},$$

where:

$$\left[\underline{D}^{(st)}, \bar{D}^{(st)}\right] = \begin{cases} \left[\frac{\underline{\mathbb{C}}^{(st)}}{\sum_v(\underline{\mathbb{C}}^{(st)}+\bar{\mathbb{C}}^{(st)})}, \frac{\bar{\mathbb{C}}^{(st)}}{\sum_v(\underline{\mathbb{C}}^{(st)}+\bar{\mathbb{C}}^{(st)})}\right], \text{ if } E_t \text{is beneficial;} \\ \left[1-\frac{\underline{\mathbb{C}}^{(st)}}{\sum_v(\underline{\mathbb{C}}^{(st)}+\bar{\mathbb{C}}^{(st)})}, 1-\frac{\bar{\mathbb{C}}^{(st)}}{\sum_v(\underline{\mathbb{C}}^{(st)}+\bar{\mathbb{C}}^{(st)})}\right], \text{if } E_t \text{ is non-beneficial.} \end{cases} \tag{17}$$

Step 3: Compute the weights of the attributes.

The difference between the sth option and other options under the tth attribute is expressed by the following rough divergence measure.

$$M_{st} = \left[\frac{1}{p-1}\sum_{z=1}^{p} e\big(\underline{D}^{(st)}, \underline{D}^{(zt)}\big), \frac{1}{p-1}\sum_{z=1}^{p} e\big(\bar{D}^{(st)}, \bar{D}^{(zt)}\big)\right], \tag{18}$$

where $e(\underline{D}^{(st)}, \underline{D}^{(zt)})$, $e(\bar{D}^{(st)}, \bar{D}^{(zt)})$ are the cross-entropy measures given by:

$$\begin{aligned} & e\big(\underline{D}^{(st)}, \underline{D}^{(zt)}\big) \\ & \quad = \underline{D}^{(st)} \times \ln\left(\frac{2\underline{D}^{(st)}}{\underline{D}^{(st)}+\underline{D}^{(zt)}}\right) + \underline{D}^{(zt)} \times \ln\left(\frac{2\underline{D}^{(zt)}}{\underline{D}^{(st)}+\underline{D}^{(zt)}}\right) + \big(1-\underline{D}^{(st)}\big) \\ & \qquad \times \ln\left(\frac{1-\underline{D}^{(st)}}{1-\frac{1}{2}(\underline{D}^{(st)}+\underline{D}^{(zt)})}\right) + \big(1-\underline{D}^{(zt)}\big) \times \ln\left(\frac{1-\underline{D}^{(zt)}}{1-\frac{1}{2}(\underline{D}^{(st)}+\underline{D}^{(zt)})}\right), \\ & e\big(\bar{D}^{(st)}, \bar{D}^{(zt)}\big) \\ & \quad = \bar{D}^{(st)} \times \ln\left(\frac{2\bar{D}^{(st)}}{\bar{D}^{(st)}+\bar{D}^{(zt)}}\right) + \bar{D}^{(zt)} \times \ln\left(\frac{2\bar{D}^{(zt)}}{\bar{D}^{(st)}+\bar{D}^{(zt)}}\right) + \big(1-\bar{D}^{(st)}\big) \\ & \qquad \times \ln\left(\frac{1-\bar{D}^{(st)}}{1-\frac{1}{2}(\bar{D}^{(st)}+\bar{D}^{(zt)})}\right) + \big(1-\bar{D}^{(zt)}\big) \times \ln\left(\frac{1-\bar{D}^{(zt)}}{1-\frac{1}{2}(\bar{D}^{(st)}+\bar{D}^{(zt)})}\right). \end{aligned}$$

The following formula can be used to get the total rough divergence caused by the tth criterion:

$$M_t = \left[\frac{1}{p-1}\sum_{s=1}^{p}\sum_{z=1}^{p} e\big(\underline{D}^{(st)}, \underline{D}^{(zt)}\big), \frac{1}{p-1}\sum_{s=1}^{p}\sum_{z=1}^{p} e\big(\bar{D}^{(st)}, \bar{D}^{(zt)}\big)\right]. \tag{19}$$

Accordingly, the optimization model below can be used to calculate the lower and upper bounds of the attribute weights.

$$\begin{cases} \text{Max } \chi = \sum_{t=1}^{q}\Big(\underline{W}_t \times \frac{1}{p-1}\sum_{s=1}^{p}\sum_{z=1}^{p} e\big(\underline{D}^{(st)}, \underline{D}^{(zt)}\big)\Big) \\ \qquad\qquad + \sum_{t=1}^{q}\Big(\bar{W}_v \times \frac{1}{p-1}\sum_{s=1}^{p}\sum_{z=1}^{p} e\big(\bar{D}^{(st)}, \bar{D}^{(zt)}\big)\Big), \\ \text{Subject to: } \underline{W}_t \leqslant \bar{W}_t \ \forall t; \quad \sum_{t=1}^{q}\underline{W}_t = 1; \quad \sum_{t=1}^{q}\bar{W}_t = 1; \\ \underline{W}_1, \underline{W}_2, \dots, \underline{W}_q, \bar{W}_1, \bar{W}_2, \dots, \bar{W}_q \geqslant 0. \end{cases} \tag{20}$$

The final weights of the attributes are given by: $\forall t,\ W_t = \frac{1}{2}(\underline{W}_t + \bar{W}_t)$.

Step 4: Obtain the final aggregated RNs using either the RCDWA or RCDWG operator.

The final aggregation of RNs is determined using the following expression:

$$\left[\underline{D}^{(s)}, \bar{D}^{(s)}\right] = RCDWA\left(RN\left(D^{(s1)}\right), RN\left(D^{(s2)}\right), \dots, RN\left(D^{(sq)}\right)\right) \tag{21}$$

(or)

$$\left[\underline{D}^{(s)}, \bar{D}^{(s)}\right] = RCDWG\left(RN\left(D^{(s1)}\right), RN\left(D^{(s2)}\right), \dots, RN\left(D^{(sq)}\right)\right). \tag{22}$$

Step 5: Determine the ranking of alternatives based on the central values $\frac{1}{2}(\underline{D}^{(s)} + \bar{D}^{(s)})$ $(s = 1, 2, \dots, p)$ and select the alternative with the lowest (best) rank.

5. Case Study and Solution

5.1. *Description of the Case Study*

Agile software development is widely recognized among the prominent methodologies, emphasizing the management of dynamic client requirements and software development activities. Several agile methods have been designed to efficiently implement customer requirements at low development costs and with rapid delivery. Each agile method has its own nuances that differently impact the development environment. The changing in the operating environment of agile principles could have a negative impact on project's quality and success. The success and cost-effectiveness of agile projects can be significantly influenced by the effective adoption of agile methods. In this paper, a case study has been considered involving practitioners of agile development to determine and finalize alternatives (agile methods) and criteria required for agile software development projects. The study encompassed a thorough literature review and the collection of expert opinions. Questionnaires were initially used to gather input from agile practitioners with at least fifteen years of decision-making experience. The group of experts consisted of a scrum master, agile developers, system analysts, and academician, as detailed in Table 1.

In the second stage, decision-makers were assigned to compile a distinct list with significance details, outlining agile project criteria for effectively evaluating the considered

Table 1
Details of the experts (decision-makers).

DM	Duty	Experience	Graduate	Degree
DM1	Scrum master	17 years	Electrical engineering	Masters
DM2	Team lead	18 years	Computer science	Bachelor
DM3	Business Analyst	17 years	Electrical electronics Engineering	Master
DM4	Agile researcher	14 years	Software engineering	PhD
DM5	Agile researcher	16 years	Software engineering	PhD

Table 2
Criteria details.

Criteria	Significance
Project vision ($E1$)	It serves as the inspiration and focal point, outlining the objectives of the project. It is crucial that everyone on the team comprehends, communicates, and strives toward the same goal throughout the entire endeavour.
Scope of the project ($E2$)	In order to facilitate incremental development and feedback-driven improvement, the scope is flexible. This is due to the fact that agility lies in the capacity to adapt to shifting business requirements while producing value.
Team size ($E3$)	Agile methodologies allow teams to easily change processes, reprioritize tasks, and perform iterative improvements. Fast time to market: Agile encourages short development cycles known as sprints or iterations.
Organization culture ($E4$)	Organizational culture, shaped by people and experiences, enables an agile organization to succeed in volatile and uncertain environments through key values and practices.
Maturity level of the organization ($E5$)	Agile maturity benefits companies by helping them improve quality and deliver results faster. Agility means teams work closely with customers and are flexible.
Release development cycle ($E6$)	Scheduling projects into agile releases enables product managers to effectively manage project constraints, adapt to evolving needs or challenges during the development stage, and maintain a consistent delivery of product deliverables to the end user.
Communication management ($E7$)	It emphasizes on the effective communication between the project stakeholders. Moreover, there is a need to manage the effective communication between the development and customers.
Collaboration between the team members ($E8$)	It puts a strong emphasis on knowledge exchange and employee creativity, which produced creative solutions and improved project outcomes. Collaboration in agile project management goes beyond mere teamwork.
Customer involvement ($E9$)	The involvement of customers in globally distributed agile projects enhances the effectiveness of development activities. This involves defining user requirements, prioritizing client needs, and fostering team-manager feedback to enhance project quality in agile environments.
Agile values ($E10$)	Agile development emphasizes prioritizing people and collaboration over processes and tools. This approach ensures that there is alignment towards common goals and fosters clear and effective communication.
Nature of the functionalities ($E11$)	It emphasizes on various types of the functionalities in nature that impact the agility of the agile process.
Visualizing and optimizing the work progress ($E12$)	The adaptability and transparency are essential in agile process. The use of visual tools and charts plays a significant role in tracking progress, identifying trends, and making informed decisions.
Continuous improvement ($E13$)	Improved quality, higher output and efficiency, higher customer satisfaction, higher team morale and engagement, and an innovative and learning culture are all examples of continuous improvement in the agile framework.
Sequential process ($E14$)	A kind of development lifecycle model where a system is developed in its entirety in a linear fashion, with several distinct phases that do not overlap.

alternatives, including Crystal ($A1$), DSDM ($A2$), Scrum ($A3$), Kanban ($A4$), and XP ($A5$). Subsequently, the proposed model was applied to determine the criteria and alternatives for the study. Table 2 presents details of the selected criteria.

5.2. *Results*

After identifying the criteria and alternatives, the experts evaluated the criteria and then assessed each decision alternative based on these criteria. Table 3 shows the initial assessment results. To construct the RNs, a seven-point scale has been used for evaluation: 1 for "very low (VL)", 2 for "medium low (ML)", 3 for "low (L)", 4 for "medium (M)", 5 for "medium high (MH)", 6 for "high (H)", and 7 for "very high (VH)". The qualitative attributes listed in Table 4 are converted into RNs using Eqs. (13)–(16). Table 5 shows the aggregated matrix, with each entry as a RN. Eq. (17) is then applied to normalize the matrix, resulting in the normalized aggregated matrix presented in Table 5. Using Eqs. (18)–(20), the following optimization model is formulated.

$$\begin{aligned}
\text{Max } Z = {} & 0.02239\underline{W}_1 + 0.00226\underline{W}_2 + 0.01439\underline{W}_3 + 0.00838\underline{W}_4 + 0.01114\underline{W}_5 \\
& + 0.01427\underline{W}_6 + 0.00505\underline{W}_7 + 0.00743\underline{W}_8 + 0.02349\underline{W}_9 + 0.01316\underline{W}_{10} \\
& + 0.00936\underline{W}_{11} + 0.00754\underline{W}_{12} + 0.01765\underline{W}_{13} + 0.00053\underline{W}_{14} \\
& + 0.00985\bar{W}_1 + 0.00096\bar{W}_2 + 0.00322\bar{W}_3 + 0.00405\bar{W}_4 + 0.00224\bar{W}_5 \\
& + 0.00495\bar{W}_6 + 0.00423\bar{W}_7 + 0.00088\bar{W}_8 + 0.00816\bar{W}_9 + 0.00480\bar{W}_{10} \\
& + 0.00567\bar{W}_{11} + 0.00255\bar{W}_{12} + 0.00607\bar{W}_{13} + 0.00369\bar{W}_{14}.
\end{aligned}$$

Table 3
Primary assessment by experts.

DM		*E1*	*E2*	*E3*	*E4*	*E5*	*E6*	*E7*	*E8*	*E9*	*E10*	*E11*	*E12*	*E13*	*E14*
DM1	**A1**	VL	L	MH	MH	ML	M	VH	H	VH	ML	L	MH	VH	M
	A2	ML	H	M	MH	ML	H	M	VL	MH	M	M	ML	L	H
	A3	MH	MH	M	VH	VH	M	ML	L	MH	ML	M	L	L	H
	A4	M	ML	VH	H	M	H	MH	ML	L	L	VH	L	M	MH
	A5	VH	M	L	ML	MH	ML	M	VH	M	ML	M	MH	L	VH
DM2	**A1**	L	MH	H	M	H	ML	L	MH	M	H	M	MH	VH	H
	A2	H	M	VL	H	H	M	L	ML	H	MH	M	ML	L	H
	A3	H	H	L	ML	M	H	M	VH	L	ML	M	L	M	VH
	A4	VL	VH	MH	VH	VH	MH	MH	M	VH	L	VH	L	M	H
	A5	VH	L	ML	H	H	M	M	MH	ML	L	MH	MH	MH	ML
DM3	**A1**	L	VH	MH	VH	MH	VH	L	H	ML	M	MH	H	M	H
	A2	VH	M	L	M	ML	MH	VH	VH	MH	VH	MH	M	VH	L
	A3	VH	L	VL	MH	MH	H	H	L	ML	M	MH	M	ML	ML
	A4	L	H	H	MH	L	L	M	VH	M	M	H	M	VH	VH
	A5	MH	MH	ML	H	H	H	MH	MH	L	MH	VH	H	MH	M
DM4	**A1**	VH	M	L	ML	MH	ML	M	VH	M	VH	MH	H	MH	VH
	A2	M	MH	M	VL	H	MH	H	L	MH	VH	MH	MH	H	MH
	A3	VH	ML	VH	L	MH	VH	L	H	ML	M	MH	H	MH	L
	A4	L	MH	ML	VH	M	MH	M	H	H	VH	M	M	ML	ML
	A5	H	H	M	M	MH	ML	VH	L	ML	H	ML	L	H	H
DM5	**A1**	L	L	H	ML	MH	M	H	ML	MH	H	H	L	H	ML
	A2	H	VL	VH	M	M	L	VH	L	H	H	MH	VH	M	MH
	A3	M	MH	H	H	ML	MH	MH	VH	VH	VH	MH	VH	H	MH
	A4	VH	ML	H	L	H	M	MH	MH	L	H	L	H	ML	L
	A5	ML	M	VH	M	VH	M	L	ML	MH	VH	ML	M	H	H

Table 4
Aggregated matrix containing RNs.

Criteria	$A1$	$A2$	$A3$	$A4$	$A5$
$E1$	[2.38, 4.48]	[3.8, 6.083]	[5.02, 6.543]	[2.403, 4.92]	[4.217, 6.463]
$E2$	[3.496, 5.426]	[2.9, 5]	[3.24, 5.123]	[3.03, 5.66]	[3.746, 5.08]
$E3$	[4.333, 5.6]	[2.56, 5.06]	[2.673, 5.673]	[4.04, 6.173]	[2.537, 4.873]
$E4$	[2.783, 5.266]	[2.9, 5]	[3.286, 5.87]	[4.573, 6.503]	[3.493, 5.28]
$E5$	[3.87, 5.27]	[2.933, 5.066]	[3.52, 5.636]	[3.876, 5.76]	[5.36, 6.253]
$E6$	[2.76, 4.92]	[3.92, 5.253]	[4.92, 6.253]	[3.92, 5.253]	[2.72, 4.506]
$E7$	[3.586, 5.673]	[4.326, 6.413]	[3, 5]	[4.36, 4.84]	[3.786, 5.52]
$E8$	[4.04, 6.173]	[2.5, 5.683]	[3.586, 5.673]	[3.54, 5.96]	[3.28, 5.546]
$E9$	[3.363, 5.48]	[5.16, 5.64]	[2.627, 5.12]	[3.586, 5.673]	[2.457, 3.98]
$E10$	[3.8, 6.083]	[5.02, 6.543]	[2.76, 4.92]	[3.586, 5.673]	[3.286, 5.87]
$E11$	[3.92, 5.235]	[4.36, 4.84]	[4.36, 4.84]	[4.326, 6.413]	[2.783, 5.266]
$E12$	[4.333, 5.6]	[2.783, 5.266]	[3.586, 5.673]	[3.4, 4.667]	[3.92, 5.235]
$E13$	[5.02, 6.543]	[3.586, 5.673]	[3, 5]	[2.76, 4.92]	[4.333, 5.6]
$E14$	[3.8, 6.083]	[4.333, 5.6]	[3.287, 5.87]	[3.286, 5.87]	[3.8, 6.083]

Table 5
Normalized aggregated matrix with RNs as elements.

Criteria	$A1$	$A2$	$A3$	$A4$	$A5$
$E1$	[0.05139, 0.09674]	[0.08206, 0.13136]	[0.10840, 0.14129]	[0.05189, 0.10624]	[0.09106, 0.13956]
$E2$	[0.08187, 0.12707]	[0.06791, 0.11709]	[0.07588, 0.11997]	[0.07096, 0.13255]	[0.08773, 0.11897]
$E3$	[0.09956, 0.12867]	[0.05882, 0.11626]	[0.06142, 0.13035]	[0.09283, 0.14184]	[0.05829, 0.11197]
$E4$	[0.06191, 0.11714]	[0.06451, 0.11122]	[0.07310, 0.13058]	[0.10173, 0.14466]	[0.07770, 0.11745]
$E5$	[0.08140, 0.11084]	[0.06169, 0.10655]	[0.07404, 0.11854]	[0.08152, 0.12115]	[0.11274, 0.13152]
$E6$	[0.06213, 0.11075]	[0.08824, 0.11824]	[0.11075, 0.14075]	[0.08824, 0.11824]	[0.06123, 0.10143]
$E7$	[0.07711, 0.12199]	[0.09302, 0.13790]	[0.06451, 0.10752]	[0.09376, 0.10408]	[0.08141, 0.11870]
$E8$	[0.10873, 0.16614]	[0.06729, 0.15295]	[0.09651, 0.15268]	[0.09528, 0.16041]	[0.08828, 0.14927]
$E9$	[0.09176, 0.14953]	[0.14080, 0.15389]	[0.07168, 0.13970]	[0.09785, 0.15479]	[0.06704, 0.10860]
$E10$	[0.09900, 0.15847]	[0.13078, 0.17046]	[0.07190, 0.12818]	[0.09342, 0.14779]	[0.08561, 0.15292]
$E11$	[0.10237, 0.13671]	[0.11386, 0.12639]	[0.11386, 0.12639]	[0.11297, 0.16747]	[0.07267, 0.13752]
$E12$	[0.12272, 0.15860]	[0.07882, 0.14914]	[0.10156, 0.16067]	[0.09630, 0.13218]	[0.11102, 0.14827]
$E13$	[0.13753, 0.17925]	[0.09824, 0.15542]	[0.08219, 0.13698]	[0.07561, 0.13479]	[0.11871, 0.15342]
$E14$	[0.84046, 0.90034]	[0.85313, 0.88636]	[0.84605, 0.91379]	[0.84605, 0.91382]	[0.84046, 0.90034]

Subject to

$$\underline{W}_t \leqslant \bar{W}_t \quad (t = 1, 2, \dots, 14); \quad \sum_{t=1}^{14} \underline{W}_t = 1; \quad \sum_{t=1}^{14} \bar{W}_t = 1;$$

$$\underline{W}_1, \underline{W}_2, \dots, \underline{W}_{18} \geqslant 0; \quad \bar{W}_1, \bar{W}_2, \dots, \bar{W}_{18} \geqslant 0.$$

Solving the above model gives the lower and upper bounds of the attribute weights. Table 6 shows their mid-values, representing the crisp weights. The final aggregated RNs using RADWA operator ($Q = 3$) are presented in Table 7.

Thus, the ranking order is: $A_2 \succ A_3 \succ A_5 \succ A_4 \succ A_1$ where '$\succ$' means "better than" which means that 'DSDM' emerges as the best alternative. While approaches like Scrum, XP, Kanban, and Crystal mostly concentrate on particular facets of agile devel-

Table 6
Criteria weights.

Criteria	Weights	Criteria	Weights	Criteria	Weights
$E1$	0.462355	$E6$	0.028809	$E11$	0.022133
$E2$	0.013384	$E7$	0.016789	$E12$	0.017380
$E3$	0.025823	$E8$	0.016132	$E13$	0.042625
$E4$	0.019344	$E9$	0.274698	$E14$	0.013846
$E5$	0.020275	$E10$	0.026401		

Table 7
Final aggregated RNs.

Alternative	Corresponding RN	Aggregated RN using *RCDWA* operator	Mid value
$A1$	$[\underline{D}^{(1)}, \bar{D}^{(1)}]$	[0.386783,0.604107]	0.495445
$A2$	$[\underline{D}^{(2)}, \bar{D}^{(2)}]$	[0.439817, 0.63447]	0.537144
$A3$	$[\underline{D}^{(3)}, \bar{D}^{(3)}]$	[0.416596, 0.610139]	0.513367
$A4$	$[\underline{D}^{(4)}, \bar{D}^{(4)}]$	[0.383688, 0.611543]	0.497615
$A5$	$[\underline{D}^{(5)}, \bar{D}^{(5)}]$	[0.400525, 0.619055]	0.50979

opment, DSDM is frequently regarded as superior in maximum situations since (i) it has defined roles and responsibilities, such as project governance structure, clear decision-making authority, and formal documentation standards; (ii) it fixes time, cost, and quality and modifies scope instead; and (iii) it places a strong emphasis on business value and stakeholder involvement.

6. Discussions

6.1. *Sensitivity Analysis*

A sensitivity analysis was performed to study the impact of the parameter 'Q' on the ranking order, using 14 values ranging from 2 to 10. This broad range of parameter 'Q' provided a comprehensive view of the model. The score values (final) of the considered options are depicted in Fig. 4. From the figure, it is evident that the final priority scores of $A2$, $A3$, $A4$, and $A5$ increase with higher values of 'Q', while those of $A1$ remain relatively stable across different values of 'Q'. It has been observed that $A2$ consistently emerges as the top alternative in each scenario. Spearman's rank correlation coefficient (SRCC) values (Saha *et al.*, 2024) corresponding to these scenarios are calculated and summarized in Table 8, with a mean SRCC of 0.85 indicating a "very high correlation" (Saha *et al.*, 2024). Thus, the priority order of options determined using this methodology is considered reliable.

6.2. *Sensitivity Analysis for Criteria Weights*

A sensitivity analysis was conducted to study the effect of varying criteria weights on priority values and alternative rankings. Eight scenarios were generated by adjusting the

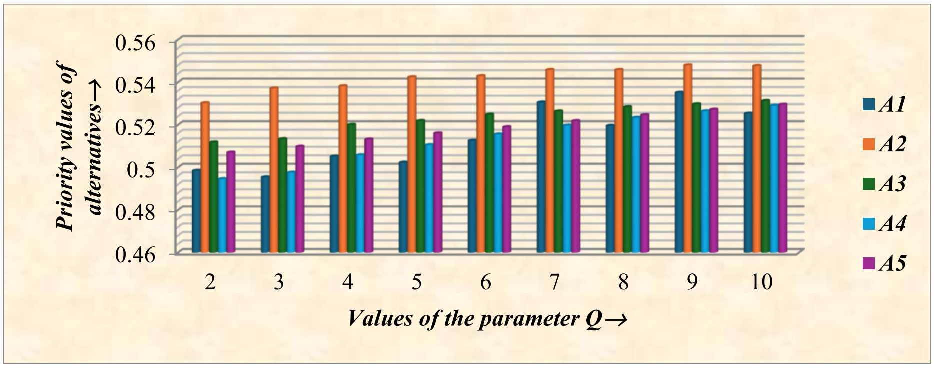

Fig. 4. Sensitivity analysis of the parameter 'Q'.

Table 8
Ranking positions with SRCC values.

Q	*A1*	*A2*	*A3*	*A4*	*A5*	*SRCC value*
2	4	1	2	5	3	0.9
3	5	1	2	4	3	1
4	5	1	2	4	3	1
5	5	1	2	4	3	1
6	5	1	2	4	3	1
7	2	1	3	5	4	0.4
8	5	1	2	4	3	1
9	2	1	3	5	4	0.4
10	5	1	2	4	3	1

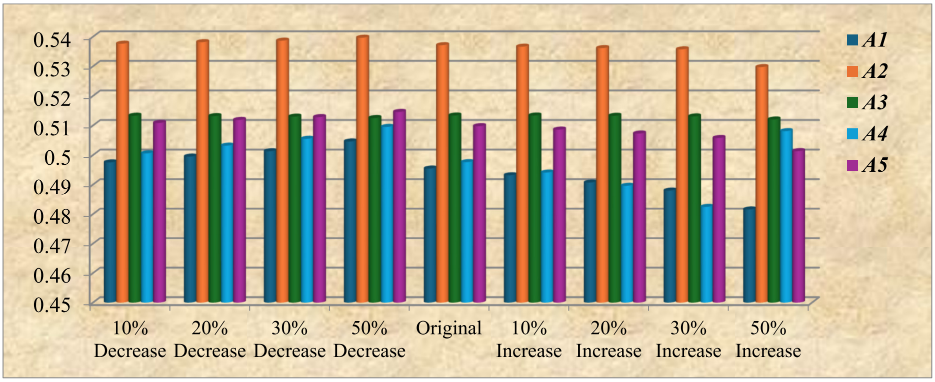

Fig. 5. Sensitivity analysis of criteria weights.

weight of the most significant criterion (E1) by ±10%, ±20%, ±30%, and ±50%, with remaining weight distributed equally among other criteria. Results in Fig. 5 show A2 as the top-ranked alternative in all scenarios. Reducing E1 weight increases priority values

Table 9
SRCC values for various weights sets of criteria.

Alternative	10% Decrease	20% Decrease	30% Decrease	50% Decrease	10% Increase	20% Increase	30% Increase	50% Increase
$A1$	5	5	4	5	5	4	4	5
$A2$	1	1	1	1	1	1	1	1
$A3$	2	2	2	3	2	2	2	2
$A4$	4	4	5	4	4	5	5	3
$A5$	3	3	3	2	3	3	3	4
SRCC value	1	1	0.9	0.9	1	0.9	0.9	0.9

of all alternatives except A3, while increasing E1 weight decreases priority values except for A4. Table 9 shows SRCC values, with an average of 0.9375, indicating very high correlation and model stability.

6.3. *Comparative Analysis*

This subsection compares the proposed approach with existing models, including rough-CoCoSo (Yazdani *et al.*, 2020), rough-TOPSIS (Alshamrani and Hezam, 2023), and rough-MARCOS (Vojinović *et al.*, 2021), applied to the same case study. Figure 6 presents the priority levels of alternatives obtained using the proposed approach together with all existing methods. Results indicate that all existing methods, namely rough-CoCoSo (Yazdani *et al.*, 2020), rough-TOPSIS (Alshamrani and Hezam, 2023), and rough-MARCOS (Vojinović *et al.*, 2021), produce the same priority order of $A_2 \succ A_3 \succ A_5 \succ A_4 \succ A_1$. The main advantages of the proposed model are explained below:

(i) The proposed model overcomes the limitations of conventional approaches that rely on generic interval limits by defining distinct interval boundaries for rating of each expert. These boundaries are determined objectively, reflecting the inherent uncertainty and imprecision in the data rather than subjective judgment.

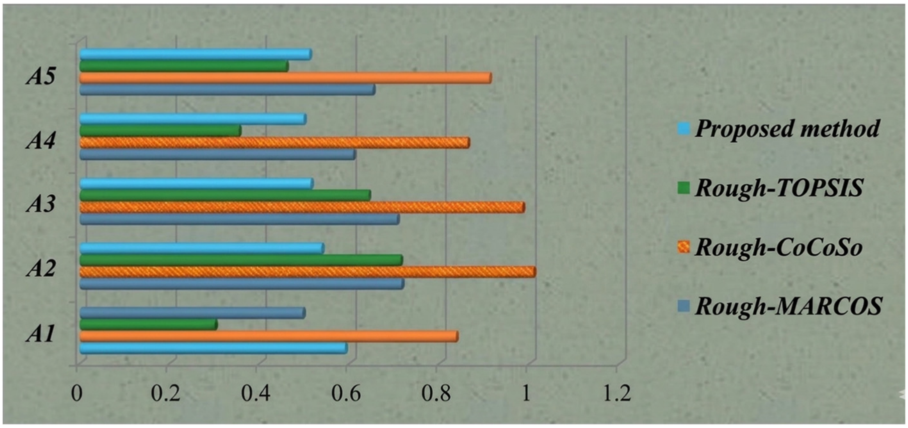

Fig. 6. Comparative analysis.

(ii) In the existing literature, Dombi operator was merged only with Hamy mean operator (Sinani *et al.*, 2020) and Archimedean operator (Görçün *et al.*, 2025) under rough set context. To make the aggregation process more logical, the suggested model combines Copula and Dombi operators. The proposed RCD operators have the following capabilities: (i) they can link several marginal distributions; (ii) they can display the correlation between variables; (iii) they cannot lose information while aggregating; and (iv) they can produce greater flexibility with the parameter 'Q'.

(iii) Prior approaches (Yazdani *et al.*, 2020; Alshamrani and Hezam, 2023; Vojinović *et al.*, 2021) did not employ optimization models, which may result in information loss during attribute weight computation. Therefore, these techniques are unable to quantify the degree of uncertainty in the data (Yazdani *et al.*, 2020; Alshamrani and Hezam, 2023; Vojinović *et al.*, 2021). In order to solve this, criteria weights were determined using an optimization model based on cross-entropy. This paradigm supports more efficient group decision-making by quantifying unclear information and determining the importance of each component.

6.4. *Validity Test*

The following test criteria (TC) (Wang and Triantaphyllou, 2008) are used validate of the developed framework:

- **TC-1**: A framework is considered effective if the top-ranked alternative remains unchanged when a non-optimal option is replaced by a worse one.
- **TC-2**: An effective framework must satisfy the property of transitivity.
- **TC-3:** The framework is valid if splitting the problem into sub-problems and applying it to each results in the same ranking of alternatives as in the original problem. Upon implementation of these criteria on the developed model, we have the following results.

By interchanging the initial ratings of $A_3\&A_4$and then executing the steps of the proposed algorithm, we obtain the ranking order $A_2 \succ A_4 \succ A_5 \succ A_3 \succ A_1$ according to which A_2 remains the best choice. Consequently, TC-1 is validated. Next, suppose that the actual case study is divided into three sub-problems by considering three sub-groups: $\{A_1, A_3, A_4\}, \{A_2, A_4, A_5\}, \{A_1, A_2, A_3\}$. Next, the developed model is applied to each of the sub-problems. Then the ranking orders obtained are: $A_3 \succ A_4 \succ A_1$, $A_2 \succ A_5 \succ A_4$, $A_2 \succ A_3 \succ A_1$ and hence the overall ranking order is: $A_2 \succ A_3 \succ A_5 \succ A_4 \succ A_1$ validating TC-2 and TC-3.

6.5. *Managerial Implications*

Agile development has become a cornerstone of modern software engineering, driving a transformative shift in how projects are managed and executed. The widespread adoption of agile methods has led to significant improvements in flexibility, customer satisfaction, and project delivery times (Tasneem *et al.*, 2025; Oyetunji *et al.*, 2025; Khatib *et al.*, 2025). However, the complexity and variety of available agile methods present a challenge for organizations in selecting the most appropriate approach for their specific needs.

This study addresses this challenge by providing a structured approach to the selection of agile methods, offering valuable insights that can be directly applied by practitioners in the field. One of the key contributions of this study is the identification of critical features that influence the selection of agile methods. These features form a comprehensive knowledge base that can guide practitioners in making informed decisions when choosing an agile approach. By aligning the selected method with the specific characteristics and requirements of a project, organizations can maximize the benefits derived from agile practices. This tailored approach ensures that the chosen method is not only theoretically sound but also practically effective, leading to better project outcomes and higher satisfaction among stakeholders. The study highlights the importance of continuous improvement in agile project management. By understanding the factors that drive the success of agile methods, organizations can develop strategies to enhance their project management capabilities. By equipping team members with the necessary skills and knowledge, organizations can improve overall competence levels, thereby increasing the likelihood of successful project execution. The insights gained from this study can also help organizations in making more strategic decisions when hiring agile software engineers. By focusing on the identified variables, companies can select candidates with specialized expertise in the targeted agile method, reducing the risk of project failures due to misalignment between team capabilities and project requirements. By modelling uncertainty and understanding the correlations between various factors, managers can anticipate potential challenges and proactively address them. This proactive approach to risk management leads to more resilient project plans, reducing the likelihood of disruptions and ensuring that projects stay on track. Organizations can use the insights gained to compare the performance of different agile methods across various projects, identifying areas for refinement and optimization. This ongoing process of evaluation and adjustment enables organizations to stay at the forefront of agile development, continuously improving their practices to meet evolving demands and expectations.

7. Conclusions

In today's fast-paced and highly competitive economy, software development organizations face substantial challenges in maintaining stability and ensuring consistent business investment in IT projects. Over the decades, software development organization have been focusing on agile software development for effectively managing the dynamic behaviour of customer requirements to deliver quality products. There are various agile methods that have been developed to implement agile principles including Scrum, XP, Crystal, etc. The study aims to investigate the criteria that could be considered as features for adopting the suitable agile methodology to meet the specific needs of projects, thereby aiding software practitioners in making informed decisions. Five agile methods including Scrum, XP, Kanban, Crystal, and DSDM have been evaluated based on existing literature. A total of 14 features have been identified for evaluating the capabilities of these agile methods. In order to generate the priority order of these agile methods, a group decision-making methodology has been proposed where concept of rough numbers was utilized for merging the primary assessment results, an optimization model was developed for generating weights of the attributes and RCD AOs were used for final aggregation. Results show that DSDM, scrum and XP are the top three choices in order. The only drawback of the proposed RCDWA and RCDWG operators is that they don't consider the relationship (if exist) among any criteria. This problem can be resolved by merging the proposed operators with Hamy mean, Bonferroni mean and Maclaurin Symmetric mean.

Valuable insights are provided to agile practitioners through the results of this study. The identified features for selecting agile methods establish a knowledge base that enables practitioners to effectively choose agile methodologies based on project nature, thereby maximizing the benefits derived from specific agile approaches. Organizations can use these features to enhance their agile project management capabilities by customizing training programs that address skill gaps and elevate team expertise.

Supplementary Material

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